

Modelling expectations in agent-based models – an application to central bank’s communication and monetary policy

Isabelle Salle*

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Abstract

Expectations play a major role in macroeconomic dynamics, especially regarding the conduct of monetary policy. Yet, modelling the interplay between communication, expectations and aggregate outcomes remains a challenging task, mainly because this requires to deviate from the paradigm of rational expectations and perfect information. While agent-based macro models allow for such a deviation, their representation of expectations dynamics often remains simplistic. This paper introduces an expectation formation model which allows to integrate a wide range of information disclosed by central banks. This expectation model is then integrated to the macroeconomic ABM developed in Salle et al. 2013 – [*Economic Modelling*, 2013, 34, 114-128], and yields aggregate results strongly in line with empirical evidence. In particular, we find that i) opacity is always sub-optimal, giving rise to the so-called opacity bias, ii) communication loosens the trade-off between the two objectives of monetary policy, and iii) forward guidance acts as a partial substitute for policy actions, and softens the optimal policy responses. This expectation model appears therefore promising to develop macroeconomic agent-based models.

Key-words – Expectations, Agent-based modelling, Neural networks, Communication, Monetary policy.

JEL codes – E52; E58; C63.

*CeNDEF, Amsterdam School of Economics, Valckenierstraat 65-67, Building J/K, 1018 XE Amsterdam & Tinbergen Institute, The Netherlands, I.L.Salle@uva.nl

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Highlights

- On the one hand, rational expectations often suppose too sophisticated knowledge and abilities from the agents.
- On the other hand, agent-based models (ABMs) assume simplistic expectation processes.
- This paper introduces an artificial neural network-based expectation model which is applied in a macroeconomic ABM.
- The resulting interplay between central bank’s communication, monetary policy, agents’ inflation expectations and macroeconomic stabilization is in line with empirical and theoretical works.

1 Introduction

Rational expectations (hereafter, RE) are not a non-controversial assumption in the economic literature. RE imply that agents know the form of the underlying economic model, and are able to process all the relevant information, so that their expectations on average coincide with the true conditional law of motion of the economic variables. An extensive literature documents the lack of plausibility of such a strong assumption by advocating information and cognitive limitations of agents in their real decision-making.¹ Furthermore, RE cannot be transposed as such in agent-based models (hereafter ABMs), because these models are highly non-linear, and imply that agents are not able to see the whole picture of the economy in which they evolve and make decisions.² Consequently, the underlying macro-economic model is not available to the agents.

The lack of alternatives to RE within such frameworks has forced the state-of-the-art agent-based literature to stick to the use of simplistic assumptions concerning agents' expectations. For instance, [Dosi et al. \(2010, 2013\)](#) assume that firms form naive expectations about their future demand. [Oeffner \(2008\)](#) makes the same assumption concerning inflation expectations. [Ashraf & Howitt \(2012\)](#) assume that they are simply equal to the central bank's inflation target. While RE are probably too sophisticated to model real agents' expectations, such simple assumptions are obviously too limited to be realistic neither. Some other ABMs even abstract from modelling explicitly the way agents form expectations, and assume that they proceed by simple adjustments of their economic decision variables. This is the case, *inter alia*, in [Seppecher \(2012\)](#) and [Lengnick \(2013\)](#). However, expectations play a major role in economic dynamics. The dynamics of expectations play a central role in the New Keynesian models, which constitute with no doubt the current paradigm in macro-modelling (see [Woodford \(2003\)](#)). Furthermore, whether agents have RE, or whether they hold homogeneous or heterogeneous expectations turn out to dramatically influence macroeconomic dynamics, and the resulting policy recommendations.³ Neglecting the expectation dynamics appears therefore as a major flaw of existing (macro)-economic ABMs. This is all the more disappoint-

¹See, notably, evidence collected in [Simon \(1996\)](#), and [Hommes \(2011\)](#) for a review in experiments with human subjects.

²See [Tesfatsion & Judd \(2006\)](#) or [Delli Gatti et al. \(2011\)](#) for an overview of ABMs.

³This has been analysed mostly for monetary policy; see e.g. [De Grauwe \(2011\)](#), [Branch & Evans \(2011\)](#), [Massaro \(2013\)](#).

ing as these models are attracting a growing attention in macroeconomics, because they offer an alternative way to optimized models of providing micro-foundations to macroeconomic dynamics. They have been proved to be able to replicate at the same time micro and macro empirical regularities, and to generate endogenous business cycles, while abstracting from the very demanding assumptions of optimization and representative agents.

In this paper, we offer an expectation model which presents several interesting features, and we provide an application of this model within a macro ABM. Our expectation model is based on an artificial neural network (hereafter ANN, see [Masters \(1993\)](#) for a comprehensive exposition). It is easy to implement, as only the list of information available to the agents is required for them to form expectations, this information being private or public. Therefore, the model can accommodate homogeneous or heterogeneous expectations. It does not require the relation between information and the resulting variable to forecast to be linear, and can deal with non-linearities. Such an expectation model is also an evolving structure, which continuously adapts to the changes in the economic environment, and notably to policy changes. Consequently, expectations formed through this model allow for policy analyses that are robust to the Lucas critique. The behavioural interpretation of this model is also quite easy: agents form and update a "mental model" of their environment, which gives them the possibility of generalizing, i.e. forming beliefs in situations that they have never encountered before. It does not require agents to have the knowledge of the structure of the economy beforehand, nor this structure to remain stable, as RE do. It rather represents a very flexible and reactive form of adaptive learning.

We then plug the ANN-based expectation model in a macroeconomic ABM (hereafter MABM). In our application, agents form inflation expectations based on the observation of macroeconomic variables, and the information disclosed by the central bank (hereafter CB), including the values of its objectives and its internal forecasts of inflation, output gap and interest rate. The issue of CB communication and expectations is of particular interest because expectations have become the primary concern of CBs over the past twenty years, and a key channel of the transmission mechanism of monetary policy ([Geraats \(2009\)](#)). However, as underlined by [Svensson \(2009, p.11\)](#), the theoretical literature has to considered departures either from RE, or from perfect information to give a rationale to CB's communication: "*in*

a hypothetical world of a fully informed and rational private sector in a stationary environment with a stationary monetary policy, symmetric information between the CB and the rest of the economy, and rational expectations, there is no specific role for CB communication". The intrinsic features of MABMs precisely allow for such departures, because they allow to release both the RE hypothesis, by instead modelling procedural rationality *à la* [Simon \(1971\)](#), and the representative agent assumption, by considering heterogeneous and interacting agents. These two elements are highly likely to make the study of communication and expectations a particularly relevant, yet challenging task.⁴

This paper pursues such a task in the MABM introduced in [Salle, Yıldızoğlu & Sénégas \(2013\)](#). The main reason why we choose to elaborate on this model is that, to the best of our knowledge, this is the only MABM designed to investigate the interplay between expectations and macroeconomic stabilization through monetary policy. Specifically, this MABM includes an explicit expectational channel of monetary policy, in line with the modern view of central bankers as "managers of expectations" ([Woodford \(2005\)](#)), while keeping the structure of the model as close as possible to the baseline New Keynesian model. In [Salle, Yıldızoğlu & Sénégas \(2013\)](#), [Salle, Sénégas & Yıldızoğlu \(2013\)](#), we provide a detailed analysis of the functioning of the MABM, by putting an emphasis on the transmission channels of monetary policy, especially the expectation channel. We show that the model displays sounds and empirically relevant aggregate behaviour, and can therefore be considered as "validated". This analysis sheds further light and credibility on the results from our numerical simulations.

With this framework at end, we consider different transparency policies of the CB, and check the consistency of our results in terms of macroeconomic performances with empirical evidence and previous theoretical results. We obtain three main observations which are fully in line with these well-established results. First, opacity is always sub-optimal, giving rise to the so-called opacity bias. Second, communication loosens the trade-off between the two objectives of monetary policy. Third, communication acts as a partial substitute for policy actions, and softens the optimal reactions of the Taylor rule, while improving the trade-off between inflation and

⁴So far, a strand of the literature has considered imperfect information, see e.g. [Walsh \(2006, 2008\)](#), [Demertzis & Viegli \(2009\)](#). Another strand has explored learning, mostly using econometric learning, see e.g. [Orphanides & Williams \(2005, 2007\)](#). For a comprehensive survey of this literature, see [Eijffinger & van der Crujisen \(2007\)](#) or [Geraats \(2014a\)](#). Nevertheless, all this literature keeps the underlying macroeconomic model, based on optimizing homogeneous agents, unchanged.

output gap stabilization through a better control of inflation expectations. The relevance of these results indicates that the suggested expectational model constitutes a promising model of boundedly-rational expectations in agent-based frameworks.

The rest of the paper is organized as follows. The ANN-based expectational model is described in Section 2, the underlying MABM is presented in Section 3, Section 4 explains the simulation protocol and the way we analyse the simulation results, which are presented in Section 5. Section 6 concludes.

2 A model of inflation expectation using CB information

We introduce a model of "boundedly rational" expectations based on an ANN, that can be applied to a wide range of economic contexts, e.g. expectations of profits in a product market, rates of return in asset-pricing models, portfolio or consumption decisions in intertemporal problem solving. We first review the economic literature using ANN as a learning mechanism, and then apply the expectation model to the formation of inflation expectations using CB information.

2.1 The use of ANN in economics: an overview

In economics, ANN have been mostly used as predictors of time series, and only in few works as a way to model learning of boundedly rational agents.⁵ For instance, [Salmon \(1995\)](#) implements an ANN in two models: a dynamic infinite-horizon game *à la* Barro & Gordon in which agents try to infer the CB's preferences (see [Cukierman \(1986\)](#)), and an hyperinflation model with two equilibria, namely a low- and a high-inflation equilibria (see [Sargent & Wallace \(1987\)](#) and [Marcet & Sargent \(1989\)](#)). Salmon shows that the ANN learning converges towards more favourable configurations than least-squares learning does, in both models.⁶ [Cho & Sargent \(1997\)](#) use an ANN in the [Kydland & Prescott \(1977\)](#) repeated game, in which agents learn the CB's credibility. They show that commitment mechanisms are desirable, because ANN learning does not necessary yield the CB to establish its reputation, and to

⁵See [Cho & Sargent \(1996\)](#) for a review of this literature, especially in game theory; see also [White \(1992\)](#), [Herbrich et al. \(1999\)](#) or [Evans & Honkapohja \(2001, Chap. 15\)](#) in macroeconomics.

⁶More precisely, ANN learning results in a limitation of the inflation bias in the first model, and in convergence towards the low inflation rate in the second model.

deliver the low inflation equilibrium. But this learning mechanism limits the set of possible rational expectations equilibria. In the same environment, [Arifovic & Yildizoğlu \(2014\)](#) apply an adaptive learning mechanism based on an ANN to the policy maker (i.e. the CB), and show that the model consistently selects the Ramsey outcome. This ANN-based learning model is the only one in line with experimental evidence. [Heinemann \(2000\)](#) shows that stability conditions of the non-linear form of the cob-web model under ANN learning are identical to those of the linear version with least-squares learning. In [Yildizoğlu \(2001\)](#), a collection of firms anticipates future profits of R & D expenditures using an ANN, and this learning behaviour allows to improve performances of the whole industry. [Sgroia & Zizzo \(2007, 2009\)](#) further show that ANN learning well replicates performances of human subjects in lab experiments, in which they have to identify Nash equilibria in simple games. [Yildizoğlu et al. \(2012\)](#) demonstrate that ANN learning is able to approximate the optimal buffer-stock rule of consumption in a dynamic set-up, which is not possible under purely adaptive or social learning, essentially modelled through genetic algorithms.

In what follows, we use such an ANN as an expectation model for inflation, and integrates the CB's information in that structure.

2.2 Learning through an ANN

2.2.1 The ANN as a "mental model"

Through their ANN, agents develop a simplified model of the mapping between information they receive in each period from the CB about the state of the economy, and the resulting inflation rate in the next period. Such a model is called a *mental model* ([Holland et al. \(1989\)](#)): it allows agents to be capable to *generalize*, *i.e.* to project past experiences onto expectations in circumstances that they have never encountered yet. This model is dynamic, and evolves according to a trial-error process. In each period, the last inflation forecast is confronted with the effective realisation of inflation, and the mental model is updated by taking into account the observed forecast error (see Figure 1).

The ANN represents such a mental model (see [Masters \(1993\)](#)). Least squares learning algorithms (see, notably, [Evans & Honkapohja \(2001\)](#)) also belong to the class of mental models, but assume a specific form of the relation between variables

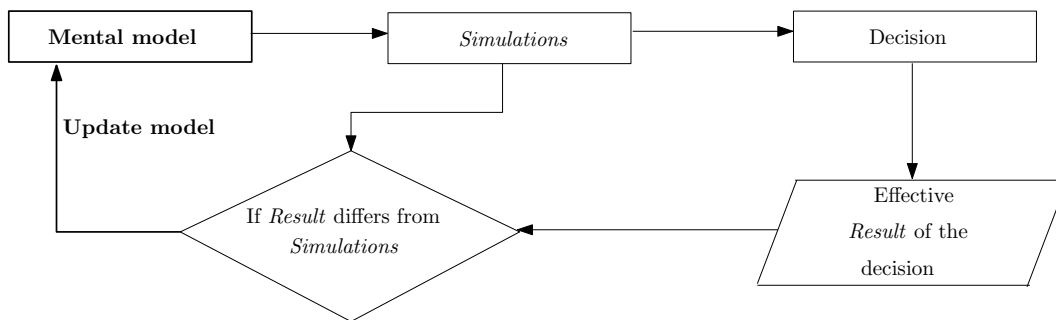


Figure 1: Dynamic functioning of a mental model (Yıldızoğlu (2001)).

– a linear form, and this linear form is assumed to be known by agents. In an ABM, the underlying economic model is presumably highly non-linear and unknown. An ANN provides a more flexible form of a mental model than least-squares models do, because an ANN only requires the list of the inputs and the output objective, without prejudging the form of the relation between these inputs and the output.

2.2.2 Structure of an ANN

Let us assume a collection of agents, indexed by $i = \{1, \dots, n\}$. Each agent is endowed with his own ANN, so that there are n ANNs in the model. The structure of each ANN is composed of I inputs, one hidden layer and an output node (see Figure 3 hereafter for an illustration). The output node is the resulting one-period ahead inflation forecast of each agent, denoted by $\pi_{i,t+1}^e$. The inputs encompass the list of information used to compute the inflation forecast. This information corresponds to the information disclosed by the CB (see Subsection 3.2). As for the hidden layer, it essentially filters irrelevant information. The number of hidden nodes in the hidden layer, denoted by hN , models the complexity of the ANN. When the hidden layer has at least two hidden nodes, the relation between inputs and output is non-linear. Accordingly, we set the number of hidden nodes to $hN = \min\{2, \sqrt{I}\}$. This setting represents a pyramidal and non-linear structure, which is usual in the design of ANN (see Masters (1993, p. 176-177) for further details). In each period t , the ANN is fed with the values of the I inputs, denoted by o_i , $i = 1, \dots, I$, and gives the inflation forecast $\pi_{i,t+1}^e$ as output. The mapping between inputs and output is described by the weights $\omega_{i,j}$ and w_j , and the corresponding inflation forecast is given by:

$$\pi_{t+1}^e = S \left(\sum_{j=1}^{hN} w_j \left(\sum_i^n \omega_{i,j} o_i \right) \right) \quad (1)$$

where $S(\cdot)$ is the sigmoid activation function. The weights are randomly initialized so that, at least at the beginning, agents' mental models and the resulting expectations differ. As new observations become available, agents' ANN are said to be "trained", i.e. the weights $\omega_{i,j}$ and w_j are updated. This updating is performed by back propagating the errors on the ANN weights (see [Rumelhart et al. \(1986\)](#)) : *epoch* iterations are performed, to reduce each time a proportion δ of the error between the predicted and the actual inflation rate. The ANN is trained for each period with the *windowsSize* $\equiv 5 * (I + 1) \times hN$ last observations, also called patterns in the related literature (see [Mehrotra et al. \(1997, pp. 86-88\)](#) for this exact specification, and related discussion). If an input i turns out to be irrelevant for forecasting inflation, its associated weight is updated in each period towards zero. An ANN is therefore an evolving structure, which is potentially more robust against model misspecification ([Heinemann \(2000\)](#)).

We now introduce the MABM that serves as a framework to apply the expectation model.

3 Overview of the agent-based framework

We use the MABM in [Salle, Yıldızoğlu & Sénégas \(2013\)](#), [Salle, Sénégas & Yıldızoğlu \(2013\)](#) as a framework, to which we refer for an exhaustive presentation. The pseudo-code of the model, together with the explicit forms of the behavioural rules, are given in [Appendix A](#). This section provides a self-contained overview of the model augmented with the ANN-based expectation mechanism.

3.1 General features of the model

This is a simple aggregate demand-aggregate supply model. The MABM is designed to reproduce the main mechanisms at work in the New Keynesian (NK) baseline model as discussed in [Woodford \(2003, Chap. 4\)](#), in particular inflation dynamics and monetary policy, while accounting for heterogeneity and learning from bounded rational agents. Bounded rationality, and the resulting learning processes of agents imply some form of price and wage stickiness, as agents do not optimally adjust their behaviour in face of variations in the environment – by optimal we mean maximising a predefined welfare criterion. They instead follow simple behavioural rules that we now describe.

3.1.1 Households

The demand side is a collection of n heterogeneous households, indexed by $i \in \llbracket 1, n \rrbracket$. Each household i is endowed with an inelastic one-unit labour supply, i.e. $h_{i,t}^s \equiv 1$, $\forall i, t$. Households follow two simple behavioural rules, evolving as they learn about their environment. For both rules, they need to forecast inflation.

The first rule adjusts household i 's reservation wage to his expected inflation rate, denoted by $\pi_{i,t+1}^e$ (see Equation (A.1)). The strength of the adjustment, represented by $\gamma_i^w > 0$, is the first strategy of household i . Reservation wages are increasing with the expected inflation rate, while assuming nominal wage downward stickiness. Equation (A.1) introduces a direct transmission channel of inflation expectations to labour costs (the wage bill), and hence to the price level. This mechanism provides the expectations channel of monetary policy.

The second rule determines households' consumption behaviour. We assume that households are concerned with consumption smoothing, while taking into account the expected real interest rate when making consumption/savings decisions. This is in line with the modelling of the consumption channel in the NK literature, which is based on the Euler relation. Precisely, households have a consumption rate, that is applied to a proxy of their permanent income, denoted by \tilde{y} . The proxy of their permanent income is computed as a weighted average of their past (real) incomes. The level of savings or debt is simply computed as the difference between current income and desired consumption. The second behavioural rule adjusts each household's consumption rate according to his expected real interest rate. The strength of the adjustment, represented by $\gamma_{i,t}^k$, is the second strategy of household i . If the expected interest rate rises, the consumption rate decreases, and the resulting savings rate increases, and vice-versa. Equation (A.3) provides the real (consumption) channel of monetary policy.

The indexation strategy $\gamma_{i,t}^w$ and the substitution strategy $\gamma_{i,t}^k$ are updated in each period using two learning operators (see, e.g., Arifovic (2000)): an imitation mechanism (occurring with a probability P^I for each household) and an innovation mechanism (with a probability P^M). The fitness criterion of the imitation process is households' utility $u(\cdot)$, i.e. an increasing and concave function of consumption. The innovation mechanism modifies agents' strategies through random draws, with noises σ_w and σ_k respectively for strategies $\gamma_{i,t}^w$ and $\gamma_{i,t}^k$. The interpretation of parameters σ_k and σ_w as shocks is provided in Subsection 3.2 (see Salle, S en egas & Yildizoglu

(2013) for an extensive discussion of this point).

3.1.2 Firm

The supply side is summarized by a single firm, mimicking the monopolistic competition framework of the baseline NK model. Labour is the only input, used to produce a perishable good, and the goods market operates under imperfect competition. The price is set according to a fixed mark-up μ over the marginal cost. The firm's strategy is her labour demand H_t^d . As for households, the firm uses a learning mechanism. We consider a gradient learning mechanism: as the firm's profit is increasing in the quantities (as soon as $\alpha \neq 0$), the firm raises her labour demand when her profit is above its (real) past trend $\tilde{\Pi}_t$, and vice-versa (see Equation A.6).

3.1.3 Markets and aggregation

Agent-based economies being decentralized economies, we need to model every interaction between agents in the markets. We assume efficient matching processes (see Benassy (1993)). The matching process in the labour market allows the firm to minimize her production costs. Aggregate hired labour is given by $H_t = \min(H_t^d, n)$. The matching process in the goods market maximises the quantity of goods exchanged. Aggregate consumption is given by $Y_t = \min\left(C_t^d \equiv \sum_{i=1}^n c_{i,t}^d, Y_t^s\right)$, and the output gap x_t by $x_t \equiv \frac{Y_t - Y^*}{Y^*}$ ($Y^* \equiv n^{1-\alpha}$ being the potential output level).

3.1.4 Monetary policy

As for monetary policy, the CB acts under flexible inflation targeting (the inflation target is denoted by π^T), using a Taylor rule. $\phi_\pi > 0$ and $\phi_x > 0$ are the reaction coefficients to inflation and output gap in the monetary policy rule. The CB is also a "manager of expectations", and chooses the amount of information that it wants to disclose to the agents about its policy, i.e. policy objectives, internal forecasts of interest rates and future economic outlooks. These internal forecasts are established using a L -lag VAR model of inflation and output gap, which is recursively updated in each period through a least squares algorithm with a constant gain, denoted by κ (see, *inter alia*, Orphanides & Williams (2007)). These forecasts are extrapolated at $horizon$ periods, and denoted by $\pi_{t+horizon}^{CB}$ and $x_{t+horizon}^{CB}$. Through the rule (A.5), the CB then forecasts the corresponding level of the interest rate, which may prevail in $horizon$ periods based on $\pi_{t+horizon}^{CB}$ and $x_{t+horizon}^{CB}$. We note $i_{t+horizon}^{CB}$ this

forecast (see Williams (2010) for such an approach). Admittedly, the CB does not make use of its forecasts to set the interest rate, as we consider a contemporaneous interest rate rule. Agents cannot therefore learn the rule through the knowledge of these forecasts. We rather assume that these forecasts are *public information*, delivered by a public statistical office in the model (see, e.g., Haber (2008) for a similar interpretation). The CB may also disclose the inflation and the output gap targets to agents.

In this paper, we assume that households use all this information to form their inflation expectations through the ANN-based mechanism described in Section 2.2. We now elaborate on the expectation channel of monetary policy in the model.

3.2 Central bank’s communication and the expectation channel in the MABM

3.2.1 Inflation dynamics in the MABM

The functioning of the model, and the resulting inflation dynamics are summarized in Figure 2. In line with the NK Phillips curve, inflation is driven by both aggregate demand and inflation expectations. The model therefore incorporates the two transmission channels of monetary policy of the baseline NK model, i.e. the consumption channel and the expectations channel.⁷

With these two transmission channels at hand, the central bank is targeting the optimal situation in the MABM.⁸ This optimal situation corresponds to $H = n$ (i.e. there is no unemployment), $Y = Y^s = n^{1-\alpha}$ (and $x = 0$, so that there is no unsold quantities in the goods market), and $\pi = \pi^T$. As discussed in Salle, Yildizoğlu & Sénégas (2013), departures from this optimal state may arise from three sources: i) the boundedly rational behaviour of agents, ii) the innovation operator in households’ learning process, which translates into heterogeneity in individual behaviour, and may create aggregate volatility, and iii) inflation expectations which may become unanchored, and endogenously drive the inflation process. Bounded rationality has been emphasized as a source of macroeconomic volatility in many related contributions; see, notably, De Grauwe (2011) for a discussion.

Concerning point ii), parameters σ_k and σ_w can be interpreted as shocks on,

⁷We refer here to Salle, Yildizoğlu & Sénégas (2013) for an exhaustive discussion and derivation of these channels.

⁸By optimal, we mean that aggregate consumption and firm’s profits are maximized.

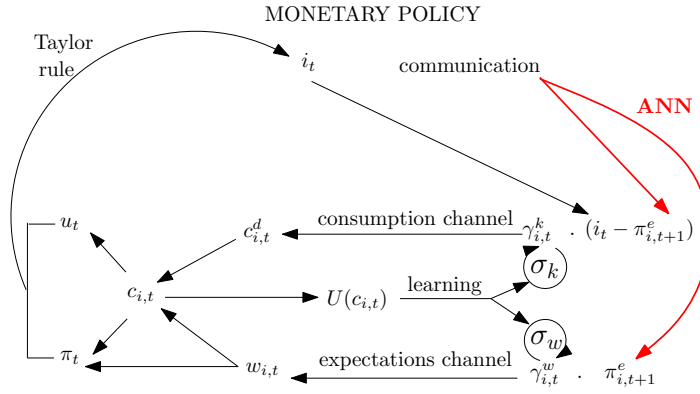


Figure 2: Functioning of the MABM (Salle, S en egas & Yildizoglu (2013))

respectively, consumption and expectations channels of monetary policy. Shocks σ_k induce heterogeneity in the behavioural rule (A.3) of households. This heterogeneity translates into variability in the consumption channel of monetary policy. This variability has been emphasized in the macroeconomic literature as *model uncertainty* (see the earlier contribution of Brainard (1967)). Shocks σ_w represent second-round effects, through which expected inflation feeds back into actual inflation through nominal wage growth rate. Hence, shocks σ_w induce heterogeneity in individual indexation behaviour (see Equation (A.1)). This behavioural heterogeneity translates into variability in the expectations channel of monetary policy. These shocks can be interpreted as *inflationary* or *cost-push shocks*. Importantly, they introduce a trade-off between inflation and output gap stabilization: as soon as inflation becomes driven by expectations, inflation does not convey changes in aggregate demand any more, and the two objectives move in opposite direction.

This naturally yields to point iii), and the importance of anchoring inflation expectations. In our model, much like in the NK literature, the gain from transparency arises from the potential control on inflation expectations the CB may exert. Coordination of inflation expectations can also be discussed regarding performances in learning. One could expect that learning through imitation would yield better performances if it takes place in an environment where households hold comparable beliefs.

In a nutshell, monetary authorities aim at driving inflation expectations through the disclosure of information, in order to anchor inflation expectations, and hence stabilize inflation and output gap. This *management of expectations* is made challenging by i) the global uncertainty context due to the boundedly rational behaviour of agents and by ii) the occurrence of shocks which introduce heterogeneity among

individual behaviour, and disturbances in the transmission channels of monetary policy.

We now detail how households form their expectations using the ANN and the CB's information.

3.2.2 Communication and inflation expectations in the MABM

In our particular application of ANNs, inputs I represent the information that agents use to forecast inflation. The more transparent the CB, the more information agents receive, and the more inputs they make use of. This mechanism well translates the role of the CB as a manager of expectations.

Following the empirical study of Minegishi & Cournède (2009), we distinguish between different degrees of transparency : transparency about objectives, transparency about policy decisions and transparency about economic analysis.⁹ As we aim at investigating the role of communication on macroeconomic outcomes, we compare different scenarios of CB communication policy. The more information agents receive from the CB, the higher the quantity of inputs in their ANN (see Table 1). As a matter of illustration, Figure 3 depicts the ANN of an household in the case of the 3-degree of transparency ($I = 5$ inputs).

Precisely, the 0-degree of transparency represents an opaque CB, which communicates no information. In that case, its instrument has an informative value (Walsh (2007)), and agents make use of the interest rate and its variation to forecast inflation ($I = 2$). The 1-degree represents *transparency about the objectives*: the CB only discloses the inflation target and the output gap target ($I = 4$). In the 2- and 3-degrees, the CB also provides *forward-guidance* to agents: it communicates its projection of interest rate ($I = 5$). Degrees 4 and 5 represent *transparency about the economic analysis*, and the CB also discloses projections of macroeconomic indicators (inflation and output gap, $I = 7$).

We further distinguish between a vague communication strategy, in which the CB only communicates about expected trend of the variables (either increasing or decreasing, in degrees 2 and 4), and an accurate communication, in which the CB communicates about the exact values of its internal forecasts (degrees 3 and 5).

Recall from Subsection 3.2 that the CB establishes forecasts of inflation, output

⁹They further distinguish transparency about the decision process in the case of monetary policy committees, but this form of transparency hardly applies in our model.

inputs of the ANN	Degree of transparency							Form of transparency
	0	1	2	3	4	5	6	
i_t	X	X	X	X	X	X	X	opacity
Δi_t^a	X	X	X	X	X	X	X	opacity
$x(t)^b$		X	X	X	X	X	X	objectives
$\pi_t - \pi^T$ ^b		X	X	X	X	X	X	objectives
$\Delta i_{t+horizon}^{CB}$			X		X			guidance/decisions
$i_{t+horizon}^{CB}$				X		X	X	guidance/decisions
$\Delta \pi_{t+horizon}^{CB}$					X			economic analysis
$\Delta x_{t+horizon}^{CB}$					X			economic analysis
$\pi_{t+horizon}^{CB}$						X	X	economic analysis
$x_{t+horizon}^{CB}$						X	X	economic analysis
$\pi_{t+horizon}^{CB} - \pi_{t+horizon}$							X	economic analysis
$x_{t+horizon}^{CB} - x_{t+horizon}$							X	economic analysis

Table 1: Inputs of households' ANN under the 7 different degrees of transparency of the CB.

^a Δx stands for the variation of variable x between $t - 1$ and t .

^b As objectives π^T and x^* are time-invariant, they cannot be integrated as such as ANN inputs.

gap and corresponding interest rate at *horizon* periods. In degree 6, the CB gives the *a posteriori* errors of its forecasts, meaning that it underlies the uncertainty surrounding its projections. In this case, agents have in principle enough information in their ANN to learn the projection model of the CB when training their ANN.

The numerical simulations below analyse the interplay between the CB's communication policy and the interest rate rule. Before turning to the simulation results, we describe the simulation protocol, and how we analyse the simulation results.

4 Simulation protocol

4.1 Calibration

Table 2 recalls the list of parameters of the model, and the corresponding values that we use in the numerical simulations. Parameters related to the NK literature¹⁰ are easily calibrated to standard values (see e.g. [Rotemberg & Woodford \(1998\)](#), [Williams \(2010\)](#)). We further have $n = 100$ households, and we run the simulation for $T = 800$ periods, with a burn-in phase of 100 periods. This choice partly responds to computational constraints, and partly results from sensitivity analyses performed

¹⁰Specifically, these are α , the rate of returns of the production function, μ the firm's mark-up, L the number of lags, and κ the constant gain in the CB's VAR model.

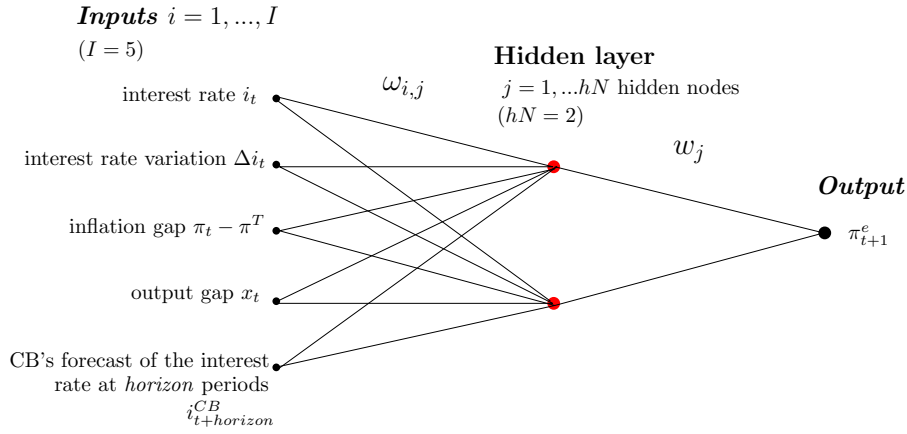


Figure 3: Representation of the ANN in case of the 3-degree of transparency.

in an earlier stage of this research. ANN parameters are set to standard values in the related literature (see [Masters \(1993\)](#)). Coefficients of the monetary policy rule – ϕ_π and ϕ_x – as well as the transparency strategy of the CB (including the *horizon* of its forecasts and the inflation target) are part of the monetary policy simulation exercise (see [Subsection 4.2](#)). We first consider a baseline simulation with $\pi^T = 2\%$ and *horizon* = 4. In [Subsection 5.4](#), we investigate the sensibility of our results to these two parameter values. As for the rest of the parameters, we use the calibration in [Salle, S en egas & Yildizođlu \(2013\)](#), in which we perform an empirical validation exercise.¹¹ We set $\sigma_w = 0.25$ and $\sigma_k = 0.05$ in order to consider an environment with a potential trade-off between the stabilization of inflation and the level of activity.

4.2 Result analysis

We interpret the simulation results under different degrees of CB's transparency in terms of the [Taylor \(1979\)](#) curve. This curve provides an intuitive description of the trade-off that the CB faces between its two objectives in conducting monetary policy. It gives the minimal variability of inflation and output gap as a function of the CB's relative preferences over these two objectives in the $(var(\pi), var(x))$ plane. More precisely, the more vertical the curve, the higher the opportunity cost of inflation stabilization in terms of output gap stabilization. The flatter the curve, the higher the inflation cost to stabilize output gap. The closer to the origin, the looser the trade-off between inflation and output gap stabilization. However, this

¹¹Extensive sensitivity analyses have been further conducted in [Salle \(2012\)](#). The main influential parameters turn out to be σ_w and σ_k , the proxy for the shocks in the MABM. The model is otherwise quite stable under a large range of parameters values.

curve is usually derived in analytical models. In these models, this curve is obtained under the assumption that the monetary policy rule is optimal, in the sense that reaction coefficients ϕ_π and ϕ_x are derived from the minimization of a loss function of the following form:

$$\mathcal{L}(\pi, x, \lambda) = \text{var}(\pi - \pi^T) + \lambda \text{var}(x) \quad (2)$$

under the constraint of the underlying economic model (where λ is the relative preference of the CB for the output gap stabilization). In our model, such an underlying macroeconomic model is unknown, and we have to adapt this method to derive optimal monetary policy in the MABM. We proceed in the following way.

We allow for $5 \times 5 = 25$ different monetary policy rules, by setting $(\phi_\pi, \phi_x) \in \{0, 0.5, 1, 1.5, 2\} \times \{0, 0.25, 0.5, 0.75, 1\}$. The model is run 20 times under each rule with different seeds of the random number generator, in order to account for the non-deterministic nature of the MABM. We collect the variance of the inflation gap and the output gap under those 25 configurations. Among those 25 pairs of inflation and output gap variances, we eliminate those which are Pareto dominated, i.e. pairs $\{\text{var}(\pi)_i, \text{var}(x)_i\}$, $i = \{1, \dots, 25\}$, for which it exists at least one pair $\{\text{var}(\pi)_j, \text{var}(x)_j\}$, $i \neq j$ among the 25 ones, for which we have $\text{var}(\pi)_i > \text{var}(\pi)_j$ and $\text{var}(x)_i > \text{var}(x)_j$. The remaining pairs are not Pareto-comparable, because they correspond to situations in which, either inflation is more volatile, but output gap is better stabilized, or the opposite. These pairs form an efficient frontier, and with each of those pairs of inflation and output gap variabilities are associated the corresponding values of ϕ_π and ϕ_x . We denote these values by ϕ_π^* and ϕ_x^* , and they define the optimal monetary policy in our model. Depending on its relative preference for either inflation or output gap stabilization (i.e. λ), the CB chooses the outcomes and its corresponding monetary policy rule in order to minimise the loss function (2). We repeat this exercise for the 7 degrees of transparency, and compare the results. We are specifically interested in assessing whether our results are in line with empirical evidence and previous theoretical results in the literature on transparency and optimal monetary policy. This would indicate that our ANN-based expectation model yields sound macroeconomic dynamics in the simple ABM that we consider, and may hence constitute a promising way of modelling expectations in ABMs.

5 Simulation results

Before turning to the results, we would like to stress an important point concerning our approach. Our expectations model is based on an ANN. ANNs provide a flexible tool to map inputs (CBs' information and macroeconomic data in our case) to output (inflation expectations in our case). However, this flexibility comes along with a major, inherent flaw, namely the "black box" aspect of the results (Yildizoglu (2001)). Results have to be obtained through numerical simulations, and the internal functioning of each agent's ANN is not observable. However, the analysis provided in two companion papers (Salle, Yildizoglu & S enegas (2013), Salle, S enegas & Yildizoglu (2013)) allows to shed some light on the underlying mechanisms at work in the MABM, and we rely on it in the discussion of our results.

Figure 4 displays two main information across the 7 degrees of transparency: the optimal monetary policy (ϕ_π^*, ϕ_x^*) as a function of the CB's preference parameter λ , and the resulting minimal loss, given by Equation (2). Figure 5a shows the results in terms of Taylor curves in the $(var(\pi), var(x))$ plane for the different degrees of transparency. We already notice that, when output gap stabilization is accounted for in the loss function (i.e. when $\lambda = 1$), the optimal reaction to inflation gap ϕ_π^* is lower, and the optimal reaction to output gap ϕ_x^* is higher than the optimal coefficient prevailing when only inflation stabilization enters the loss function (i.e. when $\lambda = 0$). This result is rather intuitive, and stresses the consistency of the underlying mechanisms in the MABM. More fundamentally, three main results jump out from our simulations.

5.1 The opacity bias (degree 0 of transparency)

Opacity is clearly suboptimal in the MABM. The so-called opacity bias (which corresponds to the case of degree 0 of transparency) is very salient. Figure 4a reports the value of the loss function (2) when $\lambda = 0$, i.e. when only inflation variability enters the CB's loss function, and Figure 4b displays the case where $\lambda = 1$, i.e. when output gap stabilisation also matters for monetary policy. From the comparison of these two figures, it ensues that the opacity bias particularly affects the variability of inflation. We therefore come up with the following result:

Result 1 *If the CB is opaque, agents form their inflation expectations from the observed values of the policy instrument (the nominal interest rate). This produces*

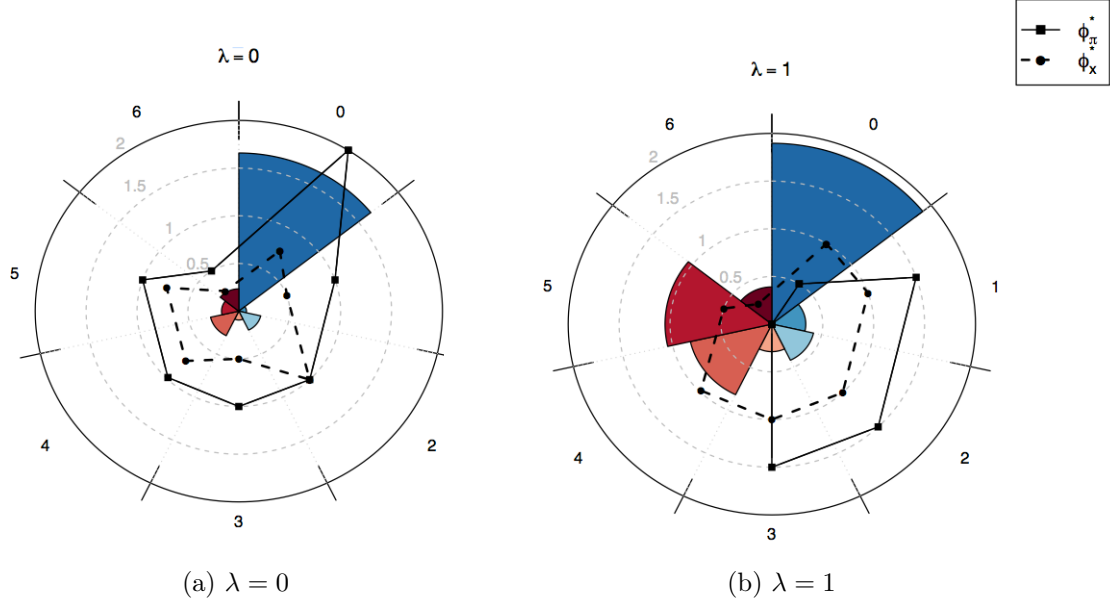


Figure 4: Values of the loss function (2) and optimal monetary policy rule (ϕ_π^*, ϕ_x^*) , $\pi^T = 0.02$ and $horizon = 4$.

The pie chart gives two pieces of information. First, each part of the pie corresponds to a degree of transparency (cf. Table 1), and represents the minimal value of the loss function (2) obtained for a given degree of transparency. The surface of each of the seven pie parts has been normalized to a 0.03 loss (as all observed losses across simulations are lower than this threshold). Second, for each degree of transparency (from 0 to 7), the corresponding optimal coefficients ϕ_π^* and ϕ_x^* are displayed. Concentric circles in dash gray report the scale, from 0 at the origin, to 2 on the circle perimeter. For instance, if $\lambda = 1$ (right panel), and the CB is opaque (degree 0), the minimal loss is close to 0.03 (as the corresponding surface of the pie is almost full), and is obtained with $\phi_\pi^* = 0.5$ and $\phi_x^* = 1$.

the so-called opacity bias, which disturbs the way the CB can actually affect the real interest rate. This opacity bias particularly increases the variability of inflation.

The opacity bias is a well-established result in the macro literature; see notably Walsh (2007, 2008, 2010), Cornand & Baeriswyl (2010).

5.2 Transparency and the inflation-output gap variability trade-off

The optimal monetary policy ϕ_π^* and ϕ_x^* depends on the degree of transparency. Transparency clearly loosens the trade-off between inflation and output gap stabilization in the MABM. An important remark is in order at this stage of the discussion. As stressed in Salle, S en egas & Yildizog lu (2013), we do not interpret optimal monetary policy coefficients with respect to the compliance or not with the so-called Taylor principle. We recall that the Taylor principle prescribes a more than one-

to-one adjustment of the nominal interest rate to the inflation gap in order to rule out indeterminacy issues, and the associated possibility of sunspot equilibria in RE models, see e.g. [Bullard & Mitra \(2002\)](#). By contrast to RE models, ABMs result by construction into out-of-equilibrium dynamics, and the analysis does not seek to select a specific path of aggregate variables. Consequently, the concept of indeterminacy hardly applies in an ABM context. We shall not conclude that the CB should not react to inflation based on an optimal ϕ_π coefficient equal to 0. We should rather interpret this result in terms of trade-off: if the optimal rule is a one-corner strategy ($\phi_\pi^* > 0$ and $\phi_x^* = 0$, and *vice-versa*), stabilizing one objective is enough to stabilize both, and the CB faces no trade-off between its two objectives. If the optimal rule implies to react to both in order to minimize its loss function, then the CB is facing such a trade-off. In light of this interpretation, it is clear from [Figures 4b](#) that transparency loosens the trade-off between inflation and output gap stabilisation, as a one-corner strategy becomes the optimal strategy when transparency increases. Efficient frontiers report in [Figure 5](#) clearly confirm this interpretation, as high degrees of transparency move the frontiers closer to the origin. We then establish the following result:

Result 2 *Increasing transparency allows the CB to loosen its trade-off between inflation and output gap stabilization.*

5.3 Transparency and optimal reactions to inflation and output gap

The more transparent the CB, the more moderate the optimal monetary policy rule. As communication directly affects inflation expectations, and hence inflation, it acts as a partial substitute to monetary policy actions, and the optimal reactions coefficients decrease when coupled to a high degree of transparency. As discussed in [Salle, S n gas & Yildizoglu \(2013\)](#), in the MABM, the expectations channel is the main driver of inflation, so that anchoring inflation expectations to the target is practically sufficient to reach the target on average. This is confirmed here. This result has been established, notably, by [Orphanides & Williams \(2005, 2007\)](#), in an economy in which agents learn how to forecast through least-squares regressions, and the CB can choose to announce its inflation target. Here, by relaxing the assumptions that agents know the true form of the underlying economic model, we

show that not only the knowledge of policy objectives, but also the disclosure of the CB's internal forecasts of interest rates and economic outlooks are needed to soften monetary policy reactions. Allowing for self-fulfilling expectations and least-squares learning based on a VAR model, [Eusepi & Preston \(2010\)](#) obtain very similar conclusions, while [Brazier et al. \(2008\)](#) and [De Grauwe \(2011\)](#) do by considering heuristic expectations. Empirical studies tend to confirm that statement as well (see e.g. [Geraats \(2009\)](#)). Nevertheless, transparency cannot completely replace actions (see [Hildebrand \(2006\)](#) for a discussion).

More precisely, a closer look at [Figure 4](#) suggests that the CB has two strategies which are likely to minimize the loss function. The first one consists in using strong reaction coefficients with a moderate transparency policy that discloses only objectives (degree 1), or possibly the future values of its instrument (degree 3). The second one prescribes adopting moderate monetary policy reactions, coupled with a high degree of transparency, that discloses instrument and policy projections, as well as uncertainty surrounding those projections (degree 6).

The first strategy, which emphasizes a limited transparency strategy, is in line with several statements in the recent literature. For instance, [Lamla & Lein \(2011\)](#) analyse how financial markets process the signals that the ECB communicates, and show that they much more integrate price level information, than information concerning future economic outlooks. Using an experimental approach, [Kahneman \(2003\)](#) show that financial markets are likely to overreact to signals from monetary authorities if the quantity of information becomes overwhelming, and challenges their cognitive ability to process this information. These two papers tend to indicate that increasing the number of information provided by the CB to the agents (in our model, this implies to increase the number of inputs to the ANN) does not necessarily make agents' expectations more accurate, and the economy more stable.

Nevertheless, [Figure 5a](#) indicates that the second strategy – consisting in adopting moderate monetary policy reactions and a high degree of transparency – delivers the more favourable trade-off, and clearly shows how the efficient frontier is moved towards the origin when the degree of transparency increases. Further descriptive statistics in [Table 3](#) in Appendix confirm this analysis. This strategy fits perfectly the trend towards more and more transparency in the conduct of monetary policy that we have been observing over the past two decades. We finally obtain the following result:

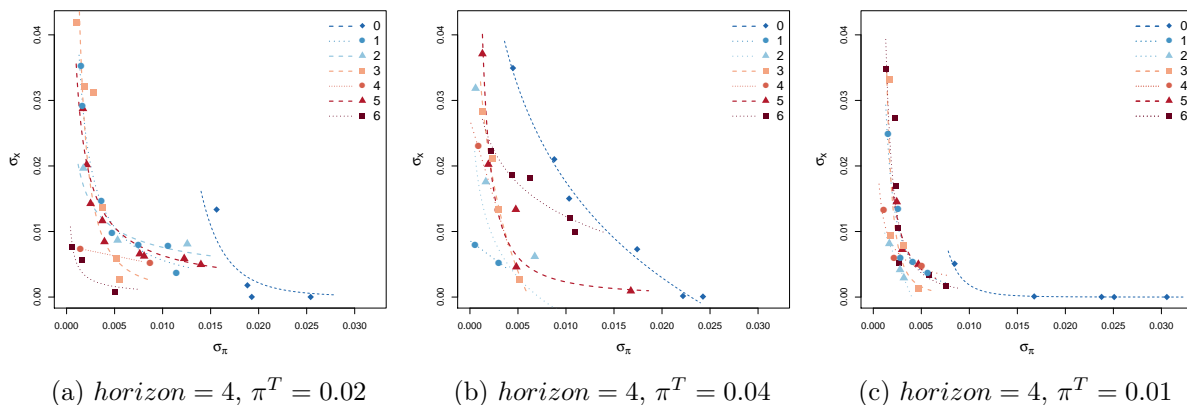


Figure 5: Efficient frontiers in the 7 degrees of transparency.

Frontiers result from a smoothing estimation, and are only displayed to make the interpretation of the plots easier.

Result 3 *Two polar strategies dramatically limit the values of the CB's loss function:*

- *Being transparent on its objectives and reacting in a strong manner to its two objectives.*
- *Being transparent on every aspect of monetary policy (including economic outlooks projections, and a posteriori errors), and reacting in a moderate way to its objectives.*

The second strategy delivers the most favourable trade-off between inflation and output gap stabilization.

These last two results are strongly in line with empirical evidence (see notably [Geraats \(2014b\)](#)), and are the main rationale behind the increasing transparency of modern CBs.

5.4 Sensitivity analyses

We recall that, so far, we have used $horizon = 4$ and $\pi^T = 2\%$.

5.4.1 horizon of the CB's projections

Table 3 in Appendix provides statistics of inflation expectations, inflation and output gap (average and variability) across the seven degrees of transparency for various ranges of the parameter $horizon$, namely 1, 4 and 8. We clearly see that inflation

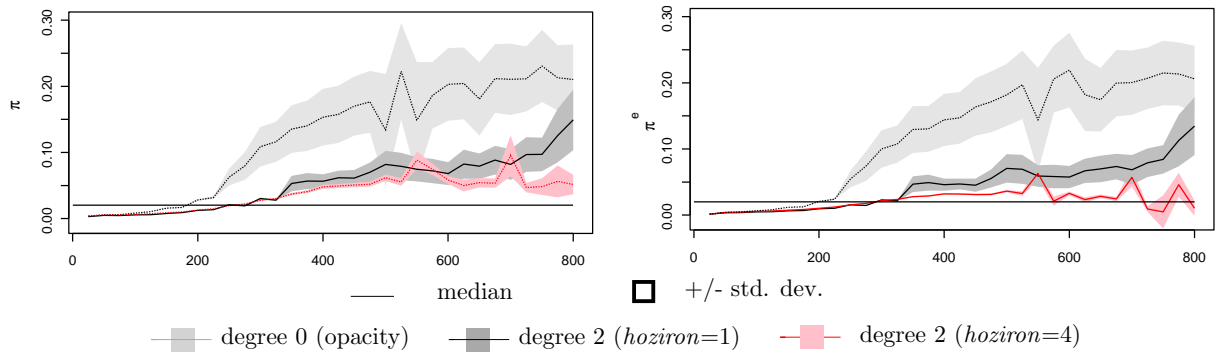


Figure 6: Illustration of the model’s dynamics (left panel: inflation, right panel: average inflation expectations).

expectations display the best stabilisation for $horizon = 4$, significantly improving upon $horizon = 1$. However, increasing the horizon of the CB’s projections to 8 periods deteriorate inflation expectations anchorage, and the resulting macroeconomic performances. The worse results obtained under a 8 period projection compared to the case with $horizon = 4$ can be explained by the number of lags in the VAR model that the CB uses to form its forecasts of inflation and output gap (and resulting interest rate levels). As we set $L = 4$ periods, projections at 8 periods are likely to be too uncertain to guide agents’ expectations.

Figures 6 provide simulated time series from the MABM under different degrees of transparency in order to illustrate this finding. First, it is clear that macroeconomic performances are mediocre under opacity (degree 0), inflation expectations are unanchored, and exhibit a high variability. The announcements of policy objectives and short-run interest rate projections limits the volatility of inflation (degree 2). However, when projections only concern the next period ($horizon = 1$), inflation expectations get unanchored, and inflation goes further from the target. Increasing the horizon of those projections allows to stabilize inflation expectations, and dramatically improves macroeconomic stabilization (degree 2, $horizon = 4$). This indicates that a medium-run horizon of projections better manage inflation expectations, and make the inflation objective easier to reach.

5.4.2 Value of the inflation target π^T

Finally, we look at the sensibility of the results to the values of the inflation target π^T (see Figures 5). Rising the inflation target up to 4% globally deteriorates performances, while setting the target at 1% produces ambivalent effects. A higher

inflation target implying a higher variability of inflation is in line with empirical evidence stating that the average and the volatility of inflation are positively correlated. A lower target reduces the relative benefit from transparency, as efficient frontiers become fairly similar across the different degrees of transparency. However, frontiers become more vertical, signalling that the opportunity cost of inflation stabilization in terms of output gap stabilization is higher. This result seems intuitive, as a lower target constitutes a more challenging objective in the presence of cost-push shocks (modelled here as second-round effects).

6 Conclusions

Rational expectations are not a non-controversial assumption in the profession, because this assumption involves extremely sophisticated cognitive abilities and knowledge from the agents. Furthermore, such an assumption cannot be transposed as such in (macro) agent-based models. The lack of alternative expectational models has forced the state-of-the-art agent-based (macro) literature to make use of simplistic assumptions, such as naive expectations. However, on the other hand, such simplistic assumptions appear too limited to capture the way agents adapt their behaviour in a realistic manner. This paper introduces an expectation model which displays several interesting features, making it an interesting candidate to model expectations in agent-based models. First, it is easy to implement, as only the list of information used to form expectations (inputs) and the resulting variable to forecast (output) are necessary. This feature obviously complies with the information and the knowledge limitations implied by bounded rationality. Second, it is flexible, as it allows agents to develop a "mental model" of the mapping between information and the variable to forecast, even if the underlying relation is unknown, and highly non-linear. This feature allows agents to continuously adapt their expectational model to changes in their environment, especially to policy changes, and complies with the requirements raised by the Lucas critique.

This model is plugged in the macroeconomic agent-based model introduced in [Salle, Yıldızoğlu & Sénégas \(2013\)](#) to model how agents form inflation expectations based on the observations of macroeconomic variables, and the information disclosed by the central bank – objective values, internal forecasts of inflation, output gap and interest rate. This agent-based model has been chosen as, to the best of our knowl-

edge, this is the only one including an explicit expectational channel of monetary policy, therefore being in line with the modern view of central bankers as "managers of expectations". Furthermore, the intrinsic features of agent-based models – mainly boundedly rational and heterogeneous agents learning in a limited information environment – make the study of communication and expectations anchorage of particular interest in this type of frameworks.

Different degrees of transparency are considered, and the resulting macroeconomic performances are analysed in light of empirical evidence and previous theoretical results. We obtain three main observations which are fully in line with these well-established results. First, opacity is always sub-optimal, giving rise to the so-called opacity bias. Second, communication loosens the trade-off between the two objectives of monetary policy. Third, communication acts as a partial substitute for policy actions, and softens the optimal policy responses. The relevance of these results indicates that the suggested expectational model constitutes a promising model of boundedly rational expectations in agent-based frameworks.

From a broader perspective, this paper highlights the potential of artificial neural networks as learning models.

References

- Arifovic, J. (2000), 'Evolutionary Algorithms In Macroeconomic Models', *Macroeconomic Dynamics* **4**(03), 373–414.
- Arifovic, J. & Yıldızoğlu, M. (2014), Learning the Ramsey outcome in a Kydland & Prescott economy, Cahiers du GREThA 2014-06, Groupe de Recherche en Economie Théorique et Appliquée.
- Ashraf, Q. & Howitt, P. (2012), How Inflation Affects Macroeconomic Performance : An Agent-Based Computational Investigation, NBER Working Papers 18225, National Bureau of Economic Research, Inc.
- Benassy, J.-P. (1993), 'Nonclearing Markets: Microeconomic Concepts and Macroeconomic Applications', *Journal of Economic Literature* **31**(2), 732–61.
- Brainard, W. C. (1967), 'Uncertainty and the Effectiveness of Policy', *The American Economic Review* **57**(2), 411–425.
- Branch, W. & Evans, G. (2011), 'Monetary policy and heterogeneous expectations', *Economic Theory* **47**(2), 365–393.
- Brazier, A., Harrison, R., King, M. & Yates, T. (2008), 'The Danger of Inflating Expectations of Macroeconomic Stability: Heuristic Switching in an

- Overlapping-Generations Monetary Model', *International Journal of Central Banking* **4**(2), 219–254.
- Bullard, M. & Mitra, K. (2002), 'Learning about monetary policy rules', *Journal of Monetary Economics* **49**(6), 1105–1129.
- Cho, I.-K. & Sargent, T. (1996), Neural Networks for Encoding and Adapting in Dynamic Economies, in H. M. Amman, D. Kendrick & J. Rust, eds, 'Handbook of Computational Economic', North-Holland, pp. 441–470.
- Cho, I.-K. & Sargent, T. (1997), 'Learning to be credible'.
URL: <https://files.nyu.edu/ts43/public/research/philnet6.pdf>
- Cornand, C. & Baeriswyl, R. (2010), 'Optimal monetary policy in response to supply inflation : the impact of central bank communication', *International Journal of Central Banking* **6**(2), 31–52.
- Cukierman, A. (1986), 'Central bank Behavior and Credibility: Some Recent Theoretical Developments', *Federal Reserve Bank of St. Louis Review* **May**, 5–17.
- De Grauwe, P. (2011), 'Animal spirits and monetary policy', *Economic Theory* **47**, 423–457.
- Delli Gatti, D., Desiderio, S., Gaffeo, E., Cirillo, P. & Gallegati, M. (2011), *Macroeconomics from the Bottom-up*, Springer Italia.
- Demertzis, M. & Viegli, N. (2009), 'Inflation targeting : a framework for communication', *The B.E. Journal of Macroeconomics* **99**(1), 44–67.
- Dosi, G., Fagiolo, ., Napoletano, M. & Roventini, A. (2013), 'Income distribution, credit and fiscal policies in an agent-based Keynesian model', *Journal of Economic Dynamics and Control* **37**(8), 1598–1625.
- Dosi, G., Fagiolo, G. & Roventini, A. (2010), 'Schumpeter Meeting Keynes: A Policy-Friendly Model of Endogenous Growth and Business Cycles', *Journal of Economic Dynamics and Control* **34**(9), 1748–1767.
- Eijffinger, S. C. & van der Cruijssen, C. A. (2007), The Economic Impact of Central Bank Transparency: A Survey, Technical Report 6070, C.E.P.R. Discussion Papers.
- Eusepi, S. & Preston, B. (2010), 'Central bank communication and expectations stabilization', *American Economic Association* **2**(3), 235–271.
- Evans, G. W. & Honkapohja, S. (2001), *Learning and Expectations in Macroeconomics*, Princeton University Press.
- Geraats, P. (2009), 'Trends in Monetary Policy Transparency', *International Finance* **12**(2), 235–268.
- Geraats, P. (2014a), Monetary Policy Transparency, CESifo Working Paper Series 4611, CESifo Group Munich.
- Geraats, P. (2014b), Transparency, Flexibility and Macroeconomic Stabilization, CESifo Working Paper Series 4642, CESifo Group Munich.

- Haber, G. (2008), ‘Monetary and Fiscal Policy Analysis with an Agent-Based Macroeconomic Model’, *Journal of Economics and Statistics (Jahrbuecher fuer Nationaloekonomie und Statistik)* **228**(2+3), 276–295.
- Heinemann, M. (2000), ‘Adaptive learning of rational expectations using neural networks’, *Journal of Economic Dynamics & Control* **24**, 1007–1026.
- Herbrich, R., Keilbach, M., Graepel, T., Bollmann-Sdorra, P. & Obermayer, K. (1999), ‘Neural Networks in Economics: Background, Applications and New Developments’, *Advances in Computational Economics Computational Techniques for Modelling Learning in Economics* **11**, 169–196.
- Hildebrand, P. M. (2006), ‘Monetary Policy and Financial Markets’, *Financial Markets and Portfolio Management* **20**, 7–18.
- Holland, J., Goldberg, D. & Booker, L. (1989), ‘Classifier Systems and Genetic Algorithms’, *Artificial Intelligence* **40**, 235–289.
- Hommes, C. (2011), ‘The heterogeneous expectations hypothesis: Some evidence from the lab’, *Journal of Economic Dynamics and Control* **35**(1), 1–24.
- Kahneman, D. (2003), ‘Maps of bounded rationality: Psychology for behavioral economics’, *American Economic Review* **93**(5), 1449–1475.
- Kydland, F. & Prescott, E. (1977), ‘Rules rather than discretion: The inconsistency of optimal plans’, *Journal of Political Economy* **85**(3), 473–91.
- Lamla, M. & Lein, S. (2011), ‘What matters when? The impact of ECB communication on financial market expectations’, *Applied Economics* **43**(28), 4289–4309.
- Lengnick, M. (2013), ‘Agent-based macroeconomics – a baseline model’, *Journal of Economic Behavior & Organization* **86**, 102–120.
- Marcet, A. & Sargent, T. (1989), Least Squares Learning and the Dynamics of Hyperinflation, in ‘Sunspots, Complexity, and Chaos’, W. Barnett, J. Geweke and K. Shell edn, Cambridge University Press.
- Massaro, D. (2013), ‘Heterogeneous expectations in monetary DSGE models’, *Journal of Economic Dynamics and Control* **37**(3), 680–692.
- Masters, T. (1993), *Practical Neural Network recipes in C++*, Academic Press, New York.
- Mehrotra, K., Mohan, C. K. & Ranka, S. (1997), *Elements of Artificial Neural Networks*, MIT Press.
- Minegishi, M. & Cournède, B. (2009), The Role of Transparency in the Conduct of Monetary Policy, OECD Economics Department Working Papers 724, OECD Publishing.
- Oeffner, M. (2008), Agent-Based Keynesian Macroeconomics – an evolutionary model embedded in an agent-based computer simulation. Doctoral dissertation, Bayerische Julius - Maximilians Universität, Würzburg.
- Orphanides, A. & Williams, J. C. (2005), Imperfect knowledge, inflation expectations and monetary policy, in B. Bernanke & M. Woodford, eds, ‘Inflation Targeting’, University of Chicago Press.

- Orphanides, A. & Williams, J. C. (2007), Inflation Targeting under Imperfect Knowledge, *in* F. S. Mishkin & K. Schmidt-Hebbel, eds, ‘Monetary Policy Under Inflation Targeting’, Vol. XI, Banco central de Chile, Santiago, Chile.
- Rotemberg, J. & Woodford, M. (1998), An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy: Expanded Version, NBER Technical Working Papers 0233, National Bureau of Economic Research, Inc.
- Rumelhart, D., Hinton, G. & Williams, R. (1986), ‘Learning representations by back-propagating errors’, *Nature* **323**, 533–536.
- Salle, I. (2012), Heterogeneity, Learning and Monetary Policy: an application to inflation targeting, PhD thesis, University of Bordeaux.
- Salle, I., Sénégas, M.-A. & Yildizoğlu, M. (2013), How Transparent About Its Inflation Target Should a Central Bank be? An Agent-Based Model Assessment, Cahiers du GREThA 2013-24, Groupe de Recherche en Economie Théorique et Appliquée.
- Salle, I., Yildizoğlu, M. & Sénégas, M.-A. (2013), ‘Inflation targeting in a learning economy: An ABM perspective’, *Economic Modelling* **34**(C), 114–128.
- Salmon, M. (1995), Bounded Rationality and Learning; Procedural Learning, *in* ‘Learning and rationality in economics’, Oxford : Basil Blackwell edn, Alan P. Kirman and Mark Salmon, chapter 8, pp. 236–275.
- Sargent, T. & Wallace, N. (1987), Inflation and the government budget constraint, *in* A. Razin & E. Sadka, eds, ‘Economic Policy in Theory and Practice’, London, Macmillan.
- Seppecher, P. (2012), ‘Flexibility of wages and macroeconomic instability in an agent-based computational model with endogenous money’, *Macroeconomic Dynamics* . forthcoming.
- Sgroia, D. & Zizzo, D. (2007), ‘Neural networks and bounded rationality’, *Physica A* **375**, 717–725.
- Sgroia, D. & Zizzo, D. (2009), ‘Learning to play 3×3 games : Neural networks as bounded-rational players’, *Journal of Economic Behavior & Organization* **69**, 27–38.
- Simon, H. (1971), The Theory of Problem Solving, *in* ‘IFIP Congress (1)’, pp. 261–277.
- Simon, H. A. (1996), *The Sciences of the Artificial*, Cambridge, Mass. : MIT Press, 3rd Edition.
- Svensson, L. (2009), ‘Transparency under Flexible Inflation Targeting: Experiences and Challenges’, *Sveriges Riksbank Economic Review* **1**, 5–44.
- Taylor, J. B. (1979), ‘Estimation and Control of a Macroeconomic Model with Rational Expectations’, *Econometrica* **47**(5), 1267–86.
- Tesfatsion, L. & Judd, K. L., eds (2006), *Handbook of Computational Economics*, Vol. 2 of *Handbook of Computational Economics*, Elsevier.

- Walsh, C. (2006), Transparency, Flexibility and Inflation Targeting, *in* F. Mishkin & K. Schmidt-Hebbel, eds, ‘Monetary Policy under Inflation Targeting’, Central Bank of Chile.
- Walsh, C. (2007), ‘Optimal Economic Transparency’, *International Journal of Central Banking* **3**(1), 5–36.
- Walsh, C. (2008), ‘Announcements and the Role of Policy Guidance’, *Federal Reserve Bank of St. Louis Review* **Jul**, 421–442.
- Walsh, C. (2010), Transparency, the Opacity Bias and Optimal Flexible Inflation Targeting. mimeo, Nov.
- White, H. (1992), *Artificial Neural Networks: Approximation and Learning Theory*, Oxford:Blackwell.
- Williams, J. (2010), ‘Monetary Policy in a Low Inflation Economy with Learning’, *FRBSF Economic Review* pp. 1–12.
- Woodford, M. (2003), *Interest and Prices : Foundations of a Theory of Monetary Policy*, Princeton University Press.
- Woodford, M. (2005), ‘Central bank communication and policy effectiveness’, *Proceedings, Federal Reserve Bank of Kansas City* (Aug), 399–474.
- Yıldızoğlu, M. (2001), ‘Connecting adaptive behaviour and expectations in models of innovation: The Potential Role of Artificial Neural Networks ’, *European Journal of Economic and Social Systems* **15**(3), 51–65.
- Yıldızoğlu, M., Sénégas, M.-A., Salle, I. & Zumpe, M. (2012), ‘Learning the optimal buffer-stock consumption rule of Carroll’, *Macroeconomic Dynamics* . forthcoming.

A Pseudo-code of the model in Salle, Yıldızoğlu & Sénégas (2013)

Initialization

1. Creating n households and initializing their individual variables (strategies, expectations and resulting behaviour);
2. Creating one firm and initializing her individual variables (price, quantity);
3. Initializing aggregate variables and parameter values;
4. Choosing one degree of transparency for the CB.

Sequence of the events

5. Computing each household's i reservation wage:

$$w_{i,t} = w_{i,t-1} \times \left(1 + \mathbb{1}_{(\pi_{i,t+1}^e > 0)} \gamma_{i,t}^w \cdot \pi_{i,t+1}^e\right) \quad (\text{A.1})$$

6. (*Labour market*)

- (a) Sorting the n households by increasing $w_{i,t}^d : (l_1, \dots, l_n)$;
- (b) Setting $h_{l_i,t} = 1$ while $i \leq H_t^d$, and then $h_{l_i,t} = 0$;
- (c) Computing H_t (aggregate hired labour);

7. Computing the corresponding good supply $Y_t^s = H_t^{1-\alpha}$, $\alpha \in]0, 1[$, the wage bill and the corresponding price P_t ;

8. Computing each household i 's individual variables:

- (a) Income flow $y_{i,t}$:

$$y_{i,t} = w_{i,t} h_{i,t} + \frac{\Pi_{t-1}}{n} + b_{i,t-1}(1 + i_{t-1}) \quad (\text{A.2})$$

- (b) The consumption rate $k_{i,t}$:

$$k_{i,t} = k_{i,t-1} - \gamma_{i,t}^k (i_t - \pi_{i,t+1}^e) \in [\underline{k}, \bar{k}] \quad (\text{A.3})$$

- (c) Goods demand:

$$c_{i,t}^d = k_{i,t} \cdot \tilde{y}_{i,t} \quad (\text{A.4})$$

where $\tilde{y}_{i,t}$ is a weighted average of past (real) incomes,

- (d) The resulting savings/debt strategy: $b_{i,t}$

9. (*Good market*)

- (a) Sorting the n households by decreasing $c_{i,t}^d : (g_1, \dots, g_n)$;
- (b) Setting $c_{g_i,t} = c_{g_i,t}^d$, and $i = i + 1$ while $c_{g_i,t}^d > 0$, and stopping as soon as $\sum c_{g_i,t} \geq Y_t^s$;
- (c) Computing sold quantities Y_t , the firm's profits Π_t , the utility of each household $u_{i,t}$, the inflation rate π_t , the output gap x_t and all other aggregate indicators.

10. while $t \leq T$ (T in the total number of periods of the run):

- (a) (*Monetary policy*): Setting the interest rate i_t according to x_t and π_t :

$$1 + i_t = (1 + \pi^T) \left(\frac{1 + \pi_t}{1 + \pi^T} \right)^{\phi_\pi} \left(\frac{1 + x_t}{1 + x^*} \right)^{\phi_x} \quad (\text{A.5})$$

- (b) (*Households' learning*): for each household i , implementing the learning process on strategies $(\gamma_{i,t}^w, \gamma_{i,t}^k)$:
- i. updating the pair of strategies by imitation, with a probability P^I ,
 - ii. updating the pair of strategies by random exploration, with a probability P^M ;
- (c) (*Households' expectations*): for each household i , updating his ANN, and computing the resulting inflation expectation $\pi_{i,t+1}^e$.
- (d) (*Firm's learning*): Adjusting the labour demand of the firm H^d :

$$\begin{cases} \text{If } \frac{\Pi_t}{P_t} \geq \tilde{\Pi}_t, \text{ then} & H_{t+1}^d = H_t \times (1 + \epsilon) \\ \text{otherwise} & H_{t+1}^d = H_t \times (1 - \epsilon) \end{cases} \quad (\text{A.6})$$

where $\epsilon > 0$ is an adjustment rate.

- (e) Running steps (5) to (10).

B Calibration

Parameter	Value(s) in the numerical simulations	Definition
<i>Structural parameters of the MABM</i>		
$n > 1$	100	Number of households
$T > 1$	800	Number of periods
$\alpha \in [0, 1[$	0.25	Rate of returns of the production technology
$\mu \geq 0$	0.10	Mark-up over the marginal cost
$\epsilon > 0$	0.01	Adjustment rate of labour demand to changes in profits
ρ	0.5	Parameter in weighted averages.
$\underline{k} \geq 0$	0.5	Lower bound of the consumption rate
$\bar{k} \geq 1$	1.5	Upper bound of the consumption rate
$P^M \in]0, 1]$	0.02	Probability of mutation in the GA
$P^I \in]0, 1]$	0.1	Probability of imitation in the GA
$\sigma_w > 0$	0.25	Shock on the expectations channel
$\sigma_k > 0$	0.05	Shock on the consumption channel
<i>ANN parameters</i>		
hN	$\min\{2, \lfloor \sqrt{I} \rfloor\}$	Number of hidden nodes in the ANN
<i>windowSize</i>	$5 * (I + 1) \times hN$	Number of past observation to train the ANN
<i>numEpoch</i>	25	Number of iterations to train the ANN
τ	0.1	Learning rate of the ANN
<i>Monetary policy parameters</i>		
$\phi_\pi \geq 0$	$\{0, 0.5, 1, 1.5, 2\}$	Reaction to coefficient to inflation gap
$\phi_x \geq 0$	$\{0, 0.25, 0.5, 0.75, 1\}$	Reaction coefficient to output gap
$\pi^T \geq 0$	$\{0.01, 0.02, 0.04\}$	Inflation target
$horizon \geq 0$	$\{1, 4, 8\}$	Horizon of the CB's previsions
$L \geq 0$	4	Number of lags in the CB's VAR prevision model
$\kappa \geq 0$	0.02	Gain in the CB's VAR prevision model

Table 2: Parameters values in numerical simulations

C Additional simulation results

		<i>Degrees of transparency</i>						
		0	1	2	3	4	5	6
horizon = 1	mean $\pi_{i,t}^e$	0.12	0.0443	0.074	0.0801	0.0942	0.0957	0.0438
	mean π_i	0.1148	0.0531	0.0856	0.0922	0.1091	0.1041	0.0427
	var π_t	0.0397	0.0132	0.0228	0.0357	0.0418	0.0516	0.0171
	mean x_t	0.1229	0.0477	0.0866	0.0902	0.072	0.0577	0.0305
	var x_t	0.0549	0.02	0.042	0.045	0.0311	0.0454	0.0115
horizon = 4	mean $\pi_{i,t}^e$	0.1397	0.023	0.0223	0.0142	0.0424	0.0244	0.0373
	mean π_i	0.1495	0.045	0.039	0.0241	0.036	0.0363	0.038
	var π_t	<i>0.0409</i>	<i>0.007</i>	<i>0.0057</i>	<i>0.0036</i>	<i>0.0069</i>	<i>0.0036</i>	<i>0.0153</i>
	mean x_t	0.1425	0.0412	0.0191	0.0499	0.1147	0.1036	0.1125
	var x_t	<i>0.06</i>	<i>0.0148</i>	<i>0.0066</i>	<i>0.0239</i>	<i>0.0856</i>	<i>0.0494</i>	<i>0.06</i>
horizon = 8	mean $\pi_{i,t}^e$	0.1487	0.0538	0.0557	0.0606	0.0662	0.0541	0.0838
	mean π_i	<i>0.156</i>	<i>0.0775</i>	<i>0.0804</i>	<i>0.0823</i>	<i>0.0822</i>	<i>0.0662</i>	<i>0.0838</i>
	var π_t	0.0399	0.0209	0.0178	0.0299	0.0158	0.0155	0.0272
	mean x_t	<i>0.1323</i>	<i>0.0273</i>	<i>0.007</i>	<i>0.026</i>	<i>0.0665</i>	<i>0.0438</i>	<i>0.1238</i>
	var x_t	0.0534	0.0085	0.0013	0.0101	0.0307	0.022	0.0473

Table 3: Further descriptive statistics (109,620 observations in total, $\pi^T = 2\%$)

