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Abstract

Two approaches have been taken in the literature to evaluate the relative importance of news shocks as a source of business cycle volatility. The first is an empirical approach that performs a structural vector autoregression to assess the relative importance of news shocks, while the second is a structural-model-based approach. The first approach suggests that anticipated technology shocks are an important source of business cycle volatility; the second finds anticipated technology shocks are incapable of generating any business cycle volatility. This paper challenges the latter conclusion by presenting a structural news shock model adapted to reproduce the cointegrating relationship between total factor productivity and the relative price of investment. With cointegrated neutral and investment-specific technology, anticipated shocks to the common stochastic trend explain approximately 22%, 32%, 34% and 20% of the variance of output, investment, hours and consumption in the United States, respectively, reconciling the discrepancy between theory and data.

Bank topics: Business fluctuations and cycles; Productivity
JEL codes: E32

Résumé

Dans la littérature, deux approches méthodologiques ont servi à évaluer l'importance relative des chocs induits par de nouvelles informations sur le futur comme source de volatilité du cycle économique. La première est une approche empirique qui fait appel à une spécification en termes de vecteur autorégressif structurel afin d'évaluer l'importance relative de pareils chocs, tandis que la seconde se fonde sur un modèle structurel d'équilibre général. Les résultats de la première approche portent à croire que les chocs technologiques attendus constituent une source importante de volatilité du cycle économique, alors que selon la deuxième, les chocs technologiques attendus ne sont pas susceptibles de provoquer une quelconque volatilité du cycle économique. La présente étude remet en question cette dernière conclusion en exposant un modèle structurel d'équilibre général comprenant des chocs induits par de nouvelles informations, adapté de façon à reproduire la relation de cointégration entre la productivité totale des facteurs et le prix relatif de l'investissement. Si l'on tient compte de la cointégration des technologies neutres et des technologies spécifiques à l'investissement, les chocs attendus en déviation par rapport à la tendance stochastique commune expliquent respectivement environ 22, 32, 34 et 20 % de la variance de la production, de l'investissement, des heures et de la consommation aux États-Unis, ce qui concilie les prédictions de la théorie avec les données.

Sujets : Cycles et fluctuations économiques; Productivité
Code JEL : E32

Non-Technical Summary

Motivation and Question

What drives business cycles? In the literature, two types of technology have been identified as potential sources of business cycle volatility. These include neutral technologies, which improve productivity economy-wide, and investment-specific technology, which improves productivity exclusively in the investment sector. The literature has typically assumed that these two technologies behave completely independently of each other. There are, however, plenty of reasons to believe that these technologies might in fact move together over time. These reasons include, but are not limited to, technological spillovers as innovations in one sector are reapplied in another sector. Does the co-movement of these two technologies impact how we understand the relative importance of anticipated changes in technology for the current economy?

Methodology

This paper adapts a standard business cycle model to allow households and firms to anticipate and respond to future changes in both technological and non-technological disturbances. The two technologies considered will follow a common time-varying trend, replicating what is observed in the US data. The model parameters are chosen using Bayesian estimation, a method that allows flexibility in the estimation process while also limiting estimates to a reasonable range of parameter values. The relative importance of innovations to the common trend are assessed by their contribution to the variance of key aggregates through a variance decomposition. These results are then contrasted with an analogous model where these two technologies move independently.

Key Contributions

This paper finds that anticipated changes to the common trend shared between neutral and investment-specific technologies explain approximately 20–35 per cent of the business cycle volatility in output, consumption, investment and hours worked. These results contrast with the current stance in the news-cycle literature, where those who have taken a structural-model-based approach have concluded that anticipated shifts in technology are incapable of generating any business cycle volatility. Allowing these two technologies to move together over time implies that anticipated increases in the growth rate of neutral technology generates a similar increase in investment-specific technology. This results in a strong increase in both hours and investment prior to the innovation being realized. This overcomes one of the shortcomings identified in the news-cycle literature, which has produced a variety of mechanisms to generate a positive response in these variables to an anticipated increase in productivity.

Future Research

The paper introduced here assumes that there is a common time-varying trend between neutral and investment-specific technologies. There could exist, however, a multitude of common time-varying trends between other sources of business cycle volatility. Any co-movement between two or more of these variables would undoubtedly challenge both these findings as well as those concluded in the literature. Future research should explore the impact this would have in the news-cycle literature.

1 Introduction

Can news about the future drive the business cycle? Empirical evidence from structural vector autoregressions (SVARs) shows that anticipated technology shocks, either neutral or investment-specific, are a non-trivial source of business cycle volatility (Beaudry and Portier (2006), Barsky and Sims (2011) and Ben Zeev and Khan (2015)). This finding stands in contrast with contributions that assess the relative importance of anticipated shocks by estimating business cycle models. Examples include Schmitt-Grohé and Uribe (2012), Fujiwara et al. (2011) and Khan and Tsoukalas (2012), who all conclude that anticipated technology shocks are incapable of generating any business cycle volatility.

The vast majority of the business cycle research, including those listed above, have assumed that both neutral and investment-specific technologies move independently over time. There are, however, plenty of reasons to believe that these two technologies might in fact move together over time, both in the short run, through technological spillovers, and in the long run, through a common trend component. This paper reassesses the relative importance of anticipated technology shocks in a standard news shock model where neutral and investment-specific technologies follow a common stochastic trend, as found by Schmitt-Grohé and Uribe (2011) for the United States.

The news shock model used here will be based on the model proposed by Schmitt-Grohé and Uribe (2012), including the use of their data for ease of comparability. This model will include Jaimovich and Rebelo's (2009) preferences with habit persistence in consumption, along with variable capital utilization rates and investment adjustment costs. Each of these components has been identified in the business cycle literature as an essential element required to produce a positive response in output, hours and investment in response to a positive anticipated neutral technology shock. Most notably, this research finds that when a vector error correction model (VECM) is incorporated into a standard news shock model, news shocks to the common stochastic trend matter, and explain a non-trivial proportion of output, consumption, investment and hours growth volatility. When both total factor productivity (TFP) and investment-specific technology (IST) follow a common stochastic trend, a positive anticipated shock to non-stationary TFP is accompanied by an anticipated boost in IST. As a result, there is an anticipated drop in the relative price of investment (RPI) at the very moment an anticipated TFP shock is realized. Knowing that the RPI will decline with a rise in TFP causes capital utilization to increase in the interim, and remain high even after the shock is realized. During the interim, the high capital utilization rates encourage hours to increase leading to an increase in output, allowing both consumption and investment to rise simultaneously.

We find that when TFP and IST are cointegrated, anticipated technology shocks regain their relevance in generating business cycle volatility. In fact, when we allow for cointegration between these two technologies, the shares of output, investment, consumption and hours variance explained by these shocks are greater than the sum of variance explained by TFP and IST without cointegration. After performing a Bayesian estimation, a variance decomposition is performed to assess the relative importance of anticipated shocks to the common stochastic trend. With cointegrated technologies, anticipated shocks to the common stochastic trend explain approximately 22%, 32%, 34% and 20% of the variance of the growth rates of output, investment, hours and consumption, respectively. These results suggest that anticipated technological shocks play a significantly larger role in business cycles when TFP and RPI are cointegrated than when they follow independent processes, as is the case for Schmitt-Grohé and Uribe (2012) and Khan and Tsoukalas (2012). Thus, the relative importance of these two shocks can be fully appreciated only when they are allowed to move together over the business cycle.

Our analysis shows that allowing both neutral and investment-specific technologies to move together over time, both in the short run, and in the long run, brings business cycle models in line with the empirical evidence from SVARs, leading to a revival in the importance of anticipated technology shocks. The response of both hours and investment to an anticipated technology shock is positive, and is enhanced when both neutral and investment-specific technologies move together over time. Allowing these technologies to follow a common stochastic trend therefore provides an additional mechanism that can be used to coax a positive response in hours and investment to an anticipated increase in neutral technology. As a measure of fit, the estimated log data density for the model proposed (-4715.43) is higher than the analogous measure (-5423.98) for the model where technologies move independently. In addition, when these technologies move independently, both anticipated wage markup shocks and anticipated and unanticipated marginal efficiency of investment (MEI) shocks are found to explain a majority of the volatility in hours and investment growth, respectively. This is corroborated by Schmitt Grohé and Uribe (2012), who propose a similar model to our benchmark without cointegrated technologies. In contrast, when neutral and investment-specific technologies are allowed to move together over time, the ability of wage markup and MEI shocks to explain volatility in these variables declines by two-thirds. Therefore, allowing neutral and investment-specific technologies to follow a common stochastic trend has important implications for our understanding of the importance of anticipated technology shocks within a structural model framework.

The remainder of the paper will be organized as follows. Section 2 outlines the model used to assess the relative importance of anticipated technology shocks. Section 3 outlines the Bayesian estimation process used to estimate the parameter values. Section 4 outlines the key results. Section 5 compares these results to the current stance in news shock literature. Section 6 concludes.

2 Model

The benchmark dynamic stochastic general-equilibrium (DSGE) model used throughout this paper incorporates both a cointegrating relationship between neutral and investment-specific technologies and a mechanism that allows households to anticipate and respond to future changes in fundamentals. Households in this model purchase consumption and investment goods from their respective producers, and are the sole providers of labour and capital services used by the firm. There will also be a variety of both anticipated and unanticipated shocks. The menu of shocks included will consist of technology shocks (both TFP and IST as discussed above) as well as a series of non-technological shocks, such as wage markup shocks, preference shocks and changes in the MEI. Each of these shocks listed is subject to both anticipated and unanticipated innovations. The growth rates of both TFP and IST will be governed by a VECM. Our benchmark model is based on the results found by Schmitt-Grohé and Uribe (2011) and hence shares many similarities with their work. Each of the components listed above is now discussed in turn.

2.1 Households

The economy is populated with a large number of identical and infinitely-lived households, which each period consume C_t consumption goods and provide H_t units of labour, with a lifetime utility given by

$$E_0 \sum_{t=0}^{\infty} \beta^t b_t \frac{[C_t - \chi C_{t-1} - \phi {H_t}^{\theta} X_t]^{1-\sigma}}{1-\sigma} \tag{1}$$

$$X_t = (C_t - \chi C_{t-1})^{\eta} X_{t-1}^{1-\eta}, \tag{2}$$

where $\quad 0 \leq \eta \leq 1, 0 < \beta < 1, \phi > 0, \theta > 1 \text{ and } \sigma > 0.$

Here β is the households' subjective discount factor, σ determines the curvature of the household utility, θ determines the level of labour supply elasticity and χ is the habit-persistence parameter for consumption. We include a preference shock b_t, which captures changes in household preferences over time. These preferences were first developed by Jaimovich and Rebelo (2009). The remaining parameter η and the latent variable X_t are the distinctive elements that make up Jaimovich and Rebelo preferences. Parameter η (bound between 0 and 1) governs the sensitivity of a household's labour supply decision to changes in wealth. When the value of η approaches zero, we have preferences similar to those used by Greenwood, Hercowitz and Huffman (1988) where the wealth effect on labour supply has been removed. When η is close to 1 we have King, Plosser and Rebelo (1988) preferences, which exhibit a strong wealth effect on labour supply. These preferences have become common in news shock research due to their ability to generate an increase in labour supply in response to positive news of future productivity.

Households maximize their lifetime utility subject to their budget constraint

$$C_t + P_t I_t^g = \frac{W_t}{\mu_t^W} H_t + R_t U_t K_t + \Phi_t + \Pi_t, \tag{3}$$

where W_t and R_t are the wage and rental rates paid by the firm for H_t hours worked and $U_t K_t$ capital services provided, respectively. A portion $1/\mu^w \leq 1$ of the households' wages are taken from households and then rebated back to households through the lump sum Φ_t. Since households own the goods-producing firms, profits earned by these producers, Π_t, are accrued by the households. With this income, a representative household can either buy consumption goods C_t or purchase investment goods I_t, which are both measured in units of consumption goods, with P_t denoting the RPI.

Households accumulate capital according to the following capital-accumulation equation:

$$K_{t+1} = (1 - \delta(U_t))K_t + \upsilon_t I_t^g (1 - S(\frac{I_t^g}{I_{t-1}^g})), \tag{4}$$

where K_t is the households' stock of capital, and U_t is the capital utilization rate. Included in the capital-accumulation equation is also an investment-adjustment cost function $S()$:

$$S(x) = \frac{\kappa}{2}(x - \mu^{i^g})^2, \tag{5}$$

where $\kappa \geq 0$, and $\bar{\mu}^{i^g}$ is the growth rate of real investment along a balanced growth path. Note that in the steady state, $S = S' = 0$, and $S'' > 0$. We allow the rate of capital depreciation $\delta(U_t)$ to increase with the rate of capital utilization, assuming the following convex function:

$$\delta(U_t) = \delta_0 + \delta_1(U_t - 1) + \frac{\delta_2}{2}(U_t - 1)^2 \tag{6}$$

with δ_0, δ_1 and $\delta_2 > 0$. Last of all, υ_t indicates the marginal efficiency of investment at period t. These MEI shocks, first suggested by Justiniano, Primiceri and Tambalotti (2011), are introduced by conceptually dividing the process of creating capital into two stages of production. The first phase of production involves transforming consumption goods into investment goods, which is altered by IST. When production technology is linear, IST is exactly identified by the RPI. However, these investment goods, fresh off the production line, remain idle until matched with a firm. Shocks that affect this latter conversion are referred to as our MEI shocks. As an example, a firm's ability to access new capital can be influenced by its ability to access the credit required to purchase new investment goods.

2.2 Firm

The consumption good in this economy is produced by an infinite number of identical and perfectly competitive firms with unit mass according to the following production function

$$Y_t = Z_t(U_t K_t)^\alpha (X_t^Z H_t)^{1-\alpha}, \tag{7}$$

where α is between 0 and 1, implying constant returns-to-scale; H_t and $U_t K_t$ denote labour and capital services used by the firm. TFP consists of a stationary component Z_t with only a transitory effect on TFP, and a non-stationary trend component X_t^Z. Given equation (7), TFP will be measured as

$$TFP_t = Z_t(X_t^Z)^{1-\alpha}. \tag{8}$$

I_t consumption goods can be converted into investment goods according to the following production function:

$$I_t^g = A_t X_t^A I_t, \tag{9}$$

where I_t^g is the quantity of investment goods produced, and $A_t X_t^A$ represents the level of IST. Shocks to IST can be divided into two components, a stationary component A_t and a non-stationary component X_t^A.[1] Since investment production is linear, the relative price of the investment good in period t P_t is equal to

$$P_t = \frac{1}{A_t X_t^A}, \tag{10}$$

where IST is measured as

$$IST_t = A_t X_t^A. \tag{11}$$

2.3 Exogenous Shock Process

In total, seven exogenous shocks processes have been incorporated into this model. There are five stationary shocks: two technology shocks, Z_t, and A_t; a shock to household preferences b_t; wage markup shock μ_t^w; and MEI shocks v_t. Each of these exogenous processes is subject to both anticipated and unanticipated shocks. These shocks $x_t \in \{Z, A, b, \mu_w, v_t\}$ evolve according to the following law of motion:

$$ln(\frac{x_t}{\bar{\mu^x}}) = \rho_x ln(x_{t-1}) + \epsilon_t^{x0} + \epsilon_{t-4}^{x4} + \epsilon_{t-8}^{x8}, \tag{12}$$

where $0 \leq \rho < 1$ is the level of persistence, and e_t^{x0} is an unanticipated shock to x_t. Two news shocks, denoted ϵ_{t-4}^{x4} and ϵ_{t-8}^{x8}, are anticipated four and eight quarters in advance. The timing of our anticipated shocks follows the timing adopted by both Schmitt-Grohé and Uribe (2012) and Khan and Tsoukalas (2012). $\bar{\mu^x}$ is the steady state value of variable x_t.

[1] By assuming investment production of $I_t^g = A_t X_t^A I_t^\zeta$, Schmitt-Grohé and Uribe (2011) estimate the curvature of investment production, where they conclude that ζ equals 1 and investment production is linear.

2.3.1 Common Trend Component

As shown by Schmitt-Grohé and Uribe (2012), there is strong empirical evidence that the logarithms of TFP and the RPI are I(1) cointegrated in the United States. Thus there exists a scalar Γ such that

$$TFP_t^{\Gamma} P_t \tag{13}$$

is a stationary I(0) process. With the definition for the P_t in equation (10) and TFP_t in equation (8) we can rewrite equation (13) as

$$\frac{Z_t X_t^{Z(1-\alpha)}}{A_t X_t^A}, \tag{14}$$

which will also be I(0) stationary. With TFP and the RPI cointegrated, then it must also hold that X_t^Z and X_t^A are also cointegrated.

Letting μ_t^Z equal the growth rate of X^Z and μ_t^A the growth rate of X^A, we have

$$\mu_t^Z = \frac{X_t^Z}{X_{t-1}^Z} \quad and \quad \mu_t^A = \frac{X_t^A}{X_{t-1}^A}. \tag{15}$$

The growth rates μ_t^Z and μ_t^A have the following law of motion

$$\begin{bmatrix} ln(\mu_t^Z/\bar{\mu}^Z) \\ ln(\mu_t^A/\bar{\mu}^A) \end{bmatrix} = \begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix} \begin{bmatrix} ln(\mu_{t-1}^Z/\bar{\mu}^Z) \\ ln(\mu_{t-1}^A/\bar{\mu}^A) \end{bmatrix} + \begin{bmatrix} \kappa_1 \\ \kappa_2 \end{bmatrix} x_{t-1}^{co} + \begin{bmatrix} \sigma_{\mu^Z}^0 \epsilon_{\mu^Z,t}^0 \\ \sigma_{\mu^A}^0 \epsilon_{\mu^A,t}^0 \end{bmatrix}$$

$$+ \begin{bmatrix} \sigma_{\mu^Z}^4 \epsilon_{\mu^Z,t-4}^4 \\ \sigma_{\mu^A}^4 \epsilon_{\mu^A,t-4}^4 \end{bmatrix} + \begin{bmatrix} \sigma_{\mu^Z}^8 \epsilon_{\mu^Z,t-8}^8 \\ \sigma_{\mu^A}^8 \epsilon_{\mu^A,t-8}^8 \end{bmatrix}, \tag{16}$$

with the error correction term x_t^{co} calculated as

$$x_t^{co} = \psi ln(X_t^Z) - ln(X_t^A). \tag{17}$$

Here $\bar{\mu}^Z$ and $\bar{\mu}^A$ are the growth rates of TFP and IST along a balanced growth path. $0 < \rho_{11} < 1$ and $0 < \rho_{22} < 1$ determine the level of persistence for growth rates of TFP and IST, respectively, while ρ_{12} and ρ_{21} determine the spillover between these two growth rates. Coefficients κ_1 and

κ_2 determine the impact that changes in the common trend have on the growth rates μ_z and μ_a, respectively. Their value will be discussed in our estimation process. $\epsilon^0_{\mu^z t}$ and $\epsilon^0_{\mu^a t}$ are unanticipated shocks to μ^z_t and μ^a_t, respectively, and $\epsilon^k_{\mu^i t}$ are anticipated shocks to μ^i_t for $i = \{A, Z\}$ observed k periods in advance. The VECM setup in this paper builds on the one presented by Schmitt-Grohé and Uribe (2011), who do not include anticipated shocks.

With both TFP and IST following a common stochastic trend, many of the economic aggregates are non-stationary. The trend in output, consumption, nominal investment and the wage and rental rates equals

$$X^Y_t = X^Z_t (X^A_t)^{\frac{\alpha}{1-\alpha}}, \tag{18}$$

whereas the trend of the capital stock, and the level of real investment, is

$$X^I_t = X^K_t = X^Y_t X^A_t. \tag{19}$$

There is no growth in hours and utilization. The later is normalized to 1 in steady state. For the remainder of the paper we work with the detrended version of our model, where all variables are measured as deviations from the balanced growth path. Since we include multiple stochastic trends, the evolution of a variable is a combination of the variable's deviation from its balanced growth path as well as the evolution of the stochastic trends X^Z_t and X^A_t.

3 Model Estimation

3.1 Parameterization

As mentioned in the introduction, a majority of the parameter values used in the benchmark model are obtained by means of Bayesian estimation, while we set some of the better understood parameters ourselves. The list of the estimated parameters includes the preference parameters θ, h^{ss}, η and χ, where θ determines the elasticity of labour supply, h^{ss} determines the level of hours worked in the steady state, η determines the level of inter-temporal substitution in consumption, and χ is the habit-persistence parameter for consumption. Parameters governing the accumulation of capital, including δ_2, which determines how capital utilization impacts the depreciation of capital, and κ_k, which is the investment adjustment cost parameter, are also estimated. In addition to these parameters, the variance and persistence parameters governing the five stationary shocks are also estimated. These include parameters ρ_z, ρ_a, ρ_v, ρ_b and ρ_{μ^w}, which govern the persistence of the TFP, IST, MEI, preference and the wage markup shock, respectively. Furthermore, we estimate the relative size of both unanticipated and anticipated shocks to these five stationary series, which are listed in Table 2. For the non-stationary shock process we estimate the persistence parameters ρ_{11} and ρ_{22}, the spillover parameters ρ_{12} and ρ_{21}, the cointegration coefficients κ_1 and κ_2 and the variance of the innovations, both anticipated and unanticipated. Aside from the parameters mentioned above, other parameters are calibrated directly. These include δ_0, δ_1, u^{ss}, β, α, ϕ, σ, $\bar{\mu^w}$, $\bar{\mu_Y}$ and $\bar{\mu_A}$.

Similar to Schmitt-Grohé and Uribe (2011), we normalize the steady-state utilization rate to 1 and set the parameter δ_0 such that the quarterly depreciation rate in steady state is equal to 0.025. In addition, we set the household discount rate β equal to 0.985, and a value of 1 for the risk-aversion parameter σ. α is set to 0.33 such that labour's share of output is equal to 0.67. The quarterly growth rate of output is estimated using seasonally adjusted non-farm output from the first quarter of 1949 to the fourth quarter of 2006, available through the US Bureau of Labor Statistics. With this information we calculate a quarterly growth rate of output $\bar{\mu^y}$ of 1.0049. The quality-adjusted RPI is calculated by Fisher (2006), who utilizes the time series created by Gordon (1989) and Cummins and Violante (2002), known as the Gordon-Cummins-Violante equipment price deflator, along with US Bureau of Labor Statistics National Income and Product Accounts Table estimates for the consumption goods deflator to derive quarterly time series data on the RPI. With this information, the estimated growth in the RPI is set equal to 0.9957, which implies a 0.43% drop in the price of investment each quarter along a balanced growth path. With constant returns to scale in investment production, this implies estimated value $\bar{\mu}^A$ equal to 1.0043. With our estimates for $\bar{\mu}^A$ and $\bar{\mu}^Y$ we set the value of $\bar{\mu}^Z$ such that the growth of output matches the data along a balanced growth path. Given the model setup, and the values above for β, $\bar{\mu}^Y$ and $\bar{\mu}^A$, we set

$$\delta_1 = \frac{1}{\beta}(\bar{\mu}^Y)^\sigma \bar{\mu}^A + \delta_0 - 1 \tag{20}$$

in order for the first-order conditions for both capital and utilization to be satisfied.

Given our estimates for $\bar{\mu}_A$, and the implied value for $\bar{\mu}^z$, we set ψ equal to $ln(\bar{\mu}^A)/ln(\bar{\mu}^Z)$ such that the common trend component of IST and TFP disappears in the steady state. The steady-state wage markup rate $\bar{\mu}^W$ is set equal to 1.1, which is the value used by Schmitt-Grohé and Uribe (2011).

The time-series data used in our Bayesian estimation will include the log difference in gross domestic product, consumption and real investment, where each variable just mentioned is divided by the US population age 16 and over. We also include the log difference of TFP and the RPI as well as the log difference in hours in our list of observables. Growth in output, investment, consumption and hours worked is included in the set of observables to capture the general movement of the economy. The growth rate for the RPI is included in the set of observables so as to pin down plausible movements in IST. As demonstrated by Justiniano, Primiceri and Tambalotti (2011), the relative importance of IST in generating business cycle volatility is heavily dependent on whether growth rates in the RPI are included in the set of observables. When the growth rate of the RPI is included, the Bayesian estimation pins down movements of IST to the inverse of the RPI. In fact, when their model is re-estimated with the RPI included in the set of observables, IST loses its ability to explain business cycle dynamics. As done by Schmitt-Grohé and Uribe (2012), we include the growth rate of TFP adjusted for capital utilization in the set of observables, which allows the estimation process to guide our estimates of the cointegration coefficients κ_1 and κ_2.

Each of these time series is observed quarterly. Altogether we include six observables in our Bayesian estimation. This data set Y_T includes

$$Y_T = \begin{bmatrix} \Delta ln(Y_t) \\ \Delta ln(C_t) \\ \Delta ln(I_t) \\ \Delta ln(P_t) \\ \Delta ln(h_t) \\ \Delta ln(TFP_t) \end{bmatrix} + \begin{bmatrix} \sigma_Y^{ME} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}. \tag{21}$$

Bayesian estimation requires prior distributions for the estimated parameters. Many of the prior distributions used are those used by Khan and Tsoukalas (2012), whose model structure is similar to that of Schmitt-Grohé and Uribe (2012). A comprehensive list of the prior distributions used in our benchmark estimation are outlined in Table 2. The persistence parameters for the five stationary shock processes ρ_z, ρ_a, ρ_v, ρ_b and ρ_{μ^w}, are given a beta prior distribution, with a mean of 0.6 and a variance of 0.2. As for the parameters governing the VECM model which determines the growth rates for the two technology shocks (i.e., ρ_{11}, ρ_{22}, ρ_{12}, ρ_{21}, κ_1, κ_2), we assume normal prior distributions with a mean set equal to the maximum likelihood estimates produced by Schmitt-Grohé and Uribe (2011) and a standard deviation equal to the standard error of their estimates. We set the standard deviation of the unanticipated and anticipated stationary TFP shocks such that in total, the sum of the standard deviations of these shocks adds up to a value similar to that estimated by Kydland and Prescott (1982). Given this goal, we choose an inverse gamma distribution with a mean of 0.5 and a variance of 2 for the standard deviation of an unanticipated shock to stationary TFP. For anticipated disturbances to stationary TFP we likewise assume an inverse-gamma distribution with a mean of 0.1 and a variance of 2. By choosing these values, we assume that unanticipated shocks account for over 90% of the volatility of TFP. For transparency, we use the same distributions described above for both anticipated and unanticipated shocks for the standard deviation of all other shock processes used in our Bayesian estimation.

For the preferences parameter θ, we assume a gamma distribution with a mean of 3 and a variance of 0.75. For the habit-persistence parameter χ we assume a beta distribution with mean of 0.5 and a standard deviation of 0.1. As for the Jaimovich and Rebelo (2009) parameter η, we assume a beta distribution with a mean of 0.5 and a standard deviation of 0.2, bounded by 0.001 and 0.999. As for steady-state hours, a normal distribution with a mean of 0.2 and a standard deviation of 0.05 is used. The investment-adjustment parameters κ_k and the depreciation parameter δ_2 are given a gamma distribution, with a mean of 2.5 and a standard deviation of 8 and a normal distribution with a mean of 0.08 and a standard deviation of 0.01, respectively. Lastly, we allow for measurement error for output volatility ϵ_{it}^{ME}, where we assume that these measurement errors are bound between zero and one-quarter of the variance of the log difference of quarterly output with a uniform prior distribution. Given the model introduced in Section 2, as well as the data set Y_T and the listed set of prior distributions for those parameters being estimated, we have all the elements required to estimate the posterior density of our parameter set.

3.2 Estimation Results and Posterior Distributions

The estimation process employed by Dynare applies a random walk Metropolis-Hastings Monte Carlo Markov Chain algorithm to estimate the posterior distribution of our estimated variables. In the case of our analysis, we run five parallel chains with 100,000 simulations each, where the first half of the draws are discarded. The results of the Bayesian estimation are available in Table 3, which lists the prior and posterior distribution along with a 95% confidence interval around the posterior mean. Of particular interest is the Jaimovich and Rebelo preference parameter η. With $\eta = 0.12$, the wealth effect on household labour supply is insubstantial. With an estimated value of χ of 0.7, households' consumption is characterized by habit persistence. For the remaining preference parameter θ and the steady state hours h^{ss} we estimate a value of 2.96 and 0.18, respectively, which leaves these estimates roughly in line with those found in the literature. The estimated value for the investment adjustment cost parameter κ is 42.99. The high cost of adjusting capital is due to joint timing of TFP and IST resulting from the cointegrating relationship in the benchmark model. The depreciation parameter δ_2 has an estimated value of 0.076, reflecting curvature in the depreciation function. The persistence parameters for the five stationary shocks (ρ_Z, ρ_A, ρ_v, ρ_{μ^w}, and ρ_b) range between 0.37 for stationary IST shocks, to as high as 0.99 for wage markup shocks.

For the parameters governing the movement of our two non-stationary components, X_t^Z and X_t^A, estimates for the persistence parameters ρ_{11} and ρ_{22} suggest that growth in TFP has little to no persistence while IST has a moderate level of persistence with $\rho_{11} = 0.27$ and $\rho_{22} = 0.55$, respectively. These values are roughly in line with the values found by Schmitt-Grohé and Uribe's (2011) maximum likelihood estimation for these parameters. Perhaps the most important values are those estimated for κ_1 and κ_2, which determine the impact our common trend component x_t has on both growth rates, and ρ_{12} and ρ_{21}, which determine the degree of spillover between shocks. For κ_1 and κ_2 we estimate values of 0.13 and 0.45, and for the spillover parameters ρ_{12} and ρ_{21}, we estimate values of 0.07 and 0.58, respectively. These estimates imply that growth rates for neutral and investment-specific technologies move together over time. Estimates for the yet to be discussed standard deviations for both anticipated and unanticipated shocks are available in Table 3.

4 Model Results

4.1 Variance Decomposition

With the parameter set estimated in the previous section, we can now begin our analysis regarding the impact both anticipated and unanticipated shocks have on our model. The variance decomposition of the benchmark model is available in Table 4.[2] Anticipated and unanticipated shocks to stationary IST explain very little of the variance of the observables included in our estimation. Anticipated and unanticipated preference shocks are also not important. Wage markup shocks are an important source of volatility in the growth rate for hours, with 9% of the volatility explained by unanticipated wage markup shocks and roughly 22% explained by anticipated wage markup shocks. Lastly, anticipated MEI shocks explain 7% of the volatility of investment growth, which is much lower than the results found by both Schmitt-Grohé and Uribe (2012) and Khan and Tsoukalas (2012).

Table 4 demonstrates that shocks to the common trend shared between TFP and IST are of particular importance. Taken together, anticipated and unanticipated shocks to the common trend explain 66% of output growth, 77% of investment growth, 70% consumption growth and approximately 51% of the growth in hours worked. Of particular interest, this research finds that shocks to the common stochastic trend explain approximately 90% of the variance in RPI growth.

[2]For each variance decomposition calculated in this section, the parameter values are set at the mean of each parameter's posterior distributions. The variance decompositions mentioned throughout this paper are contemporaneous in that they focus on the explanatory power of each shock in explaining volatility in observables and a not forecast error variance decomposition.

Thus it appears that the assumption that IST can be identified by the inverse of the RPI is particularly problematic.

Our main finding is that anticipated shocks to the common trend are an important source of business cycle volatility despite the inclusion of wage markup shocks in our model. Anticipated shocks to the common trend explain approximately 22%, 32%, 20% and 34% of the volatility of output, investment, consumption and hours growth, respectively. These findings contrast with those of Schmitt-Grohé and Uribe (2012) and Khan and Tsoukalas (2012), who find that anticipated technology shocks have only a very small role to play in business cycle fluctuations. Therefore, our analysis suggests that allowing for cointegration is important to the study of technology and news shocks.

4.1.1 No Cointegration

To test whether cointegration is important in generating the variance decomposition listed in Table 4, we set $\kappa_1 = \kappa_2 = \rho_{12} = \rho_{21} = 0$ in equation (16) and re-estimated our benchmark model with these new restrictions. As can be seen in Table 6, anticipated shocks to either TFP or IST, stationary or otherwise, play a limited role in generating business cycle volatility. Instead, anticipated MEI shocks, as found by Schmitt-Grohé and Uribe (2012), have regained their relevance in explaining business cycle volatilities, with anticipated MEI shocks now accounting for 55% of the volatility of investment growth. The relative importance of anticipated wage markup shocks in explaining volatility in hours growth has increased dramatically to 98%. Furthermore, when comparing the log data densities of these two models, the model that allows cointegrated technologies is preferred, with a value of -4715, compared with the much lower value of -5424 observed for the model without cointegrated technologies. To illustrate the impact cointegration between TFP and IST has on the time path of these two variables, we now look at the impulse-response functions.

4.2 Impulse Responses

Figure 1 plots the impact of a one-standard-error innovation to $\epsilon^4_{\mu^Z,t}$ (left panel) and $\epsilon^4_{\mu^A,t}$ (right panel) on TFP growth μ^Z_t, IST growth μ^A_t and the common trend x^{co}_t. With cointegration between non-stationary neutral and investment-specific technologies, an anticipated change in the non-stationary TFP generates an expectation that the RPI will fall in five quarters. An anticipated increase in the growth rate of IST is, however, not followed by an increase in both technologies but rather by a sudden deceleration in neutral technological growth. This is a result of the error-correction term X^{Co} as well as our positive estimates for both κ_1 and κ_2. One explanation is that when these new investment-specific technologies are being implemented and older forms of production are dismantled, measured productivity declines as these new technologies are installed. Only when enough time has passed and these new technologies are fully implemented do both technologies settle along a balanced growth path. With the error-correction term determined in levels, it begins to decelerate only when the growth rates of TFP and IST reach their steady state. Thus the growth rates of these two technologies continue to cycle around their steady-state level until the error-correction term equals zero.

As can be seen in Figure 1, both technologies increase in response one-standard-error innovation to non-stationary TFP. The impulse-response functions for consumption, hours, investment, output and capital utilization are shown in Figure 2, where variables are plotted in percentage deviations from the balanced growth path. News of future innovations to the growth rate of neutral technology are met with an increase in all variables observed. Like the vast majority of news shock models, ours includes endogenous capital utilization, Jaimovich and Rebelo preferences and investment adjustment costs. These three features have been shown to promote a positive response in hours worked and investment in response to a positive anticipated neutral technology shock. Other mechanisms exist that can generate an increase in output prior to the realized neutral technology shock. For example, the inclusion of knowledge capital by Gunn and Johri (2011) generates an increase in output in response to news of future productivity gains. Given that a μ^z news shock announces a fall in the RPI, there is an additional incentive to increase capital utilization since it will soon be much cheaper to replace depreciated capital. This immediate positive response of utilization raises output immediately. This increase in output is large enough to accommodate an increase in consumption and an increase in investment in the interim period.

As expected, the responses in Figure 2 show that prior to the shock being realized, output, consumption, capital utilization and investment and hours increase in response to news of a future increase in the common stochastic trend. To get a sense of the effects of cointegration on our model results, Figures 3 and 4 simulate the impulse-response functions implied by a four-period-ahead anticipated shock to μ^Z and μ^A when there is neither cointegration nor technological spillovers (dashed line). These results are derived by re-performing the Bayesian estimation process above with κ_1, κ_2, ρ_{12} and ρ_{21} set equal to zero. The solid lines in Figures 3 and 4 plot the impulse-response functions to a four-period-ahead anticipated shock to μ^Z and μ^A. Figure 3 makes clear that cointegration enhances the responses to a news shock regarding future TFP. Notice the much stronger response of capital utilization and hours when TFP and IST are cointegrated. As explained above, when TFP and IST are cointegrated, an anticipated increase in TFP comes with an anticipated decrease in the RPI, which makes utilization less costly. Higher utilization rates drive up wage rates, causing households to increase their labour supply. Each of these effects allows output, hours and consumption to rise simultaneously in response to an anticipated technology shock.

The mechanisms governing the response to an anticipated shock to μ^A is somewhat more involved. The response in technology to an anticipated growth rate shock to IST causes output, consumption and capital utilization to all decrease as this new technology is being diffused into production. During the interim, households, aware of a pending decrease in productivity, increase hours and decrease real investment immediately to avoid the future slump in production. Finally, perhaps the most prominent feature is that capital utilization rates decline in response to an anticipated increase in IST growth. Capital utilization rates decrease during the interim period as forward-looking households attempt to shore up their capital stock prior to the anticipated decline in the economy.

5 Comparison with Current Research

At the forefront of news shock research is the work done by Schmitt-Grohé and Uribe (2012), whose model is similar to the benchmark model with the following exceptions: First, their research only has disturbances to the stochastic growth rate of investment technology, while our research includes both stationary and non-stationary IST shocks. Second, their model has decreasing returns-to-scale in consumption production, unlike the constant returns to scale in equation (7). Third, they first perform a maximum likelihood estimation of their parameters and then use these values as the prior distribution means for their Bayesian estimation. This process assigns an abnormally high weight to MEI innovations. Instead, the Bayesian estimation process used here is more in line with that of Khan and Tsoukalas (2012), with the same standard deviation and persistence for each of the stationary shocks considered. Last of all, our benchmark model includes a cointegrating relationship between TFP and IST, while their work has these two series evolving independently. To a lesser extent we can also compare our benchmark model results with Khan and Tsoukalas (2012), who draw similar conclusions to Schmitt-Grohé and Uribe (2012); but unlike our benchmark model, they incorporate a series of nominal frictions into their news shock model. These two papers challenge the empirical findings of Beaudry and Portier (2006), who through a VAR empirical exercise find that approximately half of the volatility of output can be explained by anticipated changes in either type of technology. Schmitt-Grohé and Uribe (2012) as well as Khan and Tsoukalas (2012) find that anticipated changes in productivity, regardless of the sector, were unable to generate substantial volatility in hours, consumption, investment and output. Both papers find that only unanticipated technology shocks, rather than anticipated technology shocks, are relevant to understanding business cycle dynamics. To help understand the relevance of including cointegration into a standard news shock model, this section compares the model results outlined in the previous section to those found in these studies, beginning with Schmitt-Grohé and Uribe (2012).

Schmitt-Grohé and Uribe (2012) find that anticipated shocks to both stationary and non-stationary TFP and IST are unable to explain any variation in the observables included in their estimation process. Instead, a high weight is assigned to anticipated shocks to both MEI and wage markup shocks. In their variance decomposition, they conclude that approximately 19% of the volatility of investment growth is due to movements in the MEI. Of particular interest is the ability of anticipated wage-markup shocks to explain growth rate volatility in output, consumption, investment and hours worked, with 17%, 18%, 12% and 67% of the volatility of these observables explained by anticipated shocks to wage markups in their model. Schmitt-Grohé and Uribe (2012) argue that the high weight assigned to anticipated wage markup shocks in their variance decomposition may be due to the history of prolonged negotiations between workers and their employers. An anticipated rise in the wage markup (a drop in the real wage income earned by the household) implies that output, investment and consumption all fall in the interim. Since their Bayesian estimation assigns a value for the Jaimovich and Rebelo parameter η close to zero, the wealth effect of a future drop in wages does not impact the households' labour supply decision prior to the shock being realized. Similar to Schmitt-Grohé and Uribe (2012), we find that shocks to stationary IST are not important, while both anticipated and unanticipated wage markups shocks are of particular importantance in explaining volatility in the growth rate of hours. This is despite a stronger wealth effect on labour supply.

Schmitt-Grohé and Uribe's (2012) results are close to those found when the benchmark model has all components linking non-stationary TFP and IST removed from the VECM model outlined in equation (16). When we re-perform the Bayesian estimation outlined in Table 3 with all forms of cointegration and spillover removed (see Table 5), our results fall qualitatively in line with those found by Schmitt-Grohé and Uribe (2012). As demonstrated in Table 6, the relative importance of anticipated wage markup shocks increases substantially. When the common stochastic process is removed, anticipated wage markup shocks now explain approximately 79% of the volatility of output and 78% of the volatility in consumption growth and, most significantly, 98% of the volatility of hours growth. Anticipated MEI shocks have also increased in significance, explaining 55% of the volatility of investment growth, while explaining very little of the growth rates of output, consumption and hours worked. This is roughly in line with Schmitt-Grohé and Uribe's (2012) findings.

In contrast to Schmitt-Grohé and Uribe (2012), Khan and Tsoukalas (2012) present an alternative DSGE model with nominal frictions in both prices and wages. They conclude, like Schmitt-Grohé and Uribe (2012), that the majority of movement in output growth can be attributed to changes in the MEI, explaining an estimated 47% of the unconditional variance of output growth in their model. However, unlike Schmitt-Grohé and Uribe (2012), Khan and Tsoukalas (2012) conclude that anticipated shocks to MEI lack the ability to cause volatility in any of the observables included in their paper. Anticipated changes in wage markups are, again like Schmitt-Grohé and Uribe (2012), a source of business cycle volatility and explain approximately 8%, 14% and 60% of the variance of output growth, consumption growth and hours growth, respectively. These estimates can be found in the variance decomposition outlined in Table 3 of their paper. Similar to Khan and Tsoukalas (2012), this research finds that anticipated wage markups are an importance source of volatility in hours growth despite the inclusion of cointegrating technologies and the gained relevance of anticipated technology shocks.

These results suggest that allowing both neutral and investment-specific technologies to move together over time, both in the short run, and in the long run, leads to a revival in the relative importance of anticipated technology shocks, as found empirically. Through their SVAR-based approach to evaluate the relative importance of news shocks, Khan and Ben Zeev (2015) argue that a structural mechanism needs to be incorporated within the news shock DSGE models so as to enhance the role of anticipated IST shocks in generating business cycle volatility. The model present here finds that at most, 34% of aggregate fluctuations can be explained by anticipated technology shocks, compared with 60–70% explained by anticipated IST shocks found by Khan and Ben Zeev (2015) in their VAR exercise. While falling short of their estimates, this paper proposes that incorporating a common stochastic trend between neutral and investment-specific technologies provides a possible mechanism to enhance the role of anticipated IST shocks within a DSGE model. This is done by associating an increase in future TFP with an anticipated increase in IST.

Last of all, this paper assumes that there exists a single common stochastic trend between TFP and IST, as is done by Schmitt-Grohé and Uribe (2011). Fisher (2009), in his comment on the work done by Beaudry and Lucke (2009), calls to our attention that the chosen number of cointegrating relationships can have important implications for the relative importance of one shock over another when analyzing the variance decomposition. By assuming that there exists a single cointegrating relationship between neutral and investment-specific technologies, this paper therefore assumes that the remaining shocks do not share a common stochastic trend nor have a cointegrated relationship with either TFP or the RPI. There could, for example, exist a cointegrating relationship between neutral technology and wage markup shocks, or between MEI and the RPI. Extending this research to include multiple cointegrating relationships will have important implications not only for this research, but also for the work done by Schmitt-Grohé and Uribe (2012) as well as Khan and Tsoukalas (2012). This is left for future research.

6 Conclusion

This research began by asking whether the cointegrating relationship shared by TFP and RPI challenged our current understanding of how anticipated shocks generate volatility in US aggregates. In answering this question, we adapted a canonical news shock model to reproduce the cointegrating relationship observed between TFP and the RPI in the United States. We estimate this new model using Bayesian methods and find overwhelmingly that anticipated shocks to the common stochastic trend account for a significant portion of business cycle volatility. With cointegration, anticipated technology shocks matter, with roughly 20% to 34% of the volatility of output, consumption, investment and hours growth explained by anticipated shocks to the common stochastic trend. Without cointegration, these values drop to roughly 1%, closely matching the results found by Schmitt-Grohé and Uribe (2012) and Khan and Tsoukalas (2012), who both found that anticipated technology shocks (of any kind) lack the ability to generate any business cycle volatility. Thus, allowing for a cointegrating relationship between TFP and the RPI challenges the current understanding of the relative importance of news shocks, with anticipated technology shocks regaining their relevance for explaining business cycle volatility in the United States.

7 Appendix

United States Data

Time series data pertaining to growth in output, investment, hours worked, consumption, TFP and the RPI are gathered from the data set provided by Schmitt-Grohé and Uribe (2011) paper *Business Cycles With A Common Trend in Neutral and Investment-Specific Productivity.* Access to their data is made available through the Authors' respective websites.

References

[1] Barsky, R.B., and E.R. Sims, "News Shocks and Business Cycles," *Journal of Monetary Economics*, 2011, 58 273-289.

[2] Beaudry, P., and F. Portier, "Stock Prices, News, and Economic Fluctuations," *American Economic Review*, 2006, 96 1293-1307.

[3] Beaudry, P., and F. Portier, "Letting Different Views about Business Cycles Compete," *NBER Macroeconomics Annual*, 2009, 2010 24, 413-455.

[4] Ben Zeev, N., and H. Khan, "Investment-Specific News Shocks and U.S. Business Cycles," *Journal of Money Credit and Banking*, 2015, 47 (7), 1443-1464.

[5] Cummins, J., and G. Violante, "Investment-Specific Technical Change in the United States (1947-2000): Measurement and Macroeconomic Consequences," *Rev. Econ. Dynamics*, 2002, 5 243-284.

[6] Fisher, J. "The Dynamic Effect of Neutral and Investment-Specific Technology Shocks," *Journal of Political Economy*, 2006 114 (3), 413-451.

[7] Fisher, J., "Comment on 'Letting Different Views about Business Cycles Compete'," *NBER Chapters*, 2009, 24, 457-474.

[8] Fujiwara, I., Y. Hirose, and M. Shintani, "Can News be a Major Source of Aggregate Fluctuations? A Bayesian DSGE Approach," *Journal of Money Credit and Banking*, 2011, 43 (1), 1-29.

[9] Gordon, J. "The Measurement of Durable Goods Prices," *University of Chicago Press*, 1989, Chicago, IL.

[10] Greenwood, J., Hercowitz, Z., and P. Krusell, "The Role of Investment-Specific Technological Change in the Business Cycle," *European Economic Review*, 2000, 44 91-115.

[11] Gunn, C., and A. Johri, "News and Knowledge Capital," *Review of Economic Dynamics*, 2011, 14 (1), 92-101.

[12] Jaimovich, N., and S. Rebelo, "Can News about the Future Drive the Business Cycle?" *American Economic Review, American Economic Association*, 2009, 99 (4) 1097-1118.

[13] Justiniano, A., Primiceri, G., and A. Tambalotti, "Investment Shocks and the Relative Price of Investment," *Review of Economic Dynamics*, 2011, 14 (1), 101-121.

[14] Justiniano, A., Primiceri, G., and A. Tambalotti, "Investment Shocks and the Relative Price of Investment," *Review of Economic Dynamics*, 2011, 14 (1), 101-121.

[15] Khan, H., J. Tsoukalas, "The Quantitative Importance of News Shocks in Estimated DSGE Models," *Journal of Money, Credit and Banking* Blackwell Publishing, 2012, 44 (8), 1535-1561.

[16] Khan, H., N. Ben Zeev, "Investment-Specific News Shocks and U.S. Business Cycles," *Journal of Money, Credit and Banking* 2015, 47 (7), 1443-1464.

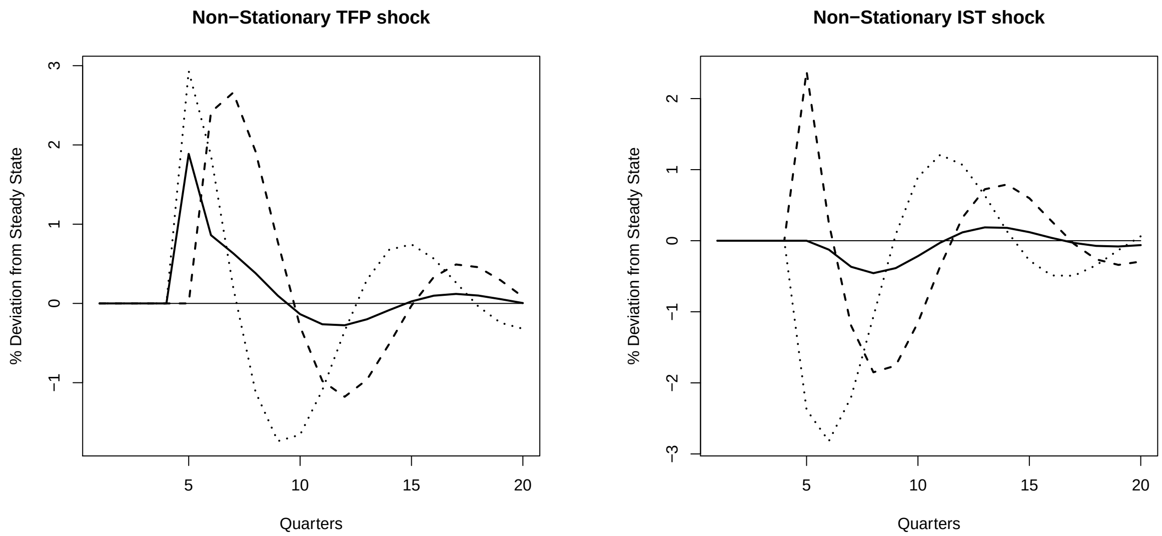
[17] King, R., Plosser, C., and S. Rebelo, "Production, Growth and Business Cycles: I. The basic Neoclassical Model," *Journal of Monetary Economics*, 1988, 21 195-232.

[18] Kydland, F., and E. Prescott, "Time to Build and Aggregate Fluctuations," *Econometrica*, 1982, 50 1345-1370.

[19] Schmitt-Grohé, S., and M. Uribe, "Business Cycles With A Common Trend in Neutral and Investment-Specific Productivity," *Review of Economic Dynamics*, 2011, 14 (1), 122-135.

[20] Schmitt-Grohé, S., and M. Uribe, "What's News in Business Cycles," *Econometrica*, 2012, 80, 2733-2764.

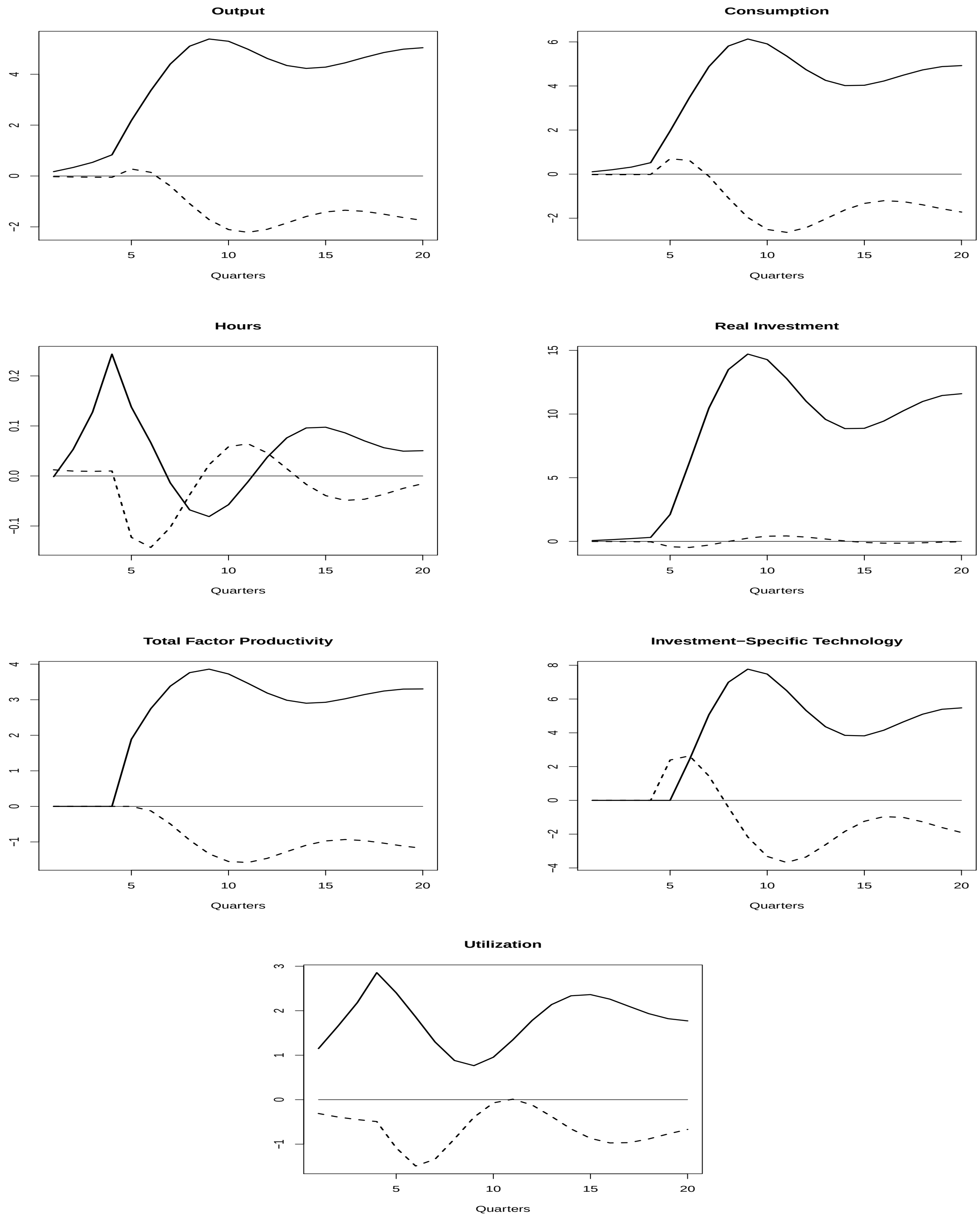
Figure 1
Benchmark Model



Impulse-response functions of μ^Z (solid line) and μ^A (dashed line) and the cointegrating term x^{co} (dotted line) to a one-standard-error innovation to $\epsilon^4_{\mu^Z,t}$ (left) and a one-standard-error innovation to $\epsilon^4_{\mu^A,t}$ (right).

Figure 2

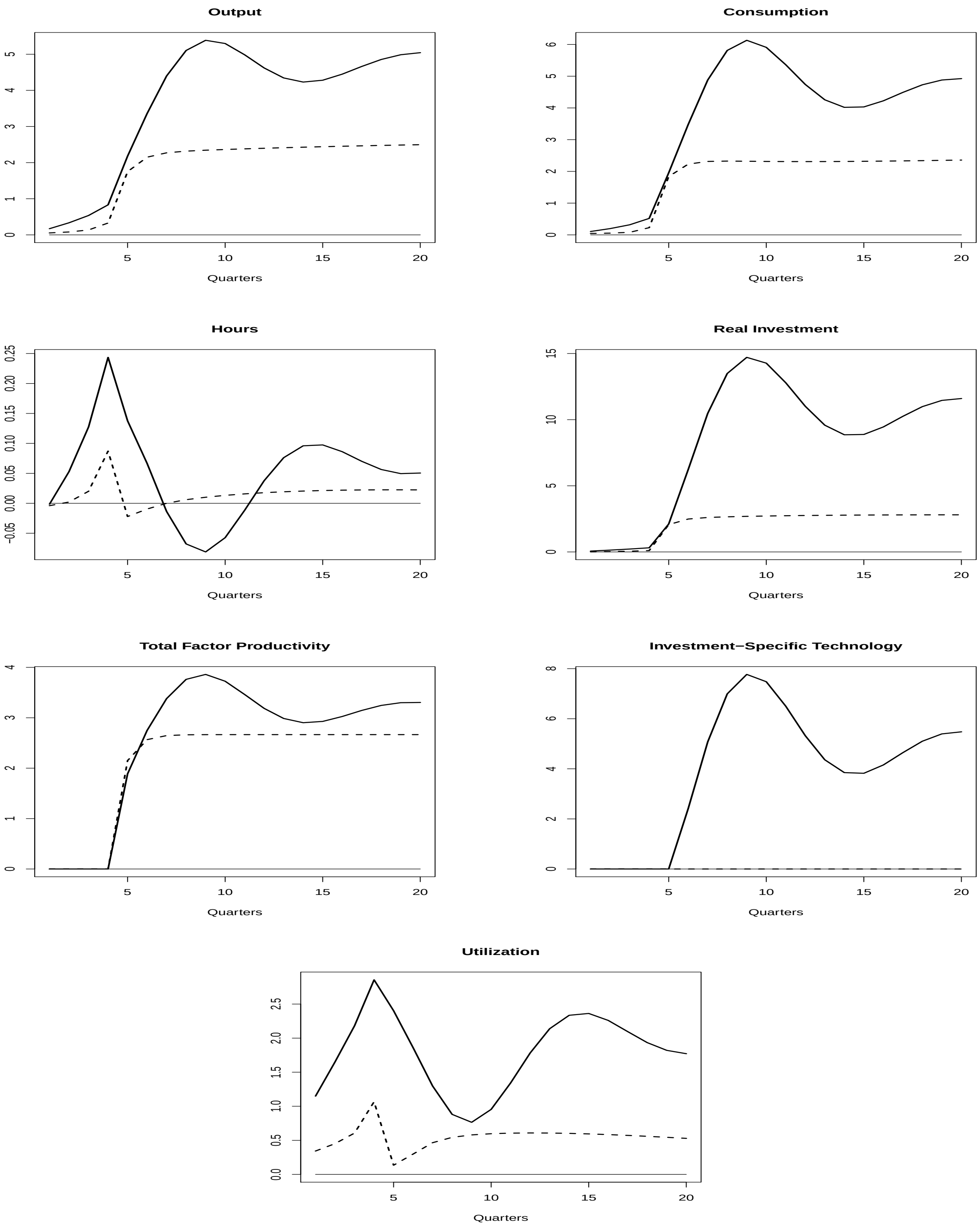
Four-Quarter Anticipated News Shocks to μ^Z and μ^A
Benchmark model



Impulse-response functions of a one-standard-error innovation to $\epsilon^4_{\mu^Z,t}$ (solid) and a one-standard-error innovation to $\epsilon^4_{\mu^A,t}$ (dashed), measured as a percentage deviation from the respective balanced growth path.

Figure 3

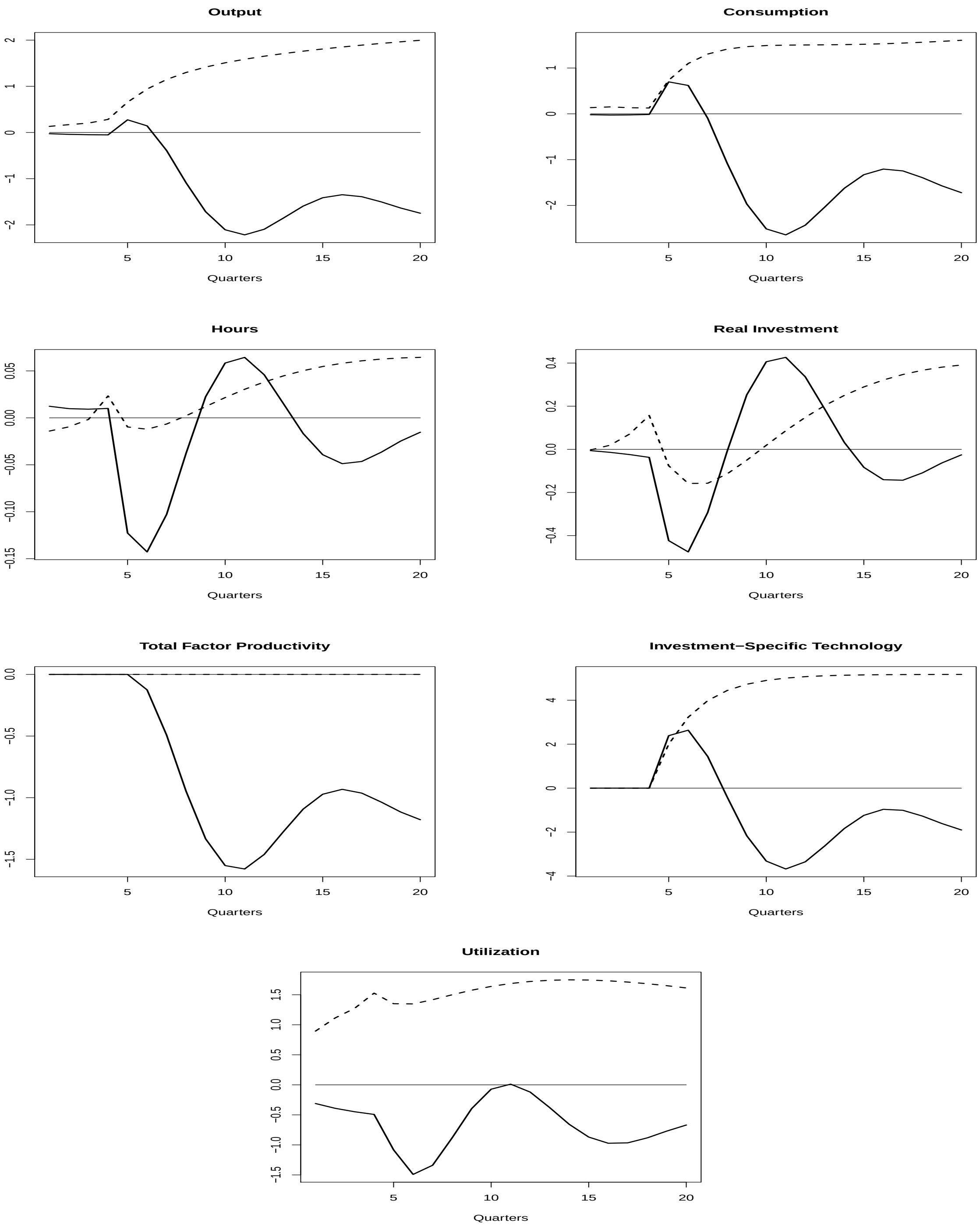
Four-Quarter Anticipated News Shocks to μ^Z
With and Without Cointegration



Impulse-response functions of a one-standard-error innovation to $\epsilon^4_{\mu^Z,t}$ (solid) with cointegration between TFP and IST and a one-standard-error innovation to $\epsilon^4_{\mu^Z,t}$ (dashed) with no cointegration between these two technologies. Each impulse response is measured as a percentage deviation from the respective balanced growth path.

Figure 4

Four-Quarter Anticipated News Shocks to μ^A
With and Without Cointegration



Impulse-response functions of a one-standard-error innovation to $\epsilon^4_{\mu^A,t}$ (solid) with cointegration between TFP and IST and a one-standard-error innovation to $\epsilon^4_{\mu^A,t}$ (dashed) with no cointegration between these two technologies. Each impulse response is measured as a percentage deviation from the respective balanced growth path.

Table 1
Calibrated Parameters

Parameter	Value	Description
σ	1	Risk aversion
$\bar{\mu}^W$	1.10	Steady state wage markup
$\bar{\mu}^Y$	1.0049	Per capita output growth along a balanced growth path
δ_0	0.025	Depreciation rate in steady state
$\bar{\mu}^A$	1.0043	Per capita IST growth along a balanced growth path
$\bar{\mu}^Z$	1.0028	Per capita TFP growth along a balanced growth path
β	0.985	Subjective discount factor
u^{ss}	1.00	Steady state capital utilization rate
α	0.33	Capital share of output
$\psi = ln(\bar{\mu}^A)/ln(\bar{\mu}^Z)$	1.5582	Cointegration coefficient

Table 2
Priors

Parameter	Description	Prior Distribution	Lower Bound	Upper Bound	Mean	Variance
θ		Gamma			3	0.75
χ		Beta			0.5	0.1
δ_2		Beta	0.01	0.99	0.08	0.01
η		Uniform	0.01	0.99	0.5	0.2
h^{ss}		Normal			0.3	0.03
κ		Gamma			2	8
ρ_Z		Beta			0.60	0.20
ρ_A		Beta			0.60	0.20
ρ_v		Beta			0.60	0.20
ρ_b		Beta			0.60	0.20
ρ_{μ^W}		Beta			0.60	0.20
ρ_{11}		Normal	0	1	0.13	0.22
ρ_{22}		Normal	0	1	0.58	0.22
ρ_{12}		Normal			0.08	0.10
ρ_{21}		Normal			1.07	0.7
κ_1		Normal			0.03	0.08
κ_2		Normal			0.39	0.28
σ_i^0		Inv Gamma			0.5	2
σ_i^k		Inv Gamma			0.1	2

σ_i^0 refers to the variance of an unanticipated shock to disturbance $i = \{Z, A, b, v, \mu^W, \mu^Z, \mu^A\}$. σ_i^k refers to the variance of an anticipated shock to disturbance i known $k = \{4, 8\}$ periods in advance.

Table 3

Bayesian Estimation

Parameter	Distribution	Prior Mean	Standard Deviation	Posterior Mean	5%	95%
θ	Normal	3	0.75	2.962	2.911	3.013
χ	Gamma	0.5	0.1	0.7	0.675	0.725
δ_2	Uniform	0.08	0.0404	0.076	0.075	0.077
η	Beta	0.50	0.20	0.116	0.079	0.153
h^{ss}	Normal	0.2	0.05	0.18	0.178	0.182
κ	Gamma	2	8	42.994	39.329	46.659
ρ_Z	Beta	0.6	0.2	0.998	0.962	1.034
ρ_A	Beta	0.6	0.2	0.369	0.34	0.398
ρ_v	Beta	0.6	0.2	0.798	0.789	0.807
ρ_b	Uniform	0.6	0.2	0.736	0.717	0.755
ρ_{μ^W}	Beta	0.6	0.2	0.993	0.96	1.026
ρ_{11}	Normal	0.13	0.22	0.274	0.259	0.289
ρ_{22}	Normal	0.58	0.22	0.554	0.534	0.574
ρ_{21}	Uniform	1.07	0.70	0.58	0.56	0.6
ρ_{12}	Uniform	0.08	0.10	0.068	0.048	0.088
κ_1	Normal	0.03	0.08	0.133	0.12	0.146
κ_2	Normal	0.39	0.28	0.448	0.434	0.462
σ_z^0	Inverse Gamma	0.5	2	0.061	0.06	0.062
σ_a^0	Inverse Gamma	0.5	2	0.062	0.061	0.063
σ_V^0	Inverse Gamma	0.5	2	0.71	0.675	0.745
σ_b^0	Inverse Gamma	0.5	2	0.07	0.056	0.084
$\sigma_{\mu^w}^0$	Inverse Gamma	0.5	2	0.089	0.027	0.151
$\sigma_{\mu^Z}^0$	Inverse Gamma	0.5	2	0.061	0.056	0.066
$\sigma_{\mu^A}^0$	Inverse Gamma	0.5	2	0.063	0.053	0.073
σ_Z^1	Inverse Gamma	0.1	2	0.016	0.012	0.02
σ_Z^2	Inverse Gamma	0.1	2	0.017	0.014	0.02
σ_A^1	Inverse Gamma	0.1	2	0.061	0.017	0.033
σ_A^2	Inverse Gamma	0.1	2	0.061	0.013	0.033

Table 3 Continued

Bayesian Estimation

Parameter	Distribution	Prior Mean	Standard Deviation	Posterior Mean	5%	95%
σ_v^1	Inverse Gamma	0.1	2	0.1	0.013	0.187
σ_v^2	Inverse Gamma	0.1	2	0.593	0.478	0.708
σ_b^1	Inverse Gamma	0.1	2	0.025	0.019	0.031
σ_b^2	Inverse Gamma	0.1	2	0.022	0.016	0.028
$\sigma_{\mu^W}^1$	Inverse Gamma	0.1	2	0.051	0	0.129
$\sigma_{\mu^W}^2$	Inverse Gamma	0.1	2	0.158	0	0.379
$\sigma_{\mu^A}^1$	Inverse Gamma	0.1	2	0.026	0.01	0.042
$\sigma_{\mu^A}^2$	Inverse Gamma	0.1	2	0.026	0.014	0.038
$\sigma_{\mu^Z}^1$	Inverse Gamma	0.1	2	0.019	0.012	0.026
$\sigma_{\mu^Z}^2$	Inverse Gamma	0.1	2	0.04	0.028	0.052
σ_Y^{ME}	Uniform	$\frac{1}{8}\hat{\sigma_Y}$	0.072	0.25	0.25	0.25

Table 4

Variance Decomposition: Benchmark Model

	g^y	g^c	g^i	g^h	g^{rpi}	g^{tfp}
Stationary TFP						
ϵ_Z^0	18	18.87	3.05	7.33	0	38.81
$\sum_{i=4,8} \epsilon_Z^i$	1.23	1.17	0.33	5.11	0	5.54
Stationary IST						
ϵ_A^0	3.11	0.01	0.03	2.87	7.85	0
$\sum_{i=4,8} \epsilon_A^i$	0.99	0.02	0.02	1.06	2.24	0
Preferences						
ϵ_b^0	1	1.74	0.14	0.49	0	0
$\sum_{i=4,8} \epsilon_b^i$	0.6	0.93	0.02	0.63	0	0
Wage Markup						
$\epsilon_{\mu^W}^0$	1.61	1.69	0.27	8.81	0	0
$\sum_{i=4,8} \epsilon_{\mu^W}^i$	3.55	3.89	0.73	21.64	0	0
MEI						
ϵ_v^0	2.87	0.62	11.47	0.44	0	0
$\sum_{i=4,8} \epsilon_v^i$	1.15	0.85	7.39	0.71	0	0
Common Trend						
$\epsilon_{\mu^Z}^0 + \epsilon_{\mu^A}^0$	44.3	50.41	44.06	16.62	50.58	28.66
$\sum_{i=4,8}\{\epsilon_{\mu^Z}^i + \epsilon_{\mu^A}^i\}$	21.6	19.82	32.47	34.29	39.33	27

Here, g^i is the growth rate of variable $i = \{y, c, i, h, rpi, tfp\}$. The variance decomposition is calculated at the mode of the posterior distribution.

Table 5

Bayesian Estimation With No Cointegration or Spillover Effects

Parameter	Distribution	Prior Mean	Standard Deviation	Posterior Mean	5%	95%
θ	Normal	3	0.75	3.54	3.43	3.65
χ	Gamma	0.5	0.1	0.475	0.473	0.477
δ_2	Normal	0.08	0.01	0.074	0.072	0.076
η	Beta	0.50	0.2	0.523	0.519	0.527
h^{ss}	Normal	0.2	0.05	0.209	0.205	0.213
κ	Gamma	2	8	9.96	9.186	10.734
ρ_Z	Beta	0.6	0.2	0.659	0.651	0.667
ρ_A	Beta	0.6	0.2	0.508	0.483	0.533
ρ_v	Beta	0.6	0.2	0.567	0.555	0.579
ρ_b	Beta	0.6	0.2	0.609	0.595	0.623
ρ_{μ^W}	Beta	0.6	0.2	0.661	0.647	0.675
ρ_{11}	Normal	0.13	0.22	0.198	0.182	0.214
ρ_{22}	Normal	0.58	0.22	0.611	0.576	0.646
σ_z^0	Inverse Gamma	0.5	2	0.061	0.059	0.063
σ_a^0	Inverse Gamma	0.5	2	0.061	0.059	0.063
σ_V^0	Inverse Gamma	0.5	2	1.509	1.105	1.913
σ_b^0	Inverse Gamma	0.5	2	0.068	0.052	0.084
$\sigma_{\mu^w}^0$	Inverse Gamma	0.5	2	0.116	0	0.402
$\sigma_{\mu^Z}^0$	Inverse Gamma	0.5	2	0.062	0.056	0.068
$\sigma_{\mu^A}^0$	Inverse Gamma	0.5	2	0.061	0	0.165
σ_Z^1	Inverse Gamma	0.1	2	0.019	0.013	0.025
σ_Z^2	Inverse Gamma	0.1	2	0.019	0.015	0.023
σ_A^1	Inverse Gamma	0.1	2	0.061	0.012	0.028
σ_A^2	Inverse Gamma	0.1	2	0.061	0.017	0.025

Table 5 Continued

Bayesian Estimation

Parameter	Distribution	Prior Mean	Standard Deviation	Posterior Mean	5%	95%
σ_v^1	Inverse Gamma	0.1	2	0.156	0.042	0.27
σ_v^2	Inverse Gamma	0.1	2	1.429	1.157	1.701
σ_b^1	Inverse Gamma	0.1	2	0.022	0.004	0.04
σ_b^2	Inverse Gamma	0.1	2	0.022	0.002	0.042
$\sigma_{\mu^W}^1$	Inverse Gamma	0.1	2	0.558	0.505	0.611
$\sigma_{\mu^W}^2$	Inverse Gamma	0.1	2	1.401	1.119	1.683
$\sigma_{\mu^A}^1$	Inverse Gamma	0.1	2	0.023	0.015	0.031
$\sigma_{\mu^A}^2$	Inverse Gamma	0.1	2	0.025	0	0.176
$\sigma_{\mu^Z}^1$	Inverse Gamma	0.1	2	0.021	0.009	0.033
$\sigma_{\mu^Z}^2$	Inverse Gamma	0.1	2	0.021	0.015	0.027
σ_Y^{ME}	Uniform	$\frac{1}{8}\hat{\sigma_Y}$	0.072	0.25	0.25	0.25

Table 6

No Cointegration

$\kappa_1 = \kappa_2 = \rho_{21} = \rho_{12} = 0$

	g^y	g^c	g^i	g^h	g^{rpi}	g^{tfp}
Stationary TFP						
ϵ_Z^0	4.91	4.62	0.23	0.24	0	59.91
$\sum_{i=4,8} \epsilon_Z^i$	0.63	0.57	0.05	0.16	0	11.9
Stationary IST						
ϵ_A^0	0.28	0.07	0.08	0.04	35.61	0
$\sum_{i=4,8} \epsilon_A^i$	0.12	0.02	0.04	0.02	10.04	0
Preferences						
ϵ_b^0	0.27	0.46	0.09	0.01	0	0
$\sum_{i=4,8} \epsilon_b^i$	0.16	0.22	0.02	0.02	0	0
Wage Markup						
$\epsilon_{\mu^W}^0$	0.53	0.52	0.01	0.61	0	0
$\sum_{i=4,8} \epsilon_{\mu^W}^i$	78.64	78.19	3.96	97.79	0	0
MEI						
ϵ_v^0	4.21	2.58	34.15	0.27	0	0
$\sum_{i=4,8} \epsilon_v^i$	4.84	8.06	54.66	0.69	0	0
Non-Stationary TFP						
$\epsilon_{\mu^Z}^0$	4.21	3.43	0.63	0.04	0	22.77
$\sum_{i=4,8} \epsilon_{\mu^Z}^i$	0.53	0.39	0.13	0.07	0	5.42
Non-Stationary IST						
$\epsilon_{\mu^A}^0$	0.5	0.72	4.7	0.04	43.02	0
$\sum_{i=4,8} \epsilon_{\mu^A}^i$	0.17	0.16	1.24	0.02	11.33	0

Here, g^i is the growth rate of variable $i = \{y, c, i, h, rpi, tfp\}$. The variance decomposition is calculated at the mode of the posterior distribution.