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Noisy News, Confusion and Aggregate Consumption Behaviour: An Empirical Study

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Abstract

The source of business cycles is a classical topic in macroeconomics. The news view of business cycles suggests that reoccurring booms and bust periods are mainly the result of agents having incentives to continuously anticipate the economy's future needs, and are direct consequences of people's incentive to speculate on information related to future developments of the economy. This thesis studies the effects of information structures on business cycle fluctuations. We estimate three different information structures: confusion, noisy news and a combination of these scenarios that is noisy news and confusion. We estimate our three models with two observable variables: real personal consumption expenditure per capita and real productivity per capita. We use quarterly U.S. observations covering the period 1947Q1 to 2015Q3. According to the Maximum Likelihood estimation results, we find that our signals in our three models are quite informative; while noise seems to have only a one-period effect on the economy, news effects are instantaneous and permanent.

Sommaire

La source des cycles économiques est un sujet classique en macroéconomie. La nouvelle vue des cycles économiques conjoncturels suggèrent que les périodes de boom et de récession récurrentes résultent principalement du fait que les agents sont incités à anticiper en permanence les besoins futurs de l'économie et résultent directement de l'incitation des individus à spéculer sur des informations relatives aux développements futurs de l'économie. Cette thèse étudie les effets des structures d'information sur les fluctuations du cycle économique. Nous estimons trois structures d'information différentes: la confusion, les nouvelles bruyantes et une combinaison de ces scénarios, nouvelles bruyantes et confusion. Nous estimons nos trois modèles avec deux variables observables: la dépense de consommation personnelle réelle par habitant et la productivité réelle par habitant. Nous utilisons les observations trimestrielles des États-Unis pour la période allant du 1947Q1 au 2015Q3. D'après les résultats de l'estimation du maximum de vraisemblance, nous constatons que nos signaux dans nos trois modèles sont assez informatifs; bien que le bruit semble affecter l'économie pendant une période, les effets de nouvelles sont instantanés et permanents.

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1. Introduction

The source of business cycles is a classical topic in macroeconomics. There are different factors explaining the business cycle, such as supply and demand shocks, fiscal or monetary shocks. Besides these factors, one possible source of business cycle fluctuations that has recently regained attention relates to the agents' information and anticipations of the above factors. This theory of business cycles, which is referred to as the "news view" of business cycles, suggests that reoccurring boom and bust periods are mainly the result of agents having incentives to continuously anticipate the economy's future needs, and are direct consequences of people's incentive to speculate on information related to future developments of the economy (Beaudry and Portier 2014).

There are two strands of studies in the news-driven business cycles; the first strand focuses on the role of news and the second studies the role of confusion in business cycle fluctuations. In this sense, news is an imperfect signal about future productivity growth which leads to significant forecast errors that are shared by a large fraction of the population. On the news view of business cycles, there are two groups of studies; the first group is based on vector autoregressive (VAR) analysis and the second one based on dynamic stochastic general equilibrium (DSGE) models. Beaudry and Portier (2014) offer an overview of news literature and compare different identification methods of news shocks. The authors use US data and estimate different combinations of two to four variables VAR. They find that when technological news is identified, it creates an aggregate boom that accords with typical business cycle co-movements of real variables. Using a DSGE model, Beaudry and Portier (2014) offer the idea that recessions and booms may arise as the result of investment swings generated by agents' difficulties in properly forecasting the economy's need in terms of capital. This model offers an equilibrium environment where anticipations and realizations of technological growth are qualitatively and quantitatively able to explain several patterns associated with the various phases of the business cycle.

The second strand of the news-driven business cycle literature introduces a new information structure, which refers to confusion; a situation where agents are not able to observe each component of productivity separately. However, the consumers observe a noisy signal about whether the realization of productivity comes from the permanent or transitory component. As long as this signal is imperfect, it is called a noisy signal. Similar to the previous news literature, we can divide the existing literature on confusion into two groups. The first group is based on VAR analysis and the second one based on DSGE models. In the VAR-based studies, authors try to study the role of confusion and identify news and noise shocks. However, they end up with an invertibility problem, also known as non-fundamentalness; which implies that if the shocks cannot be observed, then current (and past) values of the economic variables cannot convey the relevant information. So it is not possible to recover the shocks for the econometrician as well as consumers (Blanchard et al 2013). Several studies have used DSGE models to investigate the role of confusion; however, they have not reached a unique conclusion. While Van Nieuwerburgh and Veldkamp (2006), Boz et al (2011) and Blanchard et al (2013) conclude that noise shocks play an important role in business cycle fluctuations, Lorenzoni (2009) shows that they only lead to a small change in macro aggregates.

In this study, we explore empirically the role of both noisy news and confusion in business cycle fluctuations. Previous papers have studied the role of noisy news and confusion separately. We investigate the following key questions: Which information structure best describe the economy and are business cycle fluctuations primarily due to news or noise shocks? To design the hypothesis as specific as possible, we focus on the role of productivity as the major macroeconomic aggregate. Therefore, we assume that consumers receive information about future productivity and/or the components of current productivity. For this environment, we estimate consumers' adjustments through time. Specifically, we start our analysis by designing a modified version of the model of Blanchard et al. (2013) and show how consumers react to noisy information. To capture the impacts of news in our consumption model we follow Beaudry and Portier (2005) in which consumers observe a signal regarding the future realization of the permanent shock. The signal brings new information one period ahead of the occurrence of the shock. Our finding states that contrary to noise shocks that do not affect consumption and productivity in the long run, news shocks' effects are immediate and permanent.

We estimate three different information structures: confusion, noisy news and a combination of these scenarios, that is, noisy news and confusion. The confusion scenario refers to an information structure where consumers are not able to observe components of productivity separately; the noisy news scenario is characterized by an information structure where consumers are able to observe the components of productivity as well as a signal about the future realization of the permanent shock; and the noisy news and confusion scenario considers two mentioned information structures simultaneously.

The goal of this thesis is to study a scenario in which consumers face both noise and news simultaneously. Following the same idea of Blanchard et al. (2013), this coincidence of noise and news is what we capture in the "noisy news and confusion" scenario. We consider two types of signals: the first signal sheds some light about whether the realization of productivity comes from the permanent component or transitory component, the second signal provides some information about the news in period t regarding a change in productivity in period t+1.

To estimate our three models of the information structures discussed above, we use quarterly US observations covering the period 1947Q1 to 2015Q3 on productivity and consumption. We estimate each model by Maximum Likelihood. Also, since in our model consumers face a non-trivial signal extraction problem, we need to have two steps. First, we take the point of view of the consumers to write the dynamics of the unobserved states in a state-space representation and solve the consumers' filtering problem in our simulations. Then, we take the point of view of the econometrician to write down the model dynamics in a state-space representation and the appropriate observation equations (which depend on the data available). The econometrician's Kalman filter is then used to construct the likelihood function and estimate the model's parameters.

Our results show that signals brings a great deal of information to consumers; the standard deviation of the noise shock in the noise scenario is small, implying an extremely informative signal. Also, the standard deviations of news and noise shocks in the noisy news scenario are small, meaning that the signal is informative and news provides consumers almost perfect information. Finally, the standard deviations of the news and two noise shocks in the noisy news and confusion scenario imply highly informative news accompanied by relatively informative noise signals.

For the confusion scenario our findings confirm those of Blanchard et al. (2013). Our results show that after a permanent shock both productivity and consumption increase slowly to reach a plateau. After a transitory shock, while productivity and consumption increase initially, they decrease over time. Finally, noise shocks only affect consumption in the short run.

In the noisy news information structure, our results align with Beaudry and Portier (2006) who found that good news instantaneously increases consumption through a wealth effect. However, our estimation results are in sharp contrast with Beaudry and Portier’s findings on the role of noise. These authors rely on noise shocks as the central force causing recessions, while our finding shows that noise shocks have temporary effects and fades out after one period.

Also our results show that when we add the noise shocks on the future variables, these shocks are able to explain consumption volatility much more than the shocks on the current variables and so capture what noise shocks were capturing in the news scenario. Our results in terms of Likelihood ratio test and variance decomposition imply once we add the noise shocks on future variables to the news model, the shocks are able to explain consumption volatility much more than the shocks on the current variables. In fact, those noise shocks on future variables capture what the noise shocks were capturing in the news scenario. Therefore, our findings confirm the role of news shocks on the permanent component of productivity as a source of macro fluctuations.

The rest of the paper is organized as follows. Chapter 2 reviews the theoretical and empirical literature about the role of news and noise shocks. Chapter 3 outlines our empirical approach in simulating different information structures. Chapter 4 describes the data and presents the estimation results. Chapter 5 concludes.

2. Literature review

2. 1 News

The news-driven business cycle hypothesis argues that business cycles are determined by changes in expectations about future fundamentals. This theory of business cycles, which is referred to as the news view of business cycles, suggests that reoccurring boom and bust periods are mainly the result of agents having incentives to continuously anticipate the economy's future needs, and are the direct consequences of people's incentives to speculate on information related to future developments of the economy (Beaudry and Portier 2014). In this sense, news is an imperfect signal about future productivity growth which leads to significant forecast errors that are shared by a large fraction of the population.

In effect, the news view considers an environment where agents get imperfect signals about future productivity growth and use these signals to make decisions about investment, knowing that the received signals are imperfect. This strand of the literature emphasizes how information may occasionally be aggregated improperly by agents who tend to predict the future. As such, optimism means that when agents gathered information suggesting high future demand; and if their information is valid, boom occurs; otherwise boom leads to a crash, since the agent's information was just a noise and has not been realized.

Broadly speaking, there are two strands of the literature on the news view of business cycles. While both of them apply an empirical approach to study the role of news in economic fluctuations, they adopt different methods in identifying the news shocks. The first strand is based on VAR analysis and the second one based on DSGE models.

2.1.1 VAR analysis

The recent literature on news-driven business cycle begins with Beaudry and Portier`s empirical works (2005, 2006, 2007) on U.S. time-series data. They find that news shocks account for more than half of output (business cycle) fluctuations, and also induce co-movement among aggregate variables.

Beaudry and Portier (2006) provide additional empirical evidence on news driven business cycles. They show how the stock market price (SP) and total factor productivity (TFP) movements can be used to shed light on the forces driving business cycle fluctuations. To do so, they estimate a VECM (Vector Error Correction Model) including TFP and SP. Structural shocks are identified either with short-run or long-run restrictions. They find that permanent changes in productivity growth are preceded by stock market booms. They also consider three- and four-dimensional systems to include consumption, hours, and investment. The results are qualitatively similar for the first two variables; a favorable news shock leads to positive co-movement among these macroeconomic aggregates on impact. Then, the macroeconomic variables largely track movements in technology. While the identified news shock does appear to account for important long run movements in measured technology, it accounts for only modest shares of the forecast error variances of aggregate variables at short horizons.

Beaudry and Lucke (2009) employ a VECM to identify five shocks that are popular candidate explanations for macroeconomic fluctuations: unanticipated TFP, news shocks to TFP, unanticipated investment-specific technological progress, preference, and monetary shocks. The results indicate that the news shocks to TFP are the ones that explain the macro volatility at business cycle horizons. In comparison, the unanticipated changes in technology account for very little of business cycle fluctuations.

Barsky and Sims (2011) propose and implement a structural VAR approach to identify news shocks about future technology. In their model, a news shook is an expected increase in future TFP observed in advance. They show that favorable news shook lead to an increase in consumption and declines in output, hours, and investment on impact. Also, their results suggest that news shocks accounts for a significant fraction of output fluctuations only at medium frequencies and do not constitute a main driver of business cycle.

Barsky, Basu, and Lee (2014) are updating and extending the analysis of Barsky and Sims (2011). Using a VAR model, they identify a technological news shock as the innovation in the expectation of TFP at a fixed horizon j in the future. This news shook does not affect TFP on impact. The main result of their work is that the impact effects of news shocks clearly do not induce the kind of comovement that is characteristic of business cycles. They find that consumption rises when there is good news, but investment, consumer durables purchases and hours worked all fall on impact. These results echo those of Barsky and Sims (2011).

Kurmann and Sims (2017) use the quarterly utilization-adjusted series of TFP and show that these revisions in TFP measurement can substantially affect the empirical results about the role of news shocks in creating comovement in macroeconomic variables. They apply these revised TFP series to US data, using four to eight variables VAR, and find that the identified news shock does not generate comovement in real macroeconomic aggregates and is therefore not a main driver of business cycle fluctuations. This does not imply that the shock is unimportant for macroeconomics. The shock accounts for the majority of unpredictable fluctuations in real aggregates at medium- and long horizons and generates strong impact responses of inflation, the Federal Funds rate, asset prices as well as different measures of uncertainty.

As discussed above, there is no unique conclusion on the role news in creating business cycle. More recently, Beaudry and Portier (2014) offer an overview of the current strand of the news literature. They compare different identification methods of news shocks, providing reasons for the contradiction in results. The authors use U.S. data and estimate two to four variable VARs with different combinations of variables. Their model is a specific model where there is only one type of exogenous variable which is related to productivity. They find that consumption of non-durable goods and services, investment, hours and output do increase on impact and subsequently, before any sizable increase in TFP. Only consumption of durable goods does not move on impact, but displays a hump-shaped response after one period. Therefore, when technological diffusion news is identified, it creates an aggregate boom that accords with typical business cycle co-movements of real variables.

Finally, Chahrour and Jurdo (2018) argue that news and noise representations are more closely linked than the literature has recognized. Specifically, they prove that these two information structures are observationally equivalent. They find that fundamentals and people's beliefs about them always have both a news representation and a noise representation. This implies that associated with every noise representation is an observationally equivalent news representation and vice versa. Beyond clarifying the link between news and noise, their paper sheds new light on the question that how important are beliefs as an independent source of fluctuations? The authors argue that future news shocks are not very important in creating business cycles. The reason is that, in addition to mixing fluctuations due to beliefs and fundamentals, news shocks also mix fluctuations due to past, present, and future fundamentals. Current news shocks reflect changes in future fundamentals, but past news shocks show up as changes in current fundamentals. If a model is not sufficiently “forward-looking,” it may be that news shocks matter mainly through this second channel.

So far, almost all the literature applies news in the closed-economy models. However, one of the applications of news view of business cycle is to an open economy. The most well-known of these papers are by Devereux and Engel (2006), Corsetti, Dedola, and Leduc (2009), Beaudry, Dupaigne, and Portier (2011), and Kamber et al. (2017). For example, Kamber et al. (2017) focus on news-driven business cycles in small open economies. They use VARs to identify news shocks using data on 4 advanced small open economies. They find that news shocks to TFP generate business cycle co-movements in output, hours, consumption and investment. Also, the trade balance is found to be counter-cyclical in most the economies in their sample.

2.1.2 DSGE models

Beaudry and Portier (2007) offer a formalization of the idea that recessions and booms may arise as the result of investment swings generated by agents’ difficulties in properly forecasting the economy’s need in terms of capital. In their baseline model, they consider a general equilibrium structure where agents get imperfect signals about future productivity growth and use these signals to make decisions about investment; knowing that the received signals are imperfect. In this environment, periodic recessions are most likely to arise when agents’ signals about the future are precise. In this framework, occasional recessions are a sign of a well-functioning economy since they reflect the availability of good quality information upon which people act.

In their model, the economy is composed of two sectors: the production sector and household sector. The representative household has preferences defined over consumption of the final good and over the labor supplied in production sectors. For the information structure, they consider a process of technology that in every period agents observe, in addition to the level of technological progress, an i.i.d. zero mean signal. The signal brings information on the growth of technology between time t and t+i. This model offers an equilibrium environment where anticipations and realizations of technological growth are qualitatively and quantitatively able to explain several patterns associated with the various phases of the business cycle.

Barsky and Sims (2012) introduce the meaning for consumer confidence and show that surprise movements in confidence are prognostic of long-run movements in macroeconomic variables.

The authors develop a DSGE model with two main shocks. The first is a reflection of news shock and the second shock arises because they permit households to observe only a noise-ridden signal of the news shock. The authors interpret the noise as an "animal spirits shock," as it is associated with optimism or pessimism. The authors model confidence as a composite signal reflecting both fundamentals and noise, so that confidence innovations are a linear combination of the structural shocks in the model. Their confidence variable is summarizes responses to the following question: "Turning to economic conditions in the country as a whole, do you expect that over the next five years we will have mostly good times, or periods of widespread unemployment and depression, or what?" Then the variable is constructed as the percentage giving a favorable answer minus the percentage giving an unfavorable answer plus 100. Barsky and Sims conclude that fundamental news is the main driving force behind the observed relationship between the confidence and subsequent economic activity.

Schmitt-Grohe and Uribe (2012) study the importance of anticipated shocks as a source of business cycle fluctuations. They perform classical maximum likelihood and Bayesian estimations of the contribution of anticipated shocks to business cycles in the postwar US. The authors implement a real-business cycle model augmented with four rigidities: investment adjustment costs, variable capacity utilization, habit formation in consumption, and habit formation in leisure. They assume business cycles are driven by permanent and stationary neutral productivity shocks, permanent investment-specific shocks, and government spending shocks. Each of these shocks is buffeted by four types of structural innovations: unanticipated innovations and innovations anticipated one, two, and three quarters in advance. The main finding of their paper is that anticipated shocks account for more than two thirds of predicted aggregate fluctuations. This result is robust to estimating a variant of the model featuring a parametric wealth elasticity of labor supply.

Next, some works focused on the role of financial market imperfections in spreading the news in the economy. For example, Gunn and Johri (2013) examine a situation with financial intermediation where the news relates to changes in the technology of the banking sector. They use a financial-accelerator framework in a real DSGE model to study news-shocks. They study the boom that preceded the "Great Recession" and the eventual bust together. They find that changes in expectations about future default costs generate a boom-bust cycle. Also, Gortz and Tsoukalas (2011) have developed a two-sector DSGE model with financial intermediation. They find that news shocks to the future growth prospects of the economy are significant drivers of U.S. fluctuations, explaining as much as 50% and 37% of the variance in hours worked and output, respectively, at business cycle frequencies.

Some authors study the effect of news on the dynamics of house prices and fluctuations. Lambertini, Mendicino, and Punzi (2010) analyze housing market boom-bust cycles driven by changes in households' expectations. They find that, in the presence of nominal rigidities, expectations on both the conduct of monetary policy and future productivity can generate housing market boom-bust cycles in accordance with the empirical findings. Next, Lambertini, Mendicino, and Punzi (2011) study the potential gains of monetary and macro-prudential policies that lean against news-driven boom-bust cycles in housing prices and credit generated by expectations of future macroeconomic developments. Kanik and Xiao (2014) propose a model. They estimate a DSGE model in which credit-constrained borrowers use their housing assets as collateral to finance their purchases. Optimistic news raises these agents' expected future net worth, expands their borrowing capacity, and allows them to purchase more housing and consumption goods. Higher housing demand raises housing prices and creates a housing boom.

Finally, there is a new strand of literature that extends the news view to the non-linear world. For example, Bolboaca and Fischer (2015) offer a model to be as flexible as possible and estimate generalized impulse response functions that allow for transition from one state to the other. The medium-run identification with generalized impulse responses and generalized forecast error variance decomposition are brought to the nonlinear world. The results reveal quantitative nonlinearities while they are in line with the literature and the linear world.

2.2 Noise

The second strand of the news-driven business cycle hypothesis introduces a new information structure, which refers to noise and discusses its role in creating business cycle fluctuations. While news brings new information on the future growth of productivity, confusion refers to a situation where agents are not able to observe each component of productivity separately. Instead, the consumers observe a noisy signal about whether the realization of technology, a_t

comes from the permanent or transitory component. As long as this signal is imperfect, it is called a noisy signal. The signal is

$$s_t = x_t + \upsilon_t,$$

where x_t is the permanent component of productivity and $\upsilon_t$is the noise shock.

Similar to the previous section, we can divide the existing literature into two subgroups. Which adopt different methods in identifying noise. The first strand is based on VAR analysis and the second one based on DSGE models.

2.2.1 VAR Based Analysis

In this group of studies, authors try to use VAR models to study the role of confusion and identify news and noise shocks. However, they end up with a problem in VAR models which is called the invertibility problem, also known as non-fundamentalness. The non-invertibility problem argues that if the shocks cannot be observed, then current (and past) values of the economic variables cannot convey the relevant information. This implies that it is not possible to recover the shocks as linear combinations of the VAR residuals. And, if this is possible for the econometrician, it would be possible for the agents as well; contrary to the starting assumption that these noise shocks are not observable. Hence, it seems that VAR models cannot be useful empirical tools under imperfect information.

As an outstanding example, Blanchard et al (2013) show that if the econometrician has no informational advantage over the agents in the model, structural VARs cannot be used to identify news and noise shocks.

Afterwards, Dees and Zimic (2016) also show that standard structural VAR models cannot be applied to identify the two types of shocks, as the VAR model faces invertibility issues. However, by considering that the econometrician can potentially have a richer and more accurate information set, they estimate a structural VAR model which can recover both news and noise shocks. To reach this conclusion, they consider two facts: first, while economic agents can observe only current and past data, the econometrician can also observe “future” data. In other words, by using the data from the whole sample, the econometrician can have a better estimate of the technological trends than the economic agents. Second, economic agents only observe real-time data, while the econometrician also has access to revised data.

Dees and Zimic's structural VAR model includes the estimated forecast errors together with GDP, private consumption, investment, stock prices, interest rates, inflation and consumer sentiment. The estimation is conducted using US data over a period from 1970Q1 to 2012Q2. The identification of the noise and technology shocks is achieved by sign restrictions. They show empirically that the identified shocks have macroeconomic impacts that are in line with theoretical predictions. A permanent (technology) shock has an expansionary effect on the economy, which builds through time until variables settle at a new, higher value. A noise shock also has an expansionary effect on the economy, but the impact fades away over time until all variables settle at their initial value. Nevertheless, noise shocks are more important for business cycle fluctuations.

2.2.2 DSGE Models

Van Nieuwerburgh and Veldkamp (2006) focus on explaining business-cycle asymmetries in a RBC model with incomplete information in which agents receive signals with procyclical precision about the economy's fundamentals. They believe learning about the technology level over a business cycle can generate asymmetry in booms and crashes. Their explanation rests on learning about productivity. When agents believe productivity is high, they work, invest, and produce more. More production generates higher precision in information. When the boom ends, precise estimates of the slowdown prompt decisive reactions: investment and labor fall sharply. When growth resumes, low production yields noisy estimates of recovery. Noise impedes learning, slows recovery, and makes booms more gradual than downturns.

Their model is a DSGE model in which the aggregate level of technology is not observable. Also, they add a stochastic term to the output which is again not observable to the agents. Following a change in technology, the speed of learning measures how quickly beliefs converge to the truth. When the economy is in recession and inputs are low, estimates of technology are imprecise and learning is slow. In a boom, high capital and labor utilization make learning faster. This variation in the speed of learning over the business cycle produces the asymmetry in growth rates.

So Van Nieuwerburgh and Veldkamp conclude that in good times, agents react faster to shocks than in bad times. Also, during recessions, agents discount new information more heavily and the mean of their beliefs recovers slowly. Their paper provides a theory of endogenous pessimism that can explain business cycle asymmetries.

Lorenzoni (2009) introduces a model where technology determines equilibrium output in the long run, but consumers only observe noisy signals about technology in the short run. The presence of noisy signals produces expectational errors. He uses a standard new Keynesian model where he introduces both aggregate and idiosyncratic productivity shocks. The average level of productivity in the economy follows a random walk. However, agents cannot observe average productivity directly. They can only observe the productivity level in their own sector, which has a temporary idiosyncratic component, and a noisy public signal regarding average productivity. They also observe prices and quantities which provide endogenous sources of information. He concludes a positive technology shock leads to a gradual adjustment in output to its new long run level, and to a temporary fall in employment and inflation. On the other hand, a positive noise shock leads to a temporary increase in output, employment and inflation.

Boz et al (2011) introduce the role of imperfect information and learning about the underlying fundamentals of the economy in emerging market economies. They consider a standard small open economy real business cycle model with permanent shocks to technology. The representative agent is imperfectly informed about the contributions of permanent and transitory shocks to observed TFP and, thereby, solves a signal extraction problem.

Their model features production with endogenous capital and labor. There are costs associated with adjusting capital, which are typically introduced in the literature to match the variability and persistence of investment. The agent can borrow and lend in international capital markets. The asset markets are incomplete because the only financial instrument available is a one-period non contingent bond that pays an interest rate that increases with the debt level. At the beginning of every period, the agent observes TFP and the trend growth signal, updates expectations regarding the components of TFP, makes investment, labor, debt, and consumption decisions.

Boz et al (2011) conclude that when the agents are imperfectly informed about the trend-cycle decomposition of productivity shocks, and they solve a learning problem using the Kalman filter to estimate the components of TFP, the model performance improves greatly.

Finally, as mentioned in the previous part, Blanchard et al (2013) conclude that VAR models are not useful in identifying news from noise shocks. Afterwards, they develop a DSGE model which allows them to evaluate the role of news and noise shocks. Their model includes investment and capital accumulation, nominal price and wage rigidity and an accommodative monetary policy rule together to make agents' consumption decisions highly forward-looking, and allow the model to generate empirically realistic patterns of co-movement in response to a noise shock. In their model, productivity is a random walk and the sum of two components:

$$a_t = x_t + z_t,$$

where a_t is the productivity, x_t refers to the permanent and z_t refers to the temporary component of productivity. Also, the consumption random walk hypothesis holds. In each period, consumers observe current and past productivity, a_t. In addition, they receive a signal regarding the permanent component of the productivity process

$$s_t = x_t + \nu_t.$$

Since they consider productivity a random walk process, agents rely heavily on their noisy signal to forecast future productivity. Blanchard et al (2013) conclude that noise shocks play a crucial role in business cycle dynamics, especially for consumption; the contribution of noise to consumption is 57%. And future fundamental shocks play a very small role compared to current and past fundamental shocks; they are responsible for less than 7% of consumption fluctuations. For investment, the noise shock only accounts for a small fraction of investment volatility; the investment response is first positive and hump-shaped and later turns negative. Finally, the noise shocks accounts for 20% of volatility in aggregate output.

3. Model

In this chapter, we illustrate how information structures affect business cycle fluctuations. The first information structure is related to “noisy news”. This refers to an announcement in period t which may or may not take place in period $t+i$ (e.g. Beaudry and Portier 2004). The second one is related to confusion. This occurs when agents are confused between permanent shock and transitory shock to the model’s fundamentals (e.g. Blanchard et al. 2013). We then study jointly the effects of noisy news and confusion, which is the first attempt in the literature of beliefs driven business cycles.

Generally, information can be about any macroeconomic fundamental. Fundamentals reflect exogenous variables such as shocks to technology, preferences, endowments, or government policies. Agents’ decisions depend on expected future realizations of fundamentals. The two information structures discussed above specify which fundamentals agents actually observe contemporaneously and how they use these observations to form beliefs about future realizations. In our illustration, fundamentals are related to productivity a_t and the two underlying components x_t and z_t, which are the permanent and transitory components of productivity. Agents’ decisions are about consumption.

At this point, it is useful to present the part of the model that is common to the two information structures. This part is inspired from the model proposed by Blanchard et al. (2013). First, it is assumed that agents’ consumption decisions are determined as follows

$$c_t = \lim_{j \to \infty} E\left[a_{t+j} \middle| \Phi_t\right], \qquad (3.0.1)$$

where E is the expectation operator, c_t is consumption, a_t is productivity, and Φ_t is the information set available at time t.

Equation (3.0.1) has a flavour of the permanent income hypothesis. This hypothesis stipulates that consumption corresponds to the present value of expected future income. For simplification, equation (3.0.1) assumes that consumption is determined by the expectations of asymptotic future income. Equation (3.0.1) also assumes that income corresponds to productivity.

Also fundamentals correspond to

$$a_t = x_t + z_t, \qquad (3.0.2)$$

where x_t is a permanent component and z_t a transitory component. The permanent component follows the unit root process:

$$\Delta x_t = \rho \Delta x_{t-1} + \varepsilon_t, \tag{3.0.3}$$

where Δ is the first difference operator ε_t is a permanent shock, with $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. This shock introduces uncertainty about long-run productivity. The transitory component follows a stationary process:

$$z_t = \rho z_{t-1} + \eta_t, \tag{3.0.4}$$

where η_t is a transitory shock, with $\eta_t \sim N\left(0, \sigma_\eta^2\right)$. This shock introduces uncertainty about the short-run productivity. For simplicity, it is assumed that the autoregressive coefficients ρ in (3.0.3) and (3.0.4) are identical, where $|\rho| < 1$.

3.1 Benchmark information structure

The benchmark information structure corresponds to rational expectation. Under such expectations, $E[x_t|\Phi_t] = x_t$ and $E[z_t|\Phi_t] = z_t$, so that the current permanent and transitory components are parts of the consumers' information set. Also, $E\left[u_{t+j}\middle|\Phi_t\right] = 0$ and $E\left[u_{z+j}\middle|\Phi_t\right] = 0$ for j > 0, where $u_{t+j} = x_{t+j} - E[x_{t+j}|\Phi_t]$ and $u_{z_{t+j}} = z_{t+j} - E[z_{t+j}|\Phi_t]$, so that consumers do not do systematic forecast errors.

In this context, the consumption decision rule (3.0.1) reduces to

$$c_t = \lim_{j \to \infty} E\left[x_{t+j}\middle|\Phi_t\right]. \tag{3.1.1}$$

This occurs because the expectation of asymptotic future transitory productivity converges to the mean of this component which is zero, as

$$\lim_{j \to \infty} E\left[z_{t+j}\middle|\Phi_t\right] = \lim_{j \to \infty} \rho^j z_t = 0, \tag{3.1.2}$$

since $|\rho| < 1$.

Given the process (3.0.3), equation (3.1.1) becomes

$$c_t = \lim_{j \to \infty} E\left[x_{t+j}\middle|\Phi_t\right] = x_t + \lim_{j \to \infty} E[x_{t+j} - x_t|\Phi_t],$$

$$c_t = x_t + \frac{\rho}{1-\rho} \Delta x_t = [\frac{1}{1-\rho}] x_t - \left[\frac{\rho}{1-\rho}\right] x_{t-1}.$$

This is written in matrix form as:

$$c_t = R X_t, \tag{3.1.3}$$

where $R = \begin{pmatrix} \frac{1}{1-\rho} & -\frac{\rho}{1-\rho} & 0 \end{pmatrix}$ and $X_t = (x_t \quad x_{t-1} \quad z_t)'$, where X_t is the set of observable variables.

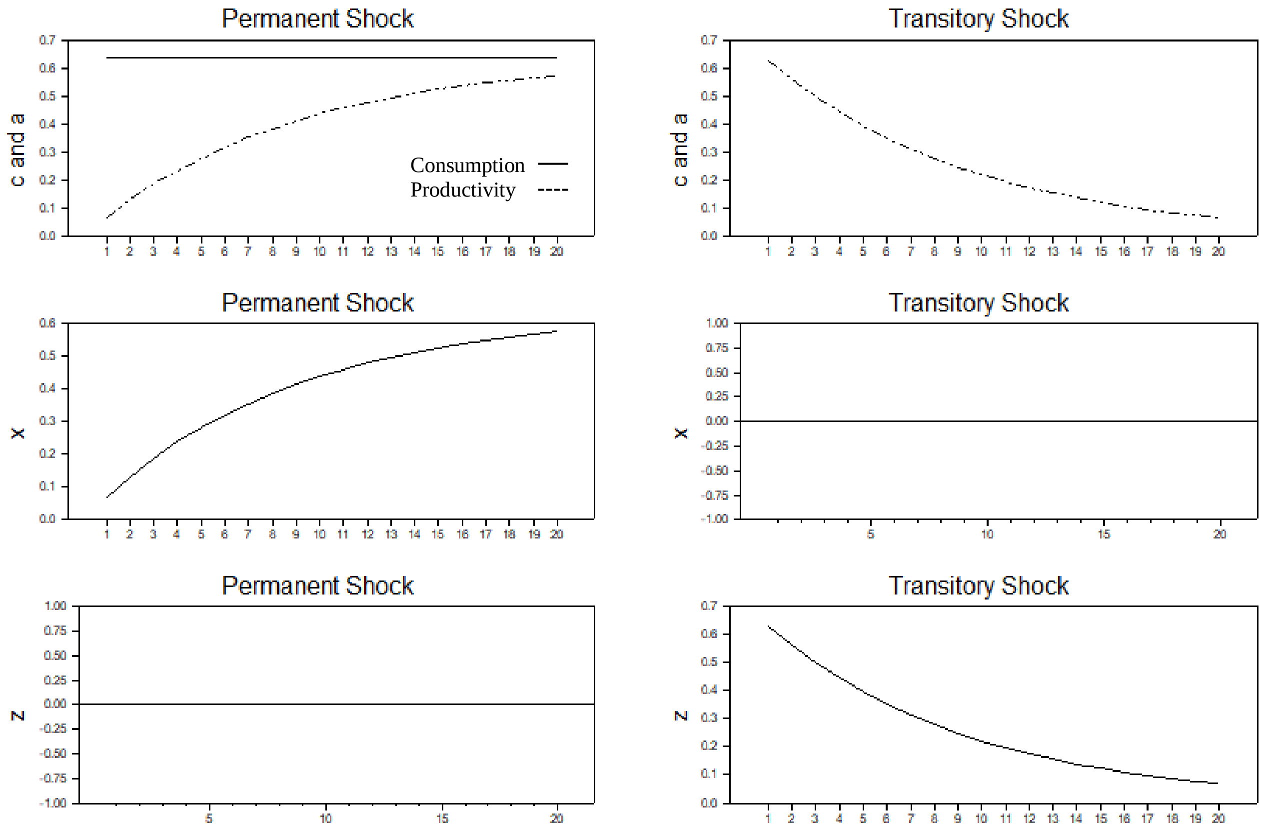
So far, we have solved mathematically the model for consumption. Now, for illustrative purposes we perform simulation by assigning specific values for the parameters. These values are similar to those in Blanchard et al. (2013).

Table 3. 1: Parameters' Values

Parameters	$\boldsymbol{\rho}$	$\boldsymbol{\sigma_\varepsilon}$	$\boldsymbol{\sigma_\eta}$
Values	0.89	0.0007	0.0063

For these values, Figure 3.1 shows the impulse response functions of consumption, productivity, as well as the permanent and transitory components of productivity following permanent and transitory shocks.

Figure 3.1: Impulse Response Functions



The first row of Figure 3.1 shows the dynamic responses of consumption and productivity to our two shocks. Also, the second and third rows display the responses of the permanent and transitory components of productivity. The time unit is a quarter and the impulses are one standard deviation positive shocks. The persistence parameter is ρ = 0.89, implying slowly building permanent shocks and slowly decaying transitory shocks.

Following a permanent shock, the permanent component increases gradually to reach a plateau, whereas the transitory component is not affected. Under rational expectations, consumers then realize that the shock to productivity is permanent. As such, they increase immediately and permanently their consumption.

Following a transitory shock, the permanent component is not affected, while the transitory component increases initially and then declines monotonically to its pre-shock level. Under rational expectations, consumers realize that the shock is transitory. For this reason, they do not adjust consumption.

3.2 Noise

This case is as in Blanchard et al. (2013). In this information structure, consumers observe a_t, but not x_t or z_t. Since agents do not observe each component of productivity separately, we refer to this case as noise. However, the consumers also observe a noisy signal about whether the realization of a_t comes from the permanent or transitory component. As long as this signal is imperfect, it is called a noisy signal.

The signal is

$$s_t = x_t + \upsilon_t, \tag{3.2.1}$$

where υ_t refers to a noise shock, with $\upsilon_t \sim$ N $(0,\sigma_\upsilon^2)$. A higher (lower) variance, σ_υ^2, means that the signal is weaker (stronger) and brings a little (much) information to consumers.

Here, we note that (3.0.3) and (3.0.4) can be written more compactly as:

$$\begin{pmatrix} x_t \\ x_{t-1} \\ z_t \end{pmatrix} = \begin{pmatrix} 1+\rho & -\rho & 0 \\ 1 & 0 & 0 \\ 0 & 0 & \rho \end{pmatrix} \begin{pmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_t \\ \upsilon_t \end{pmatrix},$$

or,

$$X_t = AX_{t-1} + BV_t. \tag{3.2.2}$$

This equation is called the state-space representation of our model, which captures the dynamics of the unobservable variables.

Also, the observable variables (productivity and signal) can be written as:

$$\begin{pmatrix} a_t \\ s_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_t \\ x_{t-1} \\ z_t \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_t \\ \upsilon_t \end{pmatrix},$$

or

$$S_t = CX_t + DV_t. \tag{3.2.3}$$

To solve for consumption, we first use the process (3.0.3) to obtain:

$$\lim_{j\to\infty} \mathrm{E}\left[x_{t+j} - x_t \,|\Phi_t\right] = \sum_{s=1}^{\infty} \mathrm{E}[\Delta x_{t+s}|\Phi_t]$$

$$= \sum_{s=1}^{\infty} \rho^s E[\Delta x_t|\Phi_t]$$

$$= (\frac{\rho}{1-\rho}) E[\Delta x_t|\Phi_t],$$

given that $E[\varepsilon_{t+s}|\Phi_t] = 0$.

Now, using the latter expression and the decision rule (3.0.1) yields:

$$c_t = \lim_{j\to\infty} E\left[x_{t+j}\middle|\Phi_t\right] = \lim_{j\to\infty} E\left[x_t + x_{t+j} - x_t\middle|\Phi_t\right],$$

$$c_t = \left[\frac{1}{1-\rho}\right] E[x_t|\Phi_t] - \left[\frac{\rho}{1-\rho}\right] E[x_{t-1}|\Phi_t],$$

or more compactly,

$$c_t = RE[X_t|\Phi_t], \tag{3.2.4}$$

where $R = \begin{pmatrix} \frac{1}{1-\rho} & -\frac{\rho}{1-\rho} & 0 \end{pmatrix}$.

Finally, the solution for consumption is obtained by computing the agents' beliefs about X_t, $E[X_t|\Phi_t]$, through the Kalman filter (see Appendix A)

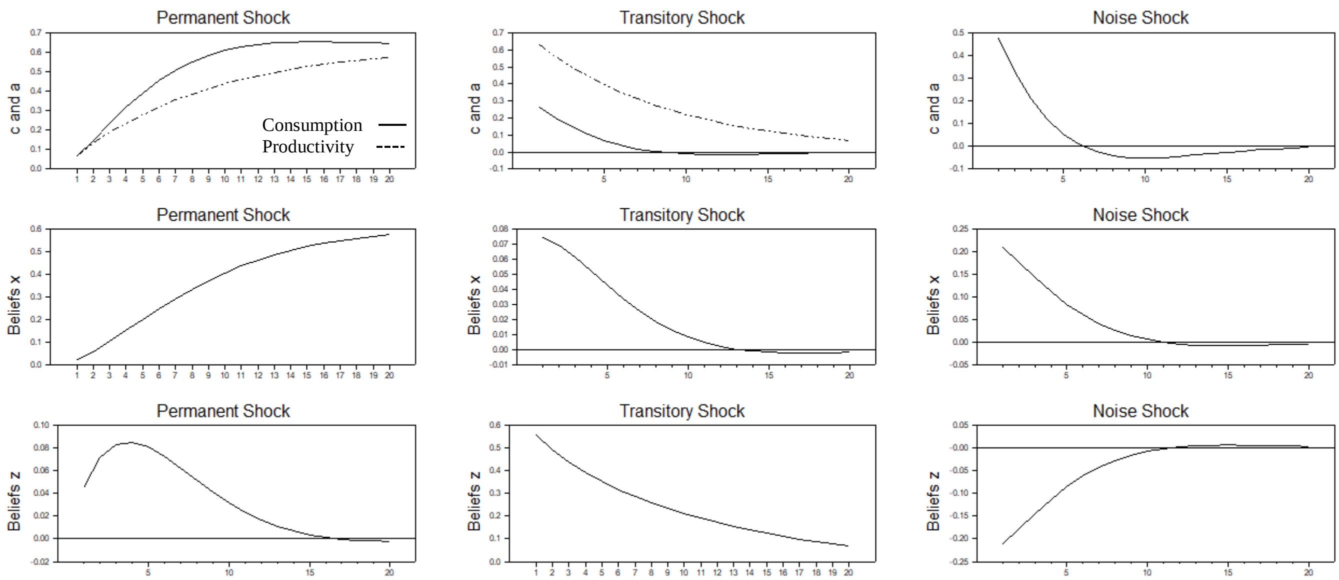
For illustrative purposes, we perform a simulation by assigning specific values for the parameters. These values are similar to those in Blanchard et al. (2013).

Table 3. 2: Parameters' Values

Parameters	$\boldsymbol{\rho}$	$\boldsymbol{\sigma_\varepsilon}$	$\boldsymbol{\sigma_\eta}$	$\boldsymbol{\sigma_\upsilon}$
Values	0.89	0.0007	0.0063	0.0089

For these values, Figure 3.2 shows the impulse response functions of consumption and productivity to our three shocks. Note that the standard deviation of the noise shock is σ_υ = 0.89%, implying a fairly noisy signal.

Figure 3.2: Impulse Response Functions



Following a permanent shock, both productivity, a_t, and consumption, c_t, increase slowly. This reflects the notion that the volatility of the noise shock is relatively large, so that it takes a while for consumers to recognize that the shock is permanent and to fully adjust consumption. A less informative signal can yields a slower consumption adjustment.

Next, since consumers are not able to observe x and z separately, we can only analyze agents' beliefs about these components, namely $E[X_{t+i}|\Phi_t]$ and $E[Z_{t+i}|\Phi_t]$. In response to a permanent shock, the beliefs about the permanent and transitory components of the productivity initially increase. This reflects the idea that consumers do not know whether the shock is permanent or transitory. After several periods, consumers observe that productivity is still increasing. As such, they learn that the actual shock is indeed permanent, so the beliefs of the permanent component gradually increase to reach a plateau. In contrast, the beliefs regarding the transitory component of productivity, they gradually decrease. Also, consumption, which is a function of the permanent component of productivity, continues to increase to reach a plateau.

The second column of the figure shows the impulse responses for our variables following a transitory shock. In response to a transitory shock productivity increases. Because of the presence of confusion, consumers are not able to realize the source of the shock. Therefore, they believe that this may be due to a permanent shock or a transitory shock, which leads to an increase in both $E[X_{t+i}|\Phi_t]$ and $E[Z_{t+i}|\Phi_t]$. As there is an increase in $E[X_{t+i}|\Phi_t]$, consumers increase consumption as well.

Over time, consumers observe that productivity decreases. Therefore, they then learn that the actual shock is a transitory shock. They thus revise their beliefs of X_t and Z_t downward and they reduce their consumption. As a result, while the impact responses for productivity and consumption are initially positive, they decrease over time.

Finally, let's consider the noise shock. Again, since the signal is not perfect, consumers initially increase their consumption since they believe that there may be an increase in the permanent component of productivity. Also, since they observe that there is no change in productivity, their beliefs regarding the transitory component initially decrease. As time goes on, consumers learn that it has been just a noise shock given that the response of the productivity is always zero. As such, consumption decreases to its pre-shock level as well as the beliefs about X_t. Corresponding to these changes, the beliefs regarding Z_t increase and return to its initial level.

3.3 Noise and news

In this section, we illustrate the noisy news proposed by Beaudry and Portier (2005) in the context of the consumption model (3.0.1)-(3.0.4).

In this environment, the consumers observe a_t, x_t, and z_t. Also, the consumers observe a signal ζ_t about the future realization of the permanent shock ε_t. In our setting, the signal brings new information one period ahead of the occurrence of the shock.

Thus the signal is

$$\zeta_t = \varepsilon_{t+1} + \upsilon_t, \qquad (3.3.1)$$

where ε_{t+1} is the news shock.

We refer to ζ_t as the signal. It is an announcement that there will be a shock on next period's permanent component of productivity. However, this news is noisy as the signal is contaminated by a noise shock υ_t, with $\upsilon_t \sim N(0, \sigma_\upsilon^2)$. The larger is σ_υ^2, the noisier is the news.

In this environment, we redefine the vector X_t as $X_t = (x_t \;\; x_{t-1} \;\; z_t \;\; \varepsilon_{t+1})'$. This vector involves the state variables when there is also a news shock. The system is then:

$$\begin{pmatrix} x_t \\ x_{t-1} \\ z_t \\ \varepsilon_{t+1} \end{pmatrix} = \begin{pmatrix} 1+\rho & -\rho & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & \rho & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \\ \varepsilon_{t-} \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} \varepsilon_{t+1} \\ \eta_t \\ \upsilon_t \end{pmatrix},$$

or

$$X_t = AX_{t-1} + BV_t.$$

Next, we can write the observable variables in the following form:

$$\begin{pmatrix} x_t \\ z_t \\ \varsigma_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_t \\ x_{t-1} \\ z_t \\ \varepsilon_{t+1} \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_{t+1} \\ \eta_t \\ \upsilon_t \end{pmatrix}$$

or more compactly

$$S_t = CX_t + DV_t. \tag{3.3.2}$$

The solution to this model requires solving the signal extraction problem. For this case, a solution for only $E[\varepsilon_{t+1}|\Phi_t]$ is required because x_t is known in period t. In this context, $E[\varepsilon_{t+1}|\Phi_t]$ is a projection obtained using $\varepsilon_{t+1} = b\zeta_t + \upsilon_t$ where υ_t is an error term. Note that the estimate of b corresponds to $\hat{b} = \frac{\sigma_\varepsilon^2}{(\sigma_\varepsilon^2+\sigma_\upsilon^2)}$. The projection is $E[\varepsilon_{t+1}|\Phi_t] = \hat{b}\zeta_t$. Alternatively, the projection can be obtained by applying the Kalman filter, where $E[\varepsilon_{t+1}|\Phi_t] = e_4' E[X_t|\Phi_t]$ with $e_4 = (0\ \ 0\ \ 0\ \ 1)'$(see Appendix B).

In this case, the solution for consumption relies on the following derivations:

$$\begin{aligned} \lim_{j\to\infty} E\big[x_{t+j} - x_t\big|\Phi_t\big] &= \sum_{s=1}^{\infty} E[\Delta x_{t+s}|\Phi_t] \\ &= \sum_{s=1}^{\infty} [\rho^s \Delta x_t + \rho^{s-1} e_4' E[X_t|\Phi_t]] \\ &= \frac{\rho}{1-\rho}\Delta x_t + \frac{e_4'}{1-\rho} E[X_t|\Phi_t], \end{aligned}$$

given that x_t is observed by the consumers.

Using the latter expression and the decision rule (3.0.1) yields:

$$c_t = \lim_{j\to\infty} E\big[x_{t+j}\big|\Phi_t\big] = x_t + \lim_{j\to\infty} E[x_{t+j} - x_t|\Phi_t]$$

$$c_t = \frac{1}{1-\rho}x_t - \frac{\rho}{1-\rho}x_{t-1} + \left[\frac{e_4'}{1-\rho}\right]E[X_t|\Phi_t],$$

or

$$c_t = RE[X_t|\Phi_t], \tag{3.3.3}$$

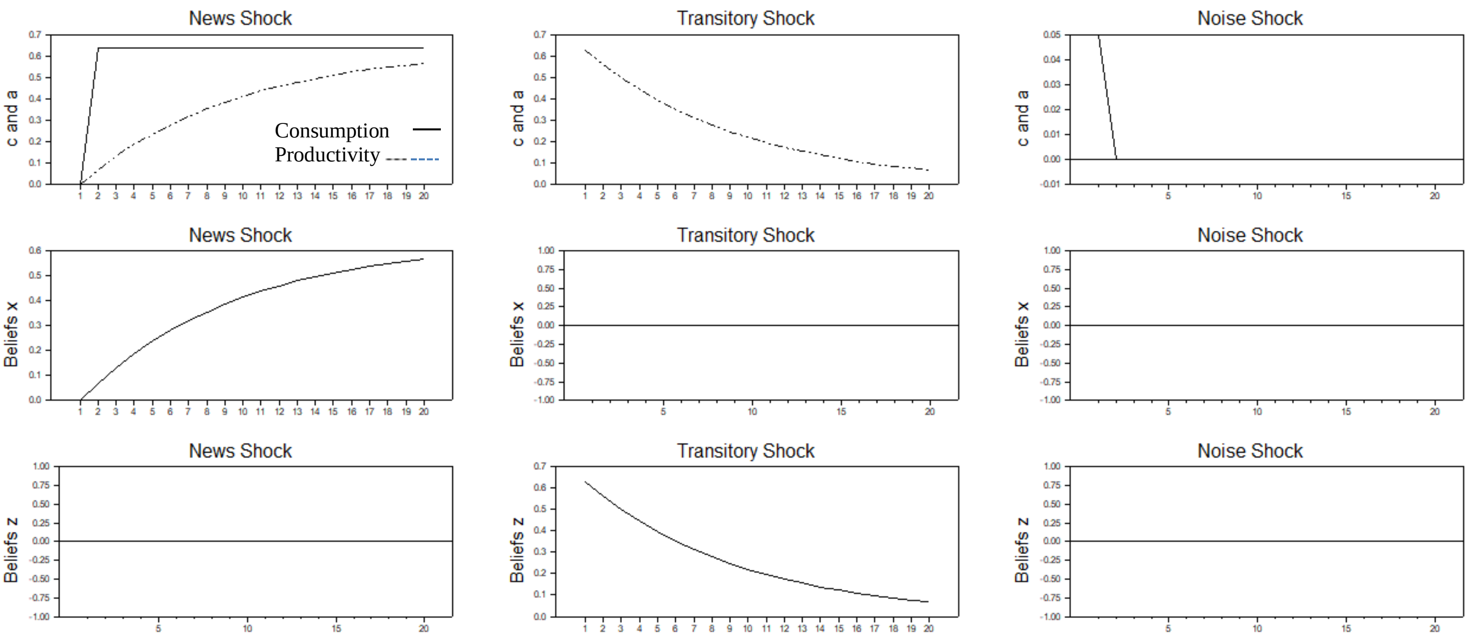
where $R = \left(\frac{1}{1-\rho} \quad -\frac{\rho}{1-\rho} \quad 0 \quad \frac{1}{1-\rho}\right)$.

we now perform a simulation for the following calibration.

Table 3. 3: Parameters' Values

Parameters	$\boldsymbol{\rho}$	$\boldsymbol{\sigma_\varepsilon}$	$\boldsymbol{\sigma_\eta}$	$\boldsymbol{\sigma_\upsilon}$
Values	0.89	0.0007	0.0063	0.0089

Figure 3.3: impulse responses functions



In Figure 3.3, we plot the responses of our model to our three shocks. The good news tells consumers that there will be an increase in future productivity. While productivity remains unchanged at period one, it gradually increases then after. At the same time, consumption, which is a function of, the expected value of productivity increases and consumers adjust their consumption. At period two, when the consumers realize that the news in period one effectively lead to an increase in productivity in this period, consumption reaches a plateau and there is full adjustment for consumption.

As can be seen in the Figure, following a transitory shock only the transitory component increases initially. However, over time since it has been a transitory shock, the effect dies out. Again, consumers observe that it has just been a transitory shock and there is no change in productivity and consumption.

The last column in Figure 3.3 shows the effects of a noise shock in this scenario. After a noise shock, consumers think that it may be a permanent shock and therefore they increase their consumption immediately. However, after one period and once they observe that there is no change in productivity, they reduce their consumption to its pre-shock level.

3.4 Noise and Noisy News

In this example the consumers observe a_t, but not x_t or z_t. For this reason, we refer to noise. Also the consumers observe two distinct signals. The first signal sheds some light about whether the realization of a_t comes from the permanent component or transitory component. This signal is:

$$s_t = x_t + \nu_t, \tag{3.4.1}$$

where ν_t is a noise shock, with $\nu_t \sim N(0, \sigma_\nu^2)$. The second signal provides some information about the news in period t regarding a change in productivity in period t+1. This signal is:

$$\zeta_t = \varepsilon_{t+1} + \upsilon_t, \tag{3.4.2}$$

where ε_{t+1} is the news shock and υ_t is the noise shock, with $\upsilon_t \sim N(0, \sigma_\upsilon^2)$. Therefore in this setup the information set, Φ_t, includes a_t, s_t and ζ_t.

The dynamics of the state variables are summarized in the following state-space form:

$$\begin{pmatrix} x_t \\ x_{t-1} \\ z_t \\ \varepsilon_{t+1} \end{pmatrix} = \begin{pmatrix} 1+\rho & -\rho & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & \rho & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \\ \varepsilon_t \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \varepsilon_{t+1} \\ \eta_t \\ \nu_t \\ \upsilon_t \end{pmatrix},$$

or

$$X_t = AX_{t-1} + BV_t. \tag{3.4.3}$$

We can then relate the observable variables to the state variables as:

$$\begin{pmatrix} a_t \\ s_t \\ \varsigma_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_t \\ x_{t-1} \\ z_t \\ \varepsilon_{t+1} \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_{t+1} \\ \eta_t \\ \nu_t \\ \upsilon_t \end{pmatrix},$$

or

$$S_t = CX_t + DV_t.$$

To solve for consumption, we exploit the following expression:

$$\lim_{j\to\infty} E\left[x_{t+j} - x_t \middle| \Phi_t\right] = \sum_{s=1}^{\infty} E[\Delta x_{t+s} | \Phi_t]$$

$$= \sum_{s=1}^{\infty} \rho^s [\Delta x_t | \Phi_t] + \rho^{s-1} e_4' E[X_t | \Phi_t]]$$

$$= \frac{\rho}{1-\rho} \mathrm{E}[\Delta x_t | \Phi_t] + \frac{e_4'}{1-\rho} E[X_t | \Phi_t],$$

given that Δx_t is not observable.

Thus, using the decision rule (3.0.1) we can write:

$$c_t = \lim_{j \to \infty} E\left[x_{t+j} \middle| \Phi_t\right] = E[x_t | \Phi_t] + \lim_{j \to \infty} E\left[x_{t+j} - x_t \middle| \Phi_t\right] e_4'/(1-\rho) E[X_t | \Phi_t]$$

$$c_t = \left[\frac{1}{1-\rho}\right] E[x_t | \Phi_t] - \left[\frac{\rho}{1-\rho}\right] E[x_{t-1} | \Phi_t] + [\frac{e_4'}{1-\rho}] E[X_t | \Phi_t].$$

or:

$$c_t = RE[X_t | \Phi_t], \tag{3.4.4}$$

Where $R = \left(\frac{1}{1-\rho} \;\; -\frac{\rho}{1-\rho} \;\; 0 \;\; \frac{1}{1-\rho}\right)$.

Once again the information problem is resolved by the Kalman Filter and we get the solution for consumption.

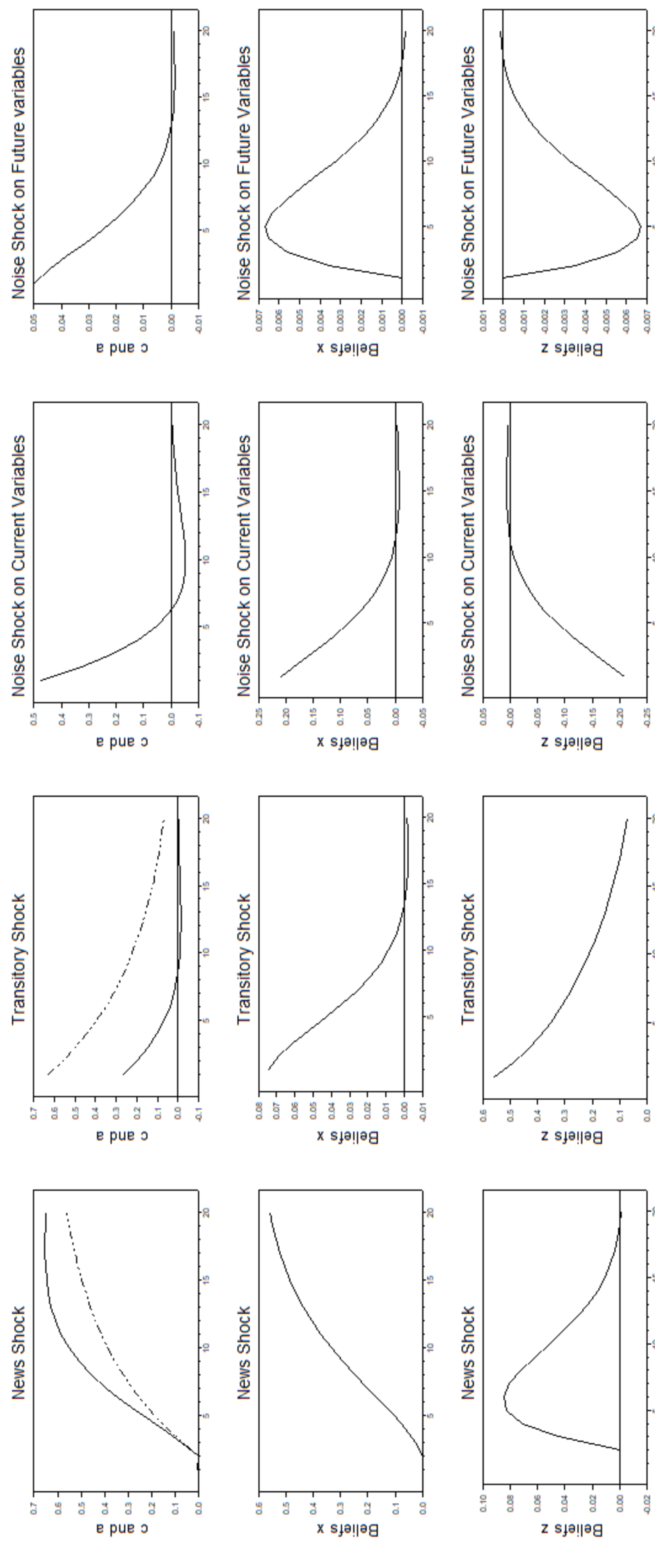
In the same way as the previous scenarios, for illustrative purposes we perform simulations by assigning specific values for the parameters. These parameters are similar to those in Blanchard et al. (2013). The only difference is considering news along with the noise and confusion. So, we add σ_v, which indicates that signal related to the news is not perfect.

Table 3. 4: Parameters' Values

Parameters	$\boldsymbol{\rho}$	$\boldsymbol{\sigma_\varepsilon}$	$\boldsymbol{\sigma_\eta}$	$\boldsymbol{\sigma_\nu}$	$\boldsymbol{\sigma_v}$
Values	0.89	0.0007	0.0063	0.0089	0.0089

We present here key properties of the model using impulse response functions derived from our simulation of the model.

Figure3.4: Impulse Responses Functions



As it is presented in Figure 3.4, after a news shock in the permanent component of technology, productivity and therefore the beliefs on its two components do not initially react, because it is a news shock which affects productivity in t+1. However, consumption increases because it is a function of the expected value of future productivity. Then in t+1 when the news shock affects a_{t+1}, the consumers observe that productivity has increased, but they do not know whether it is due to an increase in the permanent or transitory component, which is why consumption only adjusts partially, rather than fully.

As a_{t+j} increases to reach a plateau, consumers realize that it is a permanent shock, and fully adjust consumption. Also, they adjust their beliefs regarding both permanent and transitory components of productivity; the beliefs regarding the permanent component gradually increase to reach a plateau. On the contrary, the beliefs regarding the transitory component of productivity gradually decrease.

For the transitory shock, since consumers do not know the source of the shock, the beliefs about both components of productivity increase initially because they believe that this may be due to a permanent shock. Once the beliefs regarding the permanent component of productivity increase, consumers increase their consumption as well. However, over time consumers observe that a_t decreases, so they realize that it was a transitory shock. Thus, consumers update their beliefs on the permanent and transitory components and they reduce their consumption.

The third column in Figure 3.4 plots the responses of the variables to the noise shock related to the confusion. This shock increases the beliefs regarding the permanent component of productivity since consumers think that a permanent shock may happen. Thus, consumption also increases. Also, since they observe that there is no change in productivity, their beliefs regarding the transitory component of productivity decrease. Over time and when consumers realize that it has been a noise shock, they revise downward their beliefs of the permanent component and consumption turns back to its pre-shock level.

Overall, comparing the columns of Figure 3.4 to their corresponding ones in Figure 3.2 leads to the following conclusion. The first column of Figure 3.4 is similar to those in Figure 3.2; the main difference is the impact responses of $c_t, a_t, x_t,$ and z_t. The impact responses in Figure 3.2 are positive, while in Figure 3.4 they are zero due to the presence of the news shock. Then the second and third columns of Figure 3.4 are also similar to those in Figure 3.2.

Finally, after a noise shock related to the news, $a_t, x_t,$ and z_t do not react because consumers believe that there is a news shock occurring in period $t + 1$. However, c_t increases because it is mainly driven by the future expectation about the permanent component of productivity. Then in period $t + 1$, the beliefs regarding the permanent component gradually go up whereas the beliefs regarding the transitory component go down, because consumers observe that a_{t+1} remains unchanged. Again, since x_{t+1} has increased, consumers increase their consumption as well. Eventually as the consumers observe that there is no change in productivity, they adjust their beliefs as well as consumption to its pre-shock level.

4. Methodology and results

In this section, we first describe the data. Second, we present the econometric method we use, as well as the results for each scenario.

4.1 Data

As in Blanchard et al. (2013), we estimate the model with 2 observable variables. We use quarterly U.S. observations covering the period 1947Q1 to 2015Q3. The series for Real GDP, Real Personal Consumption Expenditures are from the Bureau of Economic Analysis (available through the Federal Reserve Bank of Saint Louis online database). Population and employment series are from the Bureau of Labor Statistics online database (series IDs LNS10000000Q and LNS12000000Q respectively). We measure productivity as the logarithm of the ratio of Real GDP to employment. Real GDP per capita is constructed by dividing Real GDP by population. Real consumption per capita is constructed by dividing Real Personal Consumption Expenditure by population. Then since the data for our two variables shows trends, we take logarithm.

4.2 Econometric method and results

This section describes the econometric methods used to estimate the models derived by the agents under the three information structures. We use the Maximum Likelihood method to estimate the model. Since in our model consumers face a non-trivial signal extraction problem, we need to have two steps. First, we take the point of view of the consumers to write the dynamics of the unobserved states in state-space representation and solve the consumers' filtering problem. Then, we take the point of view of the econometrician to write down the model dynamics in state-space representation and the appropriate observation equations (which depend on the data available). The econometrician's Kalman filter is then used to construct the likelihood function and estimate the model's parameters.

4.2.1 Noise

Recall that the consumer observes a_t and s_t, but not the components x_t and z_t of productivity. In this context, the agent exploits the signal to form beliefs about the components about productivity. The agent then uses its beliefs to make a decision about consumption. On the other hand, the econometrician does not observe the components x_t and z_t, but also the agents' beliefs about these components. However, the dynamics of the consumers' beliefs are:

$$X_{t|t} = [I - KC]AX_{t-1|t-1} + K(CX_t + DV_t)$$
$$X_{t|t} = [I - KC]AX_{t-1|t-1} + KCAX_{t-1} + K(CB + D)V_t.$$

The first equation is the consumer's beliefs. The second equation is obtained by substituting X_t by the process $X_t = AX_t + BV_t$.

The relevant system for the econometrician involves the state vector:

$$X_t^E = (x_t, x_{t-1}, z_t, x_{t|t}, x_{t-1|t}, z_{t|t})'.$$

Now, we can write the dynamics of the econometrician's state vector as follows:

$$X_t = TX_{t-1} + R\varepsilon_t, \tag{4.2.1.1}$$

where

$$T = \begin{bmatrix} A & 0 \\ KCA & (I - KCA) \end{bmatrix}$$

$$R = \begin{bmatrix} B \\ K(CB + D) \end{bmatrix}.$$

A, B, C, D and K matrices are identical to matrices used in order to simulate the confusion information structure.

The observable variables for the econometrician are y_t. These variables are $y_t = (a_t, c_t)'$. Then, the observation equation is, in matrix form,

$$y_t = ZX_t^E, \tag{4.2.1.2}$$

where

$$Z=\begin{bmatrix}1 & 0 & 1 & 0 & 0 & 0\\ 0 & 0 & 1 & 1+\dfrac{\rho}{1-\rho} & -\dfrac{\rho}{1-\rho} & 0\end{bmatrix}.$$

The econometrician's filtering problem can then be solved from (4.2.1.1) and (4.2.1.2).

The econometrician's Kalman filter is composed of prediction equations, error equations, and updating equations. These equations are derived under the assumption that the factors are normally distributed: $X_t \sim N(0,P_t)$. The prediction equations associated with the information set available in period (t - 1) are:

$$X_t^E = TX_{t-1}^E, \tag{4.2.1.3}$$

$$P_{t|t-1}^E = TP_{t-1}^E T' + RQR'. \tag{4.2.1.4}$$

The error equations are:

$$\upsilon_t^E = y_t - ZX_{t|t-1}^E, \tag{4.1.2.5}$$

$$F_t^E = ZP_{t|t-1}^E Z', \tag{4.2.1.6}$$

Where υ_t^E incorporates the one-step-ahead forecast errors of the observable variables y_t and F_t is the associated variance-covariance matrix.

The updating equations, obtained when the period's t information becomes available, are the following:

$$X_t^E = X_{t|t-1}^E + P_{t|t-1}^E Z' F_{t-1}^E{}' \upsilon_t^E, \tag{4.2.1.7}$$

$$P_t^E = P_{t|t-1}^E - P_{t|t-1}^E Z' F_t^{E^{-1}} Z P_{t|t-1}^E, \tag{4.2.1.8}$$

where X_t^E corresponds to the estimate of the latent factors for period t. For given values of parameters $(\rho, \sigma_\varepsilon, \sigma_\eta, \sigma_\upsilon)$, we apply the Kalman filter (4.2.1.3)–(4.2.1.8) recursively for t = 1, . . . , T. As a result, an estimate of the latent variablesX_t^E corresponds to the estimate of the latent factors for period t. Then we can construct the log-likelihood function as:

$$Log\ L = -\frac{T}{2}N\ log(2\pi) - \frac{1}{2}\sum_{t=0}^{T}\log|F_t^E| - \frac{1}{2}\sum_{t=1}^{T}\upsilon_t^E{}' F_t^E\, \upsilon_t^E\,, \quad where\ N = 2.$$

Finally, we estimate parameters such that the log-likelihood function is maximized.

The results of our estimation are summarized in Table 4.1.

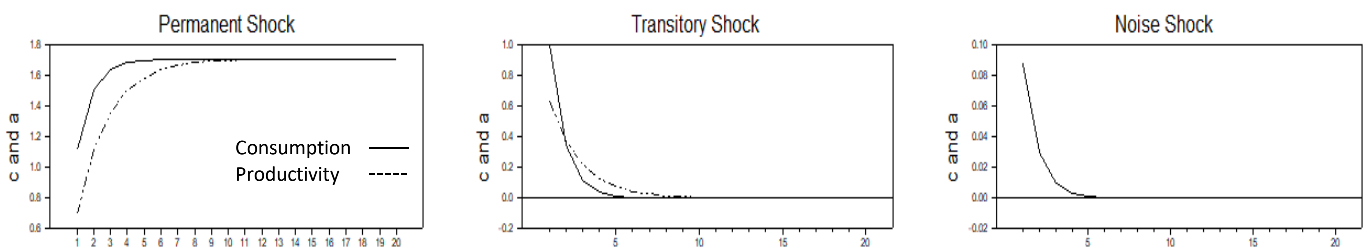
Table 4. 1: Estimation Results

Variable	Coefficient	Standard error
$\boldsymbol{\rho}$	0.7898	0.0442
$\boldsymbol{\sigma_{\varepsilon}}$	0.0008	0.0003
$\boldsymbol{\sigma_{\eta}}$	0.0038	0.0007
$\boldsymbol{\sigma_{\upsilon}}$	0.0055	0.0039

Table 4.1 shows the result of the Maximum Likelihood (ML) estimation of the confusion scenario over the period 1947Q1 to 2015Q3. The estimates are statistically significant. The estimate of ρ is large, implying a persistent building permanent shock and slowly decaying transitory shock. The estimate of σ_{υ}, is small, implying an informative signal.

Figure 4.1 shows the impulse response of productivity and consumption following the three shocks using the estimated values. All the responses are to one standard deviation shocks.

Figure 4. 1Estimation Results



Following a permanent shock, both productivity and consumption increase slowly to reach a plateau; however consumption increases less slowly. The latter result reflects the fact that the standard deviation of the noise shock is small relative to the standard deviation of the permanent shock.

Following a transitory shock while productivity and consumption increases initially, they decrease over time. The reason is that the standard deviation of the transitory shook is relatively small.

Finally, let’s consider the noise shock. Consumers initially increase their consumption since they believe that there may be an increase in the permanent component of productivity. After one period, however, consumers learn that it has been just a noise shock given that the response of the productivity is always zero. As such, consumption decreases to its pre-shock level.

4.2.2 Noise and News

In this section we describe the econometric methods used to estimate the models where agents observe a_t, x_t, and z_t. Also, they observe a signal ζ_t about the future realization of the permanent shock ε_t. We assumed that the signal brings consumers new information one period ahead of the occurrence of the shock. Thus the signal is

$$\zeta_t = \varepsilon_{t+1} + \upsilon_t,$$

where ε_{t+1} is the news shock.

However, while the consumers observe the two components of productivity separately, the econometrician can only observe a_t and c_t. Therefore, the observation equation for the econometrician is:

$$y_t = ZX_t^E,$$

where

$$Z = \left(\begin{matrix} 1 \\ \left(\frac{1}{1-\rho}\right) \end{matrix} \quad \begin{matrix} 0 \\ \left(\frac{-\rho}{1-\rho}\right) \end{matrix} \quad \begin{matrix} 1 \\ 0 \end{matrix} \quad \begin{matrix} 0 \\ \left(\frac{1}{1-\rho}\right) \end{matrix} \right).$$

X_t^E is the econometrician's state vector given by

$$X_t^E = (x_t, x_{t-1}, z_t, \varepsilon_{t+1}, x_{t|t}, x_{t-1|t}, z_{t|t}, \varepsilon_{t+1|t})'.$$

Next, we can write the dynamics of the econometrician's state vector as

$$X_t^E = TX_{t-1}^E + R\varepsilon_t,$$

where

$$T = \begin{pmatrix} A & 0 \\ KCA & [I - KCA] \end{pmatrix},$$

and

$$R = \begin{pmatrix} B \\ K[CB + D] \end{pmatrix}.$$

A, B, C, D and K matrices are identical to matrices used in order to simulate the noise and news information structure.

As the econometrician does not observe the components of productivity as well as the consumers' beliefs about the components, he needs to use the Kalman filter. By applying Kalman filtering, as it is described in section 4-2-1, the econometrician obtains X_t^E which corresponds to the estimate of the latent factors for period t, for given values of parameters $(\rho, \sigma_\varepsilon, \sigma_\eta, \sigma_\upsilon)$. Then he can construct the log-likelihood function as:

$$Log\ L = -\frac{T}{2} N\ log(2\pi) - \frac{1}{2}\sum_{t=0}^{T} \log|F_t^E| - \frac{1}{2}\sum_{t=1}^{T} \upsilon_t^{E\prime} F_t^E\ \upsilon_t^E\ , \quad where\ N = 2.$$

Finally, the econometrician estimates parameters such that the log-likelihood function is maximized.

The results of our estimation for the noise and news scenario are reported in Table 4.2.

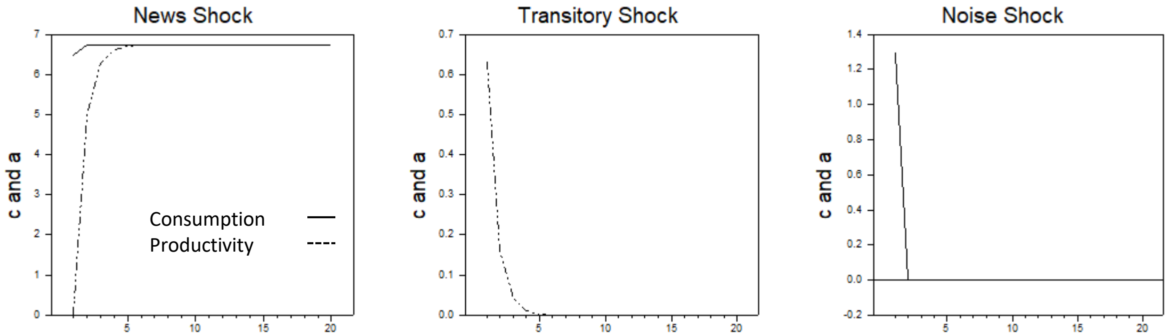
Table 4. 2: Estimation Results

Variable	Coefficient	Standard error
$\boldsymbol{\rho}$	0.5887	0.0472
$\boldsymbol{\sigma_\varepsilon}$	0.0004	0.0003
$\boldsymbol{\sigma_\eta}$	0.0055	0.0005
$\boldsymbol{\sigma_\upsilon}$	0.0088	0.0038

Table 4.2 presents the result of ML estimation of the noise and news scenario. The estimates are statistically significant. As in the previous scenario, the estimate of ρ is large. This time, however, the estimate of σ_υ, is large, implying a less informative signal.

Figure 4.2 shows the impulse response of productivity and consumption for the three shocks using the estimated values. All the responses are to one standard deviation shocks.

Figure 4. 2 Estimation Results



The good news tells consumers that there will be an increase in future productivity. The standard deviation of the news shock, σ_ε, is small implying an informative news. Therefore, while productivity increases over time, consumption increases immediately and permanently.

The second column shows the responses of consumption and productivity to a transitory shock. Following a transitory shock, since the standard deviation of the transitory shock, σ_η, is relatively high, productivity increases initially and turns back to its pre-shook level. However, since news is almost perfect, consumers do not adjust their consumption, knowing that it is only a transitory shock.

Finally the third column reveals that after a noise shock, consumers think that it may be a permanent shock and therefore they increase their consumption immediately. However, after one period and once they observe that there is no change in productivity, they reduce their consumption to its pre-shock level.

Table 4.2.1: Variance Decomposition Results

Quarter	News Shock	Trans. Shock	Noise
1	0.017	0.219	0.759
4	0.317	0.178	0.500
8	0.657	0.079	0.242
12	0.788	0.047	0.163

Next, Table 4.2.1 presents the implications of the estimated parameters for variance decomposition, showing the contribution of the three shocks to forecast error variance. We observe that while news shocks explain very little of the short run movements of consumption (less than 1% at a 1-quarter horizon), they explain most of the business-cycle-frequency variance of consumption (more than 75% after 3 years). On the other hand, noise shocks are the major source of very short run variance of consumption (more than 75% of consumption volatility at a 1-quarter and 50% at a one year horizon).

4.2.3 Noise, News and Confusion

This section describes the econometric methods used to estimate the models derived for the information structure which includes noise, news and confusion. As mentioned in the previous chapter, in this scenario the consumer observes a_t but not x_t or z_t. The consumer also observes two distinct signals. The first signal sheds some light about whether the realization of productivity comes from the permanent or transitory component. The consumers' second signal is news. However, the econometrician has only access to a_t and c_t. Therefore, the relevant system for the econometrician is:

$$y_t = ZX_t,$$

where

$$Z = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dfrac{1}{1-\rho} & -\dfrac{\rho}{1-\rho} & 0 & \dfrac{1}{1-\rho} \end{pmatrix}.$$

X_t^E is the econometrician's state vector given by

$$X_t^E = (x_t, x_{t-1}, z_t, \varepsilon_{t+1},, x_{t|t}, x_{t-1|t}, z_{t|t}, \varepsilon_{t+1|t})'.$$

Now we can write the dynamics of the econometrician's state vector as:

$$X_t^E = TX_{t-1}^E + R\varepsilon_t$$

where:

$$T = \begin{pmatrix} A & 0 \\ KCA & [I - KCA] \end{pmatrix},$$

and

$$R = \begin{pmatrix} B \\ K[CB + D] \end{pmatrix}.$$

A, B, C, D and K matrices are identical to matrices used in order to simulate noise, news and confusion information structure.

In the same way as sections 4-2-1 and 4-2-2, the econometrician needs to apply the Kalman filter. By applying this filtering he can get the estimate of X_t^E which is the estimate of the latent factors for period t, for given values of parameters $(\rho, \sigma_\varepsilon, \sigma_\eta, \sigma_\nu, \sigma_\upsilon)$. Then he can construct the log-likelihood function as:

$$Log\ L = -\frac{T}{2} N\ log(2\pi) - \frac{1}{2}\sum_{t=0}^{T} \log|F_t^E| - \frac{1}{2}\sum_{t=1}^{T} \upsilon_t^{E\prime} F_t^E\, \upsilon_t^E\,, \quad where\ N = 2.$$

Finally, the econometrician estimates the parameters such that the log-likelihood function is maximized.

The results for the noise, news and confusion scenario are presented in the table below.

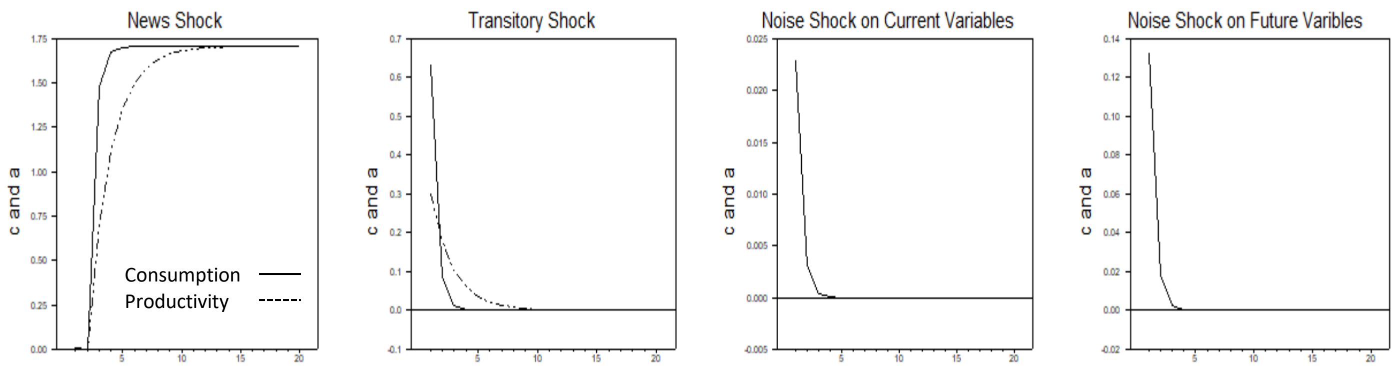
Table 4. 3: Estimation Results

	Coefficient	**Standard error**
$\boldsymbol{\rho}$	0.7888	0.0444
$\boldsymbol{\sigma_\varepsilon}$	0.0008	0.0003
$\boldsymbol{\sigma_\eta}$	0.0033	0.0007
$\boldsymbol{\sigma_\upsilon}$	0.0088	0.0038
$\boldsymbol{\sigma_\nu}$	0.0088	0.0038

Table 4.3 shows the result of the ML estimation of the “noisy news and confusion” scenario. The estimates are statistically significant. The estimate of ρ is large, implying a persistent building permanent shock and slowly decaying transitory shock. The estimates of σ_υ and σ_ν, are small, implying informative signals.

Figure 4.3 shows the impulse responses of productivity and consumption following the three shocks using the estimated values. All the responses are to one standard deviation shocks.

Figure 4. 3: Estimation Results



As is presented in Figure 4.3, after a news shock in the permanent component of technology, productivity does not react on impact. This is because it is a news shock which affects productivity in t+1. However, consumption increases because it is a function of the expected value of future productivity. Then in t+1 and when the news shock affects a_{t+1}, the consumers observe that productivity has increased, but since they do not know the source of this increase, they only adjust their consumption partially. Then as a_{t+j} start increasing, consumers realize that it has been a permanent shock, they then fully adjust consumption.

For the transitory shock, since the standard deviation of the transitory shock, σ_η, is very low, productivity increases slightly. Also, because of the presence of confusion, consumers are not able to realize the source of the shock in the first period and increase their consumption; after one period and once they observed that productivity is affected slightly, they realized that it has been a transitory shock and therefore decrease their consumption to its pre-shock level.

Following a noise shock related to the confusion, consumers initially increase their consumption since they believe that there may be an increase in the permanent component of productivity. After one period, however, consumers learn that it has been just a noise shock given that the response of productivity is always zero. As such, consumption decreases to its pre-shock level.

Finally after a noise shock related to news, c_t increases because it is mainly driven by the future expectation about the permanent component of productivity. Then in period $t+1$, as the consumers observe that there is no change in productivity, they adjust their consumption to its pre-shock level.

Table 4.3.1: Variance Decomposition Results

Quarter	News Shock	Trans. Shock	Noise shock on current Variables	Noise shock on Future Variables
1	0.006	0.175	0.22	0.58
4	0.071	0.230	0.17	0.51
8	0.330	0.188	0.14	0.34
12	0.540	0.140	0.08	0.22

Table 4.3.1 shows the results of contributions of the four shocks to forecast error variance. Noise shocks on the current variables explain very little of the short run movements of consumption (less than 25% of consumption volatility at a 1-quarter horizon), while noise shocks on future variables are the major source of short run volatility (more than 50% at a 1-quarter). Also, news shocks explain most of the long run variance of consumption movements.

At this stage, it is useful to compare the result of second and third scenarios' estimations. First, we perform a likelihood ratio test. The maximum likelihood ratio test is used in order to determine which model fits the data better. The likelihood ratio statistics (LR) is $LR_{\chi^2_{(1)}} = 104.832$ and the critical value is 3.84, so second model (nested model) is rejected in favor of third model at 5% level. Therefore, when we introduce the noise shocks on future variables, the model fits significantly better than the second model.

More importantly, we compare the results of Table 4.2.1 and 4.3.1. In terms of variance decomposition, once we add the noise shocks on future variables, the shocks are able to explain consumption volatility much more than the shocks on the current variables and capture what noise shocks were capturing in news scenario.

5. Conclusion

This thesis studied the effects of information structures on business-cycle fluctuations. We estimate three different information structures: confusion, noisy news and a combination of these scenarios that is noisy news and confusion. The confusion scenario refers to an information structure where consumers are not able to observe the components of productivity separately; the noisy news scenario is characterized by the information structure where consumers are able to observe the components of productivity as well as a signal about future realizations of the permanent shock; and the noisy news and confusion scenario considers the two information structures mentioned above simultaneously.

We estimate the models with two observable variables: real personal consumption expenditure per capita (in logs) and real productivity per capita (in logs). We use quarterly U.S. observations covering the period 1947Q1 to 2015Q3. The Maximum Likelihood estimation results show that the signals bring almost perfect information to consumers. In particular, the standard deviation of the noise shock in the confusion scenario is small, implying an extremely informative signal. Also, the standard deviations of news and noise shocks in the noisy news scenario are small, meaning that the signal is informative and news provides consumers almost perfect information. Finally, the standard deviations of news shocks and the two signal shocks in the noisy news and confusion scenario imply highly informative news accompanied by relatively informative noise signals.

For the noise scenario our findings confirm those of Blanchard et al. (2013). Our results show that while permanent shocks increase both productivity and consumption slowly and permanently, a transitory shock only leads to a temporary increase in productivity and consumption. The noise shocks only affect consumption in the short run.

In the noisy news information structure our results align with Beaudry and Portier (2006) who found that good news instantaneously increases consumption through a wealth effect. However, our estimation results is in sharp contrast with BP’s findings on the role of noise; BP rely on noise shock as the central force causing the recession, while our finding shows that noise shock has temporary effects and fades out after one period. In fact, we find that while news shocks affect productivity and consumption permanently, noise shocks only lead to a short-run effect.

Finally the third model- including both noise and noisy news together- confirms that while the news shocks have long-run effect on our variables, the noise shocks only have temporary effects.

However comparing the “noisy news” scenario and “noise, news and confusion” scenario we show that once we add the noise shocks on future variables to the model, the shocks are able to explain consumption volatility much more than the shocks on the current variables and capture what the noise shocks were capturing in news scenario.

Last but not least, as mentioned in previous chapters while the news could be about many different objects, the bulk of the literature on the news and business cycles has focused on the role of technology news: that is news regarding future realizations of productivity. Accordingly, we also focus on the role of technology shocks on the business cycles in this thesis. In this thesis we presented three information structures in order to estimate the contribution of the noise and news shocks in the business cycles. How credible are the noise and news shocks? Our findings support these forces as an important contributor to macroeconomic fluctuations.

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Appendix A - The Kalman Filter

The Kalman filter is an algorithm for sequentially updating a linear projection for a system (Hamilton 1994). In order to solve the consumers' signal extraction problem, we need to write the expectations in terms of current and lagged values of the variables. This is done using the Kalman filtering through the following three steps:

The first step consists of forming the optimal predictor (expectation) of the next observation, given all the information currently available. This is done by using the prediction equations. The second step is to forecast and compute the errors. This is performed by applying the error equations. The last step is to revise the expectations by incorporating the new observations. This is done by using the updating equations.

The measurement equation, relating the observable variables to the (unobservable) state variables, takes the following form:

$$S_t = CX_t + DV_t, \tag{A.1}$$

where $V_t \sim N(0, \Omega)$. Also, the transition equation, describing the dynamics of the state variables, is:

$$X_t = AX_{t-1} + BV_t. \tag{A.2}$$

Given (A.1) and (A.2), the prediction equations correspond to:

$$X_{t|t-1} = AX_{t-1t-1}, \tag{A.3}$$

$$P_{t|t-1} = AP_{t-1|t-1}A' + B\Omega B', \tag{A.4}$$

where

$X_{t|t-1} = E[X_t|\Phi_{t-1}]$, $X_{t|t} = E[X_t|\Phi_t]$, and $P_{t|t-1} = E\left[(X_t - X_{t|t-1})(X_t - X_{t|t-1})'|\Phi_{t-1}\right]$.

Next, the error equations corresponding to above forecasts are:

$$U_t = S_t - CX_{t|t-1} , \tag{A.5}$$

$$F_t = CP_{t|t-1}C' + D\Omega D' , \tag{A.6}$$

where $U_t = S_t - S_{t|t-1}$, $S_{t|t-1} = E[S_t|\Phi_{t-1}]$, and $F_t = E[U_t U_t']$.

Once the new observations are available, the expectations are updated. The updating equations are:

$$X_{t|t} = X_{t|t-1} + K_{t|t-1}U_t, \tag{A.7}$$

$$= \left(I - K_{t|t-1}C\right)AX_{t-1|t-1} + K_{t|t-1}S_t. \tag{A.8}$$

and

$$P_{t|t} = P_{t|t-1} - K_{t|t-1}F_t K_{t|t-1}' ,$$

where

$$K_{t|t-1} = \left[P_{t|t-1}C'F_t{}^{-1}\right] = P_{t|t-1}C'[CP_{t|t-1}C' + D\Omega \mathrm{D}']^{-1}, \tag{A.9}$$

is the Kalman gain (the revision of the expectation when new observations at time *t* becomes available), and $P_{t|t} = E[(X_t - X_{t|t})(X_t - X_{t|t})']$ is the conditional covariance matrices using information up to time t.

The responses of the variables to the different shocks reported in the text are computed from the following matrices. Specifically, the impact responses are obtained from:

$$R_{x,0} = B\Lambda, \tag{A.10}$$

$$R_{s,0} = CR_{x,0} + D\Lambda, \tag{A.11}$$

$$R_0 = KR_{s,0}, \tag{A.12}$$

where

$$\Omega = \Lambda\Lambda'$$

and Λ is a lower triangular matrix. And, the dynamic responses are obtained from:

$$R_{x,j} = AR_{x,j-1}, \quad (A.13)$$

$$R_{s,j} = CR_{x,j}, \quad (A.14)$$

$$R_j = [I - KC]AR_{j-1} + KR_{s,j}. \quad (A.15)$$

Expressions (A.10) and (A.13) are obtained from (A.2). Equations (A.11) and (A.14) are derived from (A.1). Equations (A.12) and (A.15) are computed from (A.8).

To assume that the responses do not depend on the date at which the shocks occur, expressions (A.10) - (A.15) are evaluated for the case where the Kalman gain is assumed to be constant:

$$K_{t|t-1} = K = PC'[CPC' + D\Omega D']^{-1}.$$

To do so, $P_{t|t-1}$ is evaluated at its steady state; that is,

$$P = APA' + B\Lambda B' - APC'[CPC' + D\Omega D']^{-1}CPA'.$$

Appendix B

For the case of news shock we need to show $\hat{\varepsilon}_{t+1} = \hat{b}S_t$. This can be derived from the Kalman filter. Now for illustrative purposes, we take a bivariate example where

$$S_t = CX_t + DV_t, \quad (B.1)$$

where

$$X_t = \rho X_{t-1} + \varepsilon_t,$$

$$S_t = \varepsilon_{t+1} + \upsilon_t,$$

Which can be written in matrix form as:

$$\begin{bmatrix} X_t \\ S_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_t \\ \varepsilon_{t+1} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{t+1} \\ \upsilon_t \end{bmatrix},$$

so:

$$X_t = AX_{t-1} + B\upsilon_t, \quad (B.2)$$

$$\begin{bmatrix} X_t \\ \varepsilon_{t+1} \end{bmatrix} = \begin{bmatrix} \rho & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ \varepsilon_t \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{t+1} \\ \upsilon_t \end{bmatrix}.$$

The first set of equation is prediction equation; that is, given all the information available currently, we compute the predictor of the next observation. Thus, using (A.3):

$$X_{t|t-1} = AX_{t-1|t-1}, \tag{B.3}$$

$$= \begin{bmatrix} \rho & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} X_{t-1|t-1} \\ \varepsilon_{t|t-1} \end{bmatrix} = \begin{bmatrix} X_{t|t-1} \\ 0 \end{bmatrix}$$

and according to (A.4):

$$P_{t|t-1} = AP_{t-1|t-1}A' + B\Omega B', \tag{B.4}$$

$$= \begin{bmatrix} \rho & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} P_{11,t-1} & P_{12,t-1} \\ P_{21,t-1} & P_{22,t-1} \end{bmatrix} \begin{bmatrix} \rho & 0 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & \sigma_\upsilon^2 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} P_{11} & 0 \\ 0 & \sigma_\varepsilon^2 \end{bmatrix}.$$

Next we can compute the forecast error as:

$$U_t = S_t - CX_{t|t-1} \tag{B.5}$$

$$= \begin{bmatrix} X_t \\ S_t \end{bmatrix} - \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_{t|t-1} \\ 0 \end{bmatrix} = \begin{bmatrix} X_t - X_{t|t-1} \\ S_t - 0 \end{bmatrix}.$$

Then we compute the variance of the forecast error as following:

$$F_t = CP_{t|t-1}C' + D\Omega D' \tag{B.6}$$

$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} P_{11} & 0 \\ 0 & \sigma_\varepsilon^2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \sigma_\varepsilon^2 & \omega_{12} \\ \omega_{21} & \sigma_\upsilon^2 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} P_{11} & 0 \\ 0 & \sigma_\varepsilon^2 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & \sigma_\upsilon^2 \end{bmatrix} = \begin{bmatrix} P_{11} & 0 \\ 0 & (\sigma_\varepsilon^2 + \sigma_\upsilon^2) \end{bmatrix}.$$

so

$$F_t^{-1} = \begin{bmatrix} \frac{1}{P_{11}} & 0 \\ 0 & \frac{1}{(\sigma_\varepsilon^2 + \sigma_\upsilon^2)} \end{bmatrix}.$$

Now we can compute Kalman gain:

$$K_{t|t-1} = P_{t-1}C'F_t^{-1}$$

$$= \begin{bmatrix} P_{11} & 0 \\ 0 & \omega_{11} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \dfrac{1}{P_{11}} & 0 \\ 0 & \dfrac{1}{(\sigma_\varepsilon^2 + \sigma_\upsilon^2)} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \dfrac{\sigma_\varepsilon^2}{(\sigma_\varepsilon^2 + \sigma_\upsilon^2)} \end{bmatrix}$$

Finally, the updating equations are:

$$X_{t|t} = X_{t|t-1} + K_{t|t-1}U_t, \tag{B.7}$$

$$\begin{bmatrix} X_{t|t} \\ \varepsilon_{t+1|t} \end{bmatrix} = \begin{bmatrix} X_{t|t-1} \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & \frac{\sigma_\varepsilon^2}{(\sigma_\varepsilon^2 + \sigma_\upsilon^2)} \end{bmatrix} \begin{bmatrix} X_t - X_{t|t-1} \\ S_t \end{bmatrix}.$$

So:

$$X_{t|t} = X_t, \tag{B.8}$$

$$\varepsilon_{t+1|t} = \hat{b}S_t, \tag{B.9}$$

where $\hat{b} = \frac{\sigma_\varepsilon^2}{(\sigma_\varepsilon^2 + \sigma_\upsilon^2)}$.