BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers

No 358

News driven business cycles and data on asset prices in estimated DSGE models

by Stefan Avdjiev

Monetary and Economic Department

November 2011

JEL classification: C11, E32, E44, G10

Keywords: news driven business cycles, asset prices, estimated DSGE models, bayesian MCMC methods

BIS Working Papers are written by members of the Monetary and Economic Department of the Bank for International Settlements, and from time to time by other economists, and are published by the Bank. The papers are on subjects of topical interest and are technical in character. The views expressed in them are those of their authors and not necessarily the views of the BIS.

Copies of publications are available from:

Bank for International Settlements
Communications
CH-4002 Basel, Switzerland

E-mail: publications@bis.org

Fax: +41 61 280 9100 and +41 61 280 8100

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)

ISBN 1682-7678 (online)

News Driven Business Cycles and Data on Asset Prices in Estimated DSGE Models*

Stefan Avdjiev †
Bank for International Settlements

November 2011

Abstract

The existing literature on estimated structural News Driven Business Cycle (NDBC) models has focused almost exclusively on macroeconomic data and has largely ignored asset prices. In this paper, we present evidence that including data on asset prices in the estimation of a structural NDBC model dramatically affects inference about the main sources of business cycle fluctuations. Combined with the large body of evidence that asset price movements reflect changes in expectations of future developments in the economy, our results imply that data on asset prices should always be used in the estimation of structural NDBC models because they contain information that cannot be obtained by using solely macroeconomic data.

Keywords: News Driven Business Cycles, Asset Prices, Estimated DSGE Models, Bayesian MCMC Methods

JEL Classification Codes: C11, E32, E44, G10

*I would like to thank Nathan Balke, Thomas Fomby, Pedro Amaral, Enrique Martinez-Garcia, Kostas Tsatsaronis, Christian Upper, Harald Uhlig, Timothy Fuerst, Kamal Saggi, Saltuk Ozerturk, Mine Yucel, Nikola Tarashev, and seminar participants at Southern Methodist University, the Bank for International Settlements, Temple University, the Federal Reserve Bank of Dallas, Bowling Green State University, Quantitative Micro Software, and Duquesne University for their helpful comments and suggestions. The views expressed in this paper are those of the author and do not necessarily reflect those of the BIS.

†Monetary and Economic Department, Bank for International Settlements, Centralbahnplatz 2, 4002 Basel, Switzerland. Tel: +41-61-280-8148. E-mail: Stefan.Avdjiev@bis.org.

1 Introduction

There exists a large body of literature that emphasizes the possibility that news shocks, or changes in economic agents' expectations about the future values of fundamentals, play an important role in driving macroeconomic fluctuations. This idea, whose origins can be traced back to Pigou (1926) and Clark (1934), has been recently revived by Beaudry and Portier (2004 and 2006), Christiano et al. (2008), and Jaimovich and Rebelo (2009). A major strand in this rapidly-growing literature estimates structural News Driven Business Cycle (NDBC) models (i.e. fully-specified DSGE models that feature both, unanticipated shocks and news shocks) and uses the results in order to quantify the relative contribution of news shocks in driving macroeconomic fluctuations (Davis (2007), Khan and Tsoukalas (2010), Schmitt-Grohe and Uribe (2010), and Fujiwara et al. (2011)). The essence of any estimation exercise that belongs to this strand of the literature consists of using data on directly observable variables (e.g. macroeconomic aggregates, asset prices, etc.) in combination with model-implied relationships between those variables and the model's unobserved states (e.g. unanticipated shocks and news shocks) in order to extract information about the latter.

The benchmark estimates of virtually all papers in the existing NDBC literature are obtained using mainly data on macroeconomic variables and largely ignoring data on asset prices.[1] This practice is quite surprising considering the existence of a huge empirical literature which suggests that stock price movements reflect changes in economic agents' expectations of future developments in the economy (e.g. Fama (1990), Schwert (1990), Beaudry and Portier (2006), etc.). Given this body of evidence, not including data on asset prices in the estimation of a structural NDBC model would only be justified if all the information about changes in expectations that is contained in asset prices could be extracted by using solely macroeconomic variables. If this was the case, adding data on asset prices in the estimation would be unnecessary as it would not add any new information about the unobserved shock processes and would not alter the results obtained by using solely data on macroeconomic variables.

Nevertheless, there is no paper in the existing literature that systematically examines the extent to which including data on asset prices in the estimation of a structural NDBC model has an impact on inference about the main drivers of business cycle fluctuations. The authors of several papers (Davis (2007), Khan and Tsoukalas (2010), and Schmitt-Grohe and Uribe (2010)) re-estimate their benchmark models after adding stock prices to the set

[1] A small number of papers (Davis (2007), Khan and Tsoukalas (2010), and Fujiwara et al. (2011)) have used interest rates, but not stock prices, as observables in their benchmark estimations.

of observable variables as a robustness check. All of them conclude that adding data on stock prices has only a marginal impact on inference about the main sources of business cycle fluctuations and as a result do not include such data in their benchmark estimations. As we show below, such conclusions are biased by the authors' modeling choices regarding the structure of the news shock processes and the functional form of investment adjustment costs.

This paper is the first to formally analyze the impact of including data on asset prices in the estimation of a structural NDBC model, while simultaneously allowing for alternative specifications for the structure of the news shock processes and for the functional form of investment/capital adjustment costs. We start by solving the four versions of a structural NDBC model that are generated by all possible combinations of the two alternative specifications for the structure of the news shock processes and the two alternative investment/capital adjustment costs functional forms that we consider. Next, we use Bayesian Markov Chain Monte Carlo (MCMC) methods in order to estimate each of the four model specifications twice - once using solely macroeconomic data and once using data on asset prices (aggregate stock prices and short-term interest rates) in addition to data on macroeconomic variables. We then rank the four model specifications based on their marginal likelihoods under each of the two estimation approaches (i.e. with and without using data on asset prices) and compare the variance decompositions implied by the highest ranked model specifications in each of the two cases. This lets us determine whether making inferences about the main drivers of business cycle fluctuations using solely data on macroeconomic aggregates would lead to a different set of conclusions than engaging in the same exercise while using data on asset prices in addition to data on macroeconomic aggregates. Finally, we examine the extent to which the inclusion of data on asset prices in the estimation affects the result in each of the four model specifications by comparing the variance decompositions generated by the two alternative estimation approaches for each model specification.

Our theoretical framework is most closely related to the one used in Schmitt-Grohe and Uribe (2008). It is a real business cycle model that is augmented with four real rigidities: internal habit formation in consumption, internal habit formation in leisure, investment/capital adjustment costs, and variable capacity utilization. Each of the exogenous driving processes is subject to two types of shocks – unanticipated shocks and news shocks. We expand the theoretical framework used by most of the NDBC literature along two dimensions - the structure of the news shock processes and the functional form of investment/capital adjustment costs.

We consider two alternative news shock specifications. In the first one, news shocks are modeled as one-off shocks to fundamentals which materialize n ($n = 1, 2, 3 \ldots$) periods after they enter the information set of the representative agent. We refer to it as the short-run news (SRN) specification. This is the only specification that is considered by the vast majority of the estimated structural NDBC literature (e.g. Davis (2007), Khan and Tsoukalas (2010), Schmitt-Grohe and Uribe (2010), Fujiwara et al. (2011)). As Walker and Leeper (2010) point out, it is quite surprising that, despite the centrality of the exact structure of information flows to the NDBC literature, there has been virtually no examination of alternative equally plausible information flow structures. This motivates us to explore an alternative specification for the structure of the news shock processes. Under this specification, which is inspired by Cochrane (1994), news shocks manifest themselves in the form of shocks to the long-run components of economic fundamentals, but have no impact on fundamentals in the period in which they enter the information set of the representative agent. We refer to it as the long-run news (LRN) specification. Our paper is the first to incorporate the LRN specification into an estimated structural NDBC model. Furthermore, it is also the first to compare the empirical performance of that specification against the performance of the SRN specification.

Our second point of departure from the rest of the literature on estimated structural NDBC models is related to the fact that we allow for two alternative functional forms for investment/capital adjustment costs.[2] In the first one, adjustment costs are a function of the growth rate of investment as in Christiano et al. (2005). This is the preferred specification in the existing dynamic macro modeling literature, including in its NDBC strand.[3] We refer to it as the investment adjustment costs (IAC) specification. In the second specification, which follows Hayashi (1982), Abel and Blanchard (1983), and Shapiro (1986), adjustment costs depend on the ratio of investment to existing capital. We refer to it as the capital adjustment costs (CAC) specification.

The results we obtain strongly suggest that including data on asset prices in the estimation of a structural NDBC model dramatically affects inference about the main sources of business cycle fluctuations. More precisely, when data on asset prices are not included in the estimation, business cycle fluctuations appear to be driven mainly by news shocks to labor-augmenting technology and by news shocks to the marginal efficiency of investment. However, when asset prices are included in the vector of observables, most of the variation in macroeconomic aggregates is attributed to unanticipated TFP shocks and unanticipated shocks to the marginal efficiency of investment. Furthermore, including asset prices in the

[2] Christiano et al. (2008) also consider two alternative functional forms for investment/capital adjustment costs. However, they do not estimate their model.

[3] Davis (2007), Khan and Tsoukhalas (2010), Schmitt-Grohe and Uribe (2010), and Fujiwara et al. (2011) all focus exclusively on that specification.

vector of observable variables causes significant differences not only between the variance decompositions implied by the model specifications with best relative fits under the two alternative estimation approaches, but also within three out of the four model specifications. The only exception is the model specification which is the sole focus of the above-mentioned papers in the existing literature that re-estimate their benchmark models after adding stock prices to the observable variables. This explains why the authors of all of those papers conclude that the impact of adding data on stock prices in the estimation is only marginal.

We also demonstrate that including data on asset prices in the estimation of a structural NDBC model has dramatic implications for inference about the structure of the news shock processes and about the functional form of investment/capital adjustment costs. Namely, we show that, even though the SRN specification fits the data better than the LRN specification when asset prices are not included in the set of observable variables, the opposite is true when data on asset prices are used in the estimation. Similarly, the finding that the IAC functional form is preferred by the data over the CAC functional form when only macroeconomic variables are used as observables is reversed once data on asset prices are included in the estimation.

In addition to the papers on estimated structural NDBC models listed above, our paper is related to two other branches of the expectation driven cycles literature. The first one, which includes the papers of Beaudry and Portier (2006), Beaudry and Lucke (2010), and Barsky and Sims (2011), uses empirical tools such as structural vector autoregressions and structural vector error-correction models in order to quantify the importance of news shocks in business cycle fluctuations. Our paper is also related to the purely theoretical branch of the expectation driven cycles literature (Beaudry and Portier (2004 and 2007), Christiano et al. (2008), Jaimovich and Rebelo (2009), and Karnizova (2010)), which focuses on examining mechanisms through which the comovement properties of macroeconomic aggregates over the business cycle are preserved in response to a news shock.

Finally, in a broader sense, our paper is also related to the strand of the literature that uses the results obtained from the estimation of fully-specified DSGE models which contain only unanticipated shocks (i.e. models which do not allow for news shocks) in order to make inferences about the main drivers of business cycle fluctuations. The most prominent representatives of that body of literature are Smets and Wouters (2007) and Justiniano et al. (2010 and 2011).

The rest of the paper is organized as follows. We describe our theoretical framework in Section 2. In Section 3, we go over the estimation procedure. We present the results of the paper in Section 4. In Section 5, we discuss the intuition behind our main results. Section 6 concludes.

2 Theoretical Framework

This section presents the theoretical framework that we use in this study. We start by describing the model economy. Next, we introduce the two alternative specifications for the structure of the exogenous driving processes that we consider. We then outline the four model specifications that form the basis for our empirical investigation. Finally, we go over the methodology that we use to solve each model specification.

2.1 The Model Economy

The model economy is populated by a large number of identical, infinitely lived agents. The representative agent derives utility from consumption (C_t) and leisure (l_t), and maximizes:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{\left[(C_t - \theta_c C_{t-1})(l_t - \theta_l l_{t-1})^{\chi}\right]^{1-\gamma} - 1}{1-\gamma} \right\}, \tag{1}$$

where E_0 denotes the expectation conditional on the information available at time zero, $\beta \in (0,1)$ denotes the subjective discount factor, $\gamma > 0$ is the inverse of the intertemporal elasticity of substitution, $\theta_c \in [0,1)$ governs the degree of internal habit in consumption, $\theta_l \in [0,1)$ governs the degree of internal habit in leisure, and $\chi > 0$ is the parameter that controls the Frisch elasticity of labor supply.

Agents split their time endowment between leisure and hours worked (h_t). We normalize the total time endowment per period to unity:

$$h_t + l_t = 1. \tag{2}$$

Output (Y_t) is produced with a Cobb-Douglas production function using capital services and labor:

$$Y_t = Z_t F\left(u_t K_t, X_t h_t\right) = Z_t \left[\left(u_t K_t\right)^{\alpha} \left(X_t h_t\right)^{1-\alpha}\right], \tag{3}$$

where Z_t represents the level of total factor productivity (TFP), which is assumed to be stationary, and X_t represents the level of labor-augmenting technology (LAT), which is assumed to be non-stationary. Capital services are equal to the product of the existing capital stock (K_t) and the rate of capacity utilization (u_t).

The stock of capital evolves according to the following law of motion:

$$K_{t+1} = \left(1-\delta\right) K_t + \Omega_t \left[I_t - \Phi\left(\cdot\right)\right], \tag{4}$$

where I_t denotes gross investment, Ω_t is a stationary shock to the marginal efficiency of investment (MEI), and $\Phi\left(\cdot\right)$ is the investment/capital adjustment costs function. The MEI shock (Ω_t) represents an exogenous disturbance to the process which transforms investment goods into capital goods. It has been identified by Justiniano et al. (2011) as a major source of business cycle fluctuations.

In this model economy, increasing the rate of capacity utilization is costly because it causes a faster rate of capital depreciation. More specifically, the rate of depreciation, $\delta(\cdot)$, has the following functional form:

$$\delta(u) = \delta_0 + \delta_1 (u-1) + \frac{\delta_2}{2}(u-1)^2, \tag{5}$$

where $\delta_0 > 0$, $\delta_1 > 0$,$\delta_2 > 0$.

Following Christiano et al. (2008), we consider two specifications for $\Phi(\cdot)$. In the first one, adjustment costs are a function of the growth rate of investment ($\frac{I_t}{I_{t-1}}$) as in Christiano et al. (2005):

$$\Phi(\cdot) = \Phi_I\left(\frac{I_t}{I_{t-1}}\right) I_t = \frac{\kappa}{2}\left(\frac{I_t}{I_{t-1}} - \mu^i\right)^2 I_t,$$

where $\kappa > 0$, and μ^i stands for the steady-state growth rate of investment. We refer to this specification as the investment adjustment costs (IAC) specification.

In the second specification, adjustment costs are a function of the ratio of investment to existing capital ($\frac{I_t}{K_t}$) as in Hayashi (1982), Abel and Blanchard (1983), and Shapiro (1986):

$$\Phi(\cdot) = \Phi_C\left(\frac{I_t}{K_t}\right) K_t = \frac{1}{2\delta_0\eta}\left(\frac{I_t}{K_t} - \tau\right)^2 K_t,$$

where τ is the steady-state investment-capital ratio, $\eta > 0$ is the elasticity of the investment-capital ratio with respect to Tobin's q, and δ_0 is the steady state rate of capital depreciation. We refer to this specification as the capital adjustment costs (CAC) specification.

The economy's resource constraint is:

$$Y_t = C_t + I_t A_t, \tag{6}$$

where A_t is the technical rate of transformation between consumption and investment goods. We assume that it is exogenous, stochastic, and non-stationary. In the rest of the paper, we refer to it as an investment specific productivity (ISP) shock. Note that in a decentralized economy with a competitive investment sector, A_t would be the equilibrium price of a unit of the investment good expressed in units of the consumption good.

The competitive equilibrium allocation coincides with the solution to the social planner problem, which consists of choosing non-negative processes C_t, h_t, u_t, I_t, and K_{t+1} in order to maximize (1) subject to (2)-(6). Following Schmitt-Grohe and Uribe (2008), we let $\Lambda_t Q_t$ and Λ_t denote the Lagrange multipliers on (4) and (6) respectively.[4]

[4]Note that Q_t can be interpreted as marginal Tobin's q, the relative price of installed capital available for production in period $t+1$ in terms of the period t consumption good.

The first-order conditions for C_t, h_t, and u_t are:

$$\Lambda_t = \left(C_t - \theta_c C_{t-1}\right)^{-\gamma} \left(l_t - \theta_l l_{t-1}\right)^{\chi(1-\gamma)} - \theta_c \beta E_t \left(C_{t+1} - \theta_c C_t\right)^{-\gamma} \left(l_{t+1} - \theta_l l_t\right)^{\chi(1-\gamma)} \tag{7}$$

$$\Lambda_t \left[Z_t X_t F_2 \left(u_t K_t, X_t h_t\right)\right] = \left\{ \begin{array}{c} \chi \left(C_t - \theta_c C_{t-1}\right)^{1-\gamma} \left(l_t - \theta_l l_{t-1}\right)^{\chi(1-\gamma)-1} \\ -\beta \theta_l \chi E_t \left[\left(C_{t+1} - \theta_c C_t\right)^{1-\gamma} \left(l_{t+1} - \theta_l l_t\right)^{\chi(1-\gamma)-1}\right] \end{array} \right\} \tag{8}$$

$$Z_t F_1 \left(u_t K_t, X_t h_t\right) = Q_t \delta' \left(u_t\right) \tag{9}$$

In the case of investment adjustment costs, the first-order conditions for I_t and K_{t+1} are:

$$Q_t \Lambda_t \Omega_t \left[1 - \Phi_I \left(\frac{I_t}{I_{t-1}}\right) - \frac{I_t}{I_{t-1}} \Phi_I' \left(\frac{I_t}{I_{t-1}}\right)\right] = A_t \Lambda_t - \beta E_t Q_{t+1} \Lambda_{t+1} \Omega_{t+1} \left(\frac{I_{t+1}}{I_t}\right)^2 \Phi_I' \left(\frac{I_{t+1}}{I_t}\right), \tag{10}$$

$$Q_t \Lambda_t = \beta E_t \Lambda_{t+1} \left[Q_{t+1} \left(1 - \delta \left(u_{t+1}\right)\right) + Z_{t+1} u_{t+1} F_1 \left(u_{t+1} K_{t+1}, X_{t+1} h_{t+1}\right)\right]. \tag{11}$$

Capital adjustment costs imply the following first-order conditions for I_t and K_{t+1}:

$$Q_t = \frac{A_t}{\Omega_t \left[1 - \Phi_C' \left(\frac{I_t}{K_t}\right)\right]}, \tag{12}$$

$$Q_t \Lambda_t = \beta E_t \Lambda_{t+1} \left[\begin{array}{c} Q_{t+1} \left[1 - \delta \left(u_{t+1}\right) + \Omega_{t+1} \left\{\frac{I_{t+1}}{K_{t+1}} \Phi_C' \left(\frac{I_{t+1}}{K_{t+1}}\right) - \Phi_C \left(\frac{I_{t+1}}{K_{t+1}}\right)\right\}\right] \\ + Z_{t+1} u_{t+1} F_1 \left(u_{t+1} K_{t+1}, X_{t+1} h_{t+1}\right) \end{array} \right]. \tag{13}$$

As result, the first-order conditions associated with the social planner's problem for the investment adjustment costs specification are given by (2)-(11), while those for the capital adjustment costs specification are given by (2)-(9) and (12)-(13).

Next, we turn to the asset pricing implications of the model. The one-period ahead gross real risk-free rate in the economy is given by:

$$R_t^{rf} = \frac{1}{\beta} \left[\frac{\Lambda_t}{E_t \left(\Lambda_{t+1}\right)}\right]. \tag{14}$$

Combining the solutions to the problems solved by the representative agent and by the representative firm in a decentralized economy, we obtain the well-known expression for the equilibrium ex-dividend value (V_t) of the representative firm:

$$V_t = \beta E_t \left(\frac{\Lambda_{t+1}}{\Lambda_t}\right) \left(V_{t+1} + D_{t+1}\right), \tag{15}$$

where D_{t+1} is the dividend that the representative firm pays to its shareholders in period $t+1$. It is equal to the output produced by the firm during the period minus payments to labor and investment:

$$D_t = Y_t - W_t h_t - I_t A_t, \tag{16}$$

where W_t is the real wage in period t. The firm's first-order conditions imply that, in equilibrium, W_t is equal to the marginal product of labor (MPL):

$$W_t = MPL_t = (1-\alpha)\frac{Y_t}{h_t}, \tag{17}$$

where the second equality is implied by the assumption that the production function (3) has a Cobb-Douglas form. Plugging (17) in (16), we get:

$$D_t = \alpha Y_t - I_t A_t. \tag{18}$$

Plugging (18) into (15) allows us to rewrite the expression for the end-of period value of the firm as:

$$V_t = \beta E_t \left(\frac{\Lambda_{t+1}}{\Lambda_t}\right)\left(V_{t+1} + \alpha Y_{t+1} - I_{t+1}A_{t+1}\right). \tag{19}$$

Iterating (19) forward, we obtain:

$$V_t = \sum_{i=1}^{\infty} E_t \left\{\beta^i \left(\frac{\Lambda_{t+i}}{\Lambda_t}\right)\left(\alpha Y_{t+i} - I_{t+i}A_{t+i}\right)\right\}. \tag{20}$$

Equation (20) states that the ex-dividend value of the firm is equal to the sum of the present values of its expected future dividends. Note that the expected future dividends of the representative firm are discounted using the representative household's intertemporal marginal rate of substitution (i.e. $\beta^i \frac{\Lambda_{t+i}}{\Lambda_t}$). This is due to the fact that households are assumed to be the ultimate owners of the firms in the economy.

2.2 Structure of the Exogenous Driving Processes

The model is driven by four exogenous shock processes – a labor augmenting technology (LAT) shock, X_t; an investment-specific productivity (ISP) shock, A_t; a total factor productivity (TFP) shock, Z_t; and a marginal efficiency of investment (MEI) shock, Ω_t. Following Schmitt-Grohe and Uribe (2010), we assume that the first two processes are non-stationary, while the last two are stationary. We also assume that each of the four exogenous processes is subject to both, unanticipated innovations and anticipated innovations (i.e. news shocks). While we model unanticipated innovations in a conventional way, we examine two alternative specifications for the structure of the processes which guide the evolution of anticipated innovations.

The first specification that we explore, the short-run news (SRN) specification, is one that has now become standard in the NDBC literature (Davis (2007), Khan and Tsoukalas (2010), Schmitt-Grohe and Uribe (2010), Fujiwara et al. (2011)). It is given by:

$$\nu_t = \rho_\nu^s\left(\nu_{t-1}\right) + \epsilon^0_{\nu,t} + \epsilon^1_{\nu,t-1} + \epsilon^2_{\nu,t-2} + \epsilon^3_{\nu,t-3},$$

where $\nu_t = \widehat{\mu_{x,t}}, \widehat{\mu_{a,t}}, z_t, \omega_t$, $\widehat{\mu_{x,t}} \equiv \log\left(\mu_{x,t}/\overline{\mu_x}\right)$, $\mu_{x,t} \equiv \frac{X_t}{X_{t-1}}$, $\widehat{\mu_{a,t}} \equiv \log\left(\mu_{a,t}/\overline{\mu_a}\right)$, $\mu_{a,t} \equiv \frac{A_t}{A_{t-1}}$, $z_t \equiv \log(Z_t)$, $\omega_t \equiv \log(\Omega_t)$, $\overline{\mu_x}$ and $\overline{\mu_a}$ denote the steady state value of $\mu_{x,t}$ and $\mu_{a,t}$, respectively, $0 < \rho_\nu^s < 1$, and $\epsilon_{\nu,t-j}^j$ (for $j = 0, 1, 2, 3$) denotes a change in the level of ν_t that materializes in period t, but enters the representative agent's information set in period $t - j$. When $j \neq 0$, one can think of $\epsilon_{\nu,t-j}^j$ as a news shock. By contrast, when $j = 0$, $\epsilon_{\nu,t}^j$ represents a conventional unanticipated shock - a shock that appears in the information set of the representative agent in the period in which it occurs. We assume that $\epsilon_{\nu,t}^j \sim N(0, \sigma_{\nu,j}^2)$, $E\epsilon_{\nu,t}^j \epsilon_{\nu,t-m}^k = 0$ for $k, j = 0, 1, 2, 3$ and $m > 0$, and that $E\epsilon_{\nu,t}^j \epsilon_{\nu,t}^k = 0$ for any $k \neq j$.

The second specification that we examine, the long-run news (LRN) specification, has so far not been explored in an estimated structural NDBC model. In it, the shock process evolves according to the following law of motion:

$$\nu_t = \rho_\nu^l \left(\nu_{t-1}\right) + \left(1 - \rho_\nu^l\right) \left(\nu_{t-1}^{LR}\right) + \epsilon_{\nu,t}^u,$$

where $0 < \rho_\nu^l < 1$, $\epsilon_{\nu,t}^0$ is an i.i.d. (unanticipated) innovation to ν_t, and ν_t^{LR} is the long-run component of ν_t:

$$\nu_t^{LR} = \left(\rho_\nu^{LR}\right) \left(\nu_{t-1}^{LR}\right) + \epsilon_{\nu,t}^{LR},$$

where $0 < \rho_\nu^{LR} < 1$ and $\epsilon_{\nu,t}^{LR}$ is an i.i.d. innovation to ν_t^{LR}. We assume that $\epsilon_{\nu,t}^u \sim N(0, \sigma_{\nu,u}^2)$, $\epsilon_{\nu,t}^{LR} \sim N(0, \sigma_{\nu,LR}^2)$, and $E\epsilon_{\nu,t}^u \epsilon_{\nu,t-m}^{LR} = 0$ for all m. The parameter ρ_ν^{LR} governs the degree of persistence in ν_t^{LR}, while ρ_ν^l determines the speed with which ν_t converges to its long-run component, ν_t^{LR}.[5] The higher ρ_ν^l is, the slower ν_t converges to ν_t^{LR} and vice versa. Note that agents learn about the innovation $\epsilon_{\nu,t}^u$ in the period in which it impacts the exogenous process, ν_t. In that sense, it directly corresponds to the unanticipated shock, $\epsilon_{\nu,t}^0$, in the SRN specification. By contrast, the innovation $\epsilon_{\nu,t}^{LR}$ does not affect the level of ν_t in period t, even though agents learn about it in that period. As a result, $\epsilon_{\nu,t}^{LR}$ can be thought of as a news shock.

The LRN specification that we examine in this paper is similar to the one introduced by Cochrane (1994). He proposes a shock that is "constructed to forecast a long slow increase in technology" and shows that such a shock can improve the performance of a standard real-business cycle model along several dimensions. Our LRN specification is also related to the assumptions made in Bansal and Yaron (2006) and Croce (2008). Bansal and Yaron (2006) build a partial equilibrium asset pricing model in which they assume that consumption growth has a small predictable long-run component, which is stationary, but very persistent. They use that model to demonstrate that long-run risks in consumption and dividends play

[5]For each of the four exogenous processes, we estimate ρ_ν^l and we set the value of ρ_ν^{LR} to 0.999, so that it is very persistent, yet stationary.

an important role in reconciling the time series properties of aggregate consumption and asset prices with plausible levels of risk aversion and intertemporal elasticity of substitution. In a related paper, Croce (2008) uses post-war US data to show that the conditional mean of the growth rate of labor augmenting technology is time-varying and extremely persistent. Based on that observation, he builds a general equilibrium model in which the growth rate of labor augmenting technology contains a small and predictable long-run component. He uses the results of his model to demonstrate that news about changes in the long-run component of LAT have the potential to trigger large fluctuations in stock prices.

Figure 1 presents the impulse responses of a generic stochastic process to the three types of shocks discussed above. Note that the shape of the impulse response to a short-run news shock is very similar to that of the impulse response to an unanticipated shock, except for the fact that it is shifted to the right by j periods (i.e. the shock affects the exogenous process with a delay of j periods).[6] By contrast, the impulse response to a long-run news shock looks very different from the other two impulse responses. Namely, due to the fact that it affects the long-run component of the exogenous process, its impact gradually increases, rather than decreases, in magnitude over time.

2.3 Model Specifications

Combining each of the two news shock specifications (SRN and LRN) described in Section 2.2 with each of the two investment/capital adjustment costs specifications (CAC and IAC) presented in Section 2.1 yields the four model versions that we focus on in our empirical investigation of the impact of including data on asset prices in the estimation of a structural NDBC model:

- The Investment Adjustment Costs - Short Run News (IAC-SRN) specification;
- The Capital Adjustment Costs - Short Run News (CAC-SRN) specification;
- The Investment Adjustment Costs - Long Run News (IAC-LRN) specification;
- The Capital Adjustment Costs - Long Run News (CAC-LRN) specification.

2.4 Solution Method

As discussed above, two of the four exogenous driving processes (X_t and A_t) have stochastic trends. As a result, all of the endogenous variables in the model, with the exception of hours worked (h_t), leisure (l_t), and capacity utilization (u_t), fluctuate around a stochastic balanced growth path. In order to induce stationarity to the system, we divide each endogenous

[6] The example in the graph assumes $j = 3$.

variable which has a unit root by its trend component.

Next, we compute the non-stochastic steady state of each of the four model specifications listed in Section 2.3. We then log-linearize the stationary equilibrium conditions around the steady state. Finally, we solve the resulting system of linear rational expectation equations as in Blanchard and Kahn (1980) and Uhlig (1999) in order to obtain its state space representation:

$$O_t = A + \Psi S_t + V_t \tag{21}$$

$$S_t = G + F S_{t-1} + U_t, \tag{22}$$

where O_t is a vector of observable variables, S_t is a vector of unobserved states, $V_t \sim N(0, R)$ is a vector of observation errors, $U_t \sim N(0, Q)$ is a vector of structural shocks, R is a diagonal matrix with the variances of the observation errors on its main diagonal, and Q is a diagonal matrix with the variances of the structural shocks on its main diagonal. Note that the matrices A, G, Ψ, F, Q, and R are functions of the structural parameters of the model. We use the above state space model as the basis for our estimation procedure, which we describe in the next section.

Note that in the context of the state space model in (21) and (22), the exogenous shock processes, which are not directly observed, belong to the vector of unobserved states, S_t, and not to the vector of observable variables, O_t. Our main hypothesis is that adding asset prices to the vector of observables, which is equivalent to imposing more restrictions (i.e. (14) and (20)) on the estimation of the state space model, will have a significant impact on inference about the statistical properties and the actual realizations of the unobserved states (i.e. the unanticipated shocks and the news shocks) due to the fact that it will unveil relevant information about the unobserved shock processes - information that cannot be obtained by using solely data on macroeconomic aggregates.

3 Bayesian Inference

We use Bayesian Markov Chain Monte Carlo (MCMC) methods in order to obtain estimates of the posterior distributions of the non-calibrated structural parameters (Θ) and the unobserved states (S_t, $t = 1, \ldots, T$) of the state space model described in (21) and (22). In particular, following a methodology similar to the one described in An and Schorfheide (2007), we employ a combination of the Random Walk Metropolis-Hastings (RWMH) and the Gibbs Sampling (GS) algorithms in order to consecutively sample from the conditional distributions of the unknown parameters and the unobserved states.[7]

3.1 Observable Variables

As discussed in Section 1, we estimate each of the four model specifications twice - once using a vector of observable variables (O_t^M) that includes only macroeconomic variables (i.e. real output growth, real consumption growth, real investment growth, hours worked, and the growth rate of the relative price of investment) and once using a vector of observables (O_t^A) that includes two asset price variables (i.e. total stock market valuation and the three-month real risk-free interest rate) in addition to the five macroeconomic variables included in the former vector of observables. More specifically, the two vectors of observable variables are given by:

$$O_t^M = \begin{bmatrix} \Delta \log (Y_t) \\ \Delta \log (C_t) \\ \Delta \log (A_t I_t) \\ \log (h_t) \\ \Delta \log (A_t) \end{bmatrix}, \tag{23}$$

$$O_t^A = \begin{bmatrix} \Delta \log (Y_t) \\ \Delta \log (C_t) \\ \Delta \log (A_t I_t) \\ \log (h_t) \\ \Delta \log (A_t) \\ \Delta \log (V_t) \\ \log \left(R_t^{RF}\right) \end{bmatrix}, \tag{24}$$

where $\Delta \log (Y_t)$ is the log of the gross growth rate of real GDP per capita, $\Delta \log (C_t)$ is the log of the gross growth rate of real per capita consumption, $\Delta \log (A_t I_t)$ is the log of the gross growth rate of real per capita investment, $\log (h_t)$ is the log of total hours worked, $\Delta \log (A_t)$ is the log of the gross growth rate of the relative price of investment, $\Delta \log (V_t)$ is the log of the gross growth rate of total market valuation for the US stock market, and $\log \left(R_t^{RF}\right)$ is the log of the gross real three-month risk-free interest rate. We use quarterly US data from 1951:Q1 to 2009:Q4.[8] As mentioned in the previous section, we assume that each of the

[7] We present a detailed description of the steps involved in the Bayesian MCMC algorithm that we use to estimate the model in Appendix A.

[8] Appendix B provides a detailed description of the data that we use in order to obtain the observable variables listed above.

above series has a normally distributed, zero-mean observation error associated with it. We denote the standard deviations of these observation errors by $\sigma_{O,J}$ $(J = Y, C, I, H, A, V, R)$.

We obtain eight sets of estimates - two for each of the four model specifications listed in Section 2.3:

- The IAC-SRN specification estimated with and without data on asset prices (IAC-SRN-AP and IAC-SRN-NoAP, respectively);

- The CAC-SRN specification estimated with and without data on asset prices (CAC-SRN-AP and CAC-SRN-NoAP, respectively);

- The IAC-LRN specification estimated with and without data on asset prices (IAC-LRN-AP and IAC-LRN-NoAP, respectively);

- The CAC-LRN specification estimated with and without data on asset prices (CAC-LRN-AP and CAC-LRN-NoAP, respectively).

3.2 Structural Parameters

We fix a small number of parameters to values that are implied by the steady state conditions of our model or are commonly used in the literature. All calibrated parameters are summarized in Table 1. We estimate the rest of the model's parameters. The prior distributions for all estimated parameters are summarized in Tables 2-5. In general, unless there is a solid theoretical reason for not doing so, we impose fairly flat (uninformative) priors in order to let the data (i.e. the likelihood function) have as much weight as possible in determining the posterior distributions.

In order to "level the playing field" for the SRN and the LRN specifications as much as possible, we choose the same prior means for the standard deviations of the unanticipated innovations to each of the four exogenous driving processes in the two specifications (i.e. $\sigma_{\nu,0} = \sigma_{\nu,u}$ for $\nu = x, a, z, \omega$). We incorporate our prior information about the relative sizes of the long-run components in the LRN specification by assigning values for the prior means of the standard deviations of the innovations to these components that are five times smaller than the values for the prior means of the standard deviations of the unanticipated innovations.[9] Finally, we restrict the standard deviation of each of the observation errors to be at most 20% of the unconditional standard deviation of the corresponding observable variable.

The last six columns of Tables 2-5 summarize the posterior distributions of the estimated parameters for each of the four model specifications under the two estimation approaches (i.e.

[9] Our prior information is based on the findings of the long-run risks literature (Bansal and Yaron (2006), Croce (2008), and Avdjiev and Balke (2010)).

with and without asset prices in the vector of observable variables). Given the main focus of this paper, we choose to follow the approach of Justiniano et al. (2010) and Schmitt-Grohe and Uribe (2010) and concentrate not on discussing the estimates of individual parameters, but rather on the implications of those estimates for the relative fits of the four model specifications and for the variance decompositions associated with them.

4 Main Results

Figures 2 and 3 display plots of the actual observable variables and their model-implied counterparts for each of the four model specifications under each of the two estimation approaches (i.e. with and without using data on asset prices in the estimation). Overall, all model versions appear to fit the data reasonably well. This is partially explained by the fact that, as discussed in Section 3.2, the standard deviations of the observation errors are restricted to be no larger than 20% of the standard deviations of the respective observable variables.

4.1 Marginal Likelihoods

Table 6 presents the log-marginal likelihoods of the four model specifications obtained under each of the two estimation approaches. There is a striking contrast between the two sets of rankings. Namely, when asset prices are not included in the vector of observable variables (the second and third columns of Table 6), the model specification with the best fit is IAC-SRN. It is followed by the IAC-LRN and the CAC-SRN specifications. The specification with the worst fit is CAC-LRN. However, when asset prices are included in the vector of observables (the fourth and fifth columns of Table 6), the rankings of the four specifications are completely reversed. In this case, the CAC-LRN specification has the highest marginal likelihood, followed by the CAC-SRN and the IAC-LRN specifications. The IAC-SRN specification ranks last.

The rankings presented in Table 6 have important implications for inference about the structure of the news shock processes and about the functional form of investment/capital adjustment costs. When asset prices are not included among the observable variables, all else the same, the data favors the SRN specification over the LRN specification and the IAC functional form over the CAC functional form. However, when asset prices are included in the estimation, the LRN specification and the CAC functional form are preferred by the data over their respective counterparts.

4.2 Variance Decompositions

Tables 7 through 10 display variance decompositions at business cycle horizons (i.e. 6 to 32 quarters) for the observable variables in the four model specifications under each of the two alternative estimation approaches (i.e. with and without including asset prices in the vector of observables). They provide strong evidence that including data on asset prices in the estimation of a structural NDBC model has important implications for inference about the main drivers of business cycle fluctuations.

4.2.1 Comparing the Variance Decompositions Implied by the Highest Ranked Model Specifications under Each Estimation Approach

There are major differences between the variance decompositions implied by the model specification that has the best overall fit when data on asset prices are not included in the estimation, IAC-SRN, and those implied by the model specification that has the best overall fit when the vector of observables includes asset prices, CAC-LRN. Namely, the estimates obtained in the IAC-SRN-NoAP case (Table 7, top panel) imply that the main drivers of output growth, investment growth, and hours worked are LAT news shocks (29%, 21%, and 25% respectively) and MEI news shocks (27%, 35%, and 49%, respectively). Meanwhile, consumption growth is primarily driven by a combination of ISP news shocks (23%), LAT news shocks (21%), and the unanticipated ISP shock (19%). By contrast, the results in CAC-LRN-AP case (Table 10, bottom panel) imply that the main triggers of macroeconomic fluctuations are the unanticipated TFP shock and the unanticipated MEI shock. The former accounts for more than half of the variances of output (51%) and consumption (62%), while the latter explains 45% of the fluctuations in investment growth and 50% of those in hours.

Therefore, a researcher attempting to make inferences about the main drivers of business cycle fluctuations using solely data on macroeconomic aggregates would reach a very different set of conclusions than a researcher aiming to answer the same questions using data on asset prices in addition to data on macroeconomic aggregates. The main reason for that discrepancy would be that the two researchers would end up selecting different model specifications to base their inference upon. Namely, the former researcher would base her conclusions on the results implied by the IAC-SRN model specification, the one with the best relative fit under the estimation approach that ignores data on asset prices. By contrast, the latter researcher would focus on the results implied by the CAC-LRN model specification, the one with the best relative fit under the estimation approach that includes asset prices in the set of observable variables.

4.2.2 Comparing Variance Decompositions within Model Specifications

Including asset prices in the vector of observable variables causes significant differences not only between the variance decompositions implied by the two model specifications with best relative fits under the two alternative estimation approaches, but also within three out of the four model specification. For instance, when the CAC-LRN specification is estimated without including data on asset prices (Table 10, top panel), the main driver of fluctuations in output growth is estimated to be the unanticipated MEI shock (53%) - a finding similar to the one reported by Justiniano et al. (2011), whose benchmark estimation implies that unanticipated MEI shocks account for approximately 60% of the variance of output growth.[10] However, when the same model specification is estimated with asset prices in the vector of observables (Table 10, bottom panel), the unanticipated TFP shock emerges as the main trigger of fluctuations in output growth (51%), while the share attributed to the unanticipated MEI shock goes down to 19%. The inclusion of data on asset prices in the estimation also considerably decreases the shares assigned to the unanticipated MEI shock in the variance decompositions of the other three macroeconomic aggregates. While it remains the main driver of fluctuations in investment growth and hours, its shares in the variance decompositions of these two variables decline substantially (from 92% to 45% in the case of investment growth and from 71% to 50% in the case of hours). Similarly, its share in the variance of consumption growth declines from 23% to 11%.

The results from the CAC-SRN specification (Table 8) display a pattern similar to the one observed in results generated by the CAC-LRN specification. Namely, the inclusion of asset prices in the estimation more than doubles the share assigned to the unanticipated TFP shock in the variance of output from 28% to 60%, thus making it the main driver of fluctuations in that variable. Just as in the CAC-LRN case, this comes mainly "at the expense" of the unanticipated MEI shock, whose share in the variance of output shrinks from 44% to 28%. The significance of the unanticipated MEI shock as a driver of fluctuations in investment growth and hours also declines significantly (from 61% to 37% for investment growth and from 53% to 17% for hours) with the inclusion of data on asset prices in the estimation. This mostly benefits the unanticipated LAT shock whose variance share increase from 1% to 31% in the case of investment growth and from 10% to 39% in the case of hours. Meanwhile, the unanticipated TFP shock remains the main driver of consumption growth, even though its share declines from 52% in the case in which asset prices are not included in the estimation to 45% in the case in which they are.

The impact of the inclusion of asset prices in the vector of observables is most signifi-

[10] Note that Justiniano et al. (2011) do not allow for news shocks in their model.

cant in the IAC-LRN specification (Table 9). When the set of observables consists solely of macroeconomic aggregates, the unanticipated LAT shock is the most dominant force behind fluctuations in all four macroeconomic variables. It explains 61% of the variance of investment growth, 73% of the variance of consumption growth, 77% of the variance of hours, and 80% of the variance of output growth. When asset prices are added to the vector of observables, these shares decline dramatically for all but one of the macroeconomic aggregates studied in this exercise. Namely, even though the unanticipated LAT shock remains the main driving force behind consumption growth, explaining 73% of its variance, the shares of the variances of the other three macro variables attributed to that shock shrink to 8% for both, output growth and investment growth, and to 7% for hours worked. By contrast, the ISP news shock emerges as the main driver of fluctuations in all three of these variables, accounting for 77% of the variance of output, 65% of that of investment, and 90% of the one of hours.

The impact of including of data on asset prices in the estimation is smallest in the IAC-SRN specification (Table 7). The redistributions of variance shares among the exogenous shocks in this case are not nearly as dramatic as they are in the other three specifications. What is more, this is the only specification in which the main drivers of fluctuations in output growth (LAT news shocks) do not change after data on asset prices are included in the estimation.

Note that the small number of papers in the existing literature that have re-estimated their benchmark models after including data on stock prices (Davis (2007), Khan and Tsoukalas (2010), and Schmitt-Grohe and Uribe (2010)) have focused exclusively on the IAC-SRN specification. This explains why they all conclude that the impact of including stock prices as an observable variable is only marginal and choose not to use such data in their respective benchmark estimations. Namely, all of them consider only one of the four model specifications that we examine in this paper. What is more, the one specification that they all focus on happens to be the one in which the impact of including data on asset prices in the estimation on inference about the main sources of business cycle fluctuations is the smallest. Of course, that only implies that the effect of adding asset prices to the vector of observables is relatively small in this particular case, but not in general. On the contrary, as demonstrated above, once one allows for alternative specifications for the structure of the news shock processes and for the functional form of investment/capital adjustment costs, including data on asset prices in the estimation has a dramatic impact on inference about the main drivers of macroeconomic fluctuations.

4.3 Historical Decompositions

The historical decompositions implied by the various sets of estimates present further evidence that including data on asset prices in the estimation of a structural NDBC model has a significant impact on inference about the main sources of business cycle fluctuations. The historical decomposition of output growth based on the results from the specification with the highest marginal likelihood when asset prices are not included in the vector of observables (IAC-SRN-NoAP) and its counterpart from the specification with the highest marginal likelihood when asset prices are included in the observation vector (CAC-LRN-AP) are displayed in Figures 4 and 5, respectively.

The two alternative estimation approaches (i.e. with and without including asset prices in the vector of observables) result in starkly different interpretations of what the main drivers of macroeconomic fluctuations were during a number of historical episodes. For example, the estimates obtained in the IAC-SRN-NoAP case imply that the recession of the mid-1970s was primarily caused by a combination of MEI news shocks and unanticipated LAT shocks, whereas those from the CAC-LRN-AP case suggest that the main drivers were unanticipated TFP shocks and TFP news shocks. Similarly, according to the IAC-SRN-NoAP results, the expansion of the 1990s was mostly driven by MEI news shocks and unanticipated LAT shocks, while the CAC-LRN-AP estimates imply that it was mainly the result of unanticipated TFP and unanticipated MEI shocks.

Finally, the two sets of historical decompositions offer an interesting perspective on the 2008-09 recession. More specifically, the IAC-SRN-NoAP results suggest that the sharp decline in output during that period was mainly caused by a combination of unanticipated TFP shocks and MEI news shocks. Unanticipated TFP shocks also played an important role in that particular contraction according to the CAC-LRN-AP estimates. However, according to that set of results, unanticipated MEI shocks and ISP news shocks also contributed significantly to the decline. Note that despite the significant differences that exist between them, the two sets of historical decompositions do have an important similarity. Namely, both of them assign an important role in explaining the 2008-09 recession to MEI shocks. To the extent to which the MEI level could be broadly interpreted as a proxy for the overall efficiency of the financial intermediation process in a given economy (Justiniano et al. (2011)), this conclusion aligns our results with the conventional wisdom about the main cause of the 2008-09 downturn in the US economy (i.e. shocks originating within the financial sector).

5 Discussion

In this section, we discuss the main reasons due to which including data on asset prices in the estimation of a structural NDBC model makes such a dramatic impact on inference about the main sources of business cycle fluctuations, the structure of the news shock processes, and the functional form of investment/capital adjustment costs. We start by providing a summary of the main channels through which the inclusion of data on asset prices in the estimation affects inference. After that we go into a more detailed intuitive discussion of our main results.

5.1 The Big Picture

The inclusion of the two asset price variables in the vector of observables affects the results by imposing additional discipline on the estimation. More specifically, it imposes two new restrictions, (14) and (20), which affect inference about the leading sources of business cycle fluctuations through two main channels. First, they affect model selection by reordering the rankings of the four model specifications. Second, they affect the identification of the unobserved shocks within each model specification.

When the vector of observables consists only of macroeconomic aggregates, the estimation procedure favors specifications which can replicate the positive comovement among macro variables that is observed in the data. As a result, the SRN specification is preferred over the LRN specification mostly due to the fact that in the former case the wealth effect on leisure generated by a technology news shock tends to be weaker, which makes it relatively easier for the model to induce a positive comovement among macro variables. At the same time, the IAC functional form is favored over its CAC counterpart mainly because the former implies that capacity utilization increases after a positive anticipated technology shock, which boosts output and induces a positive comovement among macro variables. The opposite occurs in the case of CAC.

When data on asset prices are included in the estimation, the relative fit of each specification depends on its ability to replicate the joint dynamics of macro variables and asset prices. As a consequence, the LRN specification is preferred over its SRN counterpart mainly because it gives the model the quantitative wedge that it needs in order to simultaneously fit the relatively volatile total market valuation series and the much more stable macroeconomic series. Meanwhile, the estimation procedure favors the CAC functional form over its IAC counterpart mostly due to the fact that an ISP news shock, which plays a crucial role in allowing the model to simultaneously fit stock prices and investment growth under the former specification, triggers an unrealistically large response in investment under the latter specification.

The inclusion of data on asset prices in the estimation affects inference within each specification through its impact on the identification of the unobserved shocks. When the set of observable variables is augmented by the inclusion of asset prices, the number of model-implied relationships that the unobserved shocks have to satisfy increases. As a result, some of the shocks that the model uses to fit the data which consist solely of macroeconomic variables no longer satisfy the enhanced set of model-implied relationships. As a consequence, the estimated importance of such shocks in driving economic fluctuations diminishes significantly once asset prices are taken into consideration. The shocks that emerge to replace them tend to be those that have more realistic implications for the joint behavior of macroeconomic aggregates and asset prices, even if they are slightly dominated by the former group of shocks in terms of their implications for the stand-alone behavior of macroeconomic variables.

5.2 The Details

Next, we provide a more detailed intuitive explanation of the main channels discussed in the previous subsection. We do that by using the impulse response functions implied by the estimates of each of the eight cases that we examine (Figures 6 through 13).

5.2.1 What Happens When Asset Prices Are Ignored?

As discussed in Section 4.2, when asset prices are not included in the estimation, the results generated by the model specification that has the highest marginal likelihood (IAC-SRN) imply that the main drivers of business cycle fluctuations are LAT news shocks and MEI news shocks. The fact that LAT news shocks explain the largest share of the variance of output in the IAC-SRN specification is not surprising. Schmitt-Grohe and Uribe (2008) use a model whose main features are very similar to the ones assumed in our IAC-SRN specification, do not use data on asset prices in the estimation, and also find that group of shocks to be a major source of macroeconomic fluctuations.[11]

LAT news shocks emerge as the main drivers of macroeconomic fluctuations because they induce positive responses in all macroeconomic variables (the second row of Figure 6). An expected increase in LAT has a positive wealth effect, which induces agents to consume more in the current period. It also raises expectations about the future levels of the marginal product of capital, which induces agents to invest more today. The latter effect is reinforced by the presence of IAC, which makes agents desire a smooth path for investment growth.

[11] Schmitt-Grohe and Uribe (2008) refer to these shocks as "non-stationary neutral technology shocks."

Output also increases contemporaneously despite the fact that capital is predetermined and the rise in LAT has not arrived yet. Nevertheless, capacity utilization increases in the current period. This happens because in the presence of IAC, the marginal cost of increasing capacity utilization (i.e. higher depreciation of existing capital) is relatively low since capital does not help mitigate the adjustment costs associated with higher future levels of investment as it does in the presence of CAC. The rise in capacity utilization increases output both directly, by increasing the effective amount of capital services used in production, and indirectly, by increasing the marginal product of labor and hours worked. The latter effect and the presence of strong internal habits in leisure (the estimate of θ_l in the IAC-SRN-NoAP case is 0.94), which induce agents to desire a smooth leisure path, more than offset the negative wealth effect on labor supply that is generated by the anticipated increase in LAT.

The two IAC specifications (IAC-SRN and IAC-LRN) have higher marginal likelihoods than the two CAC specifications (CAC-SRN and CAC-LRN) mainly because in the case of the latter capacity utilization tends to decline after a positive technology news shock (the fifth columns of Figures 7 and 9), thus failing to provide the direct and indirect boosts to output that it does in the presence of IAC. As discussed above, this occurs due to the fact that increasing capacity utilization is relatively more costly in the presence of CAC than in the presence of IAC. As a result, it is relatively more difficult for anticipated technology shocks to produce a positive comovement among macroeconomic aggregates in the presence of CAC.

The IAC-SRN specification fits the macroeconomic data better than the IAC-LRN specification mainly because the wealth effect on leisure generated by a positive technology news shock in the LRN specification tends to be stronger than its counterpart in the SRN specification. This occurs due to the fact that in the former case, the impact of news shocks extends further into the future than in the latter case. As a consequence, upon the arrival of a news shock in the IAC-LRN case (the second row of Figure 8), labor supply and output increase by less than they do in the IAC-SRN case (the second row of Figure 6).

5.2.2 How Does Including Data on Asset Prices in the Estimation Affect Inference?

The variance decompositions of the macroeconomic aggregates in the CAC-LRN specification indicate that including data on asset prices in the estimation shifts variance shares away from the unanticipated MEI shock and towards the unanticipated TFP shock and the ISP news shock (Table 10). This occurs despite the fact that a positive unanticipated MEI shock manages to trigger a positive comovement among the four macroeconomic variables even after data on asset prices are included in the estimation (the seventh row of Figure 13). Nevertheless, such a shock generates a negative response in the value of the firm, V_t. This occurs mainly due to the fact that it causes a rightward shift in the supply of capital (induced by the lower level of adjustment costs per unit of investment) that is greater in magnitude than the rightward shift in the demand for capital (caused by the fact that capital becomes more valuable as a tool for mitigating the adjustment costs associated with the expected higher future levels of investment) triggered by the same shock (Figure 14, top panel).

With the unanticipated MEI shock incapable of generating a positive response in the value of the firm, the ISP news shock emerges as the main driver of fluctuations in total market valuation, explaining almost half (48%) of its variation at business cycle frequencies. A positive ISP news shock (i.e. a shock that reduces the relative price of investment) shifts the demand for capital to the right (Figure 14, bottom panel) due to the fact that capital becomes more valuable as a tool for mitigating the adjustment costs associated with the higher levels of investment. Qualitatively, this shift in the demand for capital is identical to the one generated by the unanticipated MEI shock described above. Quantitatively, however, it is much larger due to the fact that the persistence of the long-run ISP news shock leads agents to rationally expect a prolonged period of rising investment, which, in turn, makes capital more valuable as a mitigant for the associated increase in capital adjustment costs. This effect is weaker in the case of an unanticipated MEI shock, which is not nearly as persistent and, as a result, the increase in investment growth that it generates is not nearly as long-lived as the one triggered by the ISP news shock. The contemporaneous increase in the price of capital is further enhanced by the fact that, in contrast to what occurs in the case of an unanticipated MEI shock, the supply of capital does not shift immediately since the level of ISP remains unchanged in the period in which the ISP news shock occurs. As shown in the bottom panel of Figure 14, the large rightward shift in the demand for capital triggered by the ISP news shock also leads to a sizeable increase in investment (the fourth row of Figure 13), which explains the relatively large share (35%) of the variance decomposition of investment growth that the ISP news shock is attributed in the CAC-LRN-AP case.

Just as in the CAC-LRN-AP case, the results in the IAC-LRN-AP case also attribute the majority (58%) of the variation in total market valuation to the ISP news shock. Furthermore, a positive ISP news shock triggers a large and positive response in the value of the firm and generates a positive comovement among the four macroeconomic variables (the fourth row of Figure 12). Why is it then that the marginal likelihood of the IAC-LRN specification is much lower than that of the CAC-LRN specification when data on asset prices are used in the estimation?

The answer to the above question is related to the fact that the ISP news shock triggers an unrealistically large response in investment under the IAC-LRN specification. As Figure 15 illustrates, this is caused by a combination of two effects. First, in the presence of IAC, a positive ISP news shock shifts the supply of capital to the right, in contrast to what occurs under CAC. This takes place due to the fact that a positive ISP news shock increases the term that captures the value of today's investment as a mitigant for tomorrow's investment adjustment costs in the equation describing the supply of capital in the IAC case (10). Since this term does not appear in the equation describing the supply of capital in the CAC case (12), the supply of capital does not shift to the right in that case.

Second, in the IAC specification, a positive ISP news shock of a given size shifts the demand for capital by less than it does in the CAC specification. This occurs because the term that captures the value of capital as a mitigant for future investment/capital adjustment costs appears in the equation describing the demand for capital in the CAC case (13), but does not appear in the respective equation in the IAC case (11). Since a positive ISP news shock increases that term (due to the fact that it increases expected future investment), the shift in the demand curve for capital is smaller in the IAC case than in the CAC case.

As a result of the above two effects, in the presence of IAC, a positive ISP news shock increases the value of the firm by less and investment by more than a shock of the same size in the CAC case (Figure 15). As a consequence, in the IAC-LRN specification, an ISP news shock that is large enough to induce an empirically plausible response in the value of the firm causes unrealistically large fluctuations in investment (the fourth row of Figure 12). This causes the fit of the IAC-LRN model specification to deteriorate significantly relative to that of the CAC-LRN specification.

Furthermore, the real risk-free rate is much more volatile in the IAC-LRN specification than in the CAC-LRN specification and in the data. The standard deviation of that variable implied by the former model specification is 1.53%. By contrast, the one implied by the latter model specification is 0.75%, substantially closer to the one observed in the data (0.58%).[12] The impulse response functions displayed in the last columns of Figure 12 and Figure 13 provide a visual explanation for that fact. Namely, the main drivers of the real interest rate in the IAC-LRN specification (the unanticipated MEI and TFP shocks and the ISP news shock) trigger a much larger response in that variable than their counterparts in the CAC-LRN specification (the unanticipated MEI and TFP shocks and the TFP news shock). As a consequence, the fit of the IAC-LRN specification deteriorates further relative to that of the CAC-LRN specification when asset prices are added to the set of observable variables.

[12] A table with selected data- and model-implied moments for all model specifications studied in this paper is available upon request.

The CAC-LRN specification outperform the two SRN specifications (i.e. CAC-SRN and IAC-SRN) mainly due to the ability of the long-run ISP news shock to drive a wedge between the volatility of macroeconomic variables and short-term interest rates, on the one side, and the value of the firm, on the other side. In the data, the growth rate of total market valuation is a lot more volatile than each of the macroeconomic variables used in the estimation - its standard deviation (8.74%) is almost four times larger than that of investment growth (2.56%), more than nine times larger than that of output growth (0.95%), and approximately 16 times larger than that of consumption growth (0.55%). In addition, its standard deviation is more than 15 times larger than that of the short-term real interest rate (0.58%). As a result, in order for a model specification to be able to simultaneously fit all of those series, it must generate shocks that not only trigger a positive comovement among the key endogenous variables of the model (i.e. match the qualitative features of the data), but also create a wedge between the scale of variation in macroeconomic variables and short-term interest rates, on the one side, and stock prices, on the other side (i.e. match the quantitative features of the data). While all model specifications examined in this paper contain at least one shock that satisfies the former condition, the latter one turns out to be elusive for all but one of them (the CAC-LRN specification).

By construction, the SRN specifications have two groups of shocks to select from - unanticipated shocks and short-run news shocks. An unanticipated shock is not able to create a wedge between the degree of variability in macroeconomic variables and short-term interest rates and that in stock prices due to the fact that it fails to generate the persistence in the dividend process that is needed to do that (20). Short-run news shocks suffer from the same problem since, by design, the structure of their dynamics is identical to that of unanticipated shocks, save for the fact that they are delayed by one, two, or three periods (Figure 1). As a result, any shock that belongs to one of the above two groups and causes sufficiently small responses in macroeconomic variables and short-term interest rates to be able to successfully match the data, fails to generate large enough fluctuations in total market valuation. Alternatively, if such a shock triggers adequately large fluctuations in total market valuation, it also causes implausibly large responses in macroeconomic aggregates (Figures 10 and 11).

By contrast, the inherent persistence of a long-run news shock allows it to create the quantitative wedge between macro variables and stock prices that the other two groups of shocks fail to generate. Namely, the combination of the fact that the impact of a long-run news shock on the determinants of the representative firm's dividends extends many periods into the future and the fact that stock prices are simultaneously forward-looking and much more flexible than macroeconomic variables allows long-run news shocks that are small enough in magnitude to have an impact on macroeconomic aggregates and short-term interest rates of an empirically plausible scale to also be able to trigger a sufficiently large response in the value of the firm.

6 Conclusion

In this paper, we formally analyze the impact of including data on asset prices in the estimation of a structural NDBC model, while simultaneously allowing for alternative specifications for the structure of the news shock processes and for the functional form of investment/capital adjustment costs. We demonstrate that using data on asset prices dramatically affects inference about the main sources of business cycle fluctuations. Namely, we show that when data on asset prices are not used in the estimation, fluctuations in macroeconomic variables appear to be mainly driven by LAT news shocks and MEI news shocks. However, when asset prices are included in the vector of observables, most of the variation in macroeconomic aggregates is attributed to unanticipated TFP shocks and unanticipated MEI shocks.

We also demonstrate that when asset prices are used as observables, an alternative long-run specification for the structure of the news shock processes is preferred by the data over the canonical short-run specification currently assumed throughout the NDBC literature. In addition, we show that, when asset prices are included in the vector of observables, model specifications with capital adjustment costs fit the data better than specifications with investment adjustment costs, which dominate the existing literature. We demonstrate that the last two results represent reversals of conclusions that would be reached if asset prices are not used as observable variables, thus providing additional evidence that asset prices contain valuable information which cannot be obtained by using solely data on macroeconomic variables.

Combining our results with the large body of evidence that asset price movements reflect changes in expectations of future developments in the economy implies that data on asset prices should always be used in the estimation of structural NDBC models because not doing so would be equivalent to ignoring crucial information about the unobserved stochastic processes that drive macroeconomic fluctuations. It further suggests that some of the main results in the existing literature on estimated NDBC models are biased because they depend on restrictive assumptions about the structure of the news shock processes and the functional form of investment/capital adjustment costs.

The paper presents several possible directions for future research. First, it would be intriguing to adopt the estimation approach proposed by Justiniano and Primiceri (2008) in order to investigate whether allowing for time-varying volatility of the structural innovations in our model would have a significant impact on the main results. It is well-known that second moments have crucial asset pricing implications. Therefore, allowing for time-variation in them has the potential to shed further light on the questions that are studied in this paper. The second extension that would be worth pursuing is related to relaxing the assumption that agents have perfect information about the levels of the long-run components of the exogenous processes in the LRN specification. This would introduce a signal extraction problem and would have the potential to significantly affect the dynamics of all endogenous variables in the model. Finally, it would be interesting to examine how the results presented in this paper would be affected by the introduction of a financial sector as in Christiano et al. (2010). As pointed out by Justiniano et al. (2011), one can broadly think of MEI shocks as proxies for shocks to the efficiency of the financial intermediation process in the economy. Since MEI shocks are estimated to be among the main sources of business cycle fluctuations under both estimation approaches that we explore, we believe that incorporating financial intermediation into the theoretical environment of this paper would be a worthwhile endeavor.

Appendix A: Bayesian Estimation

Given the data, O_T, and the set of structural parameters, Θ, we obtain estimates of the conditional distributions of the unobserved states by using the Kalman Filter. Given the conditional distributions of the unobserved states, the predictive log-likelihood of the state space model is given by:

$$l(O_T,\Theta) = \sum_{t=1}^{T} \left\{ \begin{array}{c} -0.5\log(\det(\Psi(\Theta)P_{t|t-1}\Psi(\Theta)' + R)) - \\ 0.5(O_T - \Psi(\Theta)S_{t|t-1} - A)'(\Psi(\Theta)P_{t|t-1}\Psi(\Theta)' + R)^{-1}(O_T - \Psi(\Theta)S_{t|t-1} - A) \end{array} \right\}, \tag{25}$$

where $S_{t|t-1}$ is the conditional mean and $P_{t|t-1}$ is the conditional variance of S_t, obtained from the Kalman Filter. Given the prior distribution of the vector of structural parameters, $\pi(\Theta)$, the posterior distribution, $P(\Theta|O_T)$, can be written as:

$$P(\Theta|O_T) \propto [\exp(l(O_T,\theta))]\,[\pi(\theta)]\,. \tag{26}$$

It is not possible to obtain an analytical expression for the posterior distribution given in (26) because the log-likelihood (25) is a highly non-linear function of the vector of structural parameters, Θ. That is why we use Bayesian Markov Chain Monte Carlo (MCMC) methods in order to obtain estimates of the joint posterior distribution of the structural parameters and the unobserved states. Namely, we use a combination of the Random Walk Metropolis-Hastings (RWMH) and the Gibbs Sampling (GS) algorithms in the following way:

1. We choose arbitrary initial values for the structural parameters, $\Theta^{(0)}$, and for the unobserved states, $S^{(0)}$.

2. For $i = 1, ..., n_{sim}$, we use the Kalman Filter to obtain the conditional distributions of the unobserved states given $\Theta^{(i-1)}$: $P(S_T|\Theta^{(i-1)}, Y_T)$. We obtain a draw, $S_T^{(i)}$, from $P(S_T|\Theta^{(i-1)}, Y_T)$. In this step, we use the "filter forward, sample backward" approach proposed by Carter and Kohn (1994) and discussed in Kim and Nelson (1999).

3. Given $\Theta^{(i-1)}$, we draw a candidate set of parameters, $\Theta^{(c)}$, from a pre-specified distribution: $g(\Theta^{(c)}|\Theta^{(i-1)})$. In our application of the procedure, $g(\cdot)$ is such that, $\Theta^{(c)} = \Theta^{(i-1)} + v$, where v is drawn from a multivariate t-distribution with five degrees of freedom and a covariance matrix Σ. We set Σ to be a scaled version of the Hessian matrix of the log posterior probability, evaluated at the posterior mode. We choose the scale so that $20\% - 30\%$ of the candidate draws are accepted.

4. We determine the acceptance probability, α, for the candidate draw:

$$\alpha(\Theta^{(c)}, \Theta^{(i-1)}) = \min\left\{ \frac{\left[\exp(l(O_T, \Theta^{(c)}))\right]\left[\pi(\Theta^{(c)})\right]}{\left[\exp(l(O_T, \Theta^{(i-1)}))\right]\left[\pi(\Theta^{(i-1)})\right]}, 1 \right\}.$$

5. We select $\Theta^{(i)}$ according to the following rule:

$$\Theta^{(i)} = \Theta^{(c)} \text{ with probability } \alpha;$$
$$\Theta^{(i)} = \Theta^{(i-1)} \text{ with probability } 1 - \alpha.$$

6. If $i < n_{sim}$, we return to step 2. Once $i = n_{sim}$, we move on to step 7.

7. We discard the first m draws ($m < n_{sim}$) in order to ensure that the initial conditions do not influence our estimates in any way. We approximate the expected value of any function of interest, $f(\Theta)$, by using the following formula:

$$\widehat{f(\Theta)} = \left(\frac{1}{n_{sim} - m}\right) \sum_{i=m+1}^{n_{sim}} f(\Theta^{(i)}).$$

In this particular application, we run 200, 000 iterations of the sampling procedure (i.e. we set $n_{sim} = 200,000$) and we use only the last 10, 000 draws (i.e. $m = 190,000$) to make inference about the posterior distributions of the structural parameters and the unobserved states.

Appendix B: Data Sources

The data that we use is quarterly and runs from 1951:Q1 to 2009:Q4. We construct the nominal total market valuation series by using the CRSP data set which includes all stocks listed on the NYSE, the AMEX, and the NASDAQ. We obtain data on nominal output, nominal consumption, and nominal investment from Bureau of Economic Analysis National Income and Product Accounts (NIPA) table 1.1.5. We convert each of the above aggregate nominal series into per-capita real series by dividing it by the GDP deflator that is implied by the data on nominal and real GDP (NIPA tables 1.1.5. and 1.1.6.) and by the civilian noninstitutional population over 16 (BLS LNU00000000Q). We construct the real one-period ahead interest rate series by subtracting the inflation rate implied by the GDP deflator series (constructed as described above) from the nominal yield on the three-month Treasury bill (obtained from the Federal Reserve Board of Governors website).The relative price of investment is obtained by dividing the implicit price deflator for gross private fixed investment (NIPA table 1.1.9., line 7) by the implicit price deflator for personal consumption expenditures (NIPA table 1.1.9., line 2). Data on per capita hours is obtained by dividing the Bureau of Labor Statistics' seasonally adjusted non-farm business hours worked index (BLS PRS85006033) by the civilian noninstitutional population over 16 (BLS LNU00000000Q).

References

[1] Abel, Andrew and Olivier Blanchard (1983), “An Intertemporal Equilibrium Model of Savings and Investment,” *Econometrica* 51, 675-692.

[2] An, Sungbae, and Frank Schorfheide (2007), "Bayesian Analysis of DSGE Models," *Econometric Reviews* 24, 113-172.

[3] Avdjiev, Stefan and Nathan S. Balke (2010), "Stochastic Volatility, Long Run Risks, and Aggregate Stock Market Fluctuations," Working Paper 323, Bank for International Settlements.

[4] Bansal, Ravi and Amir Yaron (2006), "Risks for the Long-Run: A Potential Resolution of Asset Pricing Puzzles," *Journal of Finance* 59, 1481-1509.

[5] Barsky, Robert B. and Eric R. Sims (2011), “News Shocks and Business Cycles,” *Journal of Monetary Economics*, forthcoming.

[6] Beaudry, Paul, and Bernd Lucke (2010), “Letting Different Views about Business Cycles Compete,” *NBER Macroeconomics Annual*.

[7] Beaudry, Paul, and Frank Portier (2004), “An Exploration in to Pigou’s Theory of Cycles,” *Journal of Monetary Economics* 51, 1183-1216.

[8] Beaudry, Paul, and Frank Portier (2006), “Stock Prices, News, and Economic Fluctuations,” *American Economic Review* 96, 1293-1307.

[9] Beaudry, Paul, and Frank Portier (2007), “When Can Changes in Expectations Cause Business Cycle Fluctuations in Neo-Classical Settings,” *Journal of Economic Theory* 135, 458-477.

[10] Blanchard, Olivier and C. Kahn (1980), “The Solution of Linear Difference Equations under Rational Expectations,” *Econometrica* 48, 1305-1310.

[11] Campbell, John Y., and John H. Cochrane (1999), "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior," *Journal of Political Economy* 107, 207-251.

[12] Carter, C.K. and P. Kohn (1994), "On Gibbs Sampling for State Space Models," *Biometrica* 81, 541-553.

[13] Christiano, Lawrence J., Martin Eichenbaum, and Charles Evans (2005), "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy* 113, 1-45.

[14] Christiano, Lawrence J., Cosmin Ilut, Robert Motto, and Massimo Rostagno (2008), "Monetary Policy and Stock Market Boom-Bust Cycles," Working Paper 955, European Central Bank.

[15] Christiano, Lawrence J., Robert Motto, and Massimo Rostagno (2010), "Financial Factors in Economic Fluctuations," Working Paper 1192, European Central Bank.

[16] Clark, John Maurice (1934), "Strategic Factors in Business Cycles," National Bureau of Economic Research.

[17] Cochrane, John H. (1994), "Shocks," *Carnegie-Rochester Conference Series on Public Policy*, 41, 295-364.

[18] Croce, Mariano M. (2008), "Long-Run Productivity Risk: A New Hope for Production-Based Asset Pricing," Mimeo, University of North Carolina.

[19] Del Negro, M., F. Schorfheide, F. Smets, and R. Wouters (2007), "On the Fit and Forecasting Performance of New Keynesian Models," *Journal of Business and Economic Statistics* 25, 123-162.

[20] Epstein, Larry G. and Stanley E. Zin (1989), "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework," *Econometrica* 57, 937-968.

[21] Fama, E. (1990), "Stock Returns Expected Returns, and Real Activity," *The Journal of Finance* 45, 1089-1108.

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

[23] Fujiwara, Ippei, Yasuo Hirose, and Mototsugu Shintani (2011), "Can News Be a Major Source of Aggregate Fluctuations? A Bayesian DSGE Approach," *Journal of Money, Credit and Banking* 43, 1-29.

[24] Greenwood, J., Z. Hercowitz, and P.Krusell (1997), "Long Run Implications of Investment-Specific Technological Change," *American Economic Review* 87, 342-362.

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

[26] Groth, Charlotta and Hashmat Kahn (2006), "Investment Adjustment Cost: An Empirical Assessment," Working Paper, Bank of England.

[27] Hayashi, Fumio (1982), "Tobin's Marginal q and Average q: A Neoclassical Interpretation," *Econometrica* 50, 213-224

[28] Jaimovich, Nir and Sergio Rebelo (2009), "Can News about the Future Drive the Business Cycle?" *American Economic Review* 99, 1097-1118.

[29] Justiniano, Alejandro and Giorgio Primiceri (2008), "The Time-Varying Volatility of Macroeconomic Fluctuations," *American Economic Review* 98, 604-641.

[30] Justiniano, Alejandro, Giorgio Primiceri, and Andrea Tambalotti (2010), "Investment Shocks and Business Cycles," *Journal of Monetary Economics* 57, 132-145.

[31] Justiniano, Alejandro, Giorgio Primiceri, and Andrea Tambalotti (2011), "Investment Shocks and the Relative Price of Investment," *Review of Economic Dynamics* 14, 102-121.

[32] Karnizova, Lilia (2010), "The Spirit of Capitalism and Expectation-Driven Business Cycles," *Journal of Monetary Economics* 57, 739-752.

[33] Khan, Hashmat and John Tsoukalas (2010), "The Quantitative Importance of News Shocks in Estimated DSGE Models," Mimeo, Carleton University.

[34] Kim, Chang-Jin and Charles R. Nelson (1999), *State-Space Models with Regime Switching*, MIT Press.

[35] Lettau Martin and Harald Uhlig (2000), "Can Habit Formation be Reconciled with Business Cycle Facts?" *Review of Economic Dynamics* 3, 79-99.

[36] Lubik, T. and F. Schorfheide (2004), "Testing for Indeterminacy: An Application to U.S. Monetary Policy," *American Economic Review* 94, 190-217.

[37] Pigou, A. (1926), *Industrial Fluctuations*, MacMillan, London.

[38] Schmitt-Grohe, Stephanie and Martin Uribe (2004), "Solving Dynamic General Equilibrium Models Using a Second-Order Approximation to the Policy Function," *Journal of Economic Dynamics and Control* 28, 755-775.

[39] Schmitt-Grohe, Stephanie and Martin Uribe (2008), "What's News in Business Cycles," NBER Working Paper 14215.

[40] Schmitt-Grohe, Stephanie and Martin Uribe (2010), "What's News in Business Cycles," Working Paper, Columbia University.

[41] Schwert, G. (1990), "Stock Returns and Real Activity: A Century of Evidence," *Journal of Finance* 45, 1237-1257.

[42] Shapiro, M. (1986), "The Dynamic Demand for Capital and Labor," *Quarterly Journal of Economics* 101, 512-542.

[43] Smets, F., and R. Wouters (2007), "Shocks and Frictions in U.S. Business Cycles: A Bayesian Approach," *American Economic Review* 97, 586-606.

[44] Uhlig, Harald (1999), "A Toolkit for Analyzing Dynamic Stochastic Models Easily," in Ramon Marimon and Andrew Scott, eds, *Computational Methods for the Study of Dynamic Economies*, Oxford University Press, Oxford, 30-61.

[45] Walker, Todd B. and Eric M. Leeper (2010), "Information Flows and News Driven Business Cycles," *Review of Economic Dynamics* 14, 55-71.

Table 1: Calibrated Parameters

Parameter	Value
β	0.9966
α	0.30
ρ_x^{LR}	0.999
ρ_a^{LR}	0.999
ρ_z^{LR}	0.999
ρ_ω^{LR}	0.999
$\overline{\mu_a}$	0.9986
$\overline{\mu_y}$	1.0046
δ_0	0.025
$\bar{h}$	0.20
$\bar{u}$	1.00
$\bar{Z}$	1.00
$\bar{\Omega}$	1.00
$\bar{q}$	1.00

Table 2: Prior and Posterior Densities for the IAC-SRN Model Specification

Parameter	**Prior**			**Posterior** Estimation without Asset Prices in the Vector of Observables			**Posterior** Estimation with Asset Prices in the Vector of Observable		
	Density	**Mean**	**Std**	**Median**	**5%**	**95%**	**Median**	**5%**	**95%**
γ	Γ	2	2	0.85	0.83	0.86	2.00	1.91	2.11
χ	Γ	3	3	6.40	5.75	7.14	13.03	11.10	15.41
θ_I	B	0.5	0.3	0.94	0.93	0.94	0.78	0.76	0.79
θ_c	B	0.5	0.3	0.76	0.74	0.78	0.43	0.41	0.45
δ_2	Γ	0.25	1	0.05	0.04	0.05	0.40	0.31	0.49
κ	Γ	5	5	1.18	1.01	1.46	1.58	1.42	1.86
ρ_x^s	B	0.5	0.3	0.92	0.91	0.93	0.93	0.91	0.94
ρ_a^s	B	0.5	0.3	0.35	0.33	0.38	0.25	0.23	0.29
ρ_z^s	B	0.5	0.3	0.96	0.96	0.96	0.91	0.89	0.94
ρ_ω^s	B	0.5	0.3	0.85	0.83	0.86	0.97	0.95	0.98
$\sigma_{x,0}$	IΓ	0.1	2	0.10	0.09	0.11	0.16	0.14	0.22
$\sigma_{x,1}$	IΓ	0.058	2	0.10	0.09	0.12	0.22	0.21	0.22
$\sigma_{x,2}$	IΓ	0.058	2	0.02	0.02	0.02	0.09	0.07	0.11
$\sigma_{x,3}$	IΓ	0.058	2	0.04	0.03	0.05	0.05	0.04	0.06
$\sigma_{a,0}$	IΓ	0.1	2	0.62	0.58	0.69	0.76	0.70	0.88
$\sigma_{a,1}$	IΓ	0.058	2	0.42	0.40	0.43	0.28	0.22	0.41
$\sigma_{a,2}$	IΓ	0.058	2	0.38	0.35	0.41	0.09	0.07	0.11
$\sigma_{a,3}$	IΓ	0.058	2	0.04	0.03	0.05	0.13	0.12	0.15
$\sigma_{z,0}$	IΓ	0.5	2	0.41	0.35	0.50	0.47	0.34	0.54
$\sigma_{z,1}$	IΓ	0.289	2	0.22	0.18	0.25	0.25	0.21	0.39
$\sigma_{z,2}$	IΓ	0.289	2	0.43	0.41	0.43	0.14	0.10	0.18
$\sigma_{z,3}$	IΓ	0.289	2	0.05	0.05	0.05	0.11	0.10	0.13
$\sigma_{\omega,0}$	IΓ	0.5	2	0.56	0.45	0.69	3.91	2.80	4.93
$\sigma_{\omega,1}$	IΓ	0.289	2	1.11	0.99	1.22	2.59	2.30	2.93
$\sigma_{\omega,2}$	IΓ	0.289	2	2.54	2.34	2.85	1.81	1.29	2.65
$\sigma_{\omega,3}$	IΓ	0.289	2	1.21	0.87	1.47	2.00	1.77	2.36
$\sigma_{O,Y}$	IΓ*	0.095	0.308	0.19	0.19	0.19	0.19	0.19	0.19
$\sigma_{O,C}$	IΓ*	0.055	0.235	0.11	0.11	0.11	0.11	0.11	0.11
$\sigma_{O,I}$	IΓ*	0.256	0.506	0.51	0.51	0.51	0.51	0.51	0.51
$\sigma_{O,H}$	IΓ*	0.419	0.647	0.21	0.21	0.21	0.84	0.84	0.84
$\sigma_{O,A}$	IΓ*	0.091	0.302	0.18	0.18	0.18	0.18	0.18	0.18
$\sigma_{O,V}$	IΓ*	0.874	0.935	-	-	-	1.75	1.75	1.75
$\sigma_{O,R}$	IΓ*	0.058	0.241	-	-	-	0.07	0.04	0.12

Note: Γ = Gamma distribution, B = Beta distribution, and IΓ = Inverted Gamma distribution. The posterior medians and the posterior 5th and 95th percentiles are obtained using the Random Walk Metropolis-Hastings algorithm as described in Appendix A.

* Distribution truncated at 20% of the unconditional standard deviation of the corresponding observable variable, as described in Section 3.2 of the main text.

Table 3: Prior and Posterior Densities for the CAC-SRN Model Specification

Parameter	**Prior**			**Posterior** Estimation without Asset Prices in the Vector of Observables			**Posterior** Estimation with Asset Prices in the Vector of Observable		
	Density	**Mean**	**Std**	**Median**	**5%**	**95%**	**Median**	**5%**	**95%**
γ	Γ	2	2	0.69	0.63	0.77	4.07	3.77	4.32
χ	Γ	3	3	1.70	1.23	1.96	1.92	1.76	2.05
θ_l	B	0.5	0.3	0.56	0.53	0.59	0.63	0.61	0.66
θ_c	B	0.5	0.3	0.25	0.23	0.28	0.08	0.08	0.09
δ_2	Γ	0.25	1	0.01	0.01	0.01	0.99	0.80	1.16
η	Γ	0.1	1	0.45	0.38	0.54	0.60	0.55	0.76
ρ_x^s	B	0.5	0.3	0.70	0.63	0.73	0.95	0.94	0.96
ρ_a^s	B	0.5	0.3	0.04	0.04	0.05	0.35	0.32	0.36
ρ_z^s	B	0.5	0.3	0.98	0.98	0.98	0.96	0.95	0.97
ρ_ω^s	B	0.5	0.3	0.95	0.94	0.97	0.97	0.95	0.97
$\sigma_{x,0}$	IΓ	0.1	2	0.5	0.5	0.5	0.19	0.17	0.21
$\sigma_{x,1}$	IΓ	0.058	2	0.03	0.02	0.03	0.03	0.02	0.03
$\sigma_{x,2}$	IΓ	0.058	2	0.03	0.02	0.03	0.04	0.03	0.04
$\sigma_{x,3}$	IΓ	0.058	2	0.03	0.03	0.05	0.11	0.10	0.13
$\sigma_{a,0}$	IΓ	0.1	2	0.72	0.64	0.79	0.85	0.79	0.92
$\sigma_{a,1}$	IΓ	0.058	2	0.43	0.35	0.43	0.08	0.07	0.09
$\sigma_{a,2}$	IΓ	0.058	2	0.06	0.05	0.07	0.13	0.12	0.14
$\sigma_{a,3}$	IΓ	0.058	2	0.07	0.06	0.07	0.08	0.06	0.09
$\sigma_{z,0}$	IΓ	0.5	2	0.57	0.53	0.63	0.62	0.55	0.68
$\sigma_{z,1}$	IΓ	0.289	2	0.03	0.03	0.04	0.10	0.08	0.11
$\sigma_{z,2}$	IΓ	0.289	2	0.07	0.06	0.08	0.04	0.03	0.04
$\sigma_{z,3}$	IΓ	0.289	2	0.02	0.01	0.02	0.06	0.05	0.08
$\sigma_{\omega,0}$	IΓ	0.5	2	6.07	4.67	7.04	9.64	9.34	9.92
$\sigma_{\omega,1}$	IΓ	0.289	2	0.42	0.33	0.48	0.99	0.69	1.07
$\sigma_{\omega,2}$	IΓ	0.289	2	4.33	4.33	4.33	1.35	1.06	1.50
$\sigma_{\omega,3}$	IΓ	0.289	2	0.40	0.36	0.47	0.91	0.76	1.14
$\sigma_{O,Y}$	IΓ*	0.095	0.308	0.19	0.19	0.19	0.19	0.19	0.19
$\sigma_{O,C}$	IΓ*	0.055	0.235	0.11	0.11	0.11	0.11	0.11	0.11
$\sigma_{O,I}$	IΓ*	0.256	0.506	0.51	0.51	0.51	0.51	0.51	0.51
$\sigma_{O,H}$	IΓ*	0.419	0.647	0.29	0.27	0.32	0.58	0.54	0.62
$\sigma_{O,A}$	IΓ*	0.091	0.302	0.15	0.11	0.17	0.17	0.14	0.18
$\sigma_{O,V}$	IΓ*	0.874	0.935	-	-	-	1.75	1.75	1.75
$\sigma_{O,R}$	IΓ*	0.058	0.241	-	-	-	0.12	0.12	0.12

Note: Γ = Gamma distribution, B = Beta distribution, and IΓ = Inverted Gamma distribution. The posterior medians and the posterior 5th and 95th percentiles are obtained using the Random Walk Metropolis-Hastings algorithm as described in Appendix A.

* Distribution truncated at 20% of the unconditional standard deviation of the corresponding observable variable, as described in Section 3.2 of the main text.

Table 4: Prior and Posterior Densities for the IAC-LRN Model Specification

Parameter	**Prior**			**Posterior** Estimation without Asset Prices in the Vector of Observables			**Posterior** Estimation with Asset Prices in the Vector of Observable		
	Density	**Mean**	**Std**	**Median**	**5%**	**95%**	**Median**	**5%**	**95%**
γ	Γ	2	2	0.26	0.26	0.26	0.27	0.27	0.27
χ	Γ	3	3	0.91	0.82	1.06	0.34	0.33	0.34
θ_l	B	0.5	0.3	0.89	0.88	0.91	0.98	0.98	0.98
θ_c	B	0.5	0.3	0.76	0.74	0.78	0.93	0.93	0.94
δ_2	Γ	0.25	1	0.03	0.03	0.04	0.03	0.03	0.03
κ	Γ	5	5^0.5	5.05	4.65	5.72	4.93	4.90	4.97
ρ_x^l	B	0.5	0.3	0.97	0.97	0.97	0.79	0.79	0.80
ρ_a^l	B	0.5	0.3	0.07	0.06	0.07	0.29	0.29	0.30
ρ_z^l	B	0.5	0.3	0.68	0.64	0.71	0.89	0.89	0.90
ρ_ω^l	B	0.5	0.3	0.24	0.23	0.26	0.34	0.33	0.34
$\sigma_{x,u}$	IΓ	0.1	2	0.14	0.11	0.16	0.55	0.53	0.55
$\sigma_{x,LR}$	IΓ	0.02	2	0.01	0.01	0.01	0.03	0.03	0.03
$\sigma_{a,u}$	IΓ	0.1	2	0.87	0.82	0.95	0.85	0.84	0.87
$\sigma_{a,LR}$	IΓ	0.02	2	0.03	0.02	0.03	0.20	0.20	0.21
$\sigma_{z,u}$	IΓ	0.5	2	0.57	0.47	0.61	0.43	0.43	0.44
$\sigma_{z,LR}$	IΓ	0.1	2	0.39	0.36	0.43	0.09	0.09	0.09
$\sigma_{\omega,u}$	IΓ	0.5	2	9.59	9.36	9.87	9.94	9.85	9.98
$\sigma_{\omega,LR}$	IΓ	0.1	2	1.78	1.21	1.88	0.49	0.48	0.49
$\sigma_{O,Y}$	IΓ*	0.095	0.308	0.19	0.19	0.19	0.19	0.19	0.19
$\sigma_{O,C}$	IΓ*	0.055	0.235	0.11	0.11	0.11	0.11	0.11	0.11
$\sigma_{O,I}$	IΓ*	0.256	0.506	0.51	0.51	0.51	0.51	0.51	0.51
$\sigma_{O,H}$	IΓ*	0.419	0.647	0.21	0.21	0.21	0.75	0.74	0.76
$\sigma_{O,A}$	IΓ*	0.091	0.302	0.18	0.17	0.18	0.18	0.17	0.18
$\sigma_{O,V}$	IΓ*	0.874	0.935	-	-	-	1.75	1.75	1.75
$\sigma_{O,R}$	IΓ*	0.058	0.241	-	-	-	0.06	0.06	0.06

Note: Γ = Gamma distribution, B = Beta distribution, and IΓ = Inverted Gamma distribution. The posterior medians and the posterior 5^{th} and 95^{th} percentiles are obtained using the Random Walk Metropolis-Hastings algorithm as described in Appendix A.

* Distribution truncated at 20% of the unconditional standard deviation of the corresponding observable variable, as described in Section 3.2 of the main text.

Table 5: Prior and Posterior Densities for the CAC-LRN Model Specification

Parameter	Prior			Posterior Estimation without Asset Prices in the Vector of Observables			Posterior Estimation with Asset Prices in the Vector of Observable		
	Density	Mean	Std	Median	5%	95%	Median	5%	95%
γ	Γ	2	2	0.71	0.65	0.77	1.24	1.18	1.29
χ	Γ	3	3	2.19	1.77	2.50	0.76	0.65	1.13
θ_l	B	0.5	0.3	0.51	0.46	0.54	0.11	0.09	0.12
θ_c	B	0.5	0.3	0.26	0.24	0.27	0.17	0.16	0.18
δ_2	Γ	0.25	1	0.03	0.02	0.03	3.30	3.06	3.89
η	Γ	0.1	1	0.44	0.37	0.51	0.31	0.30	0.32
ρ_x^l	B	0.5	0.3	0.65	0.58	0.69	0.33	0.27	0.36
ρ_a^l	B	0.5	0.3	0.06	0.04	0.09	0.35	0.32	0.38
ρ_z^l	B	0.5	0.3	0.98	0.98	0.98	0.76	0.74	0.77
ρ_ω^l	B	0.5	0.3	0.95	0.93	0.96	0.96	0.95	0.96
$\sigma_{x,u}$	IΓ	0.1	2	0.59	0.52	0.74	0.78	0.70	0.88
$\sigma_{x,LR}$	IΓ	0.02	2	0.01	0.01	0.02	0.02	0.01	0.02
$\sigma_{a,u}$	IΓ	0.1	2	0.88	0.83	0.95	0.95	0.88	1.03
$\sigma_{a,LR}$	IΓ	0.02	2	0.02	0.01	0.03	0.17	0.16	0.19
$\sigma_{z,u}$	IΓ	0.5	2	0.60	0.55	0.67	0.74	0.71	0.78
$\sigma_{z,LR}$	IΓ	0.1	2	0.06	0.04	0.06	0.74	0.70	0.77
$\sigma_{\omega,u}$	IΓ	0.5	2	7.88	6.66	9.20	9.95	9.91	9.98
$\sigma_{\omega,LR}$	IΓ	0.1	2	0.12	0.10	0.15	2.49	2.39	2.50
$\sigma_{O,Y}$	IΓ*	0.095	0.308	0.19	0.19	0.19	0.19	0.19	0.19
$\sigma_{O,C}$	IΓ*	0.055	0.235	0.11	0.11	0.11	0.11	0.11	0.11
$\sigma_{O,I}$	IΓ*	0.256	0.506	0.51	0.51	0.51	0.51	0.51	0.51
$\sigma_{O,H}$	IΓ*	0.419	0.647	0.29	0.26	0.31	0.36	0.31	0.40
$\sigma_{O,A}$	IΓ*	0.091	0.302	0.09	0.07	0.12	0.18	0.18	0.18
$\sigma_{O,V}$	IΓ*	0.874	0.935	-	-	-	1.75	1.74	1.75
$\sigma_{O,R}$	IΓ*	0.058	0.241	-	-	-	0.08	0.07	0.09

Note: Γ = Gamma distribution, B = Beta distribution, and IΓ = Inverted Gamma distribution. The posterior medians and the posterior 5th and 95th percentiles are obtained using the Random Walk Metropolis-Hastings algorithm as described in Appendix A.

* Distribution truncated at 20% of the unconditional standard deviation of the corresponding observable variable, as described in Section 3.2 of the main text.

Table 6: Log Marginal Likelihoods

Model Specification	Estimation without Asset Prices in the Vector of Observables		Estimation with Asset Prices in the Vector of Observables	
	Log Marginal Likelihood	Rank	Log Marginal Likelihood	Rank
CAC-LRN	-1,068	4	-1,807	1
CAC-SRN	-1,044	3	-2,070	2
IAC-LRN	-990	2	-2,125	3
IAC-SRN	-982	1	-2,284	4

Note: IAC = investment adjustment costs, CAC= capital adjustment costs, SRN = short run news shocks, LRN = long run news shocks.

Table 7: Posterior Variance Decompositions at Business Cycle Horizons in the IAC-SRN Model Specification

Series\Shock	Unanticipated LAT	News LAT	Unanticipated ISP	News ISP	Unanticipated TFP	News TFP	Unanticipated MEI	News MEI
	Estimation <u>without</u> Asset Prices in the Vector of Observables							
Output Growth	0.14	0.29	0.02	0.08	0.13	0.06	0.01	0.27
Consumption Growth	0.15	0.21	0.19	0.23	0.02	0.06	0.00	0.13
Investment Growth	0.08	0.21	0.08	0.04	0.16	0.07	0.01	0.35
Hours	0.10	0.25	0.03	0.05	0.03	0.03	0.01	0.49
Relative Price of Investment	0.00	0.00	0.57	0.43	0.00	0.00	0.00	0.00
	Estimation <u>with</u> Asset Prices in the Vector of Observables							
Output Growth	0.15	0.34	0.02	0.00	0.24	0.10	0.10	0.06
Consumption Growth	0.14	0.26	0.19	0.02	0.09	0.12	0.04	0.13
Investment Growth	0.02	0.04	0.21	0.02	0.29	0.06	0.10	0.26
Hours	0.06	0.16	0.03	0.01	0.01	0.00	0.48	0.24
Relative Price of Investment	0.00	0.00	0.87	0.13	0.00	0.00	0.00	0.00
Total Market Valuation	0.08	0.23	0.04	0.01	0.01	0.01	0.46	0.15
Real Risk-Free Interest Rate	0.07	0.07	0.18	0.02	0.13	0.15	0.13	0.25

Note: IAC = investment adjustment costs, SRN = short run news shocks; LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. Each set of variance decompositions corresponds to medians based on 10,000 draws from the posterior distribution obtained using the Random Walk Metropolis-Hastings algorithm as described in Appendix A. Unlike means, medians need not add up to one. The entries in each of the four (short run) news shock columns represent the sums of the variance decomposition shares attributed to the three anticipated (one, two, and three periods ahead) innovations to the respective shock. Business cycle horizons = 6 to 32 quarters.

Table 8: Posterior Variance Decompositions at Business Cycle Horizons in the CAC-SRN Model Specification

Series\Shock	Unanticipated LAT	News LAT	Unanticipated ISP	News ISP	Unanticipated TFP	News TFP	Unanticipated MEI	News MEI
	Estimation without Asset Prices in the Vector of Observables							
Output Growth	0.06	0.00	0.07	0.01	0.28	0.00	0.44	0.13
Consumption Growth	0.08	0.00	0.06	0.01	0.52	0.01	0.20	0.12
Investment Growth	0.01	0.00	0.03	0.01	0.02	0.00	0.61	0.32
Hours	0.10	0.00	0.07	0.02	0.06	0.00	0.53	0.20
Relative Price of Investment	0.00	0.00	0.76	0.24	0.00	0.00	0.00	0.00
	Estimation with Asset Prices in the Vector of Observables							
Output Growth	0.01	0.02	0.04	0.00	0.60	0.03	0.28	0.02
Consumption Growth	0.11	0.06	0.02	0.00	0.45	0.02	0.28	0.06
Investment Growth	0.31	0.17	0.02	0.00	0.05	0.00	0.37	0.08
Hours	0.39	0.17	0.12	0.00	0.14	0.00	0.17	0.01
Relative Price of Investment	0.00	0.00	0.96	0.04	0.00	0.00	0.00	0.00
Total Market Valuation	0.17	0.09	0.00	0.00	0.02	0.00	0.70	0.01
Real Risk-Free Interest Rate	0.22	0.14	0.01	0.00	0.02	0.02	0.53	0.06

Note: CAC = capital adjustment costs, SRN = short run news shocks; LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. Each set of variance decompositions corresponds to medians based on 10,000 draws from the posterior distribution obtained using the Random Walk Metropolis-Hastings algorithm as described in Appendix A. Unlike means, medians need not add up to one. The entries in each of the four (short run) news shock columns represent the sums of the variance decomposition shares attributed to the three anticipated (one, two, and three periods ahead) innovations to the respective shock. Business cycle horizons = 6 to 32 quarters.

Table 9: Posterior Variance Decompositions at Business Cycle Horizons in the IAC-LRN Model Specification

Series\Shock	Unanticipated LAT	News LAT	Unanticipated ISP	News ISP	Unanticipated TFP	News TFP	Unanticipated MEI	News MEI
	Estimation without Asset Prices in the Vector of Observables							
Output Growth	0.80	0.00	0.01	0.07	0.03	0.00	0.07	0.02
Consumption Growth	0.73	0.00	0.11	0.03	0.05	0.02	0.05	0.02
Investment Growth	0.61	0.00	0.06	0.08	0.02	0.01	0.18	0.03
Hours	0.77	0.00	0.01	0.11	0.00	0.01	0.00	0.10
Relative Price of Investment	0.00	0.00	0.99	0.01	0.00	0.00	0.00	0.00
	Estimation with Asset Prices in the Vector of Observables							
Output Growth	0.08	0.02	0.01	0.77	0.03	0.00	0.10	0.00
Consumption Growth	0.73	0.01	0.15	0.11	0.00	0.00	0.00	0.00
Investment Growth	0.08	0.01	0.09	0.65	0.03	0.00	0.15	0.00
Hours	0.07	0.01	0.01	0.90	0.00	0.00	0.00	0.00
Relative Price of Investment	0.00	0.00	0.56	0.44	0.00	0.00	0.00	0.00
Total Market Valuation	0.27	0.00	0.02	0.58	0.03	0.00	0.09	0.00
Real Risk-Free Interest Rate	0.05	0.00	0.02	0.23	0.29	0.00	0.39	0.01

Note: IAC = investment adjustment costs, LRN = long run news shocks; LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. Each set of variance decompositions corresponds to medians based on 10,000 draws from the posterior distribution obtained using the Random Walk Metropolis-Hastings algorithm as described in Appendix A. Unlike means, medians need not add up to one. Business cycle horizons = 6 to 32 quarters.

Table 10: Posterior Variance Decompositions at Business Cycle Horizons in the CAC-LRN Model Specification

Series\Shock	Unanticipated LAT	News LAT	Unanticipated ISP	News ISP	Unanticipated TFP	News TFP	Unanticipated MEI	News MEI
	Estimation <u>without</u> Asset Prices in the Vector of Observables							
Output Growth	0.08	0.00	0.07	0.00	0.31	0.00	0.53	0.00
Consumption Growth	0.11	0.01	0.06	0.00	0.58	0.00	0.23	0.00
Investment Growth	0.02	0.00	0.04	0.00	0.02	0.00	0.92	0.00
Hours	0.12	0.00	0.10	0.00	0.07	0.00	0.71	0.00
Relative Price of Investment	0.00	0.00	0.99	0.01	0.00	0.00	0.00	0.00
	Estimation <u>with</u> Asset Prices in the Vector of Observables							
Output Growth	0.10	0.00	0.06	0.03	0.51	0.10	0.19	0.01
Consumption Growth	0.10	0.00	0.02	0.03	0.62	0.11	0.11	0.01
Investment Growth	0.01	0.00	0.06	0.35	0.02	0.03	0.45	0.08
Hours	0.06	0.00	0.20	0.09	0.01	0.12	0.50	0.01
Relative Price of Investment	0.00	0.00	0.69	0.31	0.00	0.00	0.00	0.00
Total Market Valuation	0.02	0.00	0.01	0.48	0.03	0.04	0.30	0.12
Real Risk-Free Interest Rate	0.11	0.01	0.01	0.06	0.35	0.25	0.20	0.00

Note: CAC = capital adjustment costs, LRN = long run news shocks; LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. Each set of variance decompositions corresponds to medians based on 10,000 draws from the posterior distribution obtained using the Random Walk Metropolis-Hastings algorithm as described in Appendix A. Unlike means, medians need not add up to one. Business cycle horizons = 6 to 32 quarters.

Figure 1: Impulse Response Functions of a Generic Stochastic Process to the Three Types of Shocks Studied in the Paper

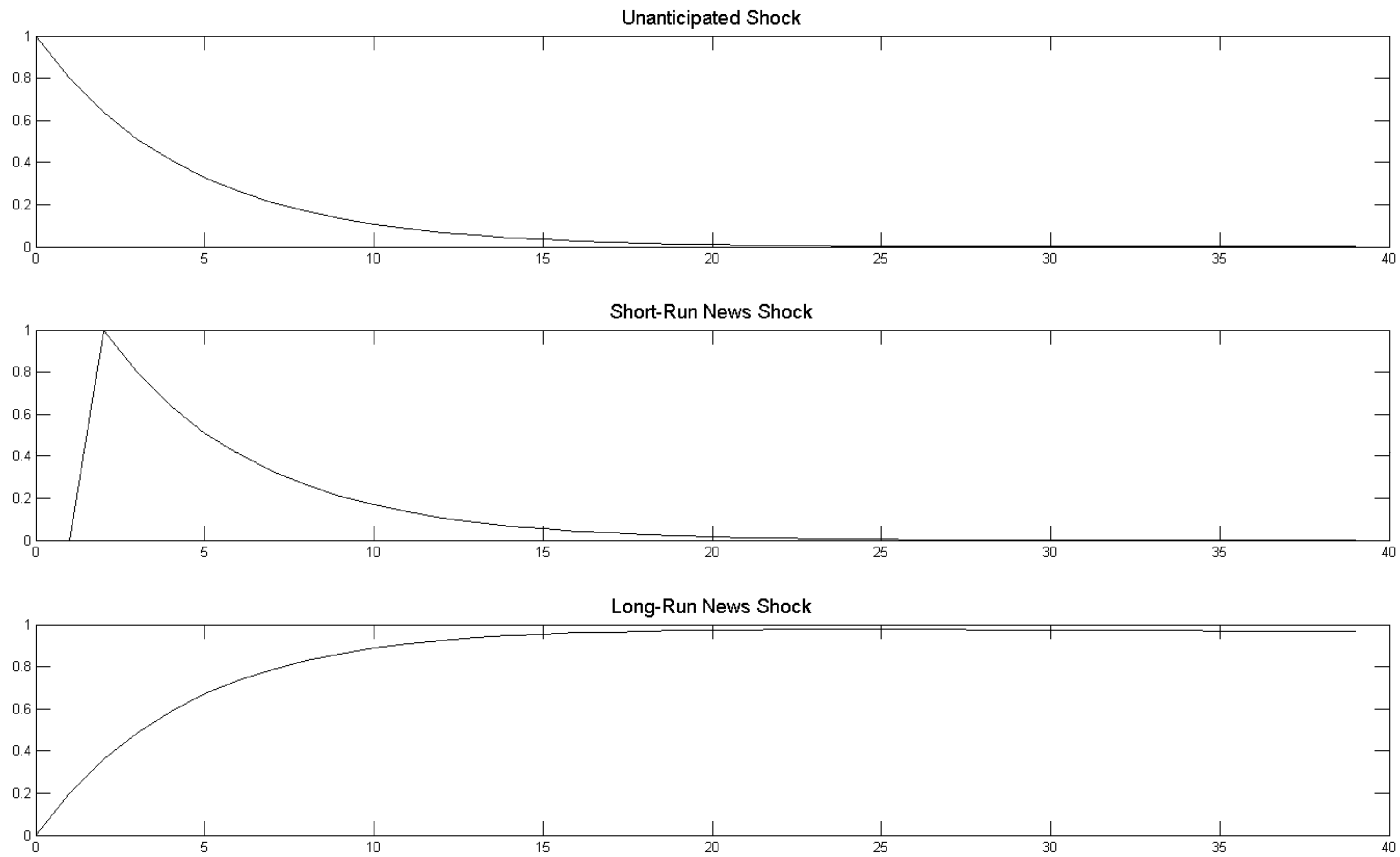
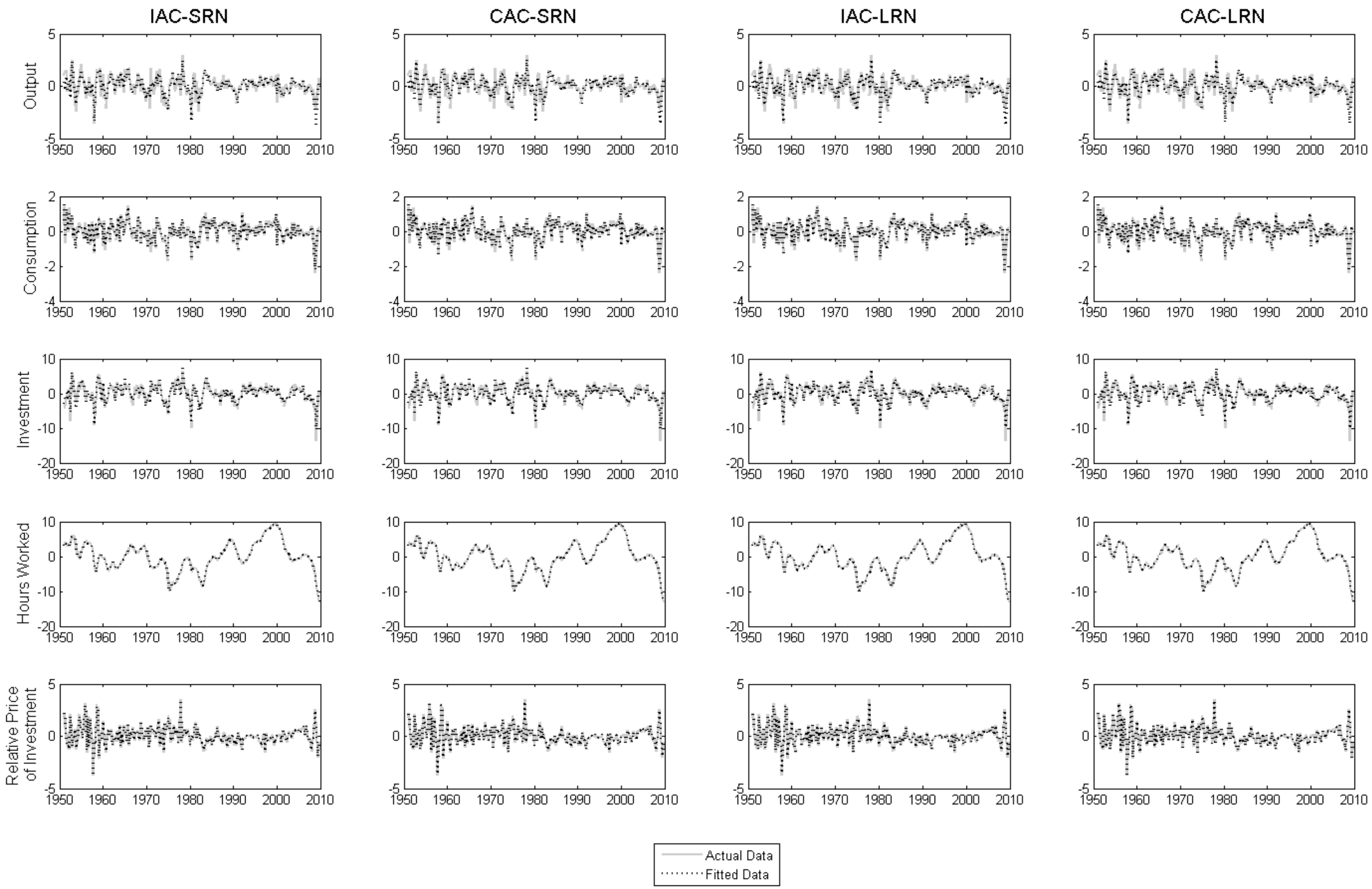
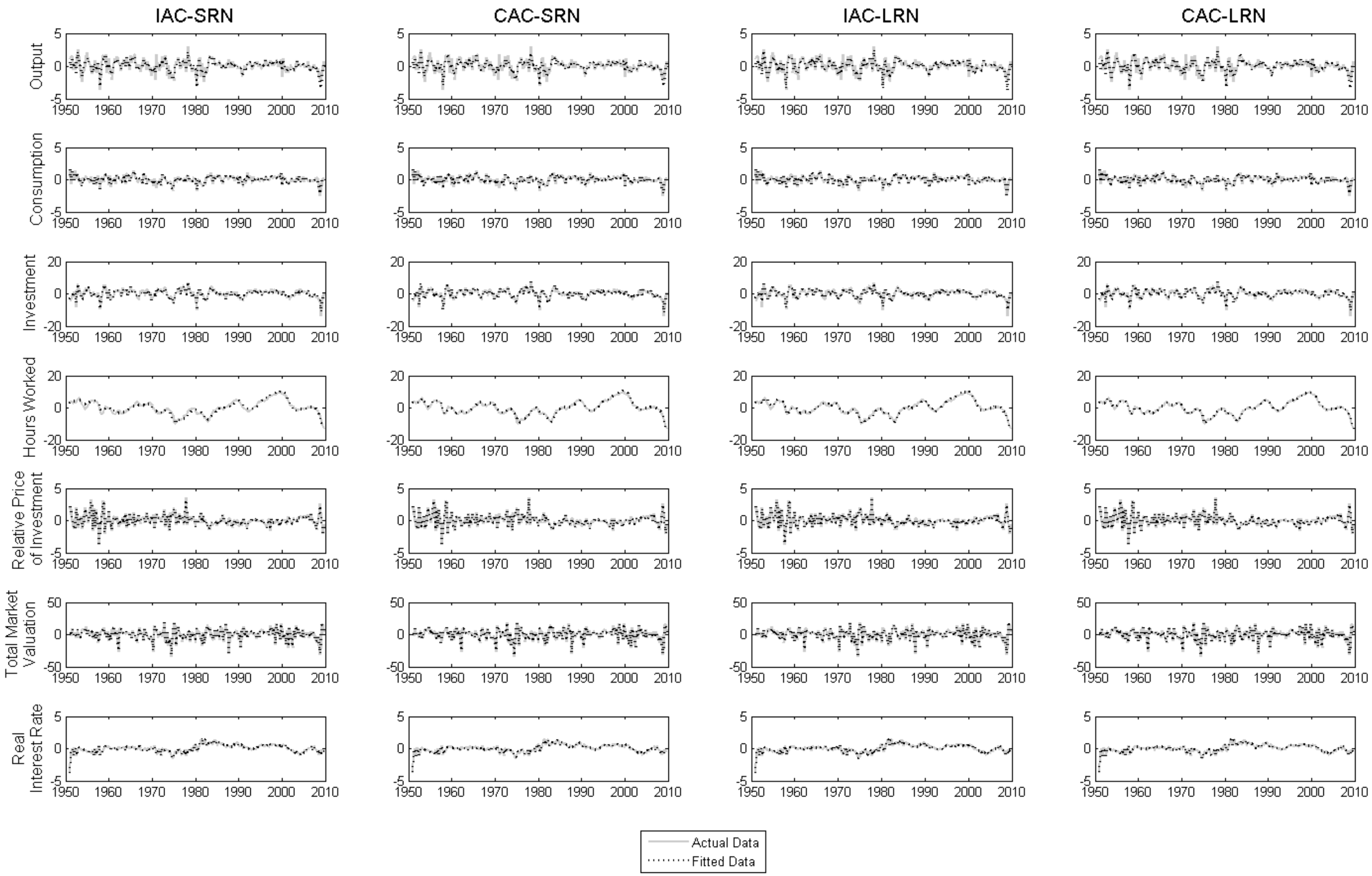


Figure 2: Actual and Fitted Data, Estimations without Asset Prices in the Vector of Observables



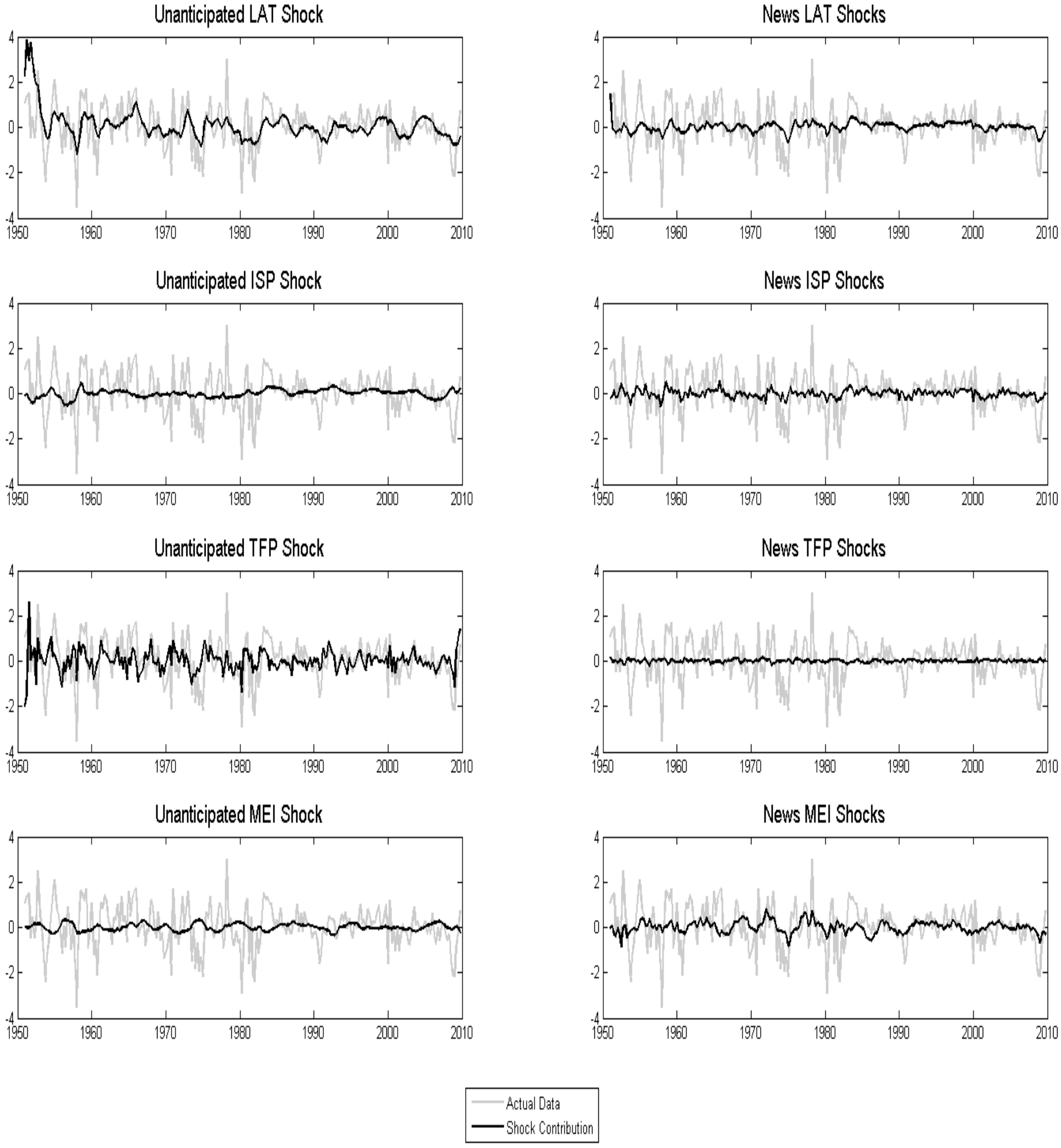
Note: IAC = investment adjustment costs, CAC= capital adjustment costs, SRN = short run news shocks, LRN = long run news shocks.

Figure 3: Actual and Fitted Data, Estimations with Asset Prices in the Vector of Observables



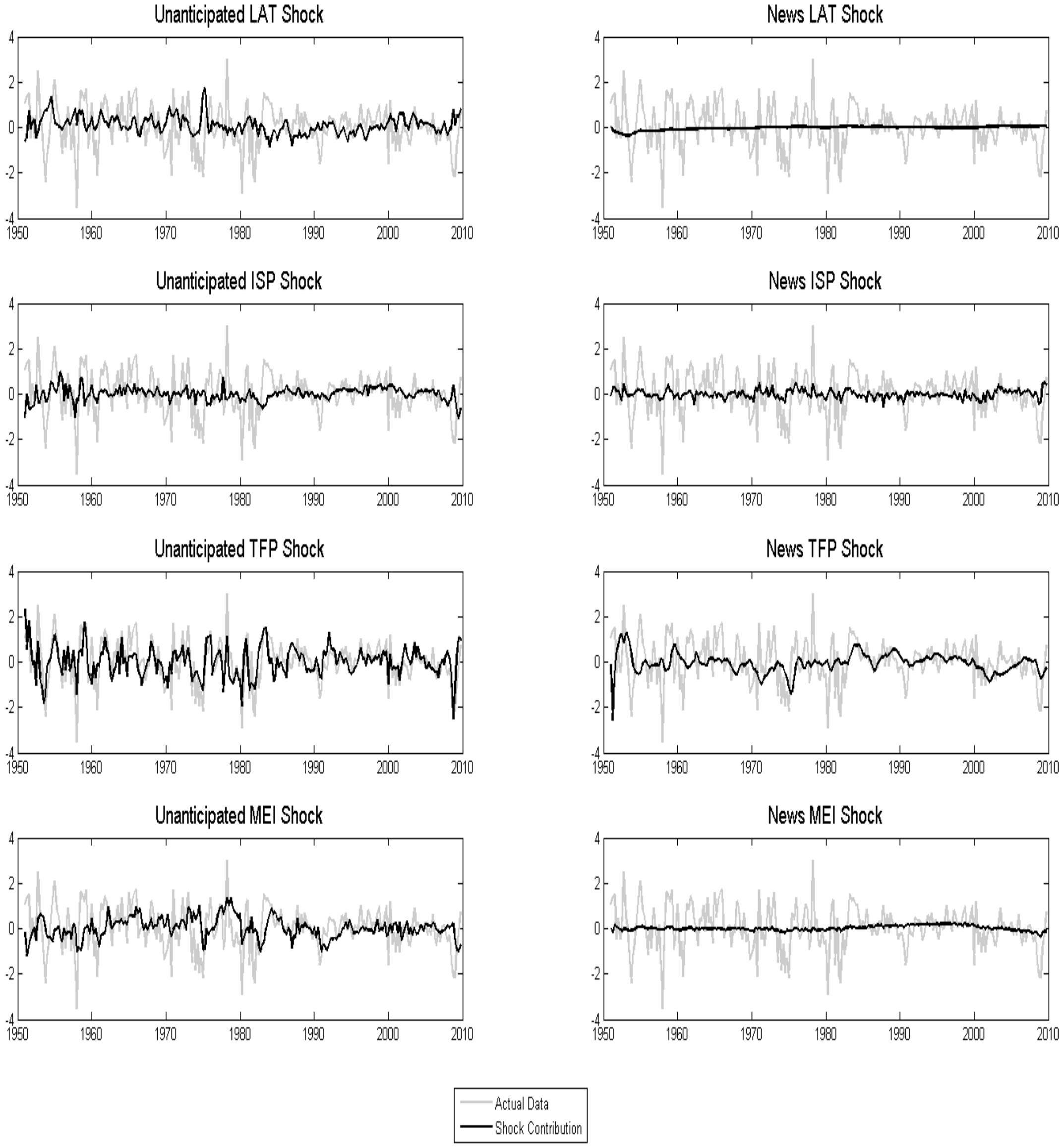
Note: IAC = investment adjustment costs, CAC= capital adjustment costs, SRN = short run news shocks, LRN = long run news shocks.

Figure 4: Historical Decomposition of Output Growth, IAC-SRN-NoAP Case



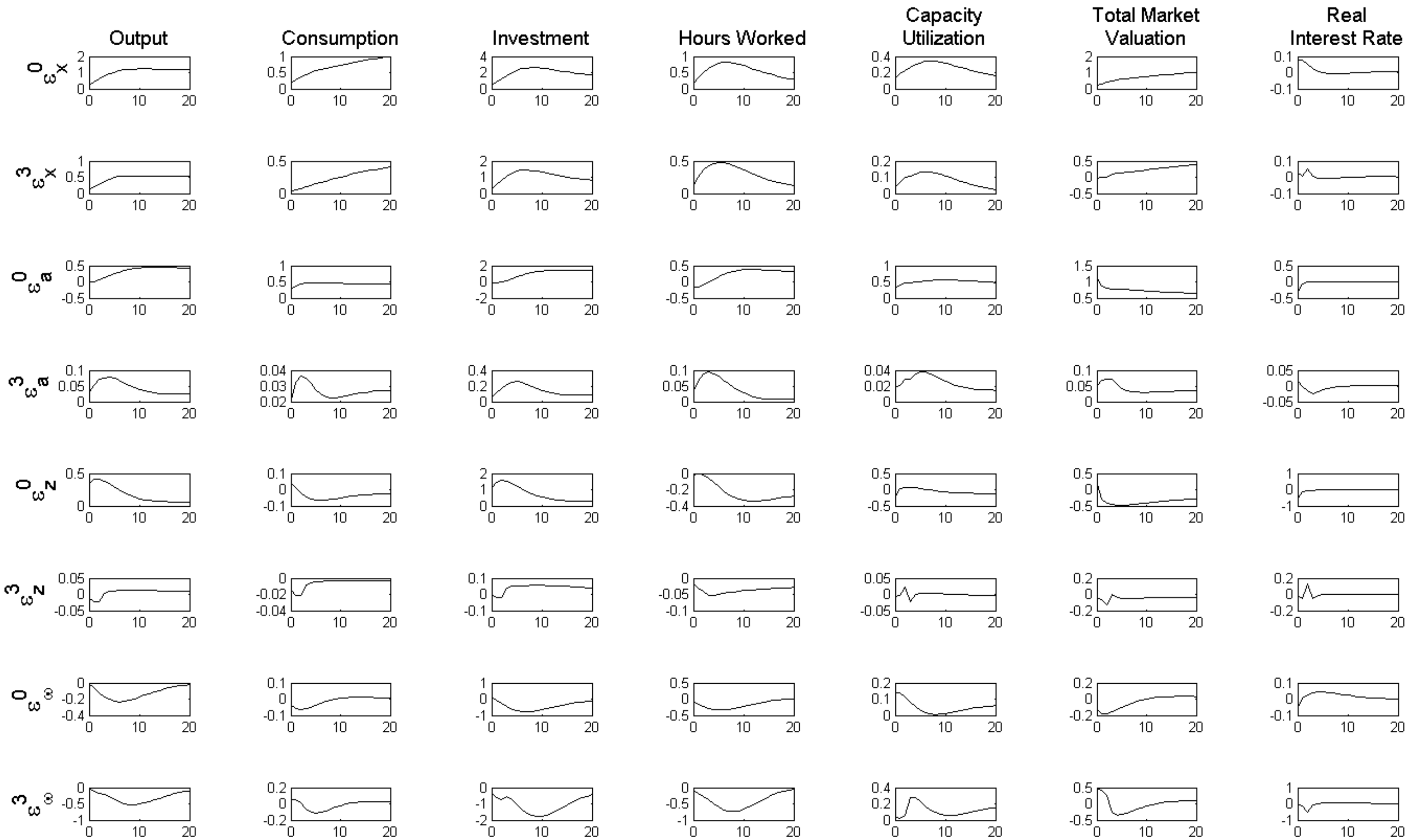
Note: IAC = investment adjustment costs, SRN = short run news shocks, NoAP = estimation without asset prices in the vector of observables; LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. The shock contributions displayed in each of the four (short run) news shock panels represent the sums of the contributions of the three anticipated (one, two, and three periods ahead) innovations to the respective shock.

Figure 5: Historical Decomposition of Output Growth, CAC-LRN-AP Case



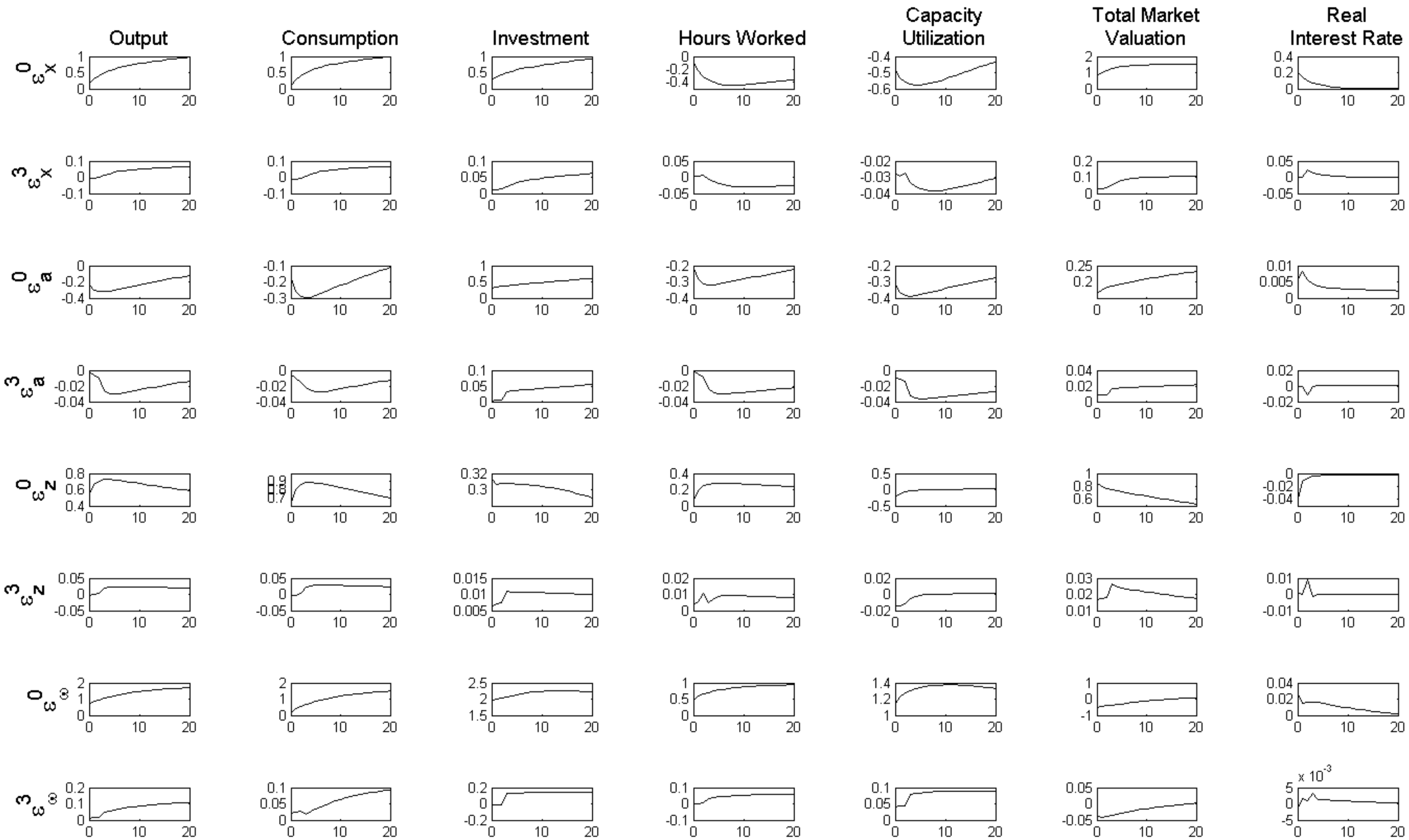
Note: CAC = capital adjustment costs, LRN = long run news shocks, AP = estimation with asset prices in the vector of observables; LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment.

Figure 6: Impulse Response Functions, IAC-SRN-NoAP case



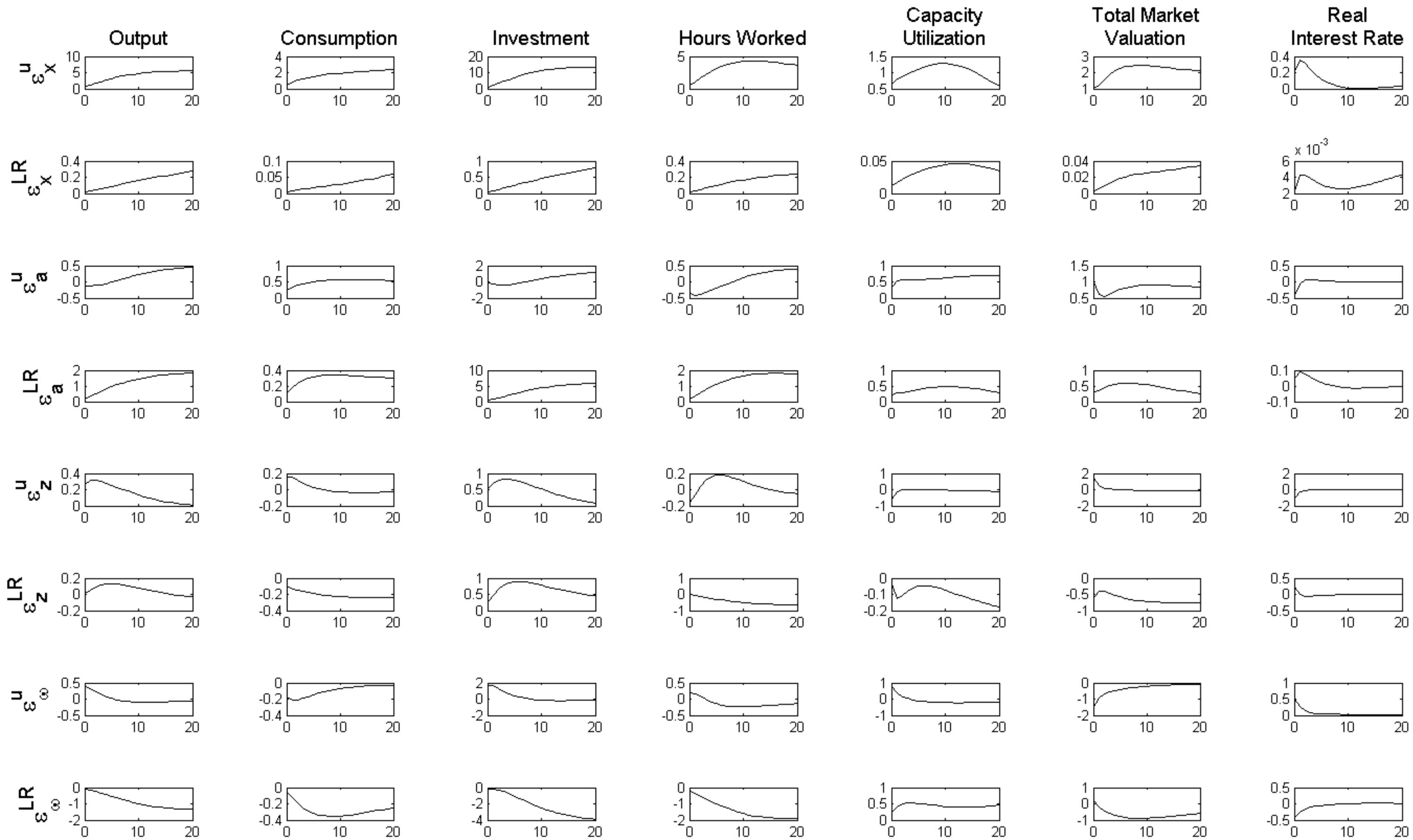
Note: IAC = investment adjustment costs, SRN = short run news shocks, NoAP = estimation without asset prices in the vector of observables; ε_x^0 = unanticipated LAT shock, ε_x^3 = 3-period ahead LAT news shock, ε_a^0 = unanticipated ISP shock, ε_a^3 = 3-period ahead ISP news shock, ε_z^0 = unanticipated TFP shock, ε_z^3 = 3-period ahead TFP news shock, ε_ω^0 = unanticipated MEI shock, ε_ω^3 = 3-period ahead MEI news shock.

Figure 7: Impulse Response Functions, CAC-SRN-NoAP case



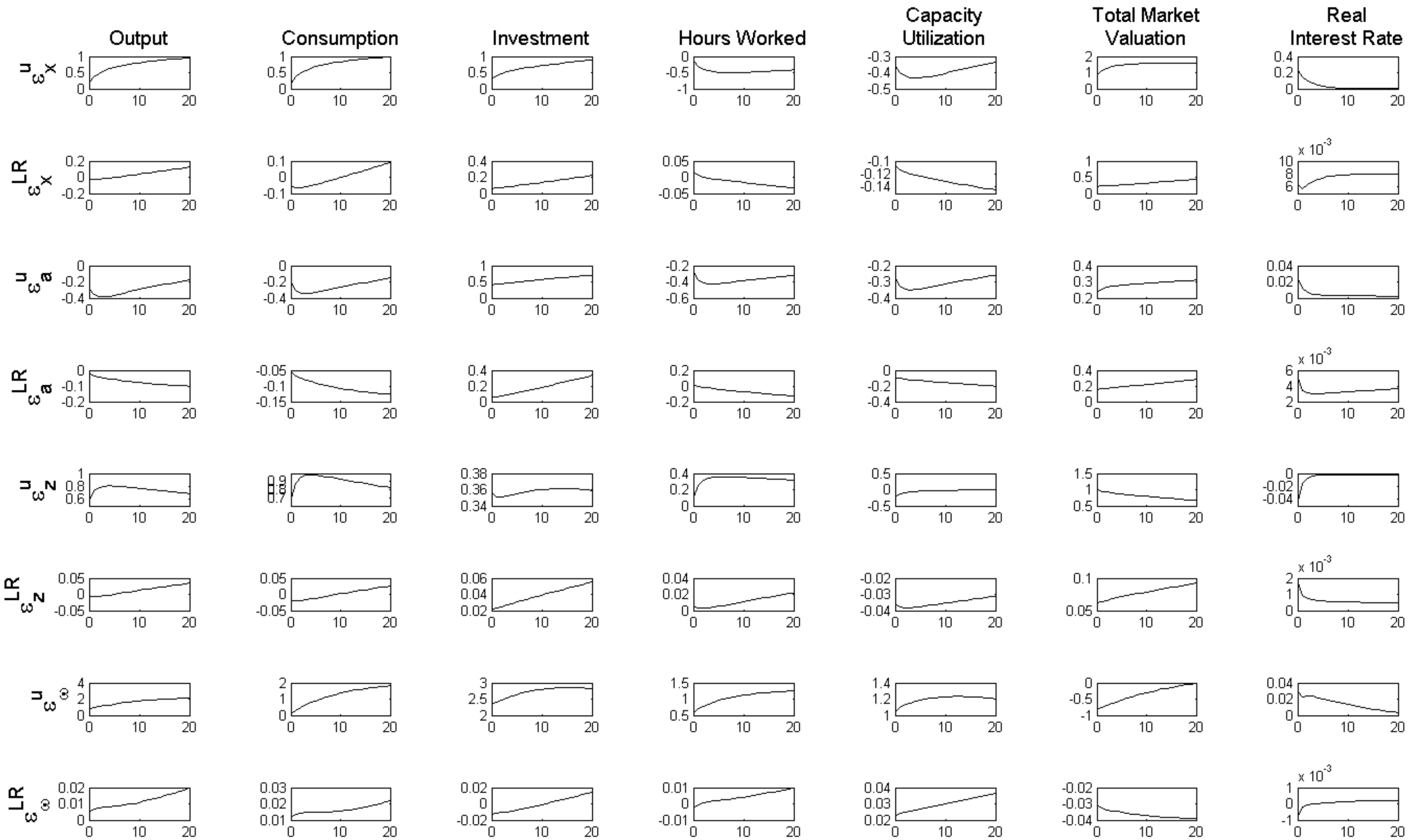
Note: CAC = capital adjustment costs, SRN = short run news shocks, NoAP = estimation without asset prices in the vector of observables; ε_x^0 = unanticipated LAT shock, ε_x^3 = 3-period ahead LAT news shock, ε_a^0 = unanticipated ISP shock, ε_a^3 = 3-period ahead ISP news shock, ε_z^0 = unanticipated TFP shock, ε_z^3 = 3-period ahead TFP news shock, ε_ω^0 = unanticipated MEI shock, ε_ω^3 = 3-period ahead MEI news shock.

Figure 8: Impulse Response Functions, IAC-LRN-NoAP case



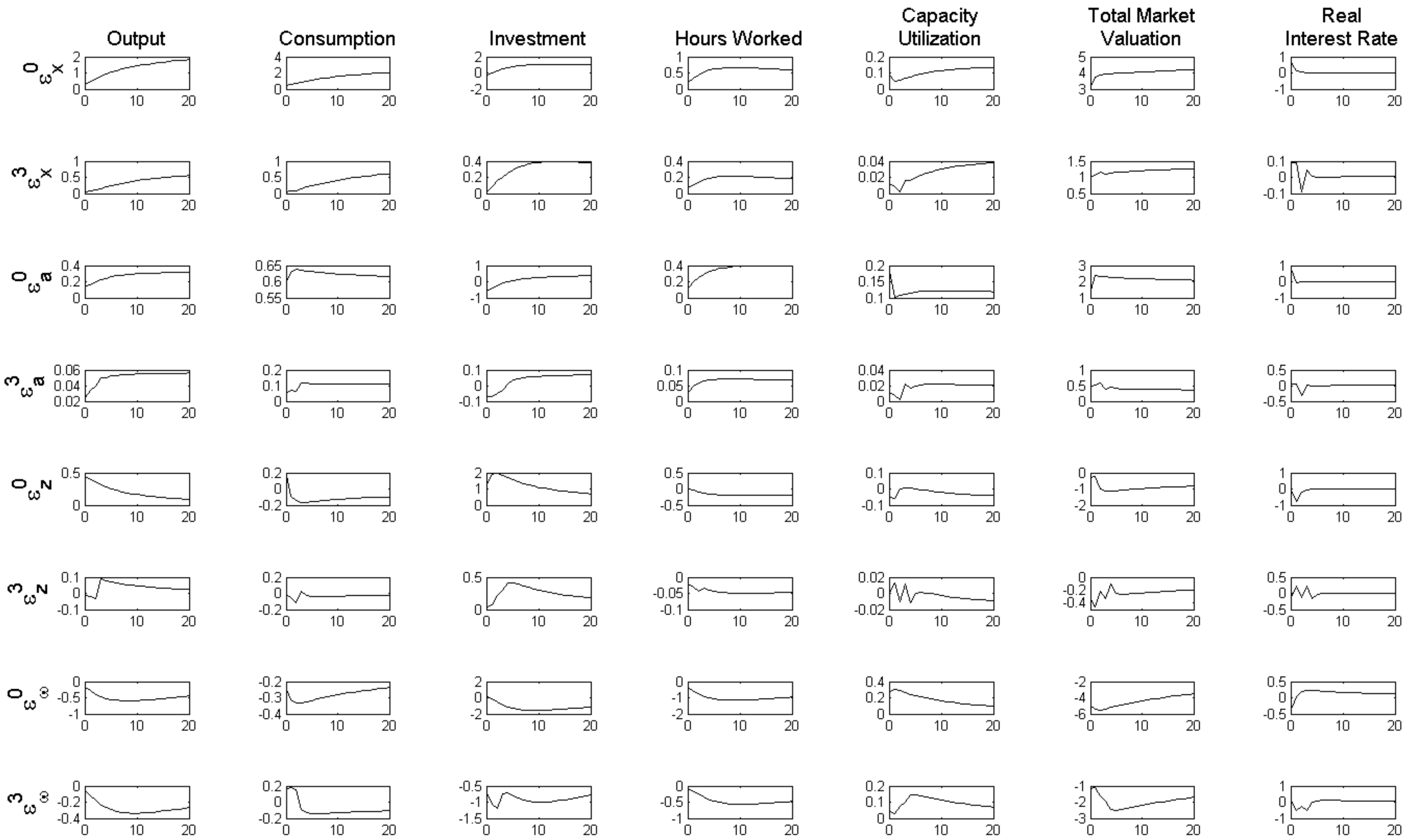
Note: IAC = investment adjustment costs, LRN = long run news shocks, NoAP = estimation without asset prices in the vector of observables; ε_x^u = unanticipated LAT shock, ε_x^{LR} = long run LAT news shock, ε_a^u = unanticipated ISP shock, ε_a^{LR} = long run ISP news shock, ε_z^u = unanticipated TFP shock, ε_z^{LR} = long run TFP news shock, ε_ω^u = unanticipated MEI shock, ε_ω^{LR} = long run MEI news shock.

Figure 9: Impulse Response Functions, CAC-LRN-NoAP case



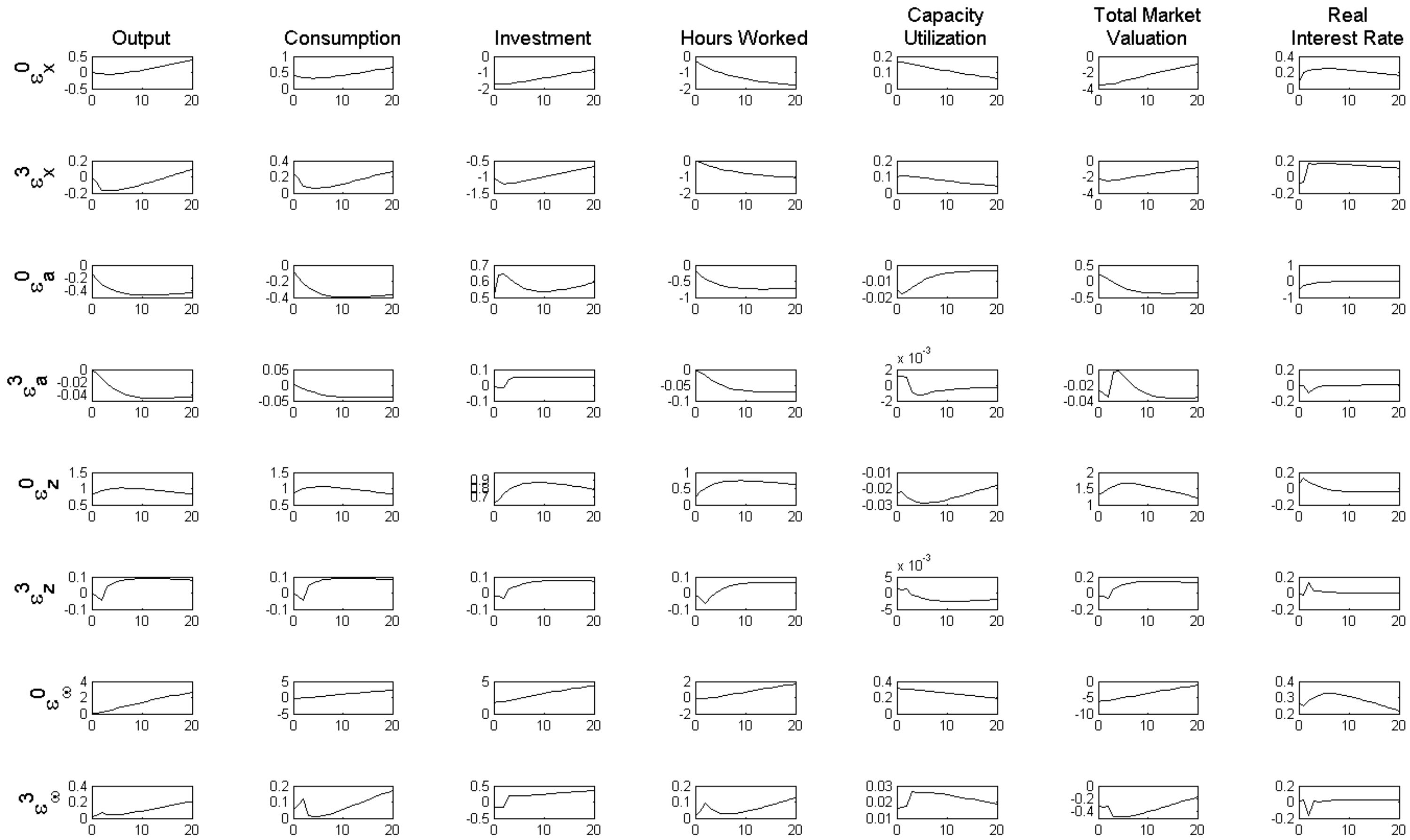
Note: CAC = capital adjustment costs, LRN = long run news shocks, NoAP = estimation without asset prices in the vector of observables; ε_x^u = unanticipated LAT shock, ε_x^{LR} = long run LAT news shock, ε_a^u = unanticipated ISP shock, ε_a^{LR} = long run ISP news shock, ε_z^u = unanticipated TFP shock, ε_z^{LR} = long run TFP news shock, ε_ω^u = unanticipated MEI shock, ε_ω^{LR} = long run MEI news shock.

Figure 10: Impulse Response Functions, IAC-SRN-AP case



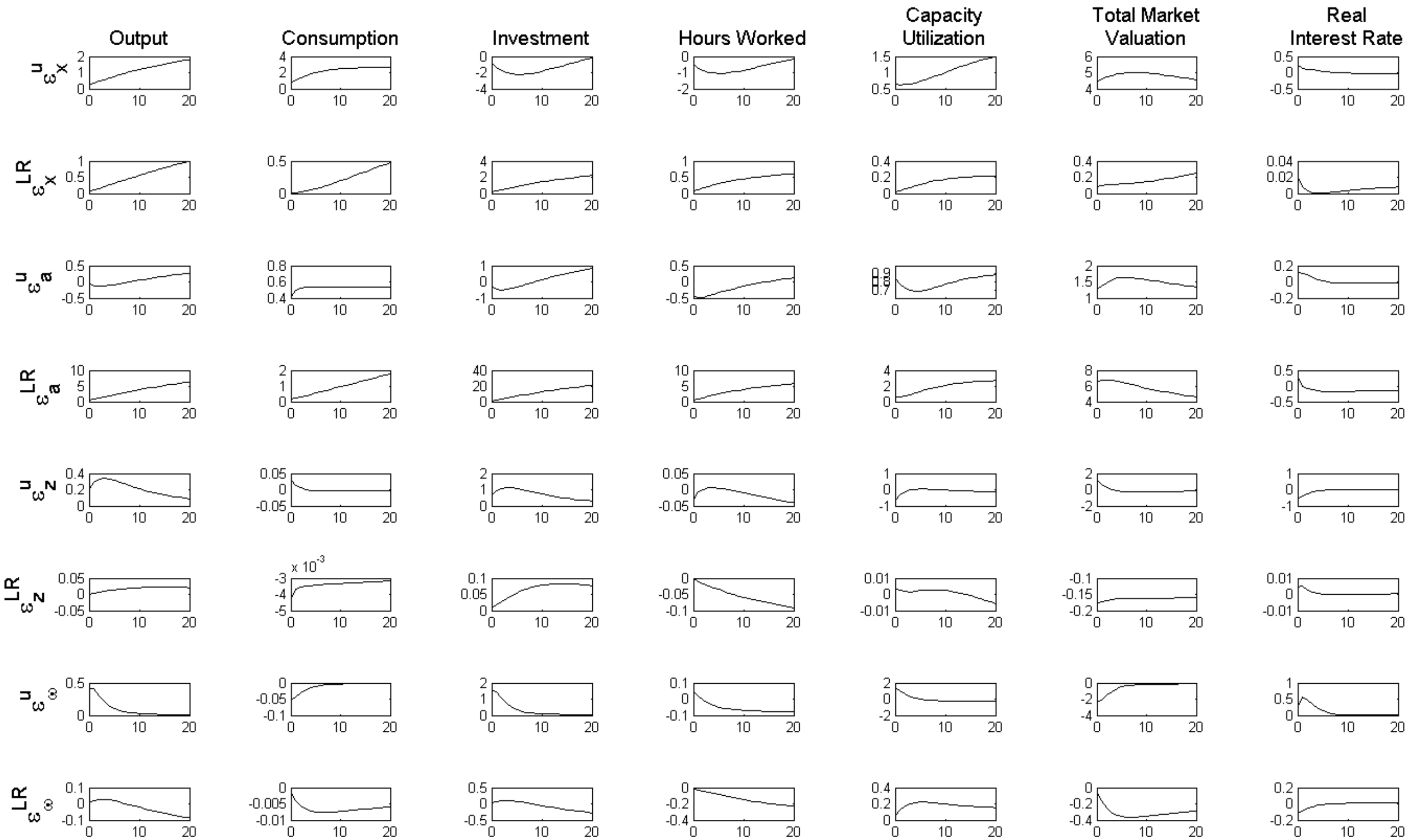
Note: IAC = investment adjustment costs, SRN = short run news shocks, AP = estimation with asset prices in the vector of observables; ε_x^0 = unanticipated LAT shock, ε_x^3 = 3-period ahead LAT news shock, ε_a^0 = unanticipated ISP shock, ε_a^3 = 3-period ahead ISP news shock, ε_z^0 = unanticipated TFP shock, ε_z^3 = 3-period ahead TFP news shock, ε_ω^0 = unanticipated MEI shock, ε_ω^3 = 3-period ahead MEI news shock.

Figure 11: Impulse Response Functions, CAC-SRN-AP case



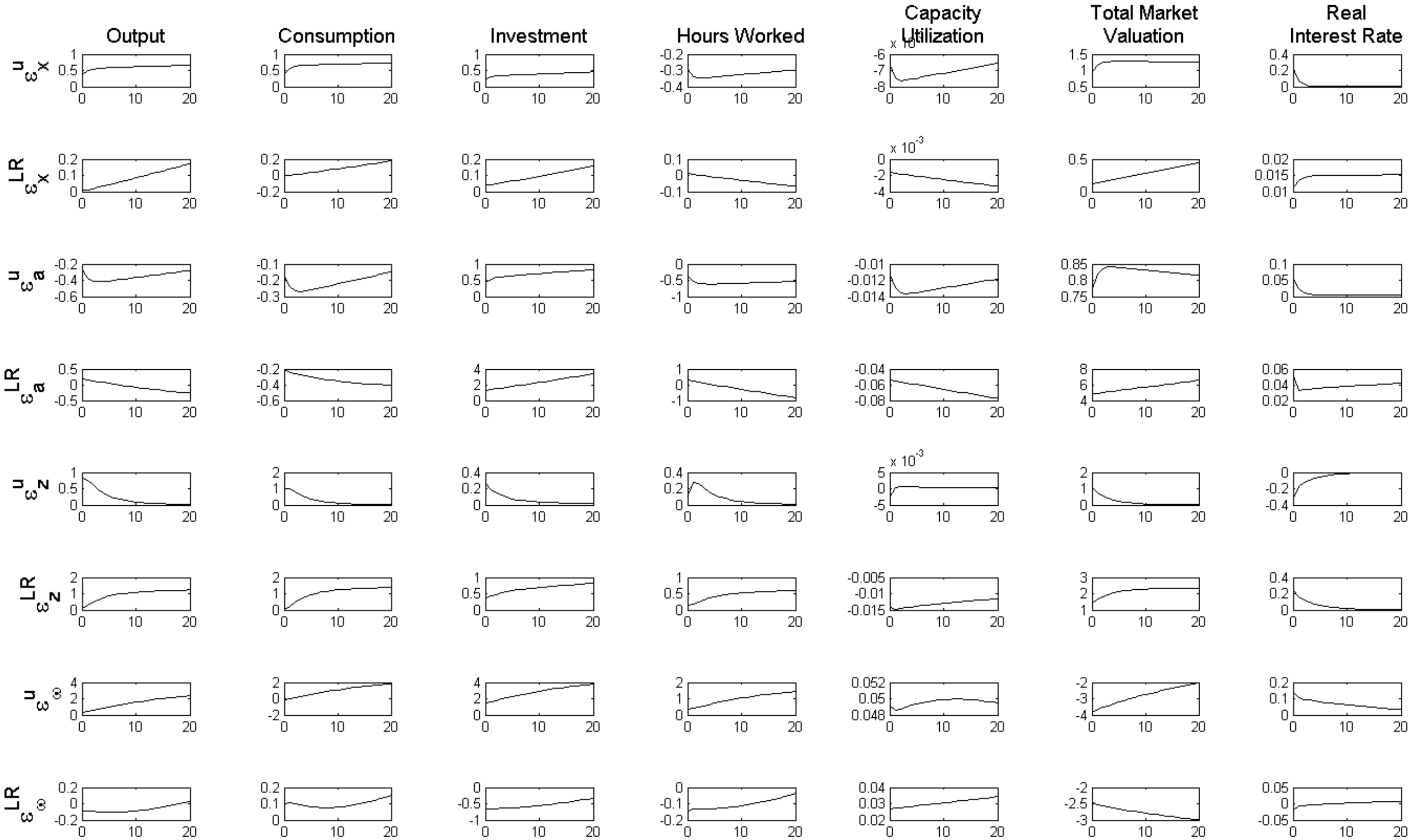
Note: CAC = capital adjustment costs, SRN = short run news shocks, AP = estimation with asset prices in the vector of observables; ε_x^0 = unanticipated LAT shock, ε_x^3 = 3-period ahead LAT news shock, ε_a^0 = unanticipated ISP shock, ε_a^3 = 3-period ahead ISP news shock, ε_z^0 = unanticipated TFP shock, ε_z^3 = 3-period ahead TFP news shock, ε_ϖ^0 = unanticipated MEI shock, ε_ϖ^3 = 3-period ahead MEI news shock.

Figure 12: Impulse Response Functions, IAC-LRN-AP case



Note: IAC = investment adjustment costs, LRN = long run news shocks, AP = estimation with asset prices in the vector of observables; ε_x^u = unanticipated LAT shock, ε_x^{LR} = long run LAT news shock, ε_a^u = unanticipated ISP shock, ε_a^{LR} = long run ISP news shock, ε_z^u = unanticipated TFP shock, ε_z^{LR} = long run TFP news shock, ε_ω^u = unanticipated MEI shock, ε_ω^{LR} = long run MEI news shock.

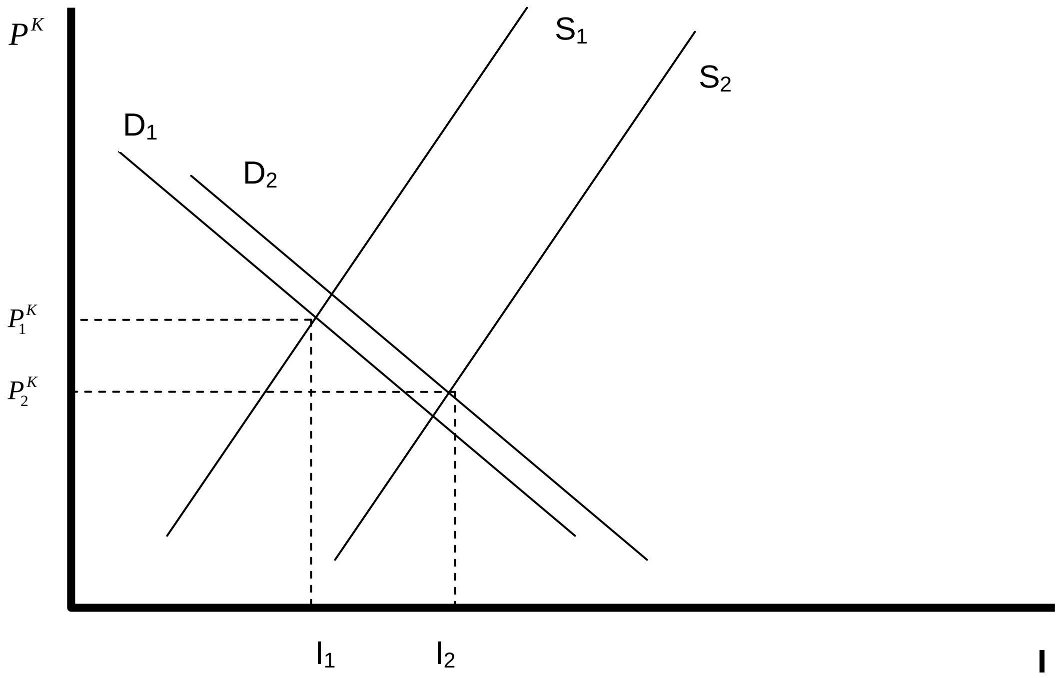
Figure 13: Impulse Response Functions, CAC-LRN-AP case



Note: CAC = capital adjustment costs, LRN = long run news shocks, AP = estimation with asset prices in the vector of observables; ε_x^u = unanticipated LAT shock, ε_x^{LR} = long run LAT news shock, ε_a^u = unanticipated ISP shock, ε_a^{LR} = long run ISP news shock, ε_z^u = unanticipated TFP shock, ε_z^{LR} = long run TFP news shock, ε_ω^u = unanticipated MEI shock, ε_ω^{LR} = long run MEI news shock.

Figure 14: The Market for Capital, Part I

Impact of an unanticipated MEI shock in the CAC-LRN specification:



Impact of an ISP news shock in the CAC-LRN specification:

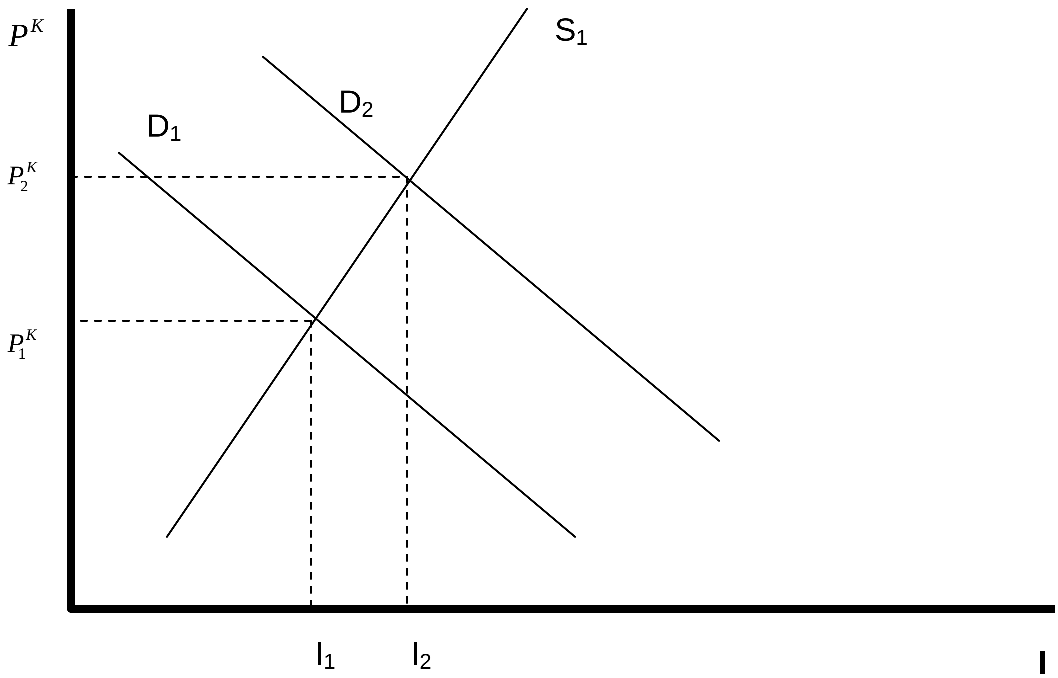
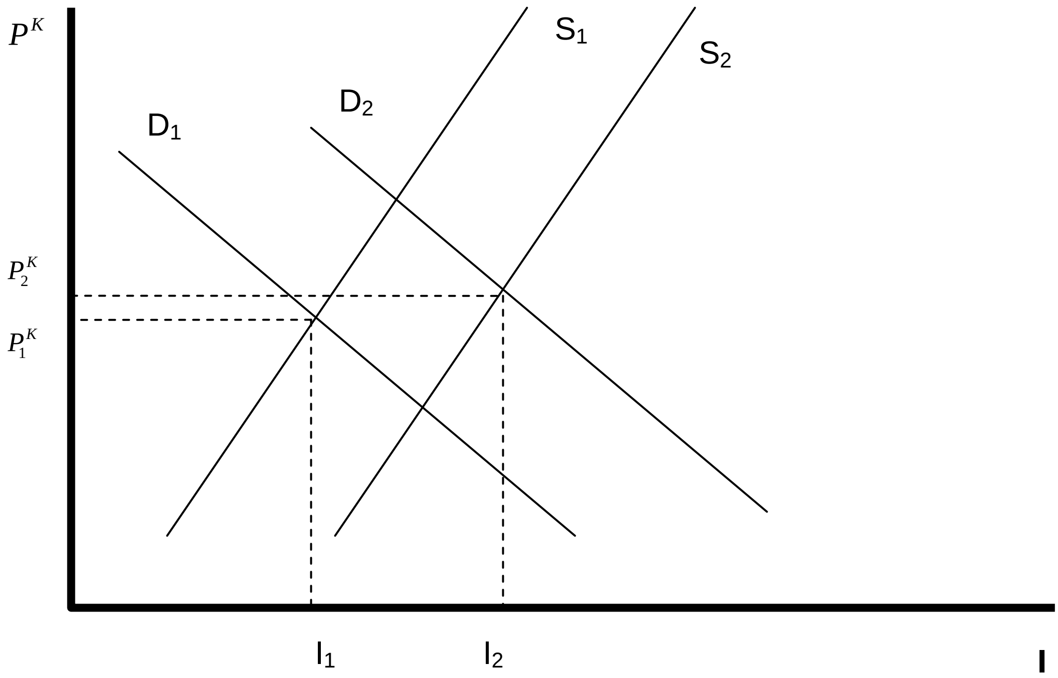


Figure 15: The Market for Capital, Part II

Impact of an ISP news shock in the IAC-LRN specification:



Impact of an ISP news shock in the CAC-LRN specification: