Learning from News

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July, 2023

ABSTRACT: This paper contributes to two strands of business cycle literature—news shocks and bounded rationality— by assessing the empirical importance of TFP news shocks while relaxing the rational expectations assumption. We estimate a medium-scale DSGE model augmented with financial frictions and TFP news shocks under two assumptions of expectation formation: Rational expectations (RE) and adaptive learning (AL). We find that the AL specification improves model fit and the ability of the model to replicate the volatility of aggregate variables. We also show that the AL assumption results in a more persistent consumption response, a deflationary response, and a more persistent response of the credit spread to TFP news shocks, while parameter estimates remain rather robust across the two expectation hypotheses. We also find that the role of pure news shocks (i.e. news featuring purely anticipated shocks as opposed to realized news shocks) increases under AL. In short, AL amplifies the effects of news shocks on the economy through the expectation and credit channels.

JEL classification: D84, E30, E32, E44
Keywords: Adaptive learning, TFP news shocks, Expectation and credit channels, DSGE model, Bayesian estimation

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[*]The authors would like to thank Marco del Negro, Johannes Pfeifer, Yuliya Rychalovska, Mridula Duggal for useful comments. This research was supported by the Spanish Ministry of Science and Innovation under grant number PID2020-118698GB-I00, and by the Basque Government under grant number IT-1461-22. The first author also acknowledges financial support from the Spanish Ministry of Science, Innovation and Universities under scholarship grant FPU17/06331. The authors have no conflict of interest to declare.

1 Introduction

There is a long tradition in macroeconomics (e.g. Pigou 1927) of viewing agents' expectations as a central pilar in explaining macroeconomic fluctuations. Changes in expectations, whether due to news shocks in fundamentals (Beaudry and Portier 2004) or to misperceptions and misinformation (Eusepi and Preston 2011), are viewed as a major source of aggregate fluctuations.

This paper builds on the growing literature that analyzes the expectation-driven business cycle. More precisely, we contribute to (i) the strand of literature that analyzes the empirical importance of TFP news shocks as a major driver of the business cycle; and (ii) to the AL literature that analyzes the consequences of deviating from RE. In principle, the AL and news shocks strands of literature are closely linked since both emphasize the role of expectations in determining aggregate fluctuations. Therefore, it is important to assess how TFP news shocks and bounded rationality interact and whether the role of TFP news shocks in explaining the business cycle is shaped by the way in which agents form their expectations. Interestingly, the two strands of literature (see, among others, Beaudry and Portier 2004; Eusepi and Preston 2011; Milani 2011) are strongly motivated on seminal insights put forward in Pigou (1927). This paper can thus be viewed as a more comprehensive approach to assess Pigou's theory of the business cycle by combining expectation shifts induced by anticipated (news) shocks and bounded rationality.

News shocks

In a seminal paper Beaudry and Portier (2004) suggests a modeling approach for Pigou's theory of the business cycle which suggests that TFP (anticipated) news shocks are a major source of business cycles. Since then, the literature has conducted extensive theoretical and empirical assessments on the importance of so-called news shocks. In particular, Beaudry and Portier (2006) identify two shocks using VAR methods; one shock results in short-run fluctuations in stock prices and is orthogonal to innovations in total factor productivity (TFP). This shock is closely correlated to a second shock that drives long-run movements in TFP. They show that these two shocks anticipate TFP growth by several years. This empirical evidence strongly supports the hypothesis of an expectation-driven business cycle in which the financial sector plays an important role in the transmission mechanism of news shocks to the macroeconomy. Beaudry and Lucke (2010) consider short- and long-run restrictions in their VAR analysis to identify TFP news shocks as an important driver of the business cycle. Barsky and Sims (2011) suggest another strategy for identifying TFP news shocks in a VAR framework. Forni et al. (2014) use a structural factor-augmented VAR approach to assess the importance of news shocks. The last two papers find that TFP news shocks play a smaller role in explaining the business cycle than that found in the previous empirical literature. Moreover, Kurmann and Sims (2021) argue that some conflicting results in the VAR literature can be due to TFP measurement errors.

More recently, Görtz and Tsoukalas (2017) highlight the importance of considering a financial sector (such as the one suggested in Gertler and Kiyotaki 2010, and Gertler and Karadi 2011; from now on GK) in a DSGE framework for assessing the role of TFP news shocks. Moran and Queralto (2018) and Queralto (2020) uncover a close link between TFP and financial shocks. These papers emphasize demand driven factors determining medium-term dynamics in TFP and show that financial shocks impact business innovation activities and thus future TFP. Görtz, Tsoukalas and Zanetti (2022) use VAR methods to show that TFP news is closely connected with credit spread indicators and that the dynamics of financial variables are decisive for the amplification of TFP news shocks in a two-sector (consumption and investment) DSGE model. In sum, this recent literature suggests that financial markets are crucial in determining the transmission mechanism of expected future events and, therefore, in assessing the empirical importance of TFP news shocks.

Bounded rationality matters in the propagation of news shocks

The effects of (news) shocks on the economy are hard to predict in reality. Policy makers, economic pundits, and economic agents in general have limited knowledge about the economic effects of news shocks regarding the impact of a new technology, a vaccine to fight a pandemic flu, an armed conflict, a labor strike, a legislation change in the regulation of a specific market (e.g. a specific policy to reform the labor market), etc. In this scenario, agents have to learn the effects of news shocks and this learning process affects agents' decisions through the expectation channel and then the transmission mechanism of news.

This paper deviates from the rational expectations (RE) hypothesis in assessing the role of TFP news shocks as a source of business cycles. This is in sharp contrast with the theoretical literature on news shocks highlighted above, which builds on the RE hypothesis, thus ignoring the possibility that agents may have misperceptions regarding the effects of news shocks. Under the RE assumption, agents have full knowledge about the underlying model, the values of the structural parameters, and the minimum set of state variables. Consequently, agents understand perfectly well the equilibrium mapping between all state variables (including news shocks) and the endogenous variables. In particular, they know the reduced-form coefficients linking endogenous variables with news shocks.

RE is a strong assumption, and one that may have deeper implications when news shocks are analyzed in a framework that includes further financial markets for several reasons. First, learning induces higher aggregate persistence in the propagation mechanism of shocks, as emphasized in the AL learning literature (among many others, Milani 2007; Eusepi and Preston 2011; Slobodyan and Wouters 2012; Cole 2021; Vázquez and Aguilar 2021), because agents may *adaptively learn* from their previous forecasting errors regarding the prospects for the real economy and the financial markets. Second, financial frictions play an important role in both the transmission mechanism of TFP news shocks and the assessment of their relative importance in DSGE frameworks (Görtz and Tsoukalas 2017; Görtz, Tsoukalas and Zanetti 2022; Herrera and Vázquez 2023). Moreover, financial variables are crucial in assessing the role of TFP news shocks in VAR frameworks (Beaudry and Portier 2006; Barsky and Sims 2011; among others). Third, the high flexibility of financial markets in incorporating information about future expected events is in sharp contrast to the sluggish/persistent behavior of real macro variables. This high flexibility also means that financial markets may often overreact to news in reality. This may be viewed by some as a major deviation from the RE assumption (see, for instance, Shiller 2016, Barberis and Thaler 2003, and references therein). In particular, the AL assumption considered in this paper brings forward a potential different mechanism for financial markets overreacting to news by affecting the credit channel which, in turn, has significant implications in the transmission of news shocks to the macroeconomy as discussed below. Finally, previous studies suggested that RE-DSGE models are misspecified in the expectations formation and deviations from RE improve DSGE models in that dimension (e.g. Slobodyan and Wouters 2012; Cole and Milani 2019). Then, it seems important to assess the role of better specified expectation formations for shocks that are spread through the expectation channel.

Our approach

We introduce bounded-rationality by assuming that agents have a somewhat limited knowledge about the underlying model: They observe the minimum set of state variables as under RE, which includes the exogenous shocks that hit the economy, but they *do not* know the structural parameter values and, consequently, they have to learn the reduced-form coefficients—featuring the equilibrium mapping between state and endogenous variables— over time through a constant-gain AL process.[1]

We consider a standard (medium-scale) New-Keynesian DSGE model enriched with financial frictions à la GK. We take this financial friction modeling approach because it has been shown that the forward-looking behavior of financial intermediaries in determining credit supply and the interest rate on loans provides a sound identification scheme for TFP news shocks (e.g. Görtz and Tsoukalas 2017; Görtz, Tsoukalas and Zanetti 2022). The rest of the model closely follows the Smets and Wouters (2007) model with the addition of only a news component in the non-stationary TFP shock, to consider a parsimonious model. We focus on this type of news shocks for a few reasons. First, as shown by Görtz and Tsoukalas (2017), nominal price and wage rigidities, and financial frictions, relative to a real business cycle model studied by Schmitt-Grohé and Uribe (2012), explain a radically different transmission mechanism of TFP news shocks relative the one associated with a real model. In particular, Görtz and Tsoukalas (2017) show that this mechanism generates a large quantitative role for TFP news shocks in contrast to a very minor role reported in

[1]This approach to AL can be considered as a minor departure from RE. Other approaches, such as the Euler equation approach to AL based on small forecasting models (see, among others, Milani 2007; Slobodyan and Wouters 2012; Vázquez and Aguilar 2021; and references therein) consider larger departures from RE where agents do not know what the state variables are and, in addition, may not observe many of them (for instance, exogenous shocks hitting the aggregate economy).

Schmitt-Grohé and Uribe (2012). Second, we focus on *non-stationary* TFP news shocks to clearly distinghished them from other sources of news shocks having only transitory effects, such as those considered in Schmitt-Grohé and Uribe (2012). Third, many papers in the literature on news shocks have focused on TFP news shocks (e.g. Barsky and Sims 2011, Beaudry and Portier 2006, Forni et al. 2014, Fujiwara et al. 2011, Görtz, Tsoukalas and Zanetti 2022). Therefore, considering only news on TFP eases the comparison with previous findings and focuses the discussion on the differences arising from the two alternative expectation hypotheses. Finally, caution is advised in considering a large number of different news shocks without including additional observables because it may affect their identification.

We estimate alternative model specifications under two expectation hypotheses with Bayesian techniques and using recent US business cycle data.

Main findings

We find that AL improves model performance across two major dimensions: The DSGE model under AL shows a better overall fit in terms of marginal data density and is able to better replicate the size of aggregate fluctuations. This is mainly due to the effects of news shocks on financial variable expectations. Indeed, we find that the transmission mechanisms of news shocks are highly affected if the RE assumption is relaxed through AL. Thus, the responses of consumption are more persistent under AL, while the reaction of the credit spread is smoother and more persistent. The latter feature amplifies the effects on consumption through the credit channel. We also find that the effects of news shocks on inflation are reversed. Thus, TFP news shocks are deflationary under AL rather than inflationary as in the RE specification. Importantly, a deflationary response of TFP news shocks is also found in the VAR analysis carried out in Görtz, Tsoukalas and Zanetti (2022) and Forni et al. (2014) in a factor-augmented VAR framework.[2] These differences in model

[2]Notice that this deflationary response of inflation to news shocks is also found in the RE-DSGE literature, where the effects of news shocks are, in one way or another, amplified through the financial sector. Thus, Görtz, Tsoukalas and Zanetti (2022) amplifies the effects of TFP news shocks by including an investment sector closely linked to financial intermediaries in their two-sector (consumption and investment) DSGE model. Herrera and Vázquez (2023) includes a quality-of-capital news shock in addition to a standard non-stationary TFP news shock, where the former has a distinctive, amplifying impact on the financial market and an anticipated effect on the aggregate production function as TFP news shocks do.

dynamics are quite striking since they are obtained in spite of rather robust parameter estimates being found across the two expectation hypotheses.

We also find that the importance of *pure* news shocks, as defined in Sims (2016) to distinguish them from realized news shocks, increases under AL. This is an especially important result since by definition a pure news shock isolates the effects of a news shock on the aggregate variables prior to the realization of the shock. Hence, the relative importance of pure news shocks is based exclusively on their ability to affect the economy through the expectation channel. Finally, we show that the effects of news shocks on both macroeconomic and financial variables featured by an AL-DSGE model are more in line with those estimated through an empirical Bayesian VAR than those implied by the RE version of the model.

The rest of the paper is structured as follows. Section 2 describes the DSGE model augmented with financial frictions. Section 3 outlines the data set and the parameters calibrated. Section 4 discusses the estimation results, highlighting the different transmission mechanisms found under RE and AL assumptions and focusing on the transmission of news shocks. The same section also assesses the relative importance of pure and realized components of news shocks. Section 5 concludes.

2 The model

This paper considers a medium-scale DSGE model with several sources of rigidity. The model closely follows the New-Keynesian DSGE model suggested in Smets and Wouters (2007), augmented with the financial frictions à la GK. We also consider that the stochastic balanced growth path is affected by non-stationary TFP shocks. Alternative versions of this model have been widely used in recent macro finance literature (see, among others, Gelain and Ilbas 2017, Herrera and Vázquez 2023, Villa 2016).

This section outlines the main features of the model, which are needed to address the main objectives of the paper.[3] The demand side of the model economy is formed by households which

[3] A more comprehensive description of the model is provided in a supplementary appendix.

choose consumption and hours worked and hold riskless assets such as bank deposits and government bonds. A standard Cobb-Douglas production function with labor services and effective capital as inputs characterizes the supply side of the economy. We also consider that both prices and wages are sticky. These nominal rigidities are modeled à la Calvo (1983).

The DSGE model with financial frictions considers that banks lend funds, obtained from household deposits, to non-financial firms (capital-good producers). Hence, banks are the intermediaries that help firms by channeling funds from household deposits to investors. However, banks would like to expand their assets by borrowing additional funds from households indefinitely since the discounted risk premium that they face are always positive by construction. To restrict their ability to do this, a moral hazard problem is introduced. The banks decide whether to divert a fraction of their assets and transfer them to the households to which they belong. The cost for banks of diverting assets is that the depositor can force them into bankruptcy and recover the remaining fraction of assets. Therefore, households only deposit their savings up to the point where the gain of banks from diverting assets is equal to the gain of not doing so. This incentive constraint introduces a credit supply rigidity. It is noteworthy that this rigidity depends on the future expected profitability of the banks since their ability to secure deposits directly depends on their incentives to divert their assets. These incentives are determined by the future expected gains of remaining in the financial intermediation business. Thus, the consideration of a forward-looking financial sector is especially important for investigating the implications of alternative expectation hypotheses.

Next, we describe how TFP (news) shocks are included in the DSGE model, the financial channel through which news shocks are amplified, the representation assumed for TFP news shocks, and the expectation formation process under AL.

Production channel

As is standard in the literature, we consider that intermediate good firms produce goods according to a Cobb-Douglas production function, where the endogenous inputs are capital and labor. This production function is affected by a TFP shock with two components. One of them is a stationary component, and it is assumed that news arises from the non-stationary component.

Formally, the production function is as follows:

$$Y_t = TFP_t \left(K_{t-1}U_t\right)^{\alpha} \left(L_t\right)^{1-\alpha} - \Psi_t \phi_p, \tag{1}$$

where $TFP_t = \epsilon_t^a \Psi_t$, ϵ_t^a is the stationary TFP shock, Ψ_t is the non-stationary TFP shock, and its growth rate is denoted by $\psi_t = ln\left(\frac{\Psi_t}{\Psi_{t-1}}\right)$. K_{t-1} denotes capital stock, U_t is the capital utilization rate, and ϕ_p is the share of fixed costs involved in production.

Financial channel

Capital services firms purchase physical capital at the end of period t at a price Q_t and sell the undepreciated component to capital good producers at the end of period $t+1$ at a price Q_{t+1}. They also decide capital utilization considering the cost of adjustment and the rate at which they rent the installed capital to the intermediate good firms. Capital services firms also finance their purchases of capital at the end of each period with funds from financial intermediaries as described below. Considering that the funding is obtained by issuing claims that are equal to the value of the capital purchased, their price is the same ($Q_t S_t = Q_t K_t$). Thus, the profit maximizing problem of a representative capital services firm is

$$\begin{aligned} &\max_{K_t} \left\{ r_{t+1}^k U_{t+1} K_t - a\left(U_{t+1}\right) K_t + (1-\delta) Q_{t+1} K_t - R_{t+1}^k Q_t S_t \right\} \\ &st. \qquad Q_t S_t = Q_t K_t, \end{aligned}$$

where r_t^k is the rental rate of capital in period t, $a\left(U_t\right)$ is the capital utilization adjustment cost function, and R_t^k is the return of each claim.

The optimal decision obtained from the above problem implies that the optimal demand for capital satisfies

$$R_{t+1}^k = \frac{r_{t+1}^k U_{t+1} - a\left(U_{t+1}\right) + (1-\delta) Q_{t+1}}{Q_t}, \tag{2}$$

which shows that the expected real interest rate on external funds is equal to the marginal return on capital. This optimal condition also implies that TFP news shocks affect the price of capital, Q_t, through general equilibrium (i.e. via the rental rate of capital, capital utilization, and the return of each claim) as further discussed below.

Görtz and Tsoukalas (2017) find that the financial sector is crucial for identifying TFP news shocks. We closely follow the characterization of financial intermediaries used in their paper, which was initially suggested by Gertler and Karadi (2011). A fixed fraction of households includes bankers, who do not supply labor but behave as financial intermediaries. These bankers face a survival probability, θ, and in order to keep their proportion constant further households become bankers in each period. As described above, the financial intermediaries finance the acquisition of physical capital by purchasing claims S_t. These purchases are funded through household liabilities. Hence, the balance sheets of financial intermediaries are

$$Q_t S_t = N_t + B_{t+1},$$

where N_t is the net worth of the bankers, and B_{t+1} represents household deposit liabilities in banks. The return on financial claims is R^k_{t+1} and the cost of liabilities is R_t, so the law of motion of the net worth of intermediaries is given by:

$$N_{t+1} = R^k_{t+1} Q_t S_t - R_t B_{t+1} = \left(R^k_{t+1} - R_t\right) Q_t S_t + R_t N_t.$$

Let $\beta\Lambda_{t+1}$ be the stochastic discount factor of financial intermediaries. Bankers' decisions are endogenously determined in the model through the following problem, in which they maximize future expected terminal wealth:

$$V_t = max\ E_t \sum_{i=0}^{\infty} (1-\theta)\, \theta^i \beta^i \Lambda_{t+1+i} N_{t+1+i} =$$

$$max\ E_t \sum_{i=0}^{\infty} (1-\theta)\, \theta^i \beta^i \Lambda_{t+1+i} \left[\left(R^k_{t+1+i} - R_{t+i}\right) Q_{t+i} S_{t+i} + R_{t+i} N_{t+i}\right].$$

However, a moral hazard issue arises in this maximization problem because $\beta^i \left(R^k_{t+1+i} - R_{t+i}\right) \geq 0$. Otherwise, bankers would not be willing to purchase assets. Therefore, bankers have an incentive to keep borrowing additional funds indefinitely from households. In order to restrict their ability to do this, an enforcement cost is introduced: At the beginning of the period bankers can divert a proportion λ of the funds available. If they do so, the depositors can then only recover a fraction $(1-\lambda)$ of the assets. Hence, for lenders to be willing to supply funds to bankers the following incentive constraint must be satisfied:

$$V_t \geq \lambda Q_t S_t,$$

where V_t, the gain from not diverting assets, can be expressed as

$$V_t = \nu_t Q_t S_t + \eta_t N_t,$$

with

$$\nu_t = E_t \left[(1-\theta) \Lambda_{t+1} \left(R^k_{t+1} - R_t \right) + \beta\theta x_{t,t+1} \nu_{t+1} \right], \tag{3}$$

$$\eta_t = E_t \left[(1-\theta) \Lambda_{t+1} R_t + \beta\theta z_{t,t+1} \eta_{t+1} \right], \tag{4}$$

where ν_t is the expected marginal gain from expanding assets with net worth held constant, η_t is the expected value of one additional future unit of wealth net worth with assets held constant, $x_{t,t+i} = Q_{t+i} S_{t+i} / Q_t S_t$ is the gross growth rate of assets, and $z_{t,t+i} = N_{t+i}/N_t$ is the gross growth rate of net worth.

The incentive constraint holds with equality at equilibrium:

$$Q_t S_t = \frac{\eta_t}{\lambda - \nu_t} N_t = \phi_t N_t, \tag{5}$$

where ϕ_t is the leverage ratio of bankers.

Notice that the leverage ratio and thus the price of capital, Q_t, depend on the forward-looking variables ν_t and η_t determined, subject to a terminal condition, by the expected future stream of the excess return on financial claims, $(1-\theta)\sum_{i=0}^{\infty} E_t \left[(\beta\theta)^i x_{t,t+i} \Lambda_{t+1+i} \left(R^k_{t+1+i} - R_{t+i} \right) \right]$, and the expected future stream of the cost of liabilities, $(1-\theta)\sum_{i=0}^{\infty} E_t \left[(\beta\theta)^i z_{t,t+i} \Lambda_{t+1+i} R_{t+i} \right]$, as can be shown by iterating forward equations (3) and (4). Thus, by affecting the expectations of financial variables through the credit channel, TFP news shocks have a distinctive transmission mechanism in addition to the standard transmission channel via the production function—the real sector of the economy.

Using the incentive constraint, the law of motion of net worth can be rewritten as

$$N_{t+1} = \left[\left(R^k_{t+1} - R_t\right)\phi_t + R_t\right] N_t.$$

Hence, the gross growth rates of assets and net worth can be written as

$$z_{t,t+1} = N_{t+1}/N_t = \left(R^k_{t+1} - R_t\right)\phi_t + R_t, \tag{6}$$

and

$$x_{t,t+1} = Q_{t+1}S_{t+1}/Q_tS_t = \left(\phi_{t+1}/\phi_t\right)\left(N_{t+1}/N_t\right) = \left(\phi_{t+1}/\phi_t\right) z_{t,t+1}. \tag{7}$$

Finally, the law of motion of bankers' net worth is given by the law of motion of the net worth of surviving bankers from the previous period plus the net worth of households that become bankers in this period:

$$\tilde{N}_t = N^s_t + N^n_t, \tag{8}$$

with

$$N^s_t = \theta\left[\left(R^k_{t+1} - R_t\right)\phi_t + R_t\right] N_{t-1}, \tag{9}$$

$$N^n_t = \omega Q_t S_{t-1}, \tag{10}$$

$$\tilde{N}_t = N_t \epsilon^{nw}_t, \tag{11}$$

where ω is the fraction of the total assets that households transfer to new bankers, which enable them to start operating in the banking sector, and the disturbance ϵ^{nw}_t captures exogenous variations in the net worth of bankers due, for instance, to exogenous changes in bank profits.

TFP news shocks

We consider that the growth rate of the non-stationary TFP shock, ψ_t, includes three types of exogenous shock: A standard surprise (unanticipated) shock; a four-quarter ahead news shock; and an eight-quarter ahead news shock. We only consider news in TFP shocks to keep the model as parsimonious as possible and facilitate comparison with previous research, which has mainly focused on this type of news.

The formulation of TFP news shocks follows Schmitt-Grohé and Uribe (2012):[4]

$$\xi_t = \rho \xi_{t-1} + \eta^0_{t|t} + \eta^4_{t|t-4} + \eta^8_{t|t-8}, \tag{12}$$

where $\eta^i_{t,t-i}$ is a TFP news shock which is expected to realize at time t but is anticipated i periods before (i.e. at period $t-i$). Consequently, agents react in advance to future shocks (i.e. agents react to newly obtained information about future shocks even though nothing fundamental has yet changed). More precisely, agents forecast future values of ξ_{t+k} as follows:

$$E_t \xi_{t+k} = \rho E_t \xi_{t+k-1} + \begin{cases} \eta^0_{t+k|t} + \eta^4_{t+k|t-4} + \eta^8_{t+k|t-8}, & for\ k = 0, \\ \eta^4_{t+k|t-4} + \eta^8_{t+k|t-8}, & for\ 0 < k \leq 4, \\ \eta^8_{t+k|t-8}, & for\ 4 < k \leq 8, \\ 0, & for\ k > 8. \end{cases} \tag{13}$$

This specification enables agents to revise their expectations about future exogenous shocks, which provides additional flexibility by allowing for anticipated future shocks that fail to materialize (i.e. a news shock anticipated by eight periods, $\eta^8_{t+k|t-8}$, can be partially or totally reversed by upcoming news, $\eta^4_{t+k|t-4}$ and $\eta^0_{t+k|t}$). It is important to emphasize that the flow of information represented by equations (12)-(13) is the same under the two expectation hypotheses and is thus not altered by the bounded-rationality assumption. The difference arises solely from the different dy-

[4]Like all the lag (and lead) variables of order more than one, auxiliary state variables are considered to keep track of the TFP news in the state-space representation: $ax^1_t = ax^2_{t-1}$; $ax^2_t = ax^3_{t-1}$...

namics of forward looking variables, which results from the different ways of processing information associated with the two alternative expectation hypotheses. In the RE case, agents are perfectly aware what the effects of a news shock on the economy are because they know the unique (RE) equilibrium mapping between the state of the economy (which includes the set of news shocks) and the endogenous variables of the model economy. Therefore, if agents anticipate a TFP shock they will perfectly understand how that shock affects the economy. AL agents still distinguish a news shock in TFP from other type of (unanticipated) shocks but, unlike fully-rational agents, they do not perfectly infer how that TFP news shock affects the economy; instead they have to forecast its effects and learn from their forecast errors.

Expectation formation

The decisions of economic agents depend on their expectations about future (aggregate) macroeconomic variables. News shocks literature typically assumes that such expectations are formed according to the RE hypothesis. Here, we relax the strong informational assumptions imposed by RE and assume that agents form expectations using a perceived law of motion (PLM) of the economy, which is assumed to include the same state variables that appear in the minimum state variable solution of the system under RE. Thus, the departure from RE relies solely on agents' lacking knowledge about the reduced-form model coefficients (Evans and Honkapohja 1999, Marcet and Sargent 1989, Milani 2007). Consequently, economic agents use historical filtered variables and news to infer unknown coefficients over time. They do so by estimating the following PLM:

$$\Gamma_t = a_t + b_t \Omega_t + c_t \varsigma_t^{TFP} + d_t \varsigma_t + \epsilon_t, \tag{14}$$

where Γ_t is a vector containing the set of forward-looking variables of the model at time t, Ω_t is a vector containing the set of endogenous pre-determined state variables, ς_t^{TFP} is a vector including TFP (unanticipated and news) shocks,[5] and ς_t includes all other unanticipated shocks, a_t, b_t, c_t and

[5] As in RE state-space representation, variables lagged by more than one period are included in the state-space form by using auxiliary variables (i.e. x_{t-2} is represented by ax_t^2, being $ax_t^0 = ax_{t-1}^1$; $ax_t^1 = ax_{t-1}^2$ and $ax_t^2 = x_{t-2}$). In our case, we consider 8 auxiliary variables since we assume that they are anticipated by up to 8 periods. All

d_t are conformable matrices of learning coefficients. As mentioned above, agents receive news at time $t-k$ about a shock that materializes at time t. Therefore, the news shock affects the economy from time $t-k$ on. The matrix of coefficients c_t includes the time-varying belief parameters that show how news shocks shape agents' expectations over time. For instance, assume a 1% shock to TFP anticipated 8 quarters in advance. Economic agents know that this shock is going to be realized at time t (unless revisions occur through the standard mechanism described in equation (12)) but can only infer its true effect on the economy through the learning process.

We assume that agents update their beliefs (i.e. the coefficients in matrices a_t, b_t, c_t and d_t) following a constant-gain recursive least square scheme:

$$\Phi_t = \Phi_{t-1} + gR_t^{-1}Z_{t-1}\left(\Gamma_t - \Phi_{t-1}^T Z_{t-1}\right)^T,$$

$$R_t = R_{t-1} + g\left(Z_{t-1}Z_{t-1}^T - R_{t-1}\right),$$

where $\Phi_t = \{a_t, b_t, c_t, d_t\}$ is a matrix containing all belief coefficients and Z_t is a matrix of regressors that includes the minimum set of state variables (i.e. an intercept, all the endogenous state variables, Ω_t, and both unanticipated and news shocks).[6]

3 Data and estimation

We estimate the model using Bayesian techniques by considering a data set with US data for nine macroeconomic variables: Output growth, consumption growth, investment growth, wage growth, hours worked, inflation, the nominal interest rate, the GZ spread suggested in Gilchrist and Zakrajšek (2012), and the growth rate of the net worth of banks. The set of observables is the same as that in Smets and Wouters (2007) with the addition of the GZ spread and the net worth

those auxiliary variables are contained in the vector ς_t^{TFP} as in Cole (2021).

[6]Notice that the RE equilibrium mapping does not contain an intercept, but it captures the uncertainty about the balanced-growth path under AL.

of banks, which seek to provide information about financial market dynamics.[7] Moreover, given that the sample period considered in the estimation includes the Great Recession, which started around 2008, we have replaced those values of the federal funds rate that reach the zero lower bound by the shadow rate constructed by Wu and Xia (2016).[8] The sample considered covers the period 1987q1-2018q4, where the starting quarter is determined by data availability for all the time series considered in the empirical analysis. All the time series used in the estimation procedure are transformed into (growth rate or log) deviations from their respective means, so the measurement equations are straightforward. Thus, sample means and long-term growth rates are removed because low frequencies may affect the estimation of business cycle dynamics.[9] We also consider a presample of 16 quarters in order to avoid the effects of estimated news that is assumed to be observed before the sample period begins.

Some of the structural parameters are calibrated due to lack of identifiability. Thus, the discount factor β is set at 0.99, which implies a quarterly real interest rate of one percent. Both wage and price markup are assumed to be 0.2. The quarterly depreciation rate is 0.025 and the share of government spending is assumed to be 0.2. The parameters associated with the financial sector, such as the time survival rate of bankers, the steady-state fraction of funds given to new bankers, and the fraction of funds that bankers may divert are set to achieve the same steady state values as in Görtz and Tsoukalas (2017).

4 Estimation results

This section discusses the estimation results from the Bayesian estimation of the medium-scale DSGE model under the two alternative expectation hypotheses considered.

[7]The net worth observable is the total equity capital for US commercial banks considered in Görtz and Tsoukalas (2017). Moreover, the GZ spread is also included in the set of observables considered in Görtz, Tsoukalas and Zanetti (2022).

[8]Recent papers (e.g. Aguirre and Vázquez 2020, Wu and Zhang 2019) use the shadow rate instead of the federal funds rate in the estimation of DSGE models.

[9]Del Negro et al. (2007) suggest this low frequency misspecification issue and several other papers in the related literature also follow this data treatment (e.g. Christiano et al. 2014, Görtz and Tsoukalas 2017).

4.1 Model fit

In this section we analyze the differences that arise in model fit when AL is used instead of RE. Table 1 shows a few alternative measures of model fit. The upper panel of Table 1 shows the (log) marginal data density (MDD) associated with each expectation hypothesis. The AL specification clearly outperforms the RE specification by roughly 20 points. This large improvement in model fit not only points to the existence of substantial differences between the two specifications but also suggests that AL provides an improved framework for assessing the role of news shocks in DSGE models.

The middle-left panel of Table 1 shows the RMSE statistics with respect to actual data for each expectation hypothesis (i.e. these statistics are computed across the differences between the one-step-ahead forecasts and the corresponding actual data). These RMSE statistics show that the AL model performs better for most of the observable variables, especially for consumption growth and hours worked. Moreover, the RMSE statistics of inflation and the growth rates of consumption and investment for the two specifications are lower than those associated with the Survey of Professional Forecasters (SPF).[10]

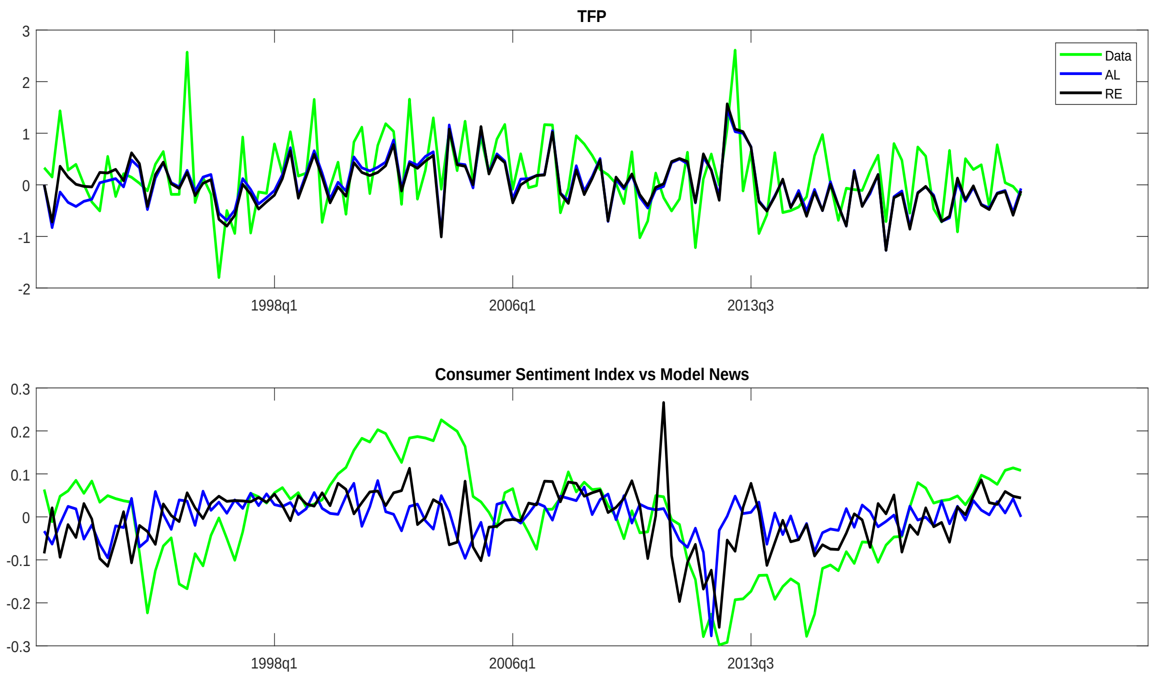
[10] This survey is conducted by the Federal Reserve Bank of Philadelphia and is publicly available on their website.

Table 1: Model fit

	RE	AL				
MDD	-856.37	-837.35				
	RMSE w.r.t. actual data			Standard deviation		
	RE	AL	SPF	Actual	RE	AL
Output growth	0.46	0.43		0.59	0.80	0.69
Consumption growth	0.36	0.27	0.49	0.55	0.72	0.64
Investment growth	0.85	0.84	1.49	1.86	3.20	2.94
Hours	0.34	0.28		4.44	2.53	2.29
Wage growth	0.90	0.88		0.90	0.98	0.93
Inflation	0.15	0.15	0.21	0.21	0.24	0.24
Spread	0.13	0.12		0.26	0.41	0.38
Interest rate	0.07	0.06		0.68	0.33	0.28
Net worth growth	1.96	2.52		1.57	7.73	6.57
	Autocorrelation			Correl. with output growth		
	Actual	RE	AL	Actual	RE	AL
Output growth	0.27	0.49	0.46	1	1	1
Consumption growth	0.36	0.54	0.57	0.68	0.65	0.62
Investment growth	0.70	0.71	0.71	0.66	0.60	0.56
Hours	0.99	0.95	0.97	0.24	0.35	0.31
Wage growth	-0.19	0.08	0.06	-0.04	0.18	0.19
Inflation	0.46	0.39	0.57	0.07	-0.06	-0.12
Spread	0.87	0.83	0.84	-0.64	-0.32	-0.33
Interest rate	0.99	0.93	0.95	0.18	0.12	0.06
Net worth growth	0.20	-0.01	0.02	0.03	0.26	0.23

The middle-right and bottom panels of Table 1 show some significant actual and model-implied second moment statistics: The standard deviation, the first-order autocorrelation, and the correlation with output growth for each observable variable. Regarding the correlations (bottom panels), the two models perform similarly. Nevertheless, in line with actual data the AL specification results in a less volatile business cycle than the model under RE.

Figure 1: TFP measures, Consumer Sentiment Index, and Model News



Notes: The actual TFP measure considered in the top graph is the growth rate of the utilization-adjusted aggregate TFP, described in Fernald (2014). The Consumer Sentiment Index takes the value 100.2 at 1998:q4. We have rescaled the Consumer Sentiment Index in order to have a measure comparable with the model news shocks shown in the bottom graph. Thus, the Consumer Sentiment Index is divided by 100, and then 1 is substracted from the previous rescaling. In this way, the resulting Consumer Sentiment Index moves around zero. The model-based news shocks is the sum of the estimated 4- and 8-quarter TFP news (i.e. $\eta^4_{t+k|t-4} + \eta^8_{t+k|t-8}$).

As is standard in the related literature, there is no explicit TFM measure in the set of observables used in the estimation of the DSGE model. Nevertheless, the estimated TFP growth rate measures obtained from the DSGE model under the two expectations hypotheses exhibit similar patterns as the first-difference of the (log of the) utilization-adjusted aggregate TFP described in Fernald (2014), as shown in the top graph of Figure 1. Thus, the two estimated model-based TFP (displayed in growth rates) are almost identical, while they show sizeable contemporaneous correlations with the growth rate of the utilization-adjusted aggregate TFP of 0.57 and 0.55 for the AL and RE models, respectively.

The bottom-graph in Figure 1 shows the Consumer Sentiment Index published by the University of Michigan,[11] together with the estimated model-based news shocks, which are computed for each expectation assumption as the sum of the estimated 4- and 8-quarter TFP news (i.e. $\eta^4_{t|t-4} + \eta^8_{t|t-8}$). We ran a regression of the Consumer Sentiment Index on a constant, its own lag, the output growth rate and the corresponding model-based news shocks estimated under each expectation hypothesis. The estimation results from this regression analysis shows that the estimated TFP-news shocks obtained under AL have explanatory power in this regression (the p-value of the corresponding coefficient is 0.039), whereas their RE counterparts do not (the p-value of the corresponding coefficient is 0.154). These results suggest that our estimated AL model news are linked to an important leading economic indicator as the Consumer Sentiment index, which provide external validity to the AL model with TFP news.

In sum, our empirical results clearly indicate that introducing bounded rationality through AL improves model fit along a few important dimensions.

4.2 Parameter estimates

This section discusses the estimates of structural parameters, including those that characterize TFP news shock processes. Interestingly, Table 2 shows that the estimation results are rather robust across the two alternative expectation hypotheses.[12] Indeed, the highest posterior density intervals associated with the estimated parameters under the two expectation assumptions largely overlap. The constant gain learning parameter points to the importance of the updating of beliefs in the AL process. The posterior mean estimate of this parameter is 0.016, which lies a bit below from the middle range of estimates (0.01 0.05) found in the related literature surveyed by Evans and McGough (2020).

These robust estimates, together with the different transmission mechanisms of TFP news shocks resulting from the two expectation hypotheses as discussed below in Section 4.3, underline

[11] University of Michigan: Consumer Sentiment Index, retrieved from https://data.sca.isr.umich.edu/data-archive/mine.php, June 18, 2023.

[12] In order to save space, we do not report here the estimated parameters describing the exogenous shock processes other than those associated with TFP shocks. The full set of parameter estimates are available from the authors upon request.

the importance of belief formation in the transmission of news shocks.

Table 2: Parameter estimates

Parameter	Prior distribution		Posterior Mean	
	Type	Mean/Std	RE	AL
Structural parameters				
Investment adjustment cost	Normal	4/1.5	1.87 [0.92,2.81]	1.71 [1.13, 2.42]
Habit formation	Normal	0.7/0.1	0.62 [0.50,0.75]	0.59 [0.52,0.66]
Calvo probability for wages	Beta	0.5/0.1	0.81 [0.76,0.89]	0.82 [0.78,0.87]
Calvo probability for prices	Beta	0.5/0.1	0.94 [0.93,0.95]	0.949 [0.94,0.95]
Indexation of past inflation in wages	Beta	0.5/0.15	0.39 [0.16,0.61]	0.26 [0.09,0.44]
Indexation of past inflation in inflation	Beta	0.5/0.15	0.19 [0.07,0.31]	0.18 [0.07,0.30]
Utilization adjustment cost	Gamma	0.5/0.15	0.86 [0.77,0.95]	0.89 [0.83,0.96]
Fixed cost in production	Normal	1.25/0.125	1.59 [1.44,1.74]	1.57 [1.42,1.71]
Capital share in production	Normal	0.3/0.05	0.16 [0.12,0.19]	0.14 [0.11,0.16]
Constant gain learning	Gamma	0.05/0.03	-	0.016 [0.01,0.03]
Monetary policy parameters				
Interest rate smoothing	Beta	0.75/0.1	0.77 [0.73,0.82]	0.78 [0.73,0.82]
Response to inflation	Normal	1.5/0.25	1.21 [1.0,1.44]	1.002 [1,1.01]
Response to output	Normal	0.125/0.05	0.09 [0.07,0.11]	0.08 [0.06,0.09]
Response to output growth	Normal	0.125/0.05	0.23 [0.16,0.30]	0.19 [0.12,0.27]
Non-stationary TFP shocks				
Persistence of TFP	Beta	0.5/0.2	0.92 [0.89, 0.96]	0.94 [0.92 , 0.97]
Std of unanticipated TFP shock	Gamma	0.1/2	0.06 [0.05, 0.08]	0.05 [0.04 , 0.06]
Std of TFP news shock - 4 quarter ahead	Gamma	0.1/2	0.05 [0.03, 0.06]	0.04 [0.03 , 0.05]
Std of TFP news shock - 8 quarter ahead	Gamma	0.1/2	0.08 [0.06 , 0.09]	0.06 [0.04 , 0.08]

4.3 News shock transmission mechanism

This section shows the major differences in the transmission mechanisms of TFP news shocks implied by RE and AL. Figure 1 shows the impulse-response functions (IRFs) of the observable variables for a one-percent 4-quarter ahead news shock.[13] The blue line shows the median pseudo-IRFs of the AL model over the sample.[14] The black line shows the IRFs of the RE model. Dashed

[13]The IRFs associated with an 8-quarter ahead TFP news shocks are more similar for the two expectation assumptions. Hence, for the sake of brevity, we have decided to only show the IRFs for 4-quarter ahead TFP news shocks.

[14]To plot the IRFs of the AL model, we consider that the PLM are fixed at the values in which the shock is realized.

lines show the associated 16%-84% posterior bands.[15]

The first two rows of graphs in Figure 1 show the IRFs for output, investment, consumption, and labor (hours worked). They clearly show the high persistence of macroeconomic variables to news shocks under the two expectation hypotheses. The median IRFs show that the effect of TFP news shocks on these real macroeconomic variables is larger under AL over most IRF horizons, but the posterior bands associated with each expectation hypothesis largely overlap. The exception to this pattern shows up for consumption, where its median IRF under RE lies well below the lower bound of the AL posterior band across all horizons. This feature highlights that the effects of TFP news shocks on consumption are larger and much more persistent under AL. This distinctive feature suggests that AL mainly amplifies the transmission mechanism of TFP news shocks in consumption through beliefs that feature bounded rationality. Notice also that the news shock is able to produce a positive comovement between output and hours worked under the two expectations hypotheses in line with the findings in Görtz and Tsoukalas (2017) and Görtz, Gunn and Lubik (2022), but in contrast to the negative comovement found by Barsky and Sims (2011) and Forni et al. (2014) using alternative approaches in identifying news shocks.[16]

The third row of IRFs in Figure 1 shows the responses of inflation and the nominal interest rate to a TFP news shock. The nominal interest rate seems to react similarly to news shocks under RE and AL, but inflation dynamics are dramatically different because news shocks are inflationary under RE but have a negative effect on inflation under AL. A positive TFP news shock acts as an aggregate supply shock under AL, because it leads to an expansionary response in output and a fall in inflation. This implication of the AL model is aligned with conventional wisdom of interpreting TFP news shocks as supply shocks. This deflationary response of TFP news shocks under AL is

[15] As in Slobodyan and Wouters (2012) and Aguilar and Vázquez (2021), we have also computed the time-varying AL pseudo-IRF, which are computed using the fixed belief coefficients obtained using the information available at each point in time, but then ignoring the updating of those beliefs driven by the shock. Since these time-varing IRFs look very similar across sample periods we do not to report them here, but they are available in a supplementary appendix.

[16] Kurmann and Sims (2021) shed some light on this debate. They argue that TFP measurement errors are likely to be confounded by business cycle fluctuations, which might be problematic with the zero-impact restriction imposed in many VAR approaches to identify TFP news shocks. Kurmann and Sims (2021) suggest to identify news shocks by maximizing the forecast error variance of TFP at a long finite horizon, as we do in the empirical VAR analysis carried out below, but without imposing a zero-impact restriction on TFP.

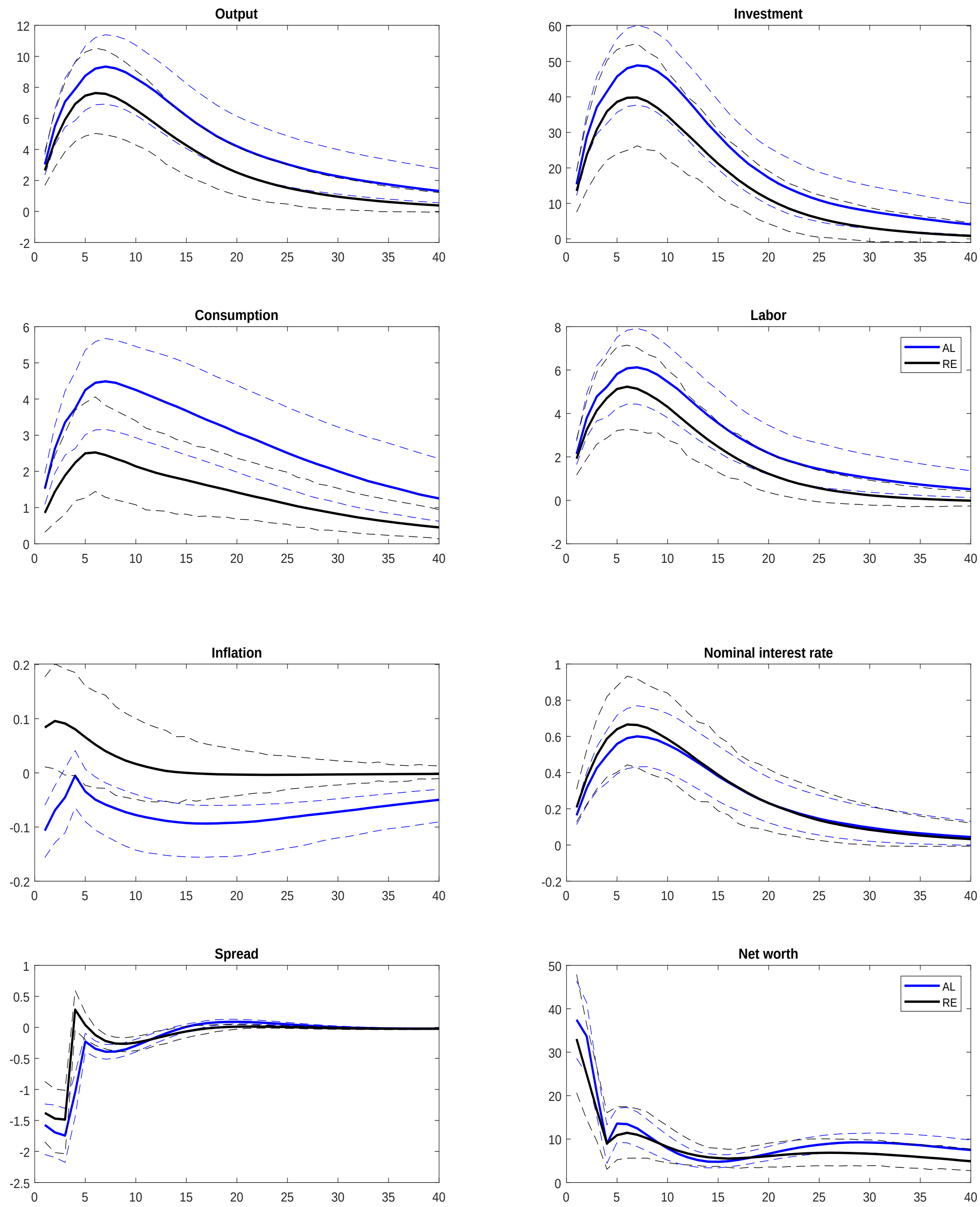
also in line with Barsky and Sims (2011), Forni et al. (2014) and Görtz, Tsoukalas and Zanetti (2022), among others, who use VAR frameworks. Moreover, as pointed out above, this deflationary response to news shocks is aligned with findings in the related DSGE literature (Görtz, Tsoukalas and Zanetti 2022; Herrera and Vázquez 2023), where the effects of news shocks are somewhat amplified through the financial sector as discussed below.

The last row of graphs in Figure 1 shows the IRFs of the two observable financial variables used in the estimation procedure for a TFP news shock. At first sight, these IRFs show rather similar dynamics under RE and AL. There are, however, substantial differences in the medium-term spread dynamics: The credit spread response is clearly more persistent in the AL model than in the RE model. Thus, the response of the credit spread under RE returns quickly to the steady state in less than a year, while the negative credit response under AL remains for more than three years. This different response of the credit spread to news shocks under the two expectation hypotheses has important implications for the role played by the credit spread in the transmission mechanism of news shocks. Thus, the short-lived responses of the credit spread to news under RE downplay the transmission mechanism of news via the financial market (i.e the credit channel) to the real economy. In contrast, the more persistent responses of the credit spread to news under AL largely amplifies the effects of news shocks on consumption through the credit channel. These more persistent credit spread responses of the AL model to news shocks are again in line with the VAR findings reported in Görtz, Tsoukalas and Zanetti (2022), where news shocks are also associated with persistent fluctuations in credit spreads. These IRFs are also somewhat in line with the findings in Beaudry and Portier (2006), who identify a shock that anticipates future fluctuations of TFP and triggers contemporaneous fluctuations in financial markets.

Notice also that in addition to the high persistence of macroeconomic variables to news shocks across the two expectations hypotheses discussed above, the relative lower persistence effects of new shocks on financial variables means that financial variables portend the future economic outlook, which is consistent with the findings in the literature.[17]

[17] Many studies have provided evidence on the predictability of future economic activity using financial variables. Among many others, Gilchrist et al. (2009) finds that corporate bond spreads help to predict the evolution of output,

Figure 2: Impulse-response functions



employment, and industrial output. Espinoza et al. (2012) shows that shocks to financial variables influence real activity. Gilchrist and Zakrajšek (2012) suggests a corporate bond credit spread index that predicts future economic activity. More recently, Aguilar and Vázquez (2021) and Vázquez and Aguilar (2021) show that the term spread provides helpful information in characterizing aggregate dynamics in DSGE models under AL.

Notes: The blue (black) solid line show the median of the responses obtained from the posterior distribution of the model under AL (RE), while dashed lines show the corresponding 16%-84% posterior bands. The units of the vertical axes are percentage deviations from the steady state.

4.4 Beliefs

Previous sections document both the robustness of the structural parameter estimates and the differences in the transmission mechanisms of TFP news shocks across the two specifications concerning expectations. Clearly suggesting that these differences are due mainly to alternative assumptions on expectation formation and, in particular, how expectation formation affects the transmission mechanism of TFP news shocks through the credit channel.

This section shows how TFP news shocks shape the PLM of several forward-looking variables under the two expectation specifications studied. More precisely, Figure 3 shows changes in the coefficients of auxiliary variables that keep track of TFP news shocks until they are realized.[18] The blue (black) lines represent belief coefficients under AL (RE), while the solid (dashed) lines show belief coefficients associated with 8-quarter (4-quarter) TFP news shocks. RE beliefs are constant by construction while AL are time-varying due to the belief updating process. The belief coefficients for news shocks associated with the PLM of consumption are relatively similar across the two alternative hypotheses on expectations. The belief coefficients for news shocks associated with investment are much smaller, and more similar across news shocks, under AL.

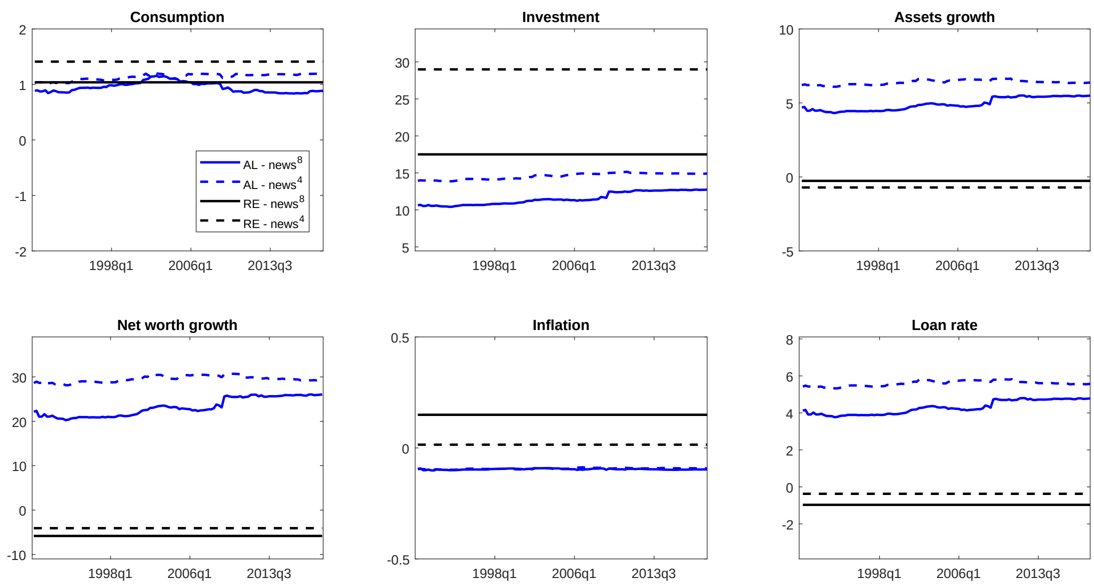
The belief coefficients for news shocks on financial variables (i.e. the growth rates of the value of assets, net worth, and the interest rate on loans) are positive under AL, which is in contrast to the negative RE belief coefficients. Moreover, these belief coefficients are much larger, in absolute terms, under AL showing a sort of overreaction of financial markets to news much in line with the irrational exhuberance hypothesis (Shiller 2016). These larger belief coefficients for news shocks on financial variables further explain the amplified power of the credit channel under AL

[18] Here, for the sake of clarity, we show only parameters associated with the auxiliary variables at time $t-4$ and $t-8$ (i.e. the parameters associated with the anticipation horizon of each news shock). The learning coefficients associated with the rest of the auxiliary variables are consistent with those shown in Figure 3 and are available upon request.

discussed above. These results also shed light on the ability of financial variables (and the credit spread in particular) to anticipate the evolution of real macroeconomic aggregates under AL. When agents are assumed to be bounded rational the transmission mechanism of the TFP news shocks is mainly triggered through the credit channel as shown by the larger effects on financial variable expectations, and a reduced impact on real variable (consumption and investment) expectations.

Finally, note also the negative (positive) response of inflation expectations to TFP news shocks under AL (RE), which is consistent with the IRF analysis discussed above showing a distinctive deflationary response to TFP news shocks under AL.

Figure 3: Belief coefficients associated with TFP news



Notes: The blue (black) lines represent belief coefficients under AL (RE), while the solid (dashed) lines show belief coefficients associated with 8-quarter (4-quarter) TFP news shocks.

4.5 Variance decomposition and pure news

Previous sections discuss at length the substantial differences in the transmission mechanisms of news shocks when one departs from the RE assumption. This section analyzes the implications of considering AL rather than RE in assessing the relative contribution of TFP news shocks in explaining the business cycle. Table 3 shows the unconditional variance decomposition for each model specification. The top panel shows the variance decomposition for the RE model while the bottom panel shows the one associated with AL. The arrows and the numbers in some entries in the bottom panel highlight the direction and the quantity of the change in the variance decomposition, respectively, when one shifts from RE to AL. Two major differences are noteworthy. First, we find an increase in the relative empirical importance of both the risk premium shock and the net worth shock. This clearly suggests that the AL specification amplifies the transmission mechanism of the (forward-looking) financial sector and, consequently, these shocks become more significant in explaining aggregate fluctuations. Second, we find that *unanticipated* monetary and non-stationary TFP shocks become less significant in explaining fluctuations in real macroeconomic variables under AL.

Table 3: Unconditional variance decomposition

	Output	Invest.	Cons.	Inflation	Wage	Interest rate	Labor	Net worth	Spread
Rational Expectations									
Stat. TFP	0	0	1	9	2	4	24	1	1
Risk premium	10	2	69	0	4	4	11	3	2
Public spending	3	1	2	0	1	1	3	1	0
IST	2	4	1	0	1	1	2	13	4
Monetary policy	12	11	6	0	4	25	9	24	8
Price markup	2	1	1	84	4	6	1	3	2
Wage markup	0	0	0	4	73	2	0	1	1
Net worth	1	3	0	0	0	1	1	19	25
Non-stat. TFP	22	29	4	0	0	14	17	22	20
News 4	14	15	4	0	2	11	10	4	9
News 8	34	33	13	2	10	31	21	8	28
Adaptive Learning									
	Output	Invest.	Cons.	Inflation	Wage	Interest rate	Labor	Net worth	Spread
Stat. TFP	0	1	0	6	1	3	21	2	1
Risk Premium	23(↑13)	5	74	2	0	23(↑19)	26(↑15)	4	3
Public spending	3	0	2	0	0	3	3	0	2
IST	8	9	3	0	0	26(↑25)	6	19	12
Monetary policy	1(↓11)	2	0	0	3	1(↓24)	1	12(↓12)	29(↑21)
Price markup	1	2	0	70(↓14)	4	5	1	2	2
Wage markup	1	4	0	2	0	1	1	29(↑28)	5
Net worth	18(↑17)	25(↑22)	5	1	0	8	13(↑12)	13	16
Non-stat. TFP	1(↓21)	4(↓25)	0	17(↑17)	87(↑87)	10	1(↓16)	7(↓15)	4(↓16)
News 4	18	21	6	1	1	9	11	5	12
News 8	26	26	10	1	2	12(↓19)	16	6	14(↓14)

Regarding the importance of TFP news shocks as a source of aggregate fluctuations, the unconditional variance decomposition shows that the sum of the two TFP news shocks considered explains a large proportion, roughly 46%, of the output and investment fluctuations under the two expectation specifications, whereas the contributions of TFP news in explaining labor and consumption fluctuations are more modest (at around 30% and 17%, respectively). Interestingly, the contribution of 8-quarter ahead news shocks is larger than that of 4-quarter ahead shocks under the two specifications, mainly due to the larger size of the former, but bounded rationality seems somewhat to shorten the anticipation period due to the larger belief coefficients in the PLM of financial variables associated with the latter.

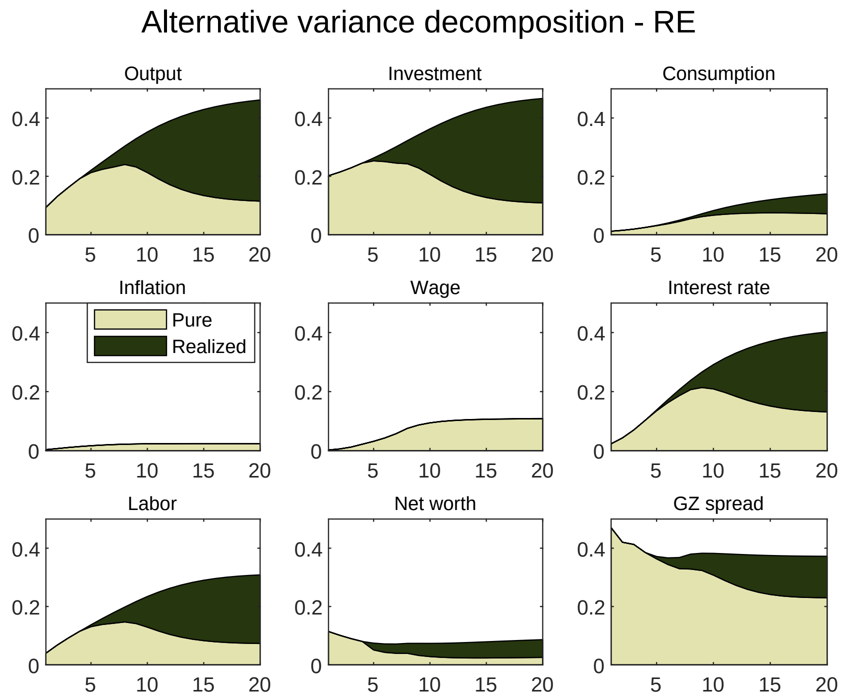
The decomposition of news shocks into pure and realized shocks might also be important, as emphasized by Sims (2016). A pure news shock captures the effects of a news shock on the aggregate variables prior to the realization of the shock, but its effect once realized is not conceptually different from that of an unanticipated shock. Indeed, in analyzing the importance of news shocks we are interested in their ability to shape agents' expectations as drivers of aggregate fluctuations. Since we are analyzing the consequences of a deviation from the RE hypothesis, it is important to assess the extent to which the contribution of pure news shocks in explaining the business cycle is affected by considering some form of bounded rationality. Figure 4 shows the sum of the proportions in the variance decomposition explained by the 4- and 8-quarter ahead news shocks considering RE (upper-panel) and AL (bottom-panel) for alternative (from 1- to 20-quarter) forecasting horizons. Following Barsky et al. (2015) and Sims (2016), the variance decomposition is further decomposed into two areas that represent pure news (yellow) and realized news shocks (dark). The effect of a pure news shock is computed by subtracting the effect of an unanticipated shock at a particular anticipation horizon from the total effect of a news shock so as to leave the relevant exogenous variable unchanged.[19]

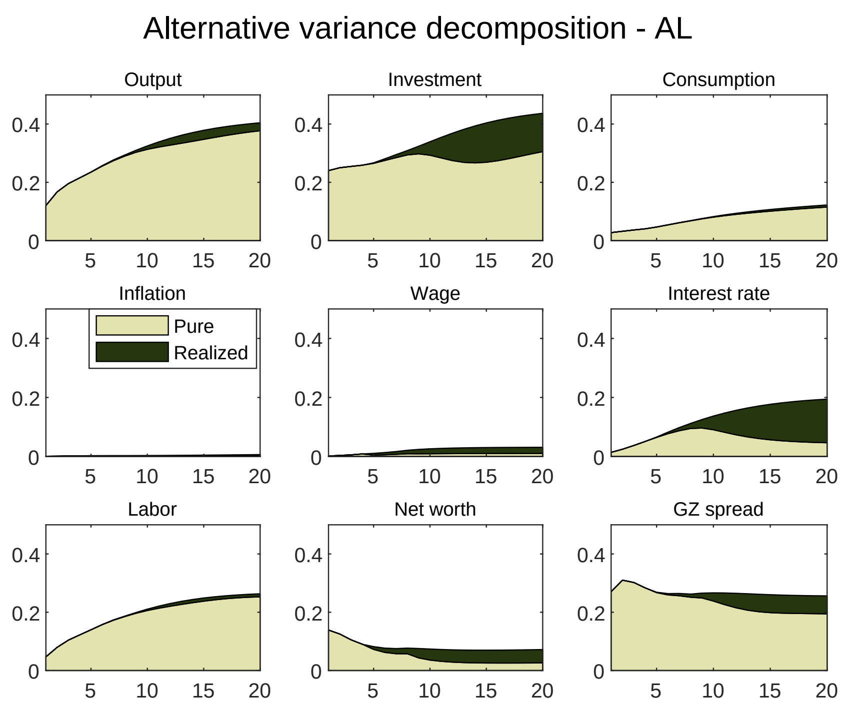
There is a noteworthy difference between the RE and AL models: The proportion in the variance decomposition attributed to pure news shocks in the AL model is much larger than in RE. These findings are clearly in contrast with Sims (2016), who finds that in the DSGE model considered in Schmitt-Grohé and Uribe (2012) (i.e. a non-financial RE-DSGE model) the proportion of pure news shocks is rather small.[20]

[19] As explained in Sims (2016), this decomposition does not deliver separate percentages of pure and realized news that add up to the total proportion explained by the total news shock. Therefore, for illustrative purposes we add up both (pure and realized news) proportions and compute their pseudo-proportion in the actual total news proportion shown in Figure 4 as follows: $\frac{\epsilon^{pure}}{\epsilon^{pure}+\epsilon^{realized}}\epsilon^{total}$, and $\frac{\epsilon^{realized}}{\epsilon^{pure}+\epsilon^{realized}}\epsilon^{total}$.

[20] The high significance of pure news shocks found is also in line with Herrera and Vázquez (2023), who consider a similar DSGE model with financial frictions à la GK but under RE. These two papers introduce two alternative specifications that boost the importance of pure news shocks by amplifying the transmission mechanism of (TFP) news shocks through the financial sector. Thus, in this paper, the departure from RE amplifies the responses of the macroeconomy to TFP news shocks, while the quality-of-capital news shocks considered in Herrera and Vázquez (2023) have a similar amplifying impact through the financial market. Altogether, these papers emphasize the importance of including an explicit financial sector in DSGE modeling to properly identify the transmission mechanisms of news shocks.

Figure 4: Decomposition of news in pure and realized



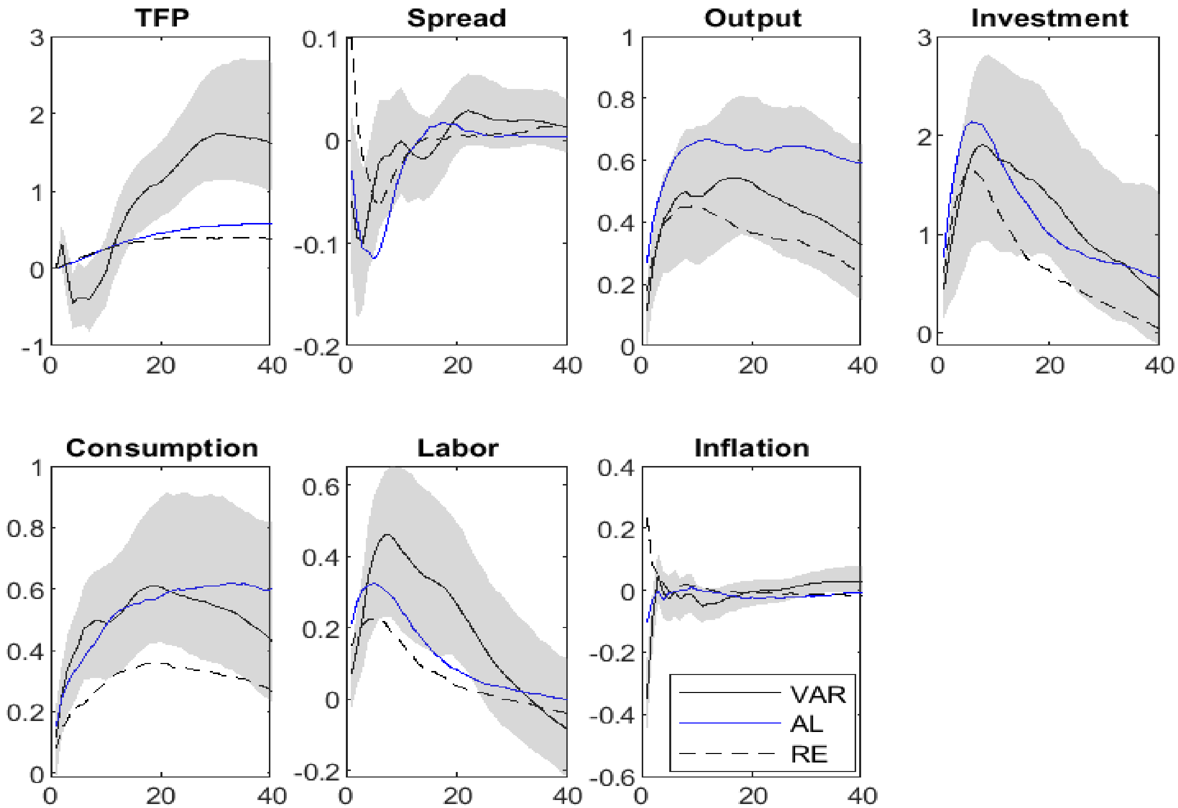


4.6 VAR evidence

In previous sections we show the differences in model fit, empirical importance and transmission mechanism of news shocks under RE and AL and provided evidence on the better performance of the latter assumption. In this section we focus on the ability of the DSGE model to match empirical responses that we estimate through a VAR model. Following closely Barsky et al. (2015) and Görtz, Tsoukalas and Zanetti (2022), we compare the empirical IRF from the VAR model with those estimated with identical VAR specification on artificial data samples generated by each (RE and AL) version of the DSGE model. All estimations consider a seven-variable empirical VAR model using five lags with a Minnesota prior. In contrast to the observables used in the estimation of the alternative versions of the DSGE model, all time series considered in the VAR enter in (log) levels as is standard practice in the empirical VAR literature. Moreover, as an observable measure of TFP we use the utilization-adjusted aggregate TFP, described in Fernald (2014) in all VARs estimated (either with actual or simulated data). We follow the identification scheme suggested in Francis et al. (2014) to identify the TFP news shock from the VAR model.[21] This identification method estimates the TFP news shock by (i) maximizing the variance of TFP at a specific long but finite horizon (we set the long horizon to 40 quarters), and (ii) imposing a zero impact restriction on TFP conditional on the news shock.

[21] The results are robust to other identification strategies that are also commonly used in news literature (e.g. long- and short-run restrictions and Barsky and Sims (2011) identification method).

Figure 5: Comparison of empirical and DSGE-simulated VAR responses to a TFP news shock



Notes: The black line shows the empirical responses to a TFP news shock, while shaded-gray areas show their corresponding 16%-84% posterior bands. The blue line (dashed line) shows the median of the responses obtained from the estimation of the VAR across 500 simulated time series resulting from the AL (RE) DSGE model. The units of the vertical axes are percentage deviations from the steady state.

Figure 5 shows the empirical responses of the seven variables to a TFP news shock (black line), their 16%-84% posterior bands (shaded-gray areas), and the median of the responses obtained from the estimation of the VAR across 500 simulated time series resulting from the AL (blue line) and the RE (dashed line) versions of the DSGE model. The empirical IRFs from the VAR are largely similar to those reported in Görtz, Tsoukalas and Zanetti (2022):[22] Namely, (i) the TFP confidence band only excludes the zero value after roughly three years; (ii) the TFP news shock rise output, consumption, investment, and hours significantly on impact, and they exhibit hump-

[22]In spite of considering a different sample period—we use the same sample period considered in the estimation of the DSGE model— and including investment (instead of S&P 500).

shaped dynamics; (iii) the spread decreases, which is in line with an economic boom favored by credit expansion; and (iv) a short-lived fall in inflation. Many of these features are well captured, at least qualitatively, by the two versions of the DSGE model, but there are a few remarkable differences. First, the median IRFs from the DSGE model under AL lie inside the confidence bands of the empirical VAR for all variables and across most forecast horizons. Meanwhile, the IRFs corresponding to the RE version of the DSGE model have trouble in capturing the short-run responses of many variables featured by the empirical VAR, such as output, investment, spread, and inflation. In particular, as pointed out above, TFP news shocks are inflationary under RE but have a negative effect on inflation both in the empirical VAR and in the DSGE under AL. Second, the medium- and long-term responses of model-based TFP are significantly smaller, but consistent with those estimated by Forni et al. (2014) using a factor-augmented VAR approach to identify TFP news shocks.

5 Conclusions

This paper builds on the growing literature that analyzes the expectation-driven business cycle by (i) analyzing the empirical importance of TFP news shocks as one of the main driving forces of the business cycle; and (ii) assessing the consequences of deviating from the rational expectations (RE) assumption through adaptive learning (AL). In principle, the AL and news shocks strands of literature are closely related since both try to assess how expectations may affect the aggregate economy. Therefore, it seems crucial to investigate how the role of news shocks in explaining the business cycle is affected by the way in which agents form their expectations. All empirical analyses in news shock literature to date have been carried out through the prism of the RE assumption, but here we consider AL instead. This introduces distinctive dynamics into the model through the effects of news shocks on the expectation channel, which substantially change their transition mechanism and their relative empirical significance.

We find that a departure from the RE assumption via AL improves model performance. The

AL specification provides a better overall fit in terms of marginal data density and also better replicates the size of aggregate fluctuations. We show that these findings are mainly due to the impact of TFP news shocks on financial expectations under AL, while the estimates of structural parameters remain fairly robust under the two specifications concerning expectations. We also find that introducing a source of bounded rationality has a significant impact on the transmission mechanism of news shocks. In particular, the responses of consumption are more persistent under AL. Moreover, the credit spread shows different effects, with TFP news shocks triggering a more persistent effect under the AL hypothesis. Altogether, these features imply that financial variables anticipate the future economic outlook, which is in line with the empirical literature. Furthermore, the effects of news shocks on inflation are reversed, so that news shocks are deflationary under AL. This finding is in line with recent literature (Forni et al. 2014; Görtz, Tsoukalas and Zanetti 2022), but in sharp contrast with the inflationary response to news shocks obtained in the RE specification.

Interestingly, we find that the importance of pure news shocks increases under AL. This is a particularly important finding because the importance of (anticipated) news shocks is usually assessed on their ability to affect the economy via the expectation channel as pure news shocks do by construction—i.e. pure news shocks are computed as in Sims (2016) to be distinguished from *realized* news shocks, which can be viewed just as unanticipated shocks. Finally, we also show that the AL-DSGE, rather than the RE-DSGE, model generates dynamics implied by news shocks that are more in line with those estimated through an empirical Bayesian VAR.

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Supplementary appendix (not intended for publication)

In this appendix, we first describe the DSGE model augmented with financial frictions à la Gertler and Karadi (2011). At the end,

Households

The representative household i decides consumption, hours worked, and savings in riskless assets to maximize a utility function that incorporates internal habit formation. Formally,

$$E_t \sum_{k=0}^{\infty} \beta^k \epsilon_{t+k}^b \left[ln\left(C_{t+k}(i) - hC_{t+k-1}\right) - \frac{L_{t+k}(i)^{1+\sigma_l}}{1+\sigma_l} \right], \tag{15}$$

where β is the household subjective discount factor, h represents the degree of habit persistence, σ_l is the elasticity of labor supply (i.e. the Frisch elasticity), and ϵ_{t+k}^b is an exogenous process that affects the intertemporal preferences of households. Household savings are represented by deposit liabilities in banks and government bonds. These riskless assets, B, are perfect substitutes and pay the same nominal interest rate, R^n. Households also receive dividends from intermediate goods firms, capital goods producers, and labor unions, D. Hence, the budget constraint is

$$C_{t+k}(i) + \frac{B_{t+k}(i)}{R_{t+k}^n P_{t+k}} - T_{t+k} = \frac{W_{t+k}(i)L_{t+k}(i)}{P_{t+k}} + \frac{B_{t+k-1}(i)}{P_{t+k}} + \frac{D_{t+k}}{P_{t+k}}, \tag{16}$$

where T represents lump-sum taxes, and W is the nominal wage.

Labor unions and wage decision

As in Smets and Wouters (2007), households supply homogeneous labor to intermediate labor unions that differentiate labor services. Intermediate labor unions set wages and sell labor services to a labor packer who aggregates the differentiated labor and resells it to intermediate goods firms. Aggregation of labor services follows

$$L_t = \left[\int_0^1 L_t(i)^{\frac{1}{1+\epsilon_t^w}} di \right]^{1+\epsilon_t^w},$$

where $1+\epsilon_t^w$ is the desired markup of wages over the household's marginal rate of substitution, which is assumed to follow a stochastic process around its steady-state value.

Labor packers maximize profits in a perfectly competitive market. Formally,

$$max_{L_t(i)} W_t L_t - \int_0^1 W_t(i) L_t(i),$$

where W_t is the aggregate wage that intermediate firms pay for labor services, and $W_t(i)$ is the wage that labor packers pay for the differentiated labor. This optimization problem results in the following labor demand function:

$$L_t(i) = \left(\frac{W_t(i)}{W_t}\right)^{-\frac{1+\epsilon_t^w}{\epsilon_t^w}} L_t.$$

The labor demand function and the labor services aggregation function together result in the wage aggregation function:

$$W_t = \left(\int_0^1 W_t(i)^{\frac{1}{\epsilon_t^w}} di\right)^{\epsilon_t^w}. \tag{17}$$

Following Calvo's lottery scheme, labor unions are assumed to adjust prices with probability $1-\xi_w$. The fraction of labor unions ξ_w that cannot adjust prices is assumed to follow the indexation rule, $W_{t+1}(i) = W_t(i)\left(\frac{P_t}{P_{t-1}}\right)^{\iota_w}$. Hence, the labor unions choose an optimal W to maximize

$$E_t \sum_{k=0}^{\infty} \beta^k \xi_w^k \left[\Lambda_{t+k} W_t(i) L_{t+k}(i) - \epsilon_{t+k}^b \frac{L_{t+k}(i)^{1+\sigma_l}}{1+\sigma_l}\right], \tag{18}$$

subject to labor demand and the indexation rule.

Final goods firms

Competitive final goods producers buy intermediate goods and combine them to finally sell homogeneous goods to households. The intermediate goods aggregation follows:

$$Y_t = \left[\int_0^1 Y_t(i)^{\frac{1}{1+\epsilon_t^p}} di\right]^{1+\epsilon_t^p},$$

where Y_t is the homogeneous good, $Y_t(i)$ is the heterogeneous good supplied by firm i, and $1+\epsilon_t^p$

is the desired markup of prices over firms' marginal cost, which is assumed to follow a stochastic process around its steady-state value.

Final goods firms maximize profits in a perfectly competitive market. Formally,

$$max_{Y_{t(i)}} P_t Y_t - \int_0^1 P_t(i) Y_t(i) di,$$

where Y_t is subject to the goods aggregation function, $P_t(i)$ is the price for differentiated goods, and P_t is the aggregate price index. The optimal condition of this maximization problem results in the following goods demand function for goods:

$$Y_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\frac{1+\epsilon_t^p}{\epsilon_t^p}} Y_t. \tag{19}$$

Hence, the goods demand function and the intermediate goods aggregator result in the following price aggregator

$$P_t = \left[\int_0^1 P_t(i)^{\frac{1}{\epsilon_t^p}} di \right]^{\frac{1}{1-\epsilon_t^p}}. \tag{20}$$

Intermediate goods firms

As in the labor market, it is assumed that intermediate goods firms can only adjust prices with probability ξ_p. Those firms which cannot adjust prices in period t simply reset their prices according to the indexation rule: $P_{t+1}(i) = P_t(i) \left(\frac{P_t}{P_{t-1}} \right)^{\iota_p}$. Firms able to set their optimal prices P_t^* at time t choose them by maximizing current and future expected profits. Denoting the marginal costs and the inflation rate by MC_t and π_t, respectively; the price setting optimization problem faced by intermediate goods firms can be written as follows:

$$max_{P_t^*(i)} E_t \sum_{k=0}^{\infty} \beta^k \xi_p^k \Lambda_{t+k} \frac{P_t}{P_{t+k}} \left[P_t^*(i) \prod_{l=1}^{k} \pi_{t+l-1}^{\iota_p} - MC_{t+k} \right] Y_{t+k}(i), \tag{21}$$

subject to the price indexation rule, and the demand function for intermediate goods.

In addition to setting prices, intermediate goods firms decide on the output of goods. They choose the amount of production inputs by maximizing the flow of discounted profits

$$E_t \left\{ \beta\Lambda_{t+1} \left[Y_{t+1}(i) - r^k_{t+1} K^s_{t+1}(i) - \frac{W_{t+1}}{P_{t+1}} L_{t+1}(i) \right] \right\}, \tag{22}$$

where $\beta\Lambda_{t+1} = \frac{\beta\lambda_{t+1}}{\lambda_t}$ is the stochastic discount factor, λ_t is the marginal utility of consumption for households at time t, r^k_{t+1} is the rental rate of capital, and $K^s_{t+1}(i)$ denotes capital services.

The production function is assumed to follow a Cobb-Douglas technology:

$$Y_t = TFP_t \left(K^s_t\right)^{\alpha} L_t^{1-\alpha} - \Psi_t \phi_p, \tag{23}$$

where ϕ_p is the share of fixed costs involved in production, and TFP_t denotes TFP shocks. The optimal inputs decision results in the following optimal conditions:

$$r^k_t = \alpha MC_t TFP_t \left(K^s_t\right)^{\alpha-1} L_t^{1-\alpha}, \tag{24}$$

$$\frac{W_t}{P_t} = (1-\alpha) MC_t TFP_t \left(K^s_t\right)^{\alpha} L_t^{-\alpha}. \tag{25}$$

Capital services firms

Capital services firms purchase physical capital from capital goods producers and turn it into effective capital by choosing the utilization rate, U_t:

$$K^s_t = U_t K_{t-1}. \tag{26}$$

Capital services firms decide the optimal capital utilization rate and face a utilization cost. They solve the following maximization problem:

$$max_{U_t} \left[r^k_t U_t - a\left(U_t\right) \right] K_{t-1},$$

where $a(U_t)$ is the utilization cost function. The optimal solution implies

$$r_t^k = a'(U_t). \tag{27}$$

This equilibrium condition states that the degree of capital utilization depends on the rental rate of capital. The utilization cost function assumes the following standard properties $U = 1$, $a(U) = 0$, and $\frac{a''(U)}{a'(U)} = \psi$ in the steady state. Hence, the parameter ψ is a positive function of the elasticity of the capital utilization cost, and is normalized to be between zero and one. A higher value of ψ means a higher cost of adjustment in capital utilization.

Capital services firms finance their physical capital acquisition by borrowing from financial intermediaries. At equilibrium, the following condition holds:

$$Q_t K_t = Q_t S_t, \tag{28}$$

which states that state-contingent claims, S_t, are equal to the number of units of physical capital acquired, K_t, where firms price their claims at the price of one unit of capital, Q_t. Each claim pays the stochastic return R_{t+1}^k over period t. Capital services firms operate in a perfectly competitive market, so the revenue from renting effective capital must be equal to the cost of purchasing physical capital. Hence, the optimal capital demand satisfies

$$R_{t+1}^k = \frac{r_{t+1}^k U_{t+1} - a(U_{t+1}) + (1-\delta)Q_{t+1}}{Q_t}, \tag{29}$$

which shows that the expected real interest rate on external funds is equal to the marginal return on capital.

Capital goods producers

Capital goods producers turn out physical capital and sell it to capital services firms at price Q_t. Investment goods are purchased from final good producers. Capital goods producers are assumed to face quadratic adjustment costs, $S(I_t/I_{t-1})$. This adjustment costs function is assumed to be a strictly increasing twice differentiable function. The optimization problem of the capital goods producers is

$$max_{I_t} E_t \left\{ \sum_{k=0}^{\infty} \beta^k \Lambda_{t+k} \left[Q_{t+k} I_{t+k} \epsilon^i_{t+k} - I_{t+k} - Q_{t+k} I_{t+k} \epsilon^i_{t+k} S\left(\frac{I_{t+k}}{I_{t+k-1}} \right) \right] \right\}, \tag{30}$$

where $S(.)$ is assumed to have the properties $S(1) = S'(1) = 0$, $S''(1) = \varphi > 0$. Therefore, the parameter φ measures the degree of investment adjustment cost, and the disturbance ϵ^i_t is the investment specific-technology shock. Capital accumulation evolves following the standard equation

$$K_t = (1-\delta)K_{t-1} + \left[1 - S\left(\frac{I_t}{I_{t-1}} \right) \right] I_t. \tag{31}$$

Financial intermediaries

Görtz and Tsoukalas (2017) find that the financial sector is crucial for identifiying TFP news shocks. We closely follow their characterization of financial intermediaries, which was suggested by Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). A fixed fraction of households includes bankers, who do not supply labor but behave as financial intermediaries. These bankers face a survival probability, θ, and in order to keep thei proportion constant further households become bankers in each period.

The financial intermediaries finance the acquisition of physical capital by purchasing claims S_t. These purchases are funded through household liabilities. Hence, the balance sheets of financial intermediaries are

$$Q_t S_t = N_t + B_{t+1},$$

where N_t is the net worth of the bankers. Since the return on financial claims is R^k_{t+1} and the cost of liabilities is R_t, the law of motion of the net worth of intermediaries is given by:

$$N_{t+1} = R^k_{t+1} Q_t S_t - R_t B_{t+1} = \left(R^k_{t+1} - R_t \right) Q_t S_t + R_t N_t.$$

Let $\beta \Lambda_{t+1}$ be the stochastic discount factor of financial intermediaries. The bankers' decisions are endogenously determined in the model through the following problem in which they maximize future expected terminal wealth:

$$V_t = max\ E_t \sum_{i=0}^{\infty} (1-\theta)\,\theta^i \beta^i \Lambda_{t+1+i} N_{t+1+i} =$$

$$max\ E_t \sum_{i=0}^{\infty} (1-\theta)\,\theta^i \beta^i \Lambda_{t+1+i} \left[\left(R^k_{t+1+i} - R_{t+i} \right) Q_{t+i} S_{t+i} + R_{t+i} N_{t+i} \right].$$

However, a moral hazard issue arises in this maximization problem because $\beta^i \left(R^k_{t+1+i} - R_{t+i} \right) \geq 0$. Otherwise bankers would not be willing to purchase assets. Thus, bankers have an incentive to keep borrowing additional funds indefinitely from households. In order to restrict their ability to do this, an enforcement cost is introduced: At the beginning of the period bankers can divert a proportion λ of the funds available. If that is the case, the depositors can then only recover a fraction $(1-\lambda)$ of the assets. Hence, for lenders to be willing to supply funds to bankers the following incentive constraint must be satisfied:

$$V_t \geq \lambda Q_t S_t,$$

where V_t, the gain from not diverting assets, can be expressed as follows

$$V_t = \nu_t Q_t S_t + \eta_t N_t,$$

with

$$\nu_t = E_t \left[(1-\theta)\,\Lambda_{t+1} \left(R^k_{t+1} - R_t \right) + \beta\theta x_{t,t+1} \nu_{t+1} \right], \tag{32}$$

$$\eta_t = E_t \left[(1-\theta)\,\Lambda_{t+1} R_t + \beta\theta z_{t,t+1} \eta_{t+1} \right], \tag{33}$$

where ν_t is the marginal gain from expanding assets with net worth held constant, η_t is the expected value of one additional future unit of wealth net worth with assets held constant, $x_{t,t+i} = Q_{t+i}S_{t+i}/Q_t S_t$ is the gross growth rate of assets, and $z_{t,t+i} = N_{t+i}/N_t$ is the gross growth rate of net worth.

The incentive constraint holds with equality at equilibrium:

$$Q_t S_t = \frac{\eta_t}{\lambda - \nu_t} N_t = \phi_t N_t, \tag{34}$$

where ϕ_t is the leverage ratio of bankers. Thus, from the law of motion of net worth and the incentive constraint, net worth can be rewritten as

$$N_{t+1} = \left[\left(R^k_{t+1} - R_t\right)\phi_t + R_t\right] N_t.$$

Using this equation, the gross growth rates of assets and net worth can be written as

$$z_{t,t+1} = N_{t+1}/N_t = \left(R^k_{t+1} - R_t\right)\phi_t + R_t, \tag{35}$$

and

$$x_{t,t+1} = Q_{t+1}S_{t+1}/Q_t S_t = \left(\phi_{t+1}/\phi_t\right)\left(N_{t+1}/N_t\right) = \left(\phi_{t+1}/\phi_t\right) z_{t,t+1}. \tag{36}$$

Finally, the law of motion of bankers' net worth is given by the law of motion of the net worth of existing bankers plus the net worth of households that become bankers in this period:

$$\tilde{N}_t = N^e_t + N^n_t, \tag{37}$$

with

$$N^e_t = \theta\left[\left(R^k_{t+1} - R_t\right)\phi_t + R_t\right] N_{t-1}, \tag{38}$$

$$N^n_t = \omega Q_t S_{t-1}, \tag{39}$$

$$\tilde{N}_t = N_t \epsilon^{nw}_t, \tag{40}$$

where ω is the fraction of the total assets that households transfer to new bankers, which enable them to start operating in the banking sector, and the disturbance ϵ^{nw}_t captures exogenous variations in the net worth of bankers due, for instance, to exogenous changes in bank profits.

Market clearing condition

The market clearing condition is

$$Y_t = C_t + I_t + a(U_t) + \epsilon_t^g, \tag{41}$$

where ϵ_t^g is an exogenous process that captures government spending and exogenous net export shocks.

The central bank

The model is closed with a Taylor-type rule in which the nominal interest rate set by the central banker reacts to inflation, output, and output growth (where all variables are measured in deviations from their steady-state values) in addition to a smoothing component, $\left[\frac{R_{t-1}^n}{R^n}\right]^\rho$:

$$\frac{R_t^n}{R^n} = \left[\frac{R_{t-1}^n}{R^n}\right]^\rho \left\{\left[\frac{\pi_t}{\pi}\right]^{r_\pi} \left[\frac{Y_t}{Y}\right]^{r_y}\right\}^{1-\rho} \left[\frac{Y_t}{Y_{t-1}}\right]^{r_{\Delta y}} exp(\epsilon_t^R). \tag{42}$$

Time-varying AL-IRFs to a TFP news shock

Figure 6: Time-varying impulse-response functions to a TFP news shock