News and Noise in the Great Depression

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Abstract

The empirical work of L'Huillier and Yoo (2017) finds that bad news unrelated to fundamentals had a prominent role in the Great Depression. Their results suggest that a very important element is missing in the existing analyses of the recession, providing a potential solution to the Great Depression puzzle. After reviewing the mechanisms through which news can affect the economy, we test whether noise shocks, once embedded in a general equilibrium framework, are relevant sources of variation in the period of the Great Depression. In particular, we estimate a medium-scale DSGE model with a signal extraction on productivity as in Blanchard et al. (2013). We find that noise shocks, while significant, are not important sources of variation in the Great Depression period, particularly because of their low persistence. Additionally, we claim that the exploratory results of L'Huillier and Yoo (2017) are mainly driven by the failure of taking into account other sources of disturbances.

Contents

1 Introduction

The idea that changes in expectation about future economic conditions are an important driver of business cycles is a very old one in the economic literature (Pigou, 1927; Keynes, 1936). The view that anticipatory movements could have a significant role in determining swings in aggregate variables is fairly intuitive, but it has been formalized in the modern macroeconomic literature only recently (Beaudry and Portier, 2004, 2006). According to this view, economic agents continuously try to forecast future economic variables, usually productivity, and react today to news concerning a future state of the economy. If the news turns out to be correct, the economy converges to its new state. If the news was instead just "noise", with no impact on the fundamentals, the economy gradually returns to its former state. The dynamics of this noisy process can induce both low-frequency and high-frequency changes in the business cycle.

The course of history is not equally noisy, with some periods being characterized by large swings in uncertainty. This idea has been exploited in the recent empirical work of L'Huillier and Yoo (2017), in which they assess the presence of negative information unrelated to fundamentals in the US recessions, from 1920 to these days. They found that the Great Recession and the Great Depression are the two episodes with the highest level of "bad news". This result suggests a new possible interpretation of the Great Depression, which is the longest and most widespread recession of the twentieth century. Its extraordinary depth and length had a profound impact on the way the economic thinking was perceived, as the event defied any economic interpretation in the classical sense. To reading this episode from an equilibrium perspective has been a challenge that was only recently addressed with the seminal work of Cole and Ohanian (1999). Since then, several economists attempted to shed some light on the causes of the recession of the 30s, and, in particular, to its sluggish recovery.

The objective of this work is to provide a synthesis of the news literature and the Great Depression literature, improving on the work of L'Huillier and Yoo (2017). Indeed, in their analysis, they consider a very simple model, which only focuses on consumption and productivity and abstract from all other considerations. In this work, we want to assess whether their exploratory results hold in a general equilibrium model. In order to better assess the role of news and noise, we estimate a medium-scale DSGE model augmented with a signal extraction for consumer's information (Blanchard et al., 2013) on the Great Depression period. With the use of a structural estimation, it is possible to understand how a noise shock impacts the different aggregate variables, including investment, and to appreciate the relative importance of different kinds of shocks to the economy.

The rest of the paper is organized as follows. In the next section, we review the literature that tries to assess the role of anticipatory movements in aggregate fluctuations, underlining the several difficulties of this exercise and the mechanisms through which news can impact the economy. In section 3 we review what we know about the Great Depression and take a preliminary look at the data. Section 4 is devoted to the description of the model economy. Section 5 is dedicated to the description of data sources, a crucial issue in the analysis of the depression, and the methodological aspects of the estimation. The results of the estimation are presented in Section 6; a basic sensitivity exercise is included to test the robustness of the results.

2 Anticipatory Movements as Drivers of Business Cycles

2.1 Expectations and Animal Spirits

The news view of business cycles has a long tradition in macroeconomics. According to it, boom and burst in business cycles are caused by economic agents continuously trying to anticipate the future state of the economy. A first discussion about such behaviors of can be found in Pigou (1927):

> "The varying expectations of business men [...] constitute the immediate cause and direct causes or antecedents of industrial fluctuations"

A similar idea can also be found in Keynes (1936) under the notion of "animal spirits". However, the intuitive concept of waves of optimism driving the economy is quite ambiguous from a practical point of view, as it can be interpreted and formalized in different ways. One possible interpretation is the one of sunspot equilibria (Cass and Shell, 1983), in which market psychology and animal spirits are considered as sources of extrinsic uncertainty in a rational equilibrium framework. According to this view, macroeconomics is inherently unstable, as the economy is governed by self-fulfilling expectations unrelated to any economic fundamental.

A less extreme interpretation of animal spirits is the one adopted in Barsky and Sims (2012), concerning the news view of business cycles:

“We interpret the noise as an "animal spirits shock", as it is associated with optimism or pessimism that, while not ex ante irrational, is erroneous from the point of view of an outside observer with knowledge of the shock” (Barsky and Sims, 2012, pg. 1345)

“A positive animal spirits shock means that agents are overly optimistic relative to the true state of the economy” (Barsky and Sims, 2012, pg. 1353)

The key difference between the two interpretations is whether expectations are related to extrinsic or intrinsic variables. In this study, we will focus on the latter interpretation of “animal spirits”; note that this terminology has been adopted by other authors in the literature to indicate noise shocks (e.g. Blanchard et al., 2013; Beaudry and Portier, 2014).

For the purpose of our analysis, we consider a “noise formulation”; hence, anticipated information can be wrong. However, as explained in the next paragraphs, this is not the only possible information structure.

2.2 News and Noise Formulations

Following the work of Beaudry and Portier (2004), which revived the interest in the role of news-driven business cycles, two different information structures emerged in the literature. In the noise formulation, agents imperfectly anticipate future events; if the change in the information set correctly anticipates a positive event, the news generates a boom in the economy, favoring higher investment today. However, if the positive anticipation does not materialize, the economy faces a burst as it adjusts to its former level. In the so-called “news formulation”, agents receive news that is incomplete but never wrong. This difference could seem relatively marginal at first sight, but is instead a crucial one, especially when considering identification strategies in the VAR literature.

Consider an exogenous process θ_t with innovation component ϵ_t

$$\theta_t = \rho_t \theta_{t-1} + \epsilon_t$$

In the noise formulation, news received at time t is modeled as a signal S_t of ϵ_{t+q}:

$$S_t = \epsilon_{t+q} + \nu_t$$

where ν_t is the noise component of the signal with variance σ_ν^2. If the variance of ϵ_t is

σ_ϵ^2 and the processes are Gaussian, we can write the agent's conditional expectation at time t as:

$$E\left[\epsilon_{t+q}|\Omega_t = S_t\right] = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_\nu^2} S_t$$

This formulation has been adopted, for example, in Beaudry and Portier (2004); Jaimovich and Rebelo (2009); Barsky and Sims (2012); Blanchard et al. (2013); Forni et al. (2017).

In the news formulation instead, it is possible to decompose the innovation ϵ_t in an anticipated component and a surprise component:

$$\theta_t = \rho_t \theta_{t-1} + \epsilon_{1,t} + \epsilon_{2,t}$$

In this case, the signal does not have any noise

$$S_t = \epsilon_{1,t+q}$$

$$E\left[\epsilon_{t+q}|\Omega_t = S_t\right] = S_t = \epsilon_{1,t+q}$$

To provide few examples, this simpler formulation is adopted in Beaudry and Portier (2006); Christiano et al. (2010); Fujiwara et al. (2011); Schmitt-Grohé and Uribe (2012); Görtz and Tsoukalas (2017).

These two formulations have different objectives, as one studies the adjustment process of expectations while the other focuses on pure anticipatory movements. However, when put in a RBC framework, both formulations share the same initial difficulty; they struggle to generate a news-driven boom in the economy.

2.3 News in Structural Business Cycles Models

As shown in different works (e.g. Barro and King, 1984; Beaudry and Portier, 2004), the simple idea of a news-driven boom is surprisingly difficult to fit in a fully specified general equilibrium model. These kinds of model heavily rely on the underlying imposed structure in order to evaluate the impact of news with respect to other sources of fluctuations. However, the use of standard models rules out by construction the possibility of a news-driven boom. Beaudry and Portier (2004) prove that standard one-sector and two-sectors models are not able to generate a contemporaneous increase in consumption, investment and employment following the arrival of positive news. Beaudry and Portier (2014) analyze the problem in more details, highlighting two different difficulties, the "static" one and the "dynamic" one.

The static problem concerns a property of the standard RBC structure (Barro and King, 1984). Consider a one-sector economy with a representative firm with production function $F(K_t, N_t, \theta_t)$ and a representative household with the following maximization problem

$$\max_{\{C_t, K_{t+1}, N_t\}} U(C_t, N_t) + \beta E\left[\tilde{V}\left(K_{t+1}, \Gamma_{t+1}\right)|\Omega_t = \{\theta_t, S_t\}\right]$$
$$\text{s.t. } C_t + K_{t+1} = w_t N_t + K_t\left(1 - \delta + r_t\right) + \Pi_t$$

where θ_t is the current state of technology, Ω_t is the agent's information set, S_t is a signal with potential exogenous news. In order to focus on the static challenge, we temporarily assume that an increase in good news S_t increments the desire to invest:

$$\frac{\partial^2 V(K_{t+1}, \theta_t, S_t)}{\partial K_{t+1} \partial S_t} > 0, \quad \frac{\partial^2 V(K_{t+1}, \theta_t, S_t)}{\partial^2 K_{t+1}} \leq 0$$

where $V(K_{t+1}, \theta_t, S_t) = \beta E\left[\tilde{V}\left(K_{t+1}, \Gamma_{t+1}\right)|\Omega_t\right]$. By doing that we are abstracting from the dynamic problem, as we assume that good news about the future automatically increases the marginal value of entering the next period with more capital. The Walrasian equilibrium of this economy is given by the following equations:

$$\begin{aligned}
\frac{\partial V(K_{t+1}, \theta_t, S_t)}{\partial K_{t+1}} &= U_C\left(C_t, N_t\right) \\
F_K(K_t, N_t, \theta_t) &= \frac{-U_N(C_t, N_t)}{U_C(C_t, N_t)} \\
C_t + K_{t+1} &= F_K(K_t, N_t, \theta_t) + (1 - \delta)\, K_t
\end{aligned}$$

By observing the second equation, i.e. the leisure-consumption decision, we know by total differentiation that, if consumption and leisure are both normal goods, consumption and employment cannot move in the same direction. By rewriting the last two conditions (the intra-temporal ones) and abstracting from time, we obtain:

$$I = \frac{-U_N(C, N)}{U_C(C, N)} - C$$

$$\frac{dI}{dC} = \frac{-\overbrace{U_{NC}(C, N)}^{\leq 0}}{\underbrace{U_{CC}(C, N)}_{\leq 0}} - 1 \leq -1$$

Hence, consumption and investment cannot move in the same direction either. Therefore, as we now by assumption, the arrival of good news increases the desire to invest, which causes a decrease in consumption. The impossibility of co-movements of investment and consumption limits by construction the emergence of news-driven booms in the economy, both in the news and in the noise formulation. By adding more elements to the model, it is possible to overcome the static problem in several ways, with varying degrees of satisfaction. Beaudry and Portier (2007, 2014); Dupor and Mehkari (2014) provide a review of the different kinds of model in which it is possible to generate co-movements in consumption and investment.

One channel through which news can generate a boom in the economy that is worth mentioning for our study is the one that emerges in a New-Keynesian setting. According to this mechanism, the combination of sticky prices and an accommodative monetary policy is able to overcome the static problem; this path has been exploited by multiple studies, such as Christiano et al. (2010); Fujiwara et al. (2011); Khan and Tsoukalas (2012); Blanchard et al. (2013); Görtz and Tsoukalas (2017).

Consider the previous household problem augmented with money:

$$\max_{\{C_t, K_{t+1}, M_{t+1}, N_t\}} U(C_t, N_t) + \beta E\left[V\left(K_{t+1}, M_{t+1}, \theta_t, S_t\right)\right]$$
$$\text{s.t. } C_t + K_{t+1} + \frac{M_{t+1}}{P_t} = w_t N_t + K_t\left(1 - \delta + r_t\right) + \frac{M_t}{P_t} + \Pi_t + \frac{\mu_t}{P_t}$$

where τ_t in an exogenous intertemporal money transfer such that $\mu_t = M_{t+1} - M_t$. If we assume that P_t does not react to news and that the monetary rule is given by $\mu_t = \gamma\left(Y_t - \bar{Y}\right)$, it is possible to show that the co-movement in consumption and investment critically depends on the value of γ. Following a higher demand for investment, consumption increases only if $\gamma > 0$, i.e. if monetary policy is pro-cyclical. The interaction between news and monetary policy is studied in details in Christiano et al. (2010), where it is shown how news can generate an excessive expansion because of the inadequacy of standard monetary policy rule to deal with news-driven booms.

The other difficulty faced by this literature is the dynamic problem, which concerns the assumption made in the previous paragraphs; this problem is particularly relevant when considering news on technology. According to the view of Beaudry and Portier (2004), positive news on technology should cause an anticipatory boom in the economy by making investment more desirable. The increase in propensity to invest triggers a boom in the economy, with a contemporaneous rise in consumption, investment and labor. If the news does not materialize, the economy faces a liquidation period, with negative consequences for aggregate variables. However, this story is very difficult to implement, as it does not fit any standard RBC model. In standard models, as a consequence of an anticipated improvement in technology, the value of holding capital diminishes. Indeed, as the consumer anticipates a technological improvement, it becomes desirable to postpone the capital acquisition. While Dupor and Mehkari (2014) address this issue, the solution provided by Jaimovich and Rebelo (2009) is the preferred one in the literature, as it easily fits in standard business cycles models. According to their view, after the agent has received positive news concerning the future state of technology, the incentive to accumulate is reduced and current capital depreciates through increased capital utilization. In this case, the increase in capital utilization itself is able to cause a boom in the economy. The household maximization problem of this model is given by

$$
\begin{aligned}
\max_{\{C_t, N_t, K_{t+1}, u_t, I_t\}} \quad & U(C_t, N_t) \\
\text{s.t.} \quad & A_t (u_t K_t)^{1-\alpha} N_t^{\alpha} = C_t - I_t \\
& K_{t+1} = I_t \left[1 - \varphi \left(\frac{I_t}{I_{t-1}} \right) \right] + \left[1 - \delta(u_t) \right] K_t
\end{aligned}
$$

The key elements are variable capacity utilization and adjustments costs to investment, which are both usually present in medium-scale DSGE models. The interaction of these two elements, when complemented with an utility function that minimizes wealth effects on labor supply[1], are able to generate news-driven business cycles. In their framework, positive technological news reduces the incentive to accumulate capital while increasing the incentive to invest; while the two incentives seem in contradiction with each other, they can be both met thanks to the increased capital utilization.

[1]The utility function proposed by Jaimovich and Rebelo (2009) is a generalization of KPR and GHH preferences. While it is relevant from a quantitative point of view, it does not affect the qualitative response of the model. The adopted utility function is

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(C_t - \psi N_t^{\theta} X_t \right)^{1-\sigma} - 1}{1 - \sigma}$$

$$X_t = C_t^{\gamma} X_{t-1}^{1-\gamma}$$

Note that for $\gamma = 1$ preferences are of the class KPR, while for $\gamma = 0$ preferences are GHH.

2.3.1 Evaluating news and noise shocks using structural models

After having reviewed when and how news shock can impact the economy, it is now possible to report what is the estimated relative impact of news in structural models.

Concerning the news formulation, the Bayesian estimation of a real model à la Jaimovich and Rebelo (2009) is performed by Schmitt-Grohé and Uribe (2012). By including the possibility of anticipatory movements in all the shocks, they find that news shocks are responsible for about half of output fluctuations. While this seems a promising result for the literature, it is important to stress that the majority of fluctuations is due to anticipation in preference and wage mark-up shocks, with almost no relevance for anticipation in technological shocks. Similar results are obtained when departing from the real setting, augmenting a New-Keynesian model with news shocks. This exercise is performed, for example, in Fujiwara et al. (2011) and Khan and Tsoukalas (2012). In general, the literature adopting medium-scale DSGE models did not find evidence that anticipation in TFP is an important source of aggregate fluctuations. An exception to this result is represented by the work of Görtz and Tsoukalas (2017), in which a financial sector à la Gertler and Karadi (2011) is introduced in a New Keynesian framework, providing an additional transmission and propagation mechanism for TFP news. According to their estimates, TFP news shocks account for approximately one third of variation in output, consumption and investment.

Concerning the noise formulation, a quantification of the relevance of noise shocks in aggregate fluctuations is performed in Blanchard et al. (2013) and Barsky and Sims (2012) with opposite results. The two models are similar in spirit, as both of them are embedded in a New Keynesian framework and study the impact of noise in a signal extraction problem on productivity. Blanchard et al. (2013) find that noise is an important driver of high-frequency variation in consumption and output, accounting for, respectively, 51% and 20% of variation on impact. On the other hand, Barsky and Sims (2012) find that in their model the "animal spirit" (or noise) shock has almost zero impact on aggregate variables. There is a significant difference in the persistence of such shock as well; in Barsky and Sims (2012) the shock loses significance after three periods, while it takes more than 10 periods for that to happen in the Blanchard et al. (2013) model. There are several small differences in the two studies that contribute to the result; however, the main distinction between the two is the signal extraction problem faced by the agent. The signal observed by the consumer in Barsky and Sims (2012) is much more informative than the one that is observed in Blanchard et al.

(2013), allowing the agent to quickly learn what are the forces affecting productivity, without making persistent mistakes. Therefore, given the nature of noise shocks, their impact largely depends on the model's underlying structure.

3 Aggregate Variables in the U.S. Great Depression

The Great Depression has been the worst depression of the last century; its extension and duration were so unusual that contemporary economists needed to abandon the equilibrium framework to provide a satisfactory interpretation of the event. Only several decades later, after consistent methodological advancements, RBC theorists attempted an equilibrium interpretation of the Great Depression. In this section, before testing our hypothesis of a news-driven interpretation of the event, we take a preliminary look at the data, while analyzing the existing literature on the Great Depression to motivate the choice of our model.

A first consideration is that in our analysis we abstract from the international dimension, as it is usually the case in the RBC literature. The argument that the US depression can be understood from a national perspective is made, for example, in Romer (1993) and in Cole and Ohanian (1999). In figure 1 we report the levels of real per-capita output, consumption and investment; variables are in percentage of 1929 output. In figure 2 are reported the main aggregate variables from 1923Q1 to 1940Q4 relative to their 1929Q1 level; variables are not detrended and are expressed in real/per-capita terms when necessary. For more information on data sources and construction, refer to the paragraph on data in section 5.

By looking at Figure 1, it is possible to observe that GNP decreased more than one third from 1929 to 1933; even without detrending the data, it is not until 1939 that output is back to its pre-crisis level. By looking at output's components, it is possible to observe that consumption is relatively less volatile, with a 25% fall in 1933 with respect to 1929. The fall in investment is far more dramatic, as it experienced a drop of more than 80% during the same period. For this reason, some authors considered investment as a key variable in order to understand the depression (e.g. Temin, 1976; Romer, 1993). By looking at Figure 2, it is also possible to appreciate the sluggish recovery of the economy. This represents a big puzzle for the RBC interpretation of the Great Depression, as, according to this view, the economy should have returned to its trend much before then it actually did. Instead, in 1939 the US detrended output

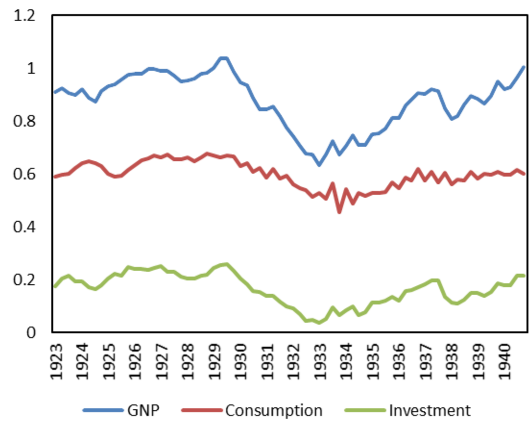
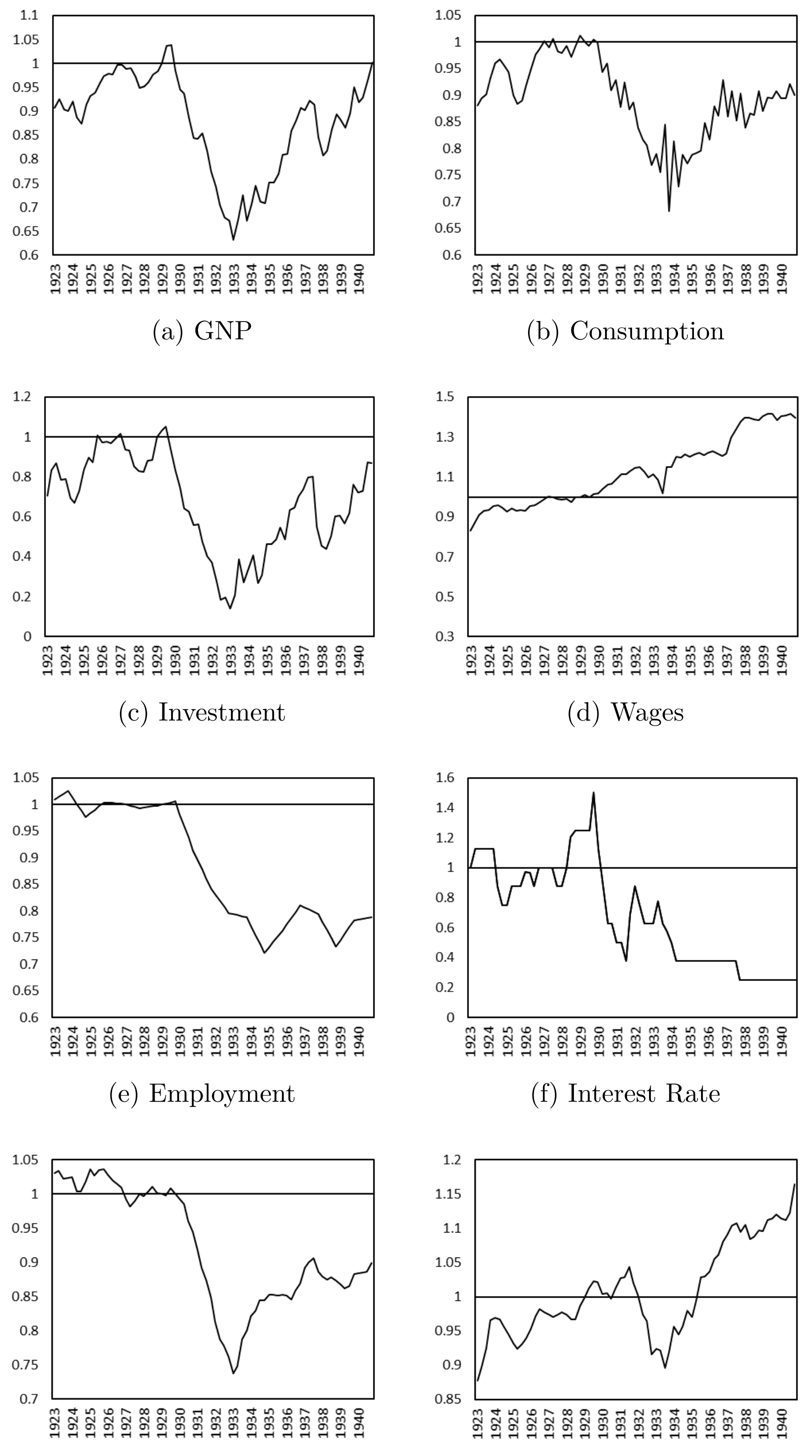


Figure 1: US GNP and its components

was still 27% below its 1929 level (Cole and Ohanian, 1999). This enduring drop has led different authors to consider the Great Depression not only as a fluctuation around the trend, but the result of a combination of temporary and permanent shocks.

Figure 2 (d - e) displays wage and hours worked in the manufacturing sector. Wages in the sector are increasing over time with respect to their 1929 level; this also holds when data are detrended (Cole and Ohanian, 1999). The story is different for normalized hours worked, as they experience a remarkable drop of around one fourth. It is also notable the lack of recovery in employment during the decade of the depression, as in 1940 it was still 20% below its 1929 level. This pattern suggests that a permanent shock affected the labor market during these years. The institutional changes that are generally considered responsible for the shock in employment are the New Deal policies, which started with the NIRA of 1933. This hypothesis, already present in Cole and Ohanian (1999) as a possible solution to the weak-recovery puzzle, is analyzed in details in Cole and Ohanian (2004).

Panels f and g of Figure 2 report, respectively, the discount rate of the FED of New York and the standardized level of prices, which both decreased after the starting point of the crisis. Concerning the monetary side of the economy, Friedman and Schwartz (1963) argue that the depression "is in fact a tragic testimonial to the importance of monetary forces". This evidence, corroborated by the work of Eichengreen (1996), fails to explain a relevant part of the recession when put in a general equilibrium perspective. Indeed, as shown in Cole and Ohanian (2000), monetary shocks appear to have had a small impact on to Great Depression, in particular during the recovery phase.



(a) GNP (b) Consumption

(c) Investment (d) Wages

(e) Employment (f) Interest Rate

(g) Price Deflator (h) Labor productivity

Figure 2: Aggregate Variables

Lastly, figure 2h shows the behavior of labor productivity[2], which was in 1933 10% lower than in 1929. The fall is more dramatic when considering detrended total factor productivity, as the economy witnessed a fall of almost 20% for the same time period (Ohanian, 2001; Cole et al., 2005). Consistently with the RBC tradition, a first attempt of the literature to explain the depression comes from the productivity side of the economy. Cole and Ohanian (1999) show how the fall in TFP alone accounts for 40% of the initial drop in output. However, the same shock does not appear to play an important role in the sluggish recovery of the following years.

3.1 Expectations in the Great Depression

The partial failure of the standard equilibrium approach to provide a satisfactory explanation of the depression led some authors to conclude that negative expectations could be the missing piece of the puzzle. Indeed, as both Temin (1976) and Romer (1993) note, the state of expectations was in crucial conditions after 1930.

By taking this idea to the extreme, Harrison and Weder (2006) build a general equilibrium model with self-fulfilling expectations and indeterminacy of equilibria. In their model, they hypothesize that the enduring extrinsic pessimism can be explained by factors unrelated to the fundamentals. After estimating the sunspots and simulating the model, they find that the combination of sunspots and increasing returns to scale are potentially able to replicate the Great Depression's size and duration with remarkable precision. Their conclusion is that the event can be reconducted to DeLong's statement:

> "The Great Depression happened in large part because people expected something bad to happen" DeLong (2001, p. 62)

Their result, however, appears somehow unsatisfactory, as they only consider sunspot shocks and abstract from all other possible considerations. Even if they are able to replicate the data, considering the depression as the consequence of exogenous shocks in expectations on factors unrelated to fundamentals does not seem like a definitive explanation of the event.

Another application of the role of expectations in the literature can be found in Eggertsson and Pugsley (2006). They claim that the main cause of the slow recovery is a recession happening in 1937-1938 because of a shift in expectations about future

[2]This series is constructed by dividing real GDP (figures taken from Gordon and Krenn (2010)) by labor input (figures taken from Kendrick (1961)) and standardizing it to 1929.

money supply. The shift in beliefs is identified using narrative evidence and is put it in a general equilibrium perspective. According to their view, monetary shocks played an important role in the slow recovery through the channel of expectations.

A recent paper by L'Huillier and Yoo (2017), attempts at evaluating the role of "bad news" in the US recessions of the last century. They define bad news as negative technological news[3] unrelated to fundamentals. The model adopted is very simple; they consider a standard signal extraction problem on productivity, with consumption being the only endogenous variable. Using this simple framework and abstracting from capital and investment considerations, they construct a bad news index that is used to rank the depressions according to the presence of negative news on technology unrelated to fundamentals. They find that the Great Recession and the Great Depression are the recessions with the highest presence of bad news; it is important to note that according to their definition, the Great Depression starts in 1929Q3 and finishes in 1933Q1. After that, they estimate their model on the years 1919Q1-1951Q4 and, using the Kalman filter, they recover the noise signal and compare it to the consumer's beliefs updated with information on productivity. We replicate their exercise by restricting the sample to 1923Q2-1940Q4 in order to exclude the effect of the second world war and to make it comparable to our model; results are reported in Figure 3. Whenever the noisy signal (solid line) is below the beliefs updated with news on productivity (dashed line), it means that there are negative expectations unrelated to the fundamentals in the economy; for more details on how this is computed refer to L'Huillier and Yoo (2017). Note that during the depression period, the economic agent receives mainly bad news, particularly in the periods 1929-1933 and 1937-1938.

The conclusion of this paper is that the fall in consumption during the Great Depression cannot be explained by only looking at the fall in productivity, and that bad news played a major role in this event. While Harrison and Weder (2006) focus on expectations completely unrelated to fundamentals, L'Huillier and Yoo (2017) studies the role of overly-pessimistic news on productivity, offering an interesting reading of the Great Depression. However, the model has several limitations, since it completely abstracts from important components of the economy, such as capital, investment and wages. Moreover, they only include productivity and noise shocks as sources of variation; this could potentially inflate the actual importance of noise shocks for that period. Ideally, before resorting to the use of expectation shifts to explain changes in aggregate

[3] In this context, the word "news" is used as an exogenous change in the information set used by the agents to forecast future economic activity.

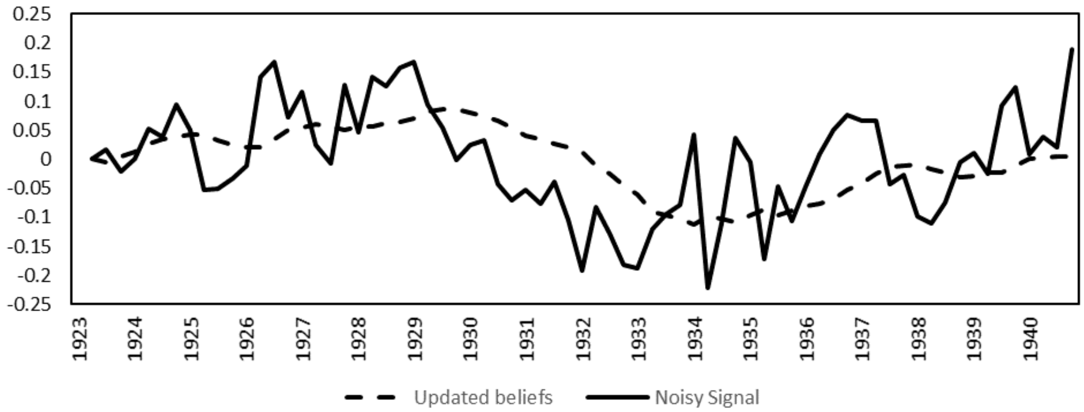


Figure 3: Smoothed belief and noisy signals

variables, one should let this shock compete with other possible types of disturbances. This is exactly the kind of exercise that is performed in our study. Our objective is to check whether the exploratory result of L'Huillier and Yoo (2017) holds when the same signal extraction problem is implemented in a DSGE model with several shocks.

In the following section, we proceed to describe the model economy.

4 The Model Economy

In this study, we consider the model developed in Blanchard et al. (2013), which is a medium-scale DSGE model similar to Smets and Wouters (2003) and Christiano et al. (2005). As it is standard with this class of models, several nominal and real rigidities are considered together with various exogenous shocks in order to match the main features of business cycles. The novelty of their approach is to consider a situation of imperfect information, in which consumers have to solve a signal extraction problem in order to assess the level of productivity.

In this section, we describe the different components of the economy; more information on the optimality condition and the log-linearized version of the model is included in the appendix.

4.1 Signal extraction on productivity

The core aspect of this model is its signal extraction, which is based on Lorenzoni (2009) and is the same one adopted in the study by L'Huillier and Yoo (2017). In this model, productivity is composed by two components, a permanent one and a transitory one. These components are driven, respectively, by a permanent shock and a transitory shock. The use of the word "permanent" refers to a shock that has a permanent effect on productivity that builds up gradually. Formally,

$$a_t = x_t + z_t \tag{1}$$

where a_t is the log of productivity, x_t the permanent component, and z_t the transitory component. While the transitory component follows the stationary process

$$z_t = \rho_z z_{t-1} + \eta_t \tag{2}$$

the permanent component follows a unit root (or difference stationary) process

$$\Delta x_t = \rho_x \Delta x_{t-1} + \varepsilon_t \tag{3}$$

where $\rho_z, \rho_x \in [0, 1)$, $\varepsilon_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma_\varepsilon^2\right)$ and $\eta_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma_\eta^2\right)$.

Consumers do not observe the two components apart, but only the realized level of productivity. Changes in the permanent component can alter the economy's long-run fundamentals. However, given the presence of a transitory component, the consumer is not able to infer the value of the permanent component by just looking at realized productivity.

In addition to productivity, we assume that consumers observe a noisy signal s_t about the permanent component x_t:

$$s_t = x_t + \nu_t \tag{4}$$

where $\nu_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \sigma_\nu^2\right)$ is the so-called "noise shock", or "animal spirits shock" in the terminology of Barsky and Sims (2012). By solving the signal extraction problem, consumers form expectations on future productivity and behave accordingly.

As in Blanchard et al. (2013), we assume that

$$\rho_x = \rho_z = \rho \tag{5}$$

and the following restriction on variances

$$\rho \sigma_\varepsilon^2 = (1 - \rho)^2 \sigma_\eta^2 \tag{6}$$

which together imply a Gaussian random walk process for a_t[4]

$$E\left[a_{t+1}|a_t, a_{t-1}, \dots\right] = a_t$$

$$a_{t+1} = a_t + u_t$$

Therefore, if we denote with u_t the innovation component and with σ_u^2 its variance, the following properties are satisfied

$$\sigma_\varepsilon^2 = (1-\rho)^2 \sigma_u^2 \tag{7}$$

$$\sigma_\eta^2 = \rho \sigma_u^2 \tag{8}$$

4.2 Households

In this economy, there is a representative household with preferences represented by the utility function

$$\mathcal{U} = E\left[\sum_{t=0}^{\infty} \beta^t \left(\log\left(C_t - hC_{t-1}\right) - \frac{1}{1+\zeta}\int_0^1 N_{jt}^{1+\zeta} dj\right)\right]$$

where C_t is consumption, h the internal habit consumption parameter and N_{jt} is specialized labor of type j. Labor specialization is functional to introduce monopolistic competition in wage setting as in Erceg et al. (2000). The budget constraint of the

[4]**Proof.** If 1-3 hold, we have that

$$\Delta a_t = \Delta x_t + \Delta z_t$$

$$\mathrm{Var}\left[\Delta a_t\right] = \frac{1}{1-\rho_x^2}\sigma_\varepsilon^2 - \frac{2}{1-\rho_z}\sigma_\eta^2$$

$$\mathrm{Cov}\left[\Delta a_t, \Delta a_{t-j}\right] = \rho_x^j \frac{1}{1-\rho_x^2}\sigma_\varepsilon^2 - \rho_z^{j-1}\frac{1-\rho_z}{1+\rho_z}\sigma_\eta^2 \quad \forall j > 0$$

By additionally assuming 5 and 6, we have, $\forall j > 0$

$$\begin{aligned}
\mathrm{Cov}\left[\Delta a_t, \Delta a_{t-j}\right] &= \rho^{j-1}\frac{1}{1-\rho^2}\rho\sigma_\varepsilon^2 - \rho^{j-1}\frac{1-\rho}{1+\rho}\sigma_\eta^2 \\
&= \rho^{j-1}\frac{1}{1-\rho^2}(1-\rho)^2\sigma_\eta^2 - \rho^{j-1}\frac{(1-\rho)^2}{(1+\rho)(1-\rho)}\sigma_\eta^2 \\
&= \rho^{j-1}\frac{(1-\rho)^2}{1-\rho^2}\sigma_\eta^2 - \rho^{j-1}\frac{(1-\rho)^2}{1-\rho^2}\sigma_\eta^2 \\
&= 0
\end{aligned}$$

representative household is given by

$$P_t C_t + P_t I_t + B_t + T_t + P_t \mathcal{C}\left(U_t\right) \bar{K}_{t-1} = R_{t-1} B_{t-1} + Y_t + R_t^k K_t + \int_0^1 W_{jt} N_{jt} dj$$

where P_t is the price level, B_t are one-period assets that pay a one-period nominal interest rate of R_t, T_t is a lump sum tax, Y_t is the output, R_t^k is the capital rental rate, W_{jt} is the wage corresponding to the j type of labor. $\bar{K}_t$ is the stock of capital of the representative agent, with capital accumulation equation of

$$\bar{K}_t = (1-\delta)\bar{K}_{t-1} + D_t \left[1 - \mathcal{G}\left(\frac{I_t}{I_{t-1}}\right)\right] I_t$$

where δ is the fixed depreciation rate, I_t the investment, D_t the stochastic investment-specific technology with the following autoregressive process

$$d_t = \log D_t = \rho_d d_{t-1} + \varepsilon_t^d$$

ε_t^d being the i.i.d. investment-specific technology shock. $\mathcal{G}$ represents the function of quadratic adjustment costs in investment

$$\mathcal{G}\left(\frac{I_t}{I_{t-1}}\right) = \frac{\chi}{2}\left(\frac{I_t}{I_{t-1}} - \Gamma\right)^2$$

where Γ is the long-run gross growth rate of total factor productivity. Variable capital utilization U_t is included in the model; therefore, the stock of capital $\bar{K}_{t-1}$ provides capital services for

$$K_t = U_t \bar{K}_{t-1}$$

with cost of capacity utilization of $\mathcal{C}\left(U_t\right)\bar{K}_{t-1}$, where

$$\mathcal{C}\left(U_t\right) = \frac{U_t^{1+\xi}}{1+\xi}$$

4.3 Firms

In this economy, there is a final good that is produced in a competitive sector using a CES production function:

$$Y_t = \left(\int_0^1 Y_{j,t}^{\frac{1}{1+\mu_t^p}} dj\right)^{1+\mu_t^p}$$

where Y_{jt} is the quantity of good j that is used in the production. μ_t^p represents a time-varying elasticity of substitution across the different j goods such that

$$\log\left(1+\mu_t^p\right) = \log\left(1+\mu^p\right) + m_t^p$$

with m_t^p following the process

$$m_t^p = \rho_p m_{t-1}^p + \varepsilon_t^p - \psi_p \varepsilon_{t-1}^p$$

and ε_t^p being an i.i.d shock. The production function of an intermediate good j is given by

$$Y_{jt} = K_{jt}^{\alpha}\left(A_t L_{jt}\right)^{1-\alpha}$$

where K_{jt} and L_{jt} are the capital and labor employed in the production of j. The technology a_t follows the process described in equations (1 - 3) and assumptions (5 - 6). The representative household does not observe both x_t and z_t, but observes their aggregation a_t and a signal s_t given by (4). The constant term in TFP growth Γ is explicitly accounted:

$$\log A_t = \left(t \log \Gamma\right) a_t$$

Prices in the intermediate good sector are sticky, as they adjust each period according to a Calvo parameter (Calvo, 1983). Each period, a fraction $1-\theta_p$ of firms in the intermediate sector can decide whether to adjust the price of good j to $P_{j,t}$, while a fraction θ_p is forced to keep the price at the former period level ($P_{j,t-1}$).

Competitive labor agencies combine specialized labor and supplies it to intermediate good producers. Specialized labor of type $j \in [0,1]$ is combined using the technology

$$N_t = \left(\int_0^1 N_{j,t}^{\frac{1}{1+\mu_t^w}}\, dj\right)^{1+\mu_t^w}$$

where μ_t^w represents a time-varying elasticity of substitution across the different j types of labor such that

$$\log\left(1+\mu_t^w\right) = \log\left(1+\mu^w\right) + m_t^w$$

with m_t^w following the process

$$m_t^w = \rho_w m_{t-1}^w + \varepsilon_t^w - \psi_w \varepsilon_{t-1}^w$$

and ε_t^w being an i.i.d shock. Specialized labor wages are sticky and are set by the household according to a Calvo parameter. For each type of labor j, wages are adjusted by the household with probability $1-\theta_w$, while a fraction θ_w of households does not adjust their wages in a given period.

4.4 Government and central bank

The government spends a fraction of output

$$G_t = Y_t\left(\psi + g_t\right)$$

with g_t following the stochastic process

$$g_t = \rho_g g_{t-1} + \varepsilon_t^g$$

where ε_t^g is an i.i.d. fiscal shock.

The central bank sets the interest rate according to the following monetary policy rule

$$r_t = \rho_r r_{t-1} + \left(1+\rho_r\right)\left(\gamma_\pi \pi_t + \gamma_y \hat{y}_t\right) + q_t$$

where q_t follows the stochastic process

$$q_t = \rho_q q_{t-1} + \varepsilon_t^q$$

with ε_t^q being an i.i.d. monetary policy shock. The other quantities refer to the log-linearized version of the model, so that $r_t = \log R_t - \log R$ and $\pi_t = \log P_t - \log P_{t-1}$.

5 Data and Methodology

5.1 Data

The log-linearized version of the model presented in the appendix is estimated using quarterly U.S. data (1923Q2-1940Q4) on six variables. The variables that are matched with the data are output, consumption, investment, employment, interest rate, inflation and wages. The choice of the starting point of our estimation is forced by the availability of data for wages; indeed, data availability is a crucial limit for studies attempting at estimating large models for the considered period.

Quarterly data on U.S. nominal GNP, GNP deflator, consumption and investment are taken from Appendix B of Balke and Gordon (1986), whose database provide quarterly estimates for several historical aggregate variables[5]. The series for output is "Nominal GNP", the series for the price deflator is "GNP Deflator (1972=100)", while the series for nominal consumption is "Consumption: Nondurable Goods and Services". The series for nominal investment is computed by adding the series for consumption in "Durable Goods" and the series for investment in "Producers' Durable Equipment", "Nonresidential Structures", "Residential Structures", and "Changes in Business Inventories".

For the labor side of the economy, we adopt the series of earnings in the manufacturing sector provided by Hanes (1996) and the measure of hours worked in the manufacturing sector provided by Jones (1963)[6]. An alternative for this last series could have been the one of hours worked for all employees plus self-employed derived in Chari et al. (2007); however, since there are no data for the corresponding wages, we prefer to favor consistency within the model.

As a measure for interest rate, we use the series "U.S. Discount Rates, Federal Reserve Bank of New York", which is provided in the National Bureau of Economic Research's Macro History database. The series for the population is obtained by linearly interpolated the measure provided by Chari et al. (2007).

Using the population deflator, we express output, consumption and investment in per capita terms. Nominal output, consumption, investment and wages are converted to real (1937 dollars) using the GNP deflator. The series for inflation rate is derived from the percentage change in the price deflator, while the interest rate series is divided by four in order to be consistent with quarterly data. Some of the obtained series are visualized in Figure 2.

5.2 Measurement equations

The observables matched to the data are: Δy_t, Δc_t, Δi_t, Δw_t, Δn_t, r_t, π_t. Variables in differences are defined as

$$\Delta y_t = \log Y_t - \log Y_{t-1}$$

[5]As we will see in the section concerning the robustness of our results, a close alternative is the database provided by Gordon and Krenn (2010).

[6]Since data on hours worked are annual, we perform a linear interpolation. This should not represent a problem given the relative low variability of the series.

Note that, even if variables in differences are already stationary, it is important to account for the trend when specifying the measurement equations that link the model with the data (Pfeifer, 2014). Indeed, as explained in the appendix, non-stationary variables are detrended in the model by dividing them by the labor-augmenting technology:

$$\hat{y}_t = \log \frac{Y_t}{A_t} - \log \frac{Y}{A},$$

Therefore, we have that

$$\begin{aligned}
\Delta y_t^{obs} &= \log Y_t^{\text{data}} - \log Y_{t-1}^{\text{data}} \\
&= \log Y_t - \log Y_{t-1} \\
&= \log \hat{y}_t - \log \hat{y}_{t-1} + \log a_t - \log a_{t-1} \\
&= \hat{y}_t - \hat{y}_{t-1} + \Delta a_t
\end{aligned}$$

Where Y_t^{data} is the series constructed in the previous subsection (i.e. real/per-capita), while Δa_t is the quarterly growth rate of labor augmenting technology. Hence, to account for trends, the observation equation used to link the data with the model are:

$$\Delta y_t^{obs} \equiv \Delta y_t = \hat{y}_t - \hat{y}_{t-1} + \Delta a_t$$

$$\Delta c_t^{obs} \equiv \Delta c_t = \hat{c}_t - \hat{c}_{t-1} + \Delta a_t$$

$$\Delta i_t^{obs} \equiv \Delta i_t = \hat{i}_t - \hat{i}_{t-1} + \Delta a_t$$

$$\Delta w_t^{obs} \equiv \Delta w_t = \hat{w}_t - \hat{w}_{t-1} + \Delta a_t$$

$$\Delta n_t^{obs} \equiv \Delta n_t = n_t - n_{t-1}$$

$$r_t^{obs} \equiv r_t$$

$$\pi_t^{obs} \equiv \pi_t$$

5.3 Estimating the model

As it is common for DSGE models with a large number of parameters, the model is estimated using Bayesian methods. In our estimates, we adopt the same priors as Blanchard et al. (2013), with some minor differences. Instead of estimating the parameter α of the production function, we fix it to 0.3, which is its standard value for the United States.

As shown in Blanchard et al. (2013), the model's information structure is observationally equivalent to a model with full information and correlated shocks; this result makes the estimation much easier. Therefore, by imposing a restriction on the shocks' correlation matrix, it is possible to estimate the full-information model and recover the parameters of the original signal extraction problem. Using these parameters, we can then compute the impulse response functions for the imperfect information model and derive its variance decomposition. Being able to formalize a model with imperfect information as one with full-information and correlated shocks is in general very convenient; however, since this method of estimation does not affect the results, we do not report the details here. For more information on this result, see the appendix of Blanchard et al. (2013).

6 The U.S. Great Depression through the Prism of the Model

Table 1 shows the results of the posterior maximization of the model's structural parameters.

By looking at nominal rigidities, we find that they are lower than the estimates of post-war data (Blanchard et al., 2013); indeed, we find that 64% of households are not able to adjust their wages in a given period. This result is in contrast with part of the literature on the Great Depression, which identifies wage rigidities as one of the crucial elements of the crisis (e.g. Dighe, 1997). Estimates on wage rigidities show that they are certainly important but their value for the period is not unusually high. By looking at Calvo's price parameter, we observe that prices during the period exhibit relatively standard stickiness, as 71% of firms are not able to adjust prices each quarter. Since, as explained in the previous sections, price stickiness is an important factor in order to generate large anticipatory movements, a lower stickiness could potentially dampen the effect of the noise shock.

Concerning rigidities in consumption and investment we estimate relatively low habit consumption and investment adjustment cost parameters during the Great Depression period, with values of, respectively 0.3 and 2.67.

Looking at the parameters for the productivity process, we observe high persistence in productivity shocks, with $\rho = 0.9310$. Since we assumed $\rho_x = \rho_z = \rho$, both com-

	Parameter	Prior	Posterior	Conf. bands		Distribution	Prior SD
h	Habit	0.5	0.295	0.2623	0.3565	Beta	0.1
ζ	Inv. Frisch elasticity	2	1.4563	1.311	1.4761	Gamma	0.75
ξ	Capacity cost	5	5.0712	3.2747	6.9211	Gamma	1
χ	Investment adjustment cost	4	2.6625	1.1319	5.3981	Normal	1
θ	Calvo prices	0.66	0.7063	0.7032	0.7515	Beta	0.1
θ_w	Calvo wages	0.66	0.6407	0.6379	0.6469	Beta	0.1
γ_π	Taylor rule inflation	1.5	1.0001	1.0001	1.0001	Normal	0.3
γ_y	Taylor rule output	0.005	0.0119	0.0119	0.0119	Normal	0.005
	Neutral technology and noise						
ρ	Persistence of prod. shocks	0.6	0.931	0.8816	0.9539	Beta	0.2
σ_u	Std. dev. of prod. shock	0.5	3.4292	3.0957	3.9719	Inv. Gamma	1
σ_ν	Std. dev. of noise shock	1	0.8880	0.3918	1.1573	Inv. Gamma	1
	(Implied parameters)						
σ_ε	Std. dev. of perm. shock	-	0.2366	-	-	-	-
σ_η	Std. dev. of trans. shock	-	3.3088	-	-	-	-
	Investment–specific						
ρ_d	Persistence of inv. spec. shock	0.6	0.8871	0.8359	0.9334	Beta	0.2
σ_d	Std. dev. of inv. spec. shock	5	10.7725	6.0517	18.1743	Inv. Gamma	1.5
	Markups						
ρ_p	Persistence of price mk.up shock	0.6	0.6076	0.4216	0.7517	Beta	0.2
ψ_p	Lag of price mk.up shock	0.5	0.0003	0.0001	0.0006	Beta	0.2
σ_p	Std. dev. of price mk.up shock	0.15	1.0593	0.8128	1.2562	Inv. Gamma	1
ρ_w	Persistence of wage mk.up shock	0.6	0.6815	0.5823	0.7944	Beta	0.2
ψ_w	Lag of wage mk.up shock	0.5	0.2586	0	0.4666	Beta	0.2
σ_w	Std. dev. of wage mk.up shock	0.5	0.3382	0.2541	0.4118	Inv. Gamma	1
	Policy						
ρ_r	Persistence of monetary rule	0.5	0.9437	0.9434	0.9439	Beta	0.2
ρ_q	Persistence of monetary shock	0.4	0.0841	0.0072	0.1425	Beta	0.2
σ_q	Std. dev. of monetary shock	0.15	0.1409	0.1163	0.163	Inv. Gamma	1
ρ_g	Persistence of fiscal shock	0.6	0.9966	0.9958	0.9967	Beta	0.2
σ_g	Std. dev. of fiscal shock	0.15	1.9063	1.5788	2.0969	Inv. Gamma	1

Table 1: Estimated Structural Parameters

ponents of productivity are quite persistent. If we compare our result with the model adopted in L'Huillier and Yoo (2017), with the sample reduced to match the one of our model, we find that in their specification the value of ρ is very close to ours (0.9295). The estimates for the standard deviation of the productivity shock and the noise shock are 3.43 and 0.89. Using the properties of our process (equations 7 and 8), we can recover the implied volatility for the permanent and transitory shock, which are, respectively, 0.24 and 3.31. Recalling that the problem that the consumer has to solve is to infer x_t and z_t by observing s_t and a_t, the relatively low level of σ_ν implies an easier problem with respect to the one observed in L'Huillier and Yoo (2017) and in Blanchard et al. (2013). Indeed, in both studies, the standard deviation of the noise shock is relatively higher compared to the productivity shocks.

Figure 4 shows the impulse responses for the seven observables plus productivity with respect to the main disturbances of our study, i.e. the permanent, transitory and noise shocks. By looking at the permanent technology shock, it is possible to observe how productivity slowly increases over time. This permanent increase in productivity causes the economy to experience a persistent boom, with output, consumption, investment and employment all increasing at the same time. The temporary technology shock causes a sharp increase in productivity, which decreases over time; the initial boom in the economy slowly vanishes as productivity returns to its former level. The hump shape in the impulse responses is due to the presence of habit consumption in the model.

A noise shock corresponds to an increase in expected productivity, without any actual movement in its true value. As it is possible to observe, a noise shock is able to create a boom in the economy in the first period, with a joint increase in consumption, investment and employment. However, since the signal is not very noisy, the agent quickly realizes the mistake in its expectations and rapidly incorporates the new information in its behavior. It is interesting to note how, after the agent realizes that productivity is not truly increasing, the economy experiences a small "recession" before returning to its original level.

There are mainly two mechanisms driving the initial increase in investment after a noise shock. The agent expects higher future investment following the increase in the expected marginal product of capital; this leads to an increase in investment today when combined with adjustment costs. Additionally, a higher consumption increases the marginal profitability of capital, directly affecting today's investment (Blanchard et al., 2013).

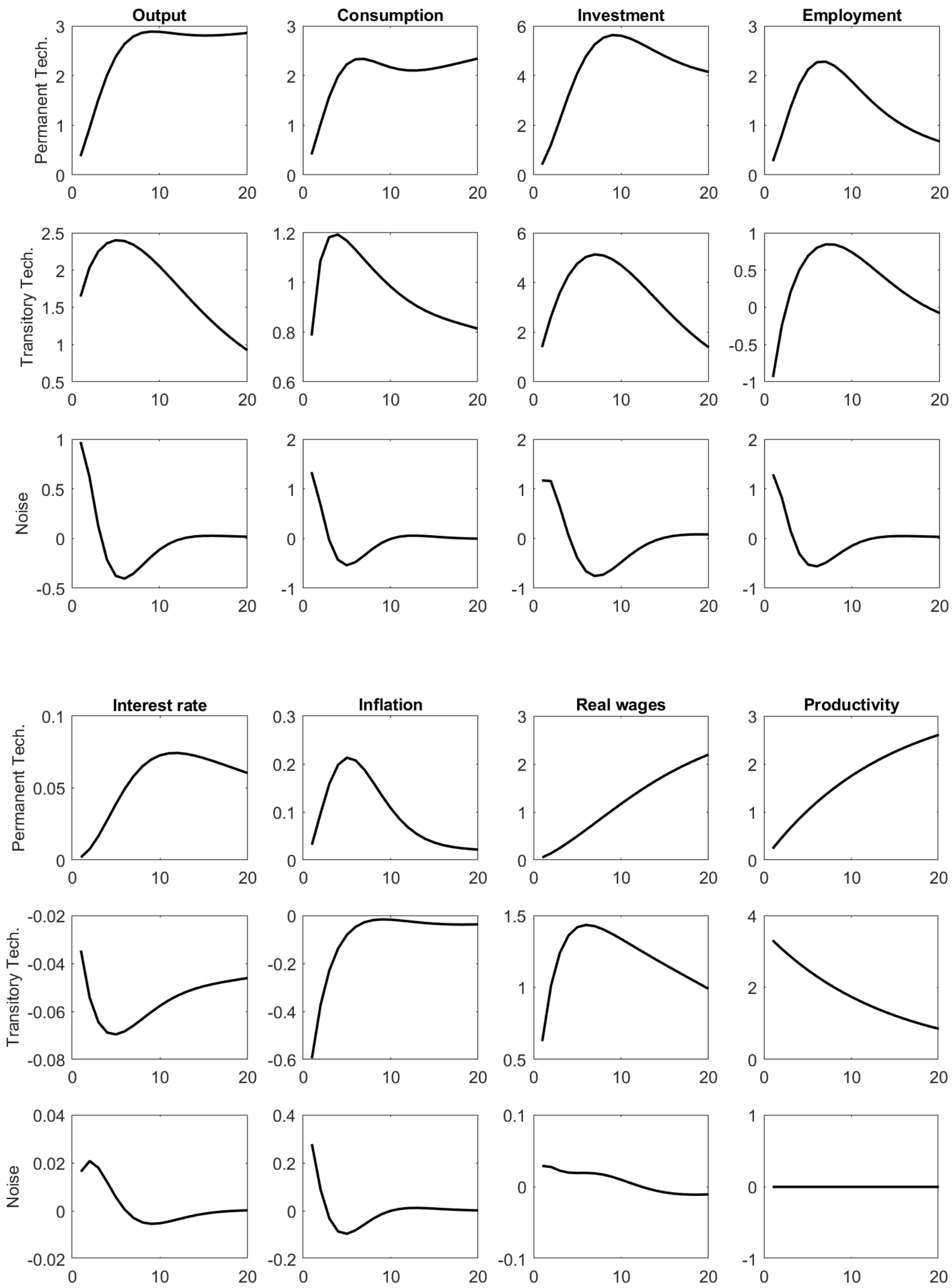


Figure 4: Impulse Responses

Quarter	Perm. tech.	Trans. tech.	Noise	Inv. specific	Price markup	Wage markup	Monetary	Fiscal
Output								
1	0.016	0.307	0.107	0.279	0.084	0.005	0.160	0.042
4	0.092	0.220	0.018	0.445	0.082	0.025	0.113	0.005
8	0.176	0.194	0.009	0.448	0.048	0.043	0.078	0.003
12	0.235	0.189	0.007	0.415	0.034	0.050	0.063	0.006
20	0.335	0.174	0.005	0.346	0.025	0.048	0.049	0.018
Consumption								
1	0.015	0.053	0.154	0.037	0.061	0.005	0.181	0.495
4	0.114	0.070	0.037	0.051	0.068	0.026	0.128	0.505
8	0.213	0.071	0.023	0.040	0.041	0.042	0.085	0.484
12	0.251	0.071	0.017	0.032	0.029	0.045	0.067	0.487
20	0.282	0.063	0.010	0.087	0.018	0.039	0.047	0.454
Investment								
1	0.002	0.024	0.016	0.875	0.030	0.004	0.043	0.006
4	0.015	0.035	0.003	0.861	0.030	0.011	0.040	0.005
8	0.039	0.047	0.002	0.827	0.022	0.023	0.037	0.004
12	0.060	0.057	0.001	0.796	0.017	0.031	0.034	0.003
20	0.093	0.064	0.001	0.755	0.016	0.035	0.032	0.004

Table 2: Variance Decomposition

Table 2 reports the variance decomposition for output, consumption and investment at different time horizons. Focusing first on output, we observe that the majority of short-run volatility is due to transitory technology shocks and investment specific shocks. Monetary shocks are also relatively important on impact, accounting for 16% of variations in output, while noise shocks account for a significant 10.7%. However, this number becomes much smaller after the one year horizon, since the agent has already realized that its expectations were unfounded. Also monetary shocks rapidly lose importance over time, while the main drivers of long-term output are technology shocks and investment specific shocks. Therefore, according to this model, the key variable to understand the huge fall in output during the depression, in addition to the extraordinary drop in productivity (Ohanian, 2001), is the dynamic of investment.

By looking at consumption, it is possible to note how a very large part of its variation is caused by shocks in government spending (or fiscal policies). This result is consistent across time horizons; however, it is surprising if compared to the rest of the literature on the Great Depression. Indeed, as explained in Cole and Ohanian (1999), government spending was below trend level only in 1933. While a distorting fiscal policy is unable to explain the 1930-1933 recession, the authors show how it significantly contributed to the slow recovery of the following years. The other most important causes of consumption changes in the short run are monetary and noise shocks, accounting respectively for 18,1% and 15,4% of the variance in the first period. Negative noise shocks can be interpreted as "bad news" or "pessimism"; while they are a relevant source of short-run variations, their impact is not as significant as potentially anticipated in the study of L'Huillier and Yoo (2017).

By focusing on the investment-specific shocks, it is possible to observe a very high estimated standard deviation (Table 1). This is more a feature of the model than a feature of the data. Indeed, following a noise shock, consumption and investment increase by the same magnitude (Figure 4). However, since investment is more volatile than consumption, the investment-specific shock accounts for this extra volatility. This also explains why noise shocks do not contribute significantly to the variance of investment.

6.1 Sensitivity analysis and robustness checks

In order to check whether our results are robust and which parameters are driving them, we perform a simple sensitivity analysis by re-estimating the model under different scenarios. The focus of our scenario analysis is the contribution of the noise shock to output and consumption variations. The results of the analysis are reported in Table 3.

The first alternative scenario that we consider is a situation in which we estimate α instead of fixing it, consistently with the original article of Blanchard et al. (2013). In their estimation, they find a value for α which is considerably lower than the standard value of 0.3. When performing a Bayesian estimation, a parameter fixed at a wrong value could negatively affect all the other estimates, as it forces the other parameters to account for that error. Therefore, we want to check whether this small difference could be the cause of the low contribution of noise shocks. Re-estimating the model, we find a value of α that is not remarkably lower from the assigned value. Therefore, while a lower value of α contributes to increasing the relative importance of a noise shock, Scenario 1 is almost identical to the baseline model.

As we have seen in Section 2, a more responsive monetary policy can potentially dampen the effect of a noise shock. We want to check whether this fact holds in our estimates. By imposing a more responsive monetary policy, i.e. $\gamma_\pi = 1.5$, we find that

Quarter	Baseline	Scenario 1[a]	Scenario 2[b]	Scenario 3[c]	Scenario 4[d]
Noise shock: Output Variance Decomposition					
1	0.107	0.114	0.038	0.071	0.040
4	0.018	0.023	0.006	0.011	0.015
8	0.009	0.013	0.003	0.005	0.008
Noise shock: Consumption Variance Decomposition					
1	0.154	0.168	0.117	0.197	0.224
4	0.037	0.044	0.023	0.041	0.058
8	0.023	0.026	0.011	0.019	0.031

[a] α is estimated with the rest of the model

[b] A more responsive monetary policy is imposed: $\gamma_\pi = 1.5,\ \gamma_y = 0.005$.

[c] High nominal rigidities are imposed: $\theta_p = \theta_w = 0.95$

[d] The dataset of Gordon and Krenn (2010) is used instead of Balke and Gordon (1986)

Table 3: Scenario analysis

this can reduce the impact of a noise shock, particularly on output (Table 3, Scenario 2).

In the third scenario, we want to check whether our result is due to relatively low estimated nominal rigidities. Indeed, as we have seen, a combination of accommodating monetary policy and high nominal rigidities should inflate the importance of noise shocks. In order to test our hypothesis, we impose on the model particularly high values of Calvo parameters, i.e. $\theta_p = \theta_w = 0.95$, before estimating it. As it is possible to observe in Table 3, the results are not remarkably different from the baseline model. In particular, the persistence of the noise shock is still very low, with a relatively irrelevant impact on the one-year horizon.

Lastly, we want to check whether our results are robust to a change in the dataset. Indeed, the Great Depression dates back to a period in which data collection was fairly limited, as output, consumption and investment series were registered in annual terms. To overcome this limit, we adopted the dataset derived in Balke and Gordon (1986), where multiple data sources are used to interpolate the series and obtain an estimate for the quarterly figures; more information on how this is done can be found in the dataset. An alternative dataset is provided by Gordon and Krenn (2010), who interpolate the data in a slightly different way. Similarly to what we have done in Figure 1, we visualize the standardized data[7] in Figure 5. By comparing Figure 1 and 5, it is possible to

[7] Using the Gordon and Krenn (2010) dataset, the GDP series is computed starting from the real GDP series; the consumption series is obtained by adding real consumption expenditures in non

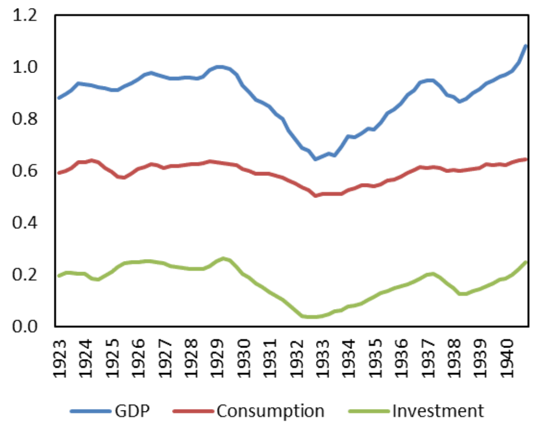


Figure 5: US GDP and its components (Gordon and Krenn, 2010)

appreciate that the two datasets are almost identical when low-frequency fluctuations are considered. However, they exhibit remarkable differences concerning high-frequency variations, with the Balke and Gordon (1986) data being much more volatile. Since short-run movements are very important from a business cycle perspective, it is possible that the contribution of the noise shock is artificially dampened because of a different interpolation technique; moreover, in deriving their results, L'Huillier and Yoo (2017) adopt the figures of consumption and GDP provided in the database of Gordon and Krenn (2010). Therefore, before drawing our conclusions, it appears necessary to perform a robustness check to this alternative dataset; we change the observables for output, consumption and investment, while leaving the other unchanged. The results of our estimation are reported in Scenario 4 in Table 3. It is possible to observe that the impact of a noise shock on output is very marginal, while the impact on consumption has a slight increase with respect to the baseline scenario. However, this increase does not change our result in a significant way, particularly when considering the very low persistence of the shock.

As we have seen in this section, our claim that noise shocks did not have a primary role in the Great Depression is quite robust. However, it remains to analyze what is the main driver of this result and why it is in contrast with the estimates of L'Huillier and Yoo (2017). First of all, it is important to notice that the relatively low relevance of wrong news does not depend on the adopted structural model. As we have seen in

durables and services; the investment series is obtained by adding real total investment and consumption durables. All real variables are expressed in 1937 dollars, consistently with the rest of our dataset.

Section 2, some structural models rule out by default the possibility of having news-driven business cycles; this is not the case here. Indeed, using a very similar version of this model estimated on post-WWII US data, Blanchard et al. (2013) show that noise shocks can account for more than 50% of consumption variation on impact and 25% after 8 quarters.

By performing several simulations under different conditions, it appears that the main cause of the estimated low impact of noise shock lies in the agent's signal extraction problem. Indeed, the process is not very noisy, since the estimated value of σ_ν is relatively low. Consequently, the agent is able to understand very quickly whether news is correct or not.

The results of L'Huillier and Yoo (2017) tell a different story because of the assumed underlying structure. In their framework, consumption depends on consumer's expectations about long-run productivity:

$$c_t = \lim_{j \to \infty} E_t \left[a_{t+j} \right]$$

However, they do not account for other variables and observables. Therefore, if consumption changes are unrelated to contemporaneous fundamentals, i.e. labor productivity, they are interpreted as pessimism, or “bad news”. When we adopt the same signal extraction problem in a DSGE model with more variables and observables, we find that these changes are mainly due to other shocks.

7 Conclusions

In this paper, we used a model-based estimation to assess the role of expectations in the period of the Great Depression. While the methodological novelties brought by the RBC literature have revived the interest in this unique historical episode, RBC theorists did not provide a completely satisfactory explanation on the origins of the Great Depression. The disproportioned fall in output, combined with an excessively long recovery, led some authors to the idea that adverse expectations played a significant role in the depression. While this idea has been explored in the past using extrinsic pessimism (Harrison and Weder, 2006), our interpretation of expectations closely follows the news literature that started with Beaudry and Portier (2004). According to this view, economic agents continuously try to predict the future state of the economy, adjusting today to news about the future and causing booms and bursts in the economy. Anticipated news can sometimes be wrong, causing the economy to go back to its initial state after a transition period.

Using a simple signal extraction model with consumption and productivity, L'Huillier and Yoo (2017) find that bad news played a more important role in the Great Depression than in other recessions of the United States. Their results suggest that a very important element is missing in the existing analyses of the recession, providing a potential solution to the Great Depression puzzle. In this work, we use the same signal extraction problem embedded in a DSGE model to test whether noise shocks are truly important sources of variation in the depression period.

By using Bayesian methods to estimate the contribution of noise shocks, we show how the conclusions reached in L'Huillier and Yoo (2017) do not hold when considering a fully specified general equilibrium model. In particular, we find that noise shocks on productivity play a significant but modest role in the variation of output and consumption. This shock has maximum relevance on impact, explaining, respectively, 10.7% and 15.4% of the variance of output and consumption. However, its contribution rapidly vanishes, accounting for only 2-3% of the variation after the one-year horizon. We find that the key parameter driving our result is the estimated variance of noise shocks, which is found to be relatively low. As a consequence, the signal extraction problem faced by the agent becomes simple to solve, causing a lack of persistence of noise shocks. Indeed, by looking at the impulse responses to a noise shock, we show how agents are able to quickly realize that their expectations are not backed by an actual increase in productivity. In addition, we show that our results are quite robust and that the low importance of noise shocks cannot be attributed to the adopted model. In our analysis, we also find that the most important shocks during the depression period were technology shocks and investment-specific technology shocks. A surprising role is also played by fiscal shocks, which account for a large part of consumption variation.

A useful extension to this work consists in recovering the series for noise shocks to further explore the results. Since we are in imperfect information, the number of structural shocks is higher than the agent's sources of information; this does not allow us to directly recover the series for structural shocks. However, as shown in the recent work of Benati et al. (2018), by exploiting the structural conditions of the model and observing the effect of the signal on other variables, the econometrician should be able to disentangle news and noise shocks.

Concerning the model, a possible extension could include financial prices in order to directly measure the agent's state of expectations. This exercise is particularly problematic when using the VAR methodology because of non-fundamentalness problems (e.g. Blanchard et al., 2013; Forni et al., 2014); however, in a structural model, it could provide additional information to isolate expectational shocks.

8 Appendix A: Model Derivation

This appendix includes the main information on the optimality conditions and the log-linearized version of the model. The purpose is to have a study that is self-referential in the model description; for a more complete treatment of the derivation, see the online appendix of Blanchard et al. (2013).

8.1 Optimality conditions

The marginal utility of consumption is given by

$$\Lambda_t = \frac{1}{C_t - hC_{t-1}} - \beta h E_t \left[\frac{1}{C_{t+1} - hC_t} \right]$$

The Euler equation is

$$\Lambda_t = \beta R_t E_t \left[\Lambda_{t+1} \frac{P_t}{P_{t+1}} \right]$$

If Φ_t represents the Lagrange multiplier in the capital constraint, the optimality conditions for capital and investment are

$$\Phi_t = \beta E_t \left[\Lambda_{t+1} \left(R^k_{t+1} \right) U_{t+1} - P_t \mathcal{C} \left(U_{t+1} \right) \right] + (1 - \delta) \beta E_t \Phi_{t+1}$$

$$P_t \Lambda_t = \Phi_t D_t \left[1 - \mathcal{G}_t - \frac{I_t}{I_{t-1}} \mathcal{G}'_t \right] + \beta E_t \left[\Phi_{t+1} D_{t+1} \left(\frac{I_{t+1}}{I_t} \right)^2 \mathcal{G}'_{t+1} \right]$$

while the one for capital utilization is given by

$$R^k_t = \mathcal{C}' \left(U_t \right)$$

Concerning the conditions for firms, the marginal cost M_t of producing Y_{jt} is

$$M_t = \left(\frac{R^k_t}{\alpha} \right)^{\alpha} \left(\frac{W_t / A_t}{1 - \alpha} \right)^{1-\alpha}$$

and the capital labor ratio is given by

$$\frac{K_t}{N_t} = \frac{\alpha}{1 - \alpha} \frac{W_t}{R^k_t}$$

The optimality conditions implied by Calvo prices and Calvo wages are, respectively,

$$E_t\left[\sum_{\tau=0}^{\infty}\theta_p^\tau\beta^\tau\frac{\Lambda_{t+\tau}}{P_{t+\tau}}\left(\frac{1}{\mu^p_{t+\tau}}-\frac{1+\mu^p_{t+\tau}}{\mu^p_{t+\tau}}\frac{M_{t+\tau}}{P^*_t}\right)Y_{it+s}\right]=0$$

$$E_t\left[\sum_{\tau=0}^{\infty}\theta_w^\tau\beta^\tau\left(\frac{\Lambda_{t+\tau}}{P_{t+\tau}}\frac{1}{\mu^w_{t+\tau}}-\frac{1+\mu^w_{t+\tau}}{\mu^w_{t+\tau}}\frac{N^\eta_{jt+\tau}}{W^*_t}\right)N_{jt+s}\right]=0$$

where P^*_t and W^*_t are the optimal prices and wages; additionally, it holds

$$Y_{jt}=Y_t\left(\frac{P_{jt}}{P_t}\right)^{-\frac{1+\mu^p_t}{\mu^p_t}}\text{, with } P_t=\left(\int P_{jt}^{1/\mu^p_t}dj\right)^{\mu^p_t}$$

$$N_{jt}=Y_t\left(\frac{W_{jt}}{W_t}\right)^{-\frac{1+\mu^w_t}{\mu^w_t}}\text{, with } W_t=\left(\int W_{jt}^{1/\mu^w_t}dj\right)^{\mu^w_t}$$

8.2 Log-linearized version of the model

The first step is to normalize non-stationary variables. The quantities $C_t, Y_t, K_t, \bar{K}_t, I_t$ are normalized using the following formula

$$\hat{c}_t=\log\frac{C_t}{A_t}-\log\frac{C}{A}$$

where C/A is the value of C_t/A_t in a deterministic version of the model where A_t growths at the previously defined rate Γ. Analogously

$$\hat{y}_t=\log\frac{Y_t}{A_t}-\log\frac{Y}{A},\qquad \hat{k}_t=\log\frac{K_t}{A_t}-\log\frac{C}{A},$$
$$\hat{\bar{k}}_t=\log\frac{\bar{K}_t}{A_t}-\log\frac{\bar{K}}{A},\qquad \hat{i}_t=\log\frac{I_t}{A_t}-\log\frac{I}{A}$$

On the other hand, already stationary variables such as N_t and U_t are simply rewritten as follows

$$n_t=\log N_t-\log N,\qquad u_t=\log U_t-\log U$$

Since nominal variables are non-stationary in prices, it is also necessary to normalize for prices

$$\hat{w}_t = \log \frac{W_t}{A_t P_t} - \log \frac{W}{AP}, \qquad r_t^k = \log \frac{R_t^k}{P_t} - \log \frac{R^k}{P},$$
$$m_t = \log \frac{M_t}{P_t} - \log \frac{M}{P}, \qquad r_t = \log R_t - \log R, \qquad \pi_t = \log \frac{P_t}{P_{t-1}} - \pi$$

Lagrange multipliers are instead defined as

$$\hat{\lambda}_t = \log \Lambda_t A_t - \log \Lambda A, \qquad \hat{\phi}_t = \log \frac{\Phi_t A_t}{P} - \log \frac{\Phi A}{P}$$

Log-linearizing the optimality conditions, the resource constraints and the market clearing conditions, we finally obtain the following system of 14 equations with 14 endogenous variables:

$$\hat{\lambda}_t = \frac{h\beta\Gamma}{(\Gamma - h\beta)(\Gamma - h)} E_t \hat{c}_{t+1} - \frac{\Gamma^2 + h^2\beta}{(\Gamma - h\beta)(\Gamma - h)} \hat{c}_t + \frac{h\Gamma}{(\Gamma - h\beta)(\Gamma - h)} \hat{c}_{t-1} + $$
$$+ \frac{h\beta\Gamma}{(\Gamma - h\beta)(\Gamma - h)} E_t [\Delta a_{t+1}] - \frac{h\Gamma}{(\Gamma - h\beta)(\Gamma - h)} \Delta a_t \tag{9}$$

$$\hat{\lambda}_t = r_t + E_t \left[\hat{\lambda}_{t+1} - \Delta a_{t+1} - \pi_{t+1}\right] \tag{10}$$

$$\hat{\phi}_t = \frac{(1-\delta)\beta}{\Gamma} E_t \left[\hat{\phi}_{t+1} - \Delta a_{t+1}\right] + \left(1 - \frac{(1-\delta)\beta}{\Gamma}\right) E_t \left[\hat{\lambda}_{t+1} - \Delta a_{t+1} + r_{t+1}^k\right] \tag{11}$$

$$\hat{\lambda}_t = \hat{\phi}_t + d_t - \chi\Gamma^2 \left(\hat{i}_t - \hat{i}_{t-1} + \Delta a_t\right) + \beta\chi\Gamma^2 E_t \left[\hat{i}_{t+1} - \hat{i}_t + \Delta a_{t+1}\right] \tag{12}$$

$$r_t^k = \xi u_t \tag{13}$$

$$m_t = \alpha r_t^k + (1-\alpha)\hat{w}_t \tag{14}$$

$$r_t^k = \hat{w}_t - \hat{k}_t + n_t \tag{15}$$

$$\hat{k}_t = u_t + \hat{\bar{k}}_{t-1} - \Delta a_t \tag{16}$$

$$\hat{\bar{k}}_t = \frac{(1-\delta)}{\Gamma} \left(\hat{\bar{k}}_{t-1} - \Delta a_t\right) + \left(1 - \frac{(1-\delta)}{\Gamma}\right) \left(d_t + \hat{i}_t\right) \tag{17}$$

$$\hat{y}_t = \alpha \hat{k}_t + (1-\alpha) n_t \tag{18}$$

$$(1-\psi)\,\hat{y}_t = \frac{C}{Y}\hat{c}_t + \frac{I}{Y}\hat{i}_t + \frac{R^k K}{PY}u_t + g_t \tag{19}$$

$$\pi_t = \beta E_t \pi_{t+1} + \frac{(1-\theta\beta)(1-\theta)}{\theta}m_t + \frac{(1-\theta\beta)(1-\theta)}{\theta}m_t^p \tag{20}$$

$$\begin{aligned}\hat{w} = &\frac{1}{1+\beta}\hat{w}_{t-1} + \frac{\beta}{1+\beta}E_t\hat{w}_{t+1} - \frac{1}{1+\beta}(\pi_t + \Delta a_t) + \frac{\beta}{1+\beta}E_t(\pi_{t+1} + \Delta a_{t+1}) + \\ &- \frac{(1-\theta_w\beta)(1-\theta_w)}{\theta_w(1+\beta)\left(1+\zeta\left(1+\frac{1}{\mu_w}\right)\right)}\left(\hat{w}_t - \zeta n_t + \hat{\lambda}_t\right) + \frac{(1-\theta_w\beta)(1-\theta_w)}{\theta_w(1+\beta)\left(1+\zeta\left(1+\frac{1}{\mu_w}\right)\right)}m_t^w\end{aligned} \tag{21}$$

$$r_t = \rho_r r_{t-1} + (1-\rho_r)(\gamma_\pi \pi_t + \gamma_y \hat{y}_t) + q_t \tag{22}$$

For completeness, we recall the 9 exogenous processes:

$$a_t = x_t + z_t \tag{23}$$

$$\Delta x_t = \rho_x \Delta x_{t-1} + \varepsilon_t \tag{24}$$

$$z_t = \rho_z z_{t-1} + \eta_t \tag{25}$$

$$s_t = x_t + \nu_t \tag{26}$$

$$d_t = \rho_d d_{t-1} + \varepsilon_t^d \tag{27}$$

$$m_t^p = \rho_p m_{t-1}^p + \varepsilon_t^p - \psi_p \varepsilon_{t-1}^p \tag{28}$$

$$m_t^w = \rho_w m_{t-1}^w + \varepsilon_t^w - \psi_p \varepsilon_{t-1}^p \tag{29}$$

$$g_t = \rho_g g_{t-1} + \varepsilon_t^g \tag{30}$$

$$q_t = \rho_q q_{t-1} + \varepsilon_t^q \tag{31}$$

9 Appendix B: Replication

All the results of this paper are replicable using the files available online at

http://leonardorizzo.com/resources/noise_gd.zip

The model is written for a modified version of Dynare 3.065, which is also available in the online resources. After having downloaded and extracted the files, it is sufficient to write in MATLAB the following command to be able to run the model:

`addpath` [directory where the files are extracted]`\dynare`

The model is estimated with the technique explained in Section 5.3; hence, it is possible to decompose the model estimation in two phases.

The first phase concerns the estimation of the model parameters in its perfect information equivalent form. It is possible to perform this passage by using `estimate.mod` inside the "estimation" folder. The mode for the Bayesian estimation is already present. In the data file are present both the baseline data and the Scenario 4 data, which are recognizable because of the suffix `-GK`.

The second phase consists in computing the IRFs starting from the parameters derived in the previous passage. This can be done by using the file `simulate.mod` inside the "simulation" folder. To facilitate the replication of the results, in this file are already present all the parameter estimates presented in the paper, i.e. baseline and scenario 1-4. After simulating the model, it is sufficient to run the file `IRF_convert.m` in order to obtain the impulse response functions and the variance decomposition, which is saved in a file called `vardecGD.txt` .

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