How Transparent About Its Inflation Target Should a Central Bank be? An Agent-Based Model Assessment

Isabelle Salle[*], Marc-Alexandre Sénégas[*], Murat Yıldızoğlu[*]

September 27, 2013

Abstract

This paper revisits the benefits of explicitly announcing an inflation target for the conduct of monetary policy in the framework of an agent-based model (ABM). This framework offers a flexible tool for modeling heterogeneity among individual agents and their bounded rationality, and to emphasize, on this basis, the role of learning in macroeconomic dynamics. We consider that those three features (heterogeneity, bounded rationality, and learning) are particularly relevant if one desires to question the rationale for the monetary authorities to be transparent about the inflation target, and to achieve credibility. Indeed, the inflation targeting's potential role in anchoring inflation expectations and stabilizing the inflation and the economy can be analyzed more realistically if we do not assume a representative agent framework based on substantial rationality in behaviors and expectations. Our results show that a dynamic loop between credibility and success can arise, and stabilize inflation, but only in the case of a learning environment that corresponds to a moderate degree in heterogeneity regarding the behavior and decisions of individual agents. In a more general way, we analyze, using this ABM, different assumptions about the nature of the economic volatility, and the degree of disclosure of the target.

JEL codes – C61 - C63 - E52 - E58

Keywords Monetary Policy, Inflation Targeting, Credibility, Expectations, Agent-Based Model.

[*]GREThA (UMR CNRS 5113), Université de Bordeaux, Avenue Léon Duguit, F-33608 PESSAC, Corresponding author: isabelle.salle@u-bordeaux4.fr

1 Introduction

What macroeconomic benefits can monetary authorities expect from announcing an explicit inflation target and, more generally, from being transparent about the conduct of monetary policy?

Since two decades at least, an important strand of the literature in monetary economics has addressed those questions by looking more particularly to the case of inflation targeting (**IT** hereafter) regimes whose distinctive features precisely rely on the announcement of an explicit inflation target, and a high degree of transparency about the central bank (**CB** henceforth) objectives and actions[1]. In that literature, IT and transparency have been emphasized as two core factors favoring the coordination and the anchoring of inflation expectations. This coordination, in turn, underlies the macroeconomic stabilization benefits that the monetary authorities can reap under IT. Empirical evidence about those benefits has proved however to be more controversial. According to several studies, and as far as both the anchoring of expectations and the stabilization evidence is concerned, non-IT countries have experienced comparable macroeconomic performances to the IT ones (see, among others, Roger 2009, Schmidt-Hebbel 2009, or Walsh 2009). Moreover, the results obtained in those studies could have been influenced by the features of the period under analysis (mainly the Great Moderation episode) while the relative merits of IT would be much more difficult to prove in front of strong adverse shocks and instability, such as those that the world economy is facing since the global crisis 2007/2008.

At the theoretical level, investigating the impact of IT by emphasizing the role of the inflation target announcement and, more generally, the communication strategy of the CB is a challenging task as it does a priori impose to deviate from the full information rational expectations (**RE** henceforth) setting that surrounds the working of most of the New Keynesian (**NK** hereafter) models and, more generally, of DSGE models that provide the usual framework of macroeconomic analysis nowadays. Such a deviation is required however since, to quote Svensson (2009, p. 11))[2]: *"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"*. Two interesting routes have been followed in the literature to address that required deviation.

The first route relaxes the assumption of a complete and symmetric information that usually

[1]The literature is impressive on these issues. For a recent survey on IT, see Svensson (2010) and the references therein. A useful reference is also Walsh (2009). On the impact of transparency and communication of the CB, see, among others, Geraats (2002, 2009) and Woodford (2005). A third feature is often associated with the adoption of IT, namely the practice of forecast-inflation targeting. For a standard reference on that aspect, see Giannoni & Woodford (2004).

[2]See also Orphanides & Williams (2007) for the same argument.

underlies agents decisions in standard NK models (we call *information route* this strand of the literature). That approach is implemented through the specification of coordination games, mostly inspired by the Keynesian beauty contest[3] or the adoption of NK modeling frameworks that retain heterogeneous information sets among agents[4]. In such settings, two opposite effects of transparency are emphasized: on the one hand, transparency reduces uncertainty surrounding monetary policy actions, and then operates as a coordination device for agents' beliefs; on the other hand, agents are likely to overestimate the value of public information, and overreact to it (Morris & Shin (2002)). It ensues that there is no consensual answer about the optimal degree of information dissemination that CBs should implement (see Walsh (2009) for a recent overview of the current stance of the debate in the context of monetary policy and IT).

The second route introduces learning dynamics into the modeling framework of the economy - often tackled as a reduced form version of a DSGE model - instead of assuming that agents do hold RE ex ante (we call *learning route* this strand of the literature). This important set of contributions (see Evans & Honkapohja (2001)) has stressed that macroeconomic stabilization becomes more challenging when agents are engaged in an adaptive learning process that may or may not make them converge to a RE equilibrium in the neighborhood of which they are supposed to be located in the first place. Usually, that learning process is modeled with least squares algorithms while information provided by the CB - when considered - simplifies and improves the forecasting exercise that the agents are supposed to implement on the basis of their econometric model[5]. Few papers go a step further than the least squares learning benchmark, and consider models with an heuristic-based expectations formation process in order to question the impact associated with the announcement of the inflation target[6]. In those contributions, the target is explicitly used as (or included in) a rule of thumb to forecast inflation and, hence, may anchor inflation expectations, favoring in turn macroeconomic stabilization. Overall, the learning literature appears to provide more consensual views about the way the effects of transparency

[3]See, notably, Morris & Shin (2002), Demertzis & Viegi (2008, 2009) or Svensson (2008)

[4]See Woodford (2003*a*) for a detailed presentation of this framework, and, for instance, Hellwig (2002), Walsh (2007*b*, 2008), Cornand & Heinemann (2008), Rudebusch & Williams (2008) or Cornand & Baeriswyl (2010) for analysis of optimal transparency in that kind of framework. For the assessment of the impact of the inflation target announcement based on an estimated DSGE model with imperfect information and credibility, see Melecký et al. (2009).

[5]See Orphanides & Williams (2005, 2007) for the analysis of the announcement of the inflation target, and Eusepi & Preston (2010) on the disclosure of the whole monetary policy rule.

[6]Discrete choices in heuristics have been introduced in macroeconomic models by several authors. The seminal paper of Brock & Hommes (1997) models agents who predict future values of endogenous variables from a finite set of heuristics, and use a discrete choice model to make a rational choice among these heuristics based upon their past performances. Branch & Evans (2006) introduce agents choosing between a list of misspecified econometric models, and base their selection on relative forecast performance. On the specific topic of the economic impact of the announcement of an inflation target when agents use heuristics to forecast inflation, see Brazier et al. (2008) in an overlapping generation model, Canzian (2009) in an *ad-hoc* aggregate model and De Grauwe (2011) in a log-linearized version of the New Keynesian model.

are likely to overcome the additional macroeconomic volatility caused by the departure from rational expectations and the ensuing learning environment.

While these developments have provided new and original insights on how the publicity over the inflation target could affect the formation process of inflation expectations and, thereby, macroeconomic outcomes, they have proceeded in that respect, however, by allowing only for a limited range of deviations from the by now standard microfoundations of macroeonomic models. By so doing, they have restricted the ground for the emergence of coordination problems in the settings under concern. For example, in the information route, the introduction of imperfect information in coordination games usually goes through the accounting for idiosyncratic, stochastic noise in the information sets of private agents[7]. Addressing the case for agents' heterogeneity in that way is of limited scope however, as other aspects of agents' behavior are left similar between them, fitting into the lines of the representative agent hypothesis. Moreover, coordination failures on the markets cannot arise because the assumption of rational expectations based on the common knowledge of the underlying economic model is maintained and ensures that agents' economic decisions are mutually consistent. Concerning the learning route, the departure from the RE benchmark is usually limited to the expectations formation process, while leaving mostly unchanged the structure of the underlying economic model. That structure is derived assuming perfect knowledge of the form of the relations between variables, coupled with a representative agent framework, within which agents' behaviors are derived from intertemporal optimization programs. Those assumptions are however very demanding in terms of agents' cognitive abilities, and may be questioned regarding psychological or experimental evidence (De Grauwe (2011)).

The present paper aims at relaxing some of these assumptions, and reassessing the likelihood of the anchoring and the coordination of expectations that an IT regime is supposed to deliver through the publicity of an explicit inflation target. To this end, we elaborate on the agent-based modeling (**ABM** hereafter) framework developed in Salle et al. (2013). This framework is deliberately constructed as closely as possible to the standard NK model, while allowing the introduction of heterogeneity, bounded rationality and learning of the individual agents in the economy. Bounded rationality is expressed as heuristic decisions processes for the agents, based on simple rules of thumb concerning the adaptation of their behavior (consumption, labor supply, labor demand, etc.). Learning of the agents concerns specific features of these heuristics, and takes the form of individual random experimenting, combined with imitation between agents. This social/experimental learning naturally creates heterogeneity between the agents at the level

[7]Usually the standard distribution of the noise variable is a Normal density distribution whose parameters are known by the agents under concern. Heterogeneous information can also be introduced by considering two categories of private agents only, see e.g. Honkapohja & Mitra (2006).

of the heuristics they each use. This framework also allows for the emergence of disequilibrium and rationing on the markets, and we can include in our analysis disequilibrium dynamics. To analyze the potential stabilizing role of IT, we build an ABM that extends this initial framework, mainly in two directions. First, we explicitly account for an inflation expectations formation process whose updating both fits into the learning process on the behavior of individual agents in the model, and incorporates the credibility of the CB such as it is perceived by the agents. On that aspect, we adapt the approach developed by Demertzis and Viegi (see Demertzis & Viegi (2008, 2009)) to the case of bounded rationality, and agents heterogeneity. This specification allows us to analyze how credibility, coordination and learning issues affect the performances of the IT regime depending on the degree of transparency displayed over the inflation target. Second, we include new dimensions in the representation of the CB's monetary policy, and analyze how these dimensions could articulate with the expectations formation process of the agents, and condition the features of the optimal monetary strategy that should be used in different environments. More specifically, we determine the optimal monetary strategy by analyzing both the communication policy of the CB, and the parameters of the monetary policy rule that we consider in the model. To our knowledge, this model is the first one to integrate the credibility, coordination, and learning dimensions of inflation targeting in a fully microfounded economic setting. Furthermore, we show that our model is able to replicate the main stylized facts that characterize inflation time series in IT countries.

Two main results stand out from our analysis.

First, we find that the announcement of an inflation target is superfluous in a stable learning environment, by which we mean that the learning dynamics come along with a moderate degree of heterogeneity in the behavior and decisions of individual agents. We can interpret such a configuration as akin to the one that has been associated, in macroeconomic terms, with the so-called *Great Moderation* episode that the Western economies did experience between the mid 1990s and the mid-2000s. Admittedly, we confirm that the IT regime works well in that case. A credibility–success loop emerges: inflation expectations remain well anchored at the CB's inflation target and as a result, inflation is stabilized. Monetary policy can focus on the stabilization of the level of activity at a lower cost in terms of inflation variability. Yet, a non-IT regime also achieves a similar virtuous circle when facing only small disturbances.

Second, we show that the performance of the IT regime is not robust to alternative learning environments that, by contrast with the stable one, come along with a significant variability in individual behavior and decisions. Two configurations of that kind are considered in our framework. In the first one, we focus on a learning configuration whose features lead to a significant level of uncertainty surrounding the transmission of monetary policy to aggregate demand and hence activity. That situation echoes the current macroeconomic context that most economies have been experiencing since 2008, where financial dislocation is impairing conventional monetary transmission. The second case refers to a context whose learning characteristics lead to strong disturbances on the inflation wage indexation process and in turn on inflation dynamics. That configuration is close to the one that usually results from the occurrence of cost-push shocks and leads to the same trade-off that those disturbances create between the macroeconomic objectives of the CB.

In both environments a limited transparency framework becomes desirable for the CB. Tying one's hands by adopting an IT regime with, moreover, a tightly defined target might prove to be quite harmful, since the anchoring properties of the inflation target are, in those conditions, impaired by the credibility problems that the CB might encounter following this official commitment. Self-validating mechanisms are likely to occur and reverse credibility loops ensue for the monetary authorities. In such environments, the choice of an *implicit* (not announced) inflation target insures the CB against significant credibility losses. We also show that, under both learning environments, the economy would benefit from partial announcements about the inflation target. That kind of communication would indeed provide a clear signal to anchor inflation expectations for the part of the public that is reached by that announcement, while it allows for a less tightly defined objective for the remaining part of the agents. It ensues that expectations are better controlled, and the trade-off between inflation stabilization and the level of activity is loosened. Overall, our results suggest that fully revealing the price stability target can deteriorate macroeconomic performances, even in a setting whose core features would a priori lead to think favorably about CB's transparency.

The paper is organized as follows. Section 2 presents the specification and building of the ABM we use in our study. Section 3 discusses the simulation protocol that we adopt in this context. That protocol is established so as to fulfill validation criteria that both comply with standard calibration exercises in the literature about the NK model and empirical evidence obtained from IT experiences. Specific techniques are used in that respect. The validation step allows in turn to provide an overview of the model functioning and outcomes across the different environments that we consider. Section 4 focuses on the results concerning the design of optimal monetary policy under the different learning environments. Finally, Section 5 concludes.

2 The model

2.1 General features

This model elaborates on the macroeconomic ABM first introduced in Salle et al. (2013). This ABM shares several general features of the baseline NK framework (see Woodford (2003*b*, Chap. 4)). In the economy we specify, individual agents do indeed interact on the consumption good and labor markets. Labor is the only input, used to produce a perishable good, and the good market operates under imperfect competition. The price/wage adjustments are characterized by nominal rigidities. Inflation is driven by both aggregate demand and inflation expectations, in line with the NK Phillips curve. The CB operates in a flexible inflation targeting regime, using a Taylor rule to implement the monetary policy. Two transmission channels of monetary policy are considered in the model: the consumption channel and the expectations channel.

In our ABM, the economy is populated by n households, indexed by i, $i \in [1, n]$, a single firm summarizing the supply side, and a CB. The sequence of events is as follows. First, the rationing mechanism on the labor market underlies the allocation of households' labor supplies to the firm. This allocation, and the quantity of hired labor determine, in turn, the unemployment rate in the economy, the firm's good supply, the labor costs and the corresponding price of the good set by the firm, as well as the labor income of each household. Second, households choose their consumption and savings/debt strategy. In a third step, the rationing mechanism on the good market determines the allocation of the good supply to each household. This allocation, as well as the previously fixed labor costs and the good's price, dictate the firm's profit and each household's utility. Fourth, the CB sets the nominal interest rate for the next period, according to a Taylor rule based on the current level of the inflation and unemployment rates. Lastly, agents update their individual behavior and inflation expectations, and the story starts all over again.

In the following, we sequentially present the main blocks of the model: the behavior, inflation expectations and learning of the households; how the CB may aim to influence these expectations; the behavior and learning of the firm; the monetary policy rule used by the CB; and how markets match individual demand and supply decisions.

2.2 Households

Households supply labor and consume according to two simple rules of thumb. To implement those two rules, they need to forecast inflation. Moreover, as they learn about their environment, they are supposed to adapt these rules according to a social learning process, and update their inflation forecasts on the basis of the realization of inflation and the CB's announcements.

2.2.1 Individual behaviors

Labor supply At each period, each household is endowed with an inelastic labor supply normalized to one, *i.e.* $h^s_{i,t} = 1$, $\forall t, i$.[8] This normalization allows to explicitly define unemployment in the model, and can be interpreted as a full-time occupation (see Delli Gatti et al. (2005), Gaffeo et al. (2008) or Raberto et al. (2008) for a comparable setting). Labor supply behavior is formulated in terms of a reservation wage, at which each household starts to supply labor. The heuristic rule that we choose introduces a direct transmission channel of inflation expectations to the growth rate of nominal wages, and hence to price inflation, leading to an expectation channel of monetary policy. For every period t, each household i sets its reservation wage following the rule:

$$w_{i,t} = w_{i,t-1} \times (1 + \mathbb{1}_{(\pi^e_{i,t+1}>0)} \gamma^w_{i,t}.\pi^e_{i,t+1}) \tag{1}$$

Heuristic (1) is the first rule of thumb. It indicates that households raise their reservation wage $w_{i,t}$ only if the expected inflation rate $\pi^e_{i,t+1}$ is positive (and, consequently, $\mathbb{1}_{()} = 1$). A wage indexation process then prevails, according to which the agents raise their wage by $\left(\gamma^w_{i,t}.\pi^e_{i,t+1}\right)$. Otherwise, they keep it unchanged ($\mathbb{1}_{()} = 0$). Thus, wages are increasing with the expected inflation rate, while being subject to nominal wage downward stickiness ($\gamma^w > 0$). Oeffner (2008) or Raberto et al. (2008) make comparable assumptions. In this set-up, coefficients γ^w_i stand for the strength of wage indexation, and thus of the wage–price spiral. Coefficient γ^w_i is the first strategy variable of households.

Consumption At each period, each household determines its desired consumption expenditures using a consumption rate $d_{i,t}$ that is applied to a moving average $\tilde{y}_{i,t}$ of past and current real income levels, denoting its desire to smooth its consumption path (in line with the consumption behavior in the NK model). More precisely, the demand for the good of each household i for period t is expressed as :

$$c^d_{i,t} = d_{i,t}.\tilde{y}_{i,t} \tag{2}$$

and the current real income is given by:

$$\frac{y_{i,t}}{P_t} = \frac{w_{i,t}}{P_t} h_{i,t} + \frac{\Pi_{t-1}}{P_t}\frac{1}{n} + \frac{b_{i,t-1}}{P_t}(1 + i_{t-1}) \tag{3}$$

[8] Lower case symbols stand for individual variables, and upper case symbols for aggregate ones. s and d superscripts indicate respectively supply and demand variables.

with $w_{i,t}h_{i,t}$ corresponding to labor income ($h_{i,t} \leq h^s_{i,t}$), P_t to the aggregate price level, Π_{t-1}/n to the share of the last period's total nominal profits distributed to each consumer, $b_{i,t-1}$ representing nominal, financial holdings (positive in case of savings and negative in case of debt), and i, the nominal riskless interest rate set by the CB.

The second rule of thumb of the household is dedicated to the adjustment of the consumption rate, $d_{i,t}$, that we have already defined in equation (2). We introduce a counterpart, in the ABM, of the standard Euler condition for consumption decisions that prevails in the NK model. Accordingly, monetary policy should influence aggregate demand through the nominal interest rate, and, for a given level of inflation expectations, the real interest rate, which is the relevant variable for consumption decisions. We specify this rule as:

$$d_{i,t} = d_{i,t-1} - \gamma^d_{i,t}(i_t - \pi^e_{i,t+1} - r^n_t) \tag{4}$$

$d_{i,t}$ is assumed to depend on the gap between the current real interest rate expected by household i, i.e. $i_t - \pi^e_{i,t+1}$ and the natural (real) rate r^n_t. The coefficient $\gamma^d_{i,t} \in \mathbb{R}$ is the households' second strategy, while the corresponding consumption decision rule takes also into account inflation expectations. As soon as $\gamma^d_{i,t} > 0$, consumption decreases when the real interest rate rises, and we obtain the standard consumption channel of monetary policy (working through the substitution effect). Otherwise (i.e., when $\gamma^d_{i,t} < 0$), the income effect dominates and the consumption channel is reversed. Both effects have been emphasized as plausible in the empirical literature (see Oeffner (2008, p. 83) for a review).

Finally, considering their desired level of consumption $c^d_{i,t}$, the amount of nominal (desired) savings or indebtedness $b_{i,t}$ is given by[9]:

$$b_{i,t} = y_{i,t} - c^d_{i,t} \cdot P_t \tag{5}$$

Now that we have described the individual labor supply (through wage demand) and consumption decisions in each period, we turn to the description of how these heuristics evolve depending on the interactions between agents, and on the resulting social learning process.

[9] In DSGE models, transversality conditions are imposed to avoid explosive dynamics in the bond accumulation process. Such restrictions cannot be set in our model, in which we have to impose period-by-period constraints. In that respect, we impose an upper limit $\bar{d} > 1$ to the consumption adjustment rate d, in order to rule out excessive debt and household defaulting, and we impose a lower bound $\underline{d} > 0$ to ensure minimal subsistence consumption at each period.

2.2.2 Adaptation through social learning

Following the assumption of perpetual learning, the two strategies $\gamma^w_{i,t}$ and $\gamma^d_{i,t}$ are updated each period. We assume two learning operators : a social learning mechanism (imitation) and random experiments in the strategy space[10].

Imitation is driven by a roulette-wheel selection process, based on a performance indicator computed using the smoothed levels of past utility, which is an increasing and concave function $u(.)$ of periodic consumption. Each period, with a probability P_{imit}, a household can imitate the strategies (γ^w, γ^d) of another agent. For each agent, the probability of being selected during this imitation process is proportional to the relative share of its performance in the agents' population. Consequently, better strategies in terms of utility are favored by the selection process, and they tend to replace less performing ones among the population of households.

Moreover, with a probability P_{mut}, a household can also perform a random experiment, in order to potentially discover better strategies than those already present among the household population. In this case, it draws a new couple of coefficients, each from a normal distribution, with a mean equal to the average value of the related strategy in the household population, and, respectively, standard deviations σ_d and σ_w. Draws for strategies γ^w are truncated at zero, as negative indexation coefficients are not relevant, but draws for strategies γ^d allow for negative coefficients, potentially giving rise to an income effect on consumption following a change in the interest rate (see Equation (4)).

Our assumption of social learning on behavioral parameters could seem restrictive, given that it is generally not very easy for the agents to observe the components of the behavior of another agent. It would be more reasonable to assume that they can, at best, observe the market behavior of others. Unfortunately, when the social learning is based directly on the observed decisions of the agents, it can drive very unrealistic dynamics on the economy, especially when the model contains inter-temporal decisions, and interdependent markets, as we have shown in (Salle et al. 2012). One potential solution to this problem is the incorporation of an individual dimension in learning (learning from experiments), but, this does not really give rise to a more realistic behavior, except when this learning is very sophisticated as we have shown in another article (see (Yıldızoğlu et al. 2012)). As a consequence, we consider that assuming that agents meet infrequently to discuss about their decisions, and learn from each other is an acceptable trade-off here, because the focus of this article is on their ability to coordinate their expectations.

Parameters σ_d and σ_w can be interpreted in terms of shocks: they control the endogenous

[10] See, notably, Holland et al. (1989) and Sargent (1993) for general statements. Applications to economic issues include, for instance, Arifovic (1995).

variability in the model, which arises from the features of the learning process.

High values of σ_d are associated with a high level of uncertainty about the way monetary policy transmit to the demand (see Equation (4)). That situation is akin to the one that has been identified as parameter uncertainty in the related literature about monetary policy under uncertainty[11].

Variability induced by high values of σ_w directly translates into variability in the inflation process through the wage-indexation scheme (see Equation (1)). High values of σ_w lead thus to similar effects on inflation dynamics as exogenous shocks on inflation expectations or, at the least, disturb the transmission of the latter within the supply-side of the economy. More generally, such values generate an economic environment akin to the one that ensues from the presence of cost-push shocks and, as such, are likely to give rise to a trade-off between inflation and real economic stabilization objectives for the CB.

From the preceding, it should be clear that households' inflation expectations play a central role in the economic dynamics in our model: i) they determine the *ex ante* real interest rate, through which the CB affects aggregate demand, and ii) they feed the inflation dynamics, and can thus endogenously drive the inflation process far from the target, and create a trade-off between the two objectives of the CB. For these reasons, it becomes important that the CB could act as a *manager of expectations* (Woodford (2003*b*)). As communication with the public is a key part of that role, we now detail how CB's announcements may affect households' inflation expectations.

2.2.3 Inflation expectations and CB's announcements

Every household needs, at each period t, to forecast the one-step-ahead inflation rate $\pi^e_{i,t+1}$ in order to estimate the rate of return on its savings (or the cost of its debt) in Heuristic (4), and to adjust its reservation wage, through Heuristic (1). We assume an inflation expectations formation mechanism that shares common features with that specified in Demertzis & Viegi (2009). Accordingly, agents update their inflation expectations on the basis of the CB's past performance, and thus of its perceived credibility. We distinguish between two regimes: *IT*, in which the CB announces to all households the inflation target π^T and the radius of tolerance around it $+/-\zeta$, and *non-IT*, in which none of these parameters is announced. Unlike Demertzis & Viegi (2009), our ABM explicitly models heterogeneous expectations, so that each household holds its own inflation expectation. In line with the procedural rationality assumption, we design a simple adaptive mechanism to determine agents' beliefs updating within the context of IT.

[11] See, for instance, Brainard (1967) for a standard reference and Söderström (2002) and Giannoni (2007) for a recent treatment of the design of monetary policy under that kind of model uncertainty

According to the concept of "perpetual learning" (see, notably, Orphanides & Williams (2005)), we assume that agents only memorize a finite number of past periods, denoted by *window*.

Under IT, agents update their expectations, depending on the degree of credibility they attribute to the CB. In order to assess this credibility, they evaluate monetary policy actions on the basis of past CB announcements and actual inflation rates. Following these past observations, they consider, with a probability P_{target} (respectively $(1-P_{target})$), that the CB is credible (resp., not credible). More precisely, in each period for which the inflation is contained between $\pi^T - \zeta$ and $\pi^T + \zeta$, they consider that the CB is successful, and if the CB has been successful in x periods over the last *window* periods, they compute P_{target} as:

$$P_{target} = \frac{x}{window} \in [0, 1] \tag{6}$$

Consequently, with a probability P_{target}, they consider that the CB is credible, and they base their expectations on its announcements: each household draws a new inflation expectation from a uniform distribution with the support $[\pi^T - \zeta, \pi^T + \zeta]$. That scheme models the role of the inflation target both as a *focal point* for heterogeneous expectations, and as a *reference point* for the evaluation of the CB's performances. This approach is perfectly in line with the definition of credibility given in Faust & Svensson (2001), as the gap between the inflation target and the average inflation expectations. Credibility of the CB, inherited from past performance in managing its objectives, has also been emphasized as the primary determinant of inflation expectations (Blinder (1998)). Like in the setting of Demertzis & Viegi (2009), our expectations scheme allows for the emergence of a credibility and success loop: the more successful the CB, the closer to the target inflation expectations will be, and the more likely the ability of the CB to maintain inflation in the announced range. The reverse is true in the case of a credibility loss. Moreover, the radius of tolerance around the target, ζ, plays an ambivalent role: the wider the radius (i.e. the higher ζ), the more likely past inflation rates within the range, and the higher, *ceteris paribus*, P_{target}. However, the higher the range, the more heterogeneous agents' expectations will be.

In the alternative case, with a probability $1 - P_{target}$, each agent considers that the CB is not credible, and does accordingly set its expectations on the basis of the actual inflation rate. Specifically, the agent formulates its expectation, in this case, as $\pi^e_{i,t+1} = \pi_t + \xi_i$, with ξ_i a noise drawn from a normal distribution with mean zero and variance σ_ξ (see De Grauwe (2011) for a comparable mechanism). That forecasting rule does well account for the unanchoring process of inflation expectations when credibility is weak. In that case indeed, this process may drive the inflation rate far away from the CB's objectives, even more as the loop between credibility and success operates in the reverse way.

Under non-IT, the explicit target is replaced by the average inflation rate over the last *window* periods[12]. This is the only difference between both regimes.[13] That choice is made for various reasons. First, that specification allows for a credibility-success loop as under IT, which may in turn favor expectations coordination, although it does not provide an anchoring device around the target as such (we follow on that point an extension of their model that is suggested by Demertzis & Viegi (2009, p. 31)). Second, that forecasting rule tackles the lack of anchor in the absence of an explicit inflation target. In our model, if the CB meets its target, the average past inflation remains close to the target, and non-IT resembles IT. However, a series of failures in keeping inflation close to the target pulls average inflation away from the implicit inflation target, and contributes to further driving inflation expectations far from the target. Third, as stressed in an experimental study by Roos & Schmidt (2012), past trends of macroeconomic variables are a key determinant of forecasts when laypeople, like households, are concerned. Eventually, the specification we use translates the Keynesian notion of "market sentiment", which has been modeled in the context of monetary policy by Canzian (2009) or De Grauwe (2011).

From the preceding, it ensues that, in our set-up, the benefit of being transparent mainly arises from the potential anchoring effect of the announcement of the inflation target on households' inflation expectations. If that anchoring takes place, the inflation process is stabilized. Other economic effects of transparency have been considered in the literature. We do not take them into consideration as such in this paper however. For example, the role of policy objective announcements as an implicit commitment device has been stressed in models where the CB has an incentive to create inflation surprises (see, for example, Walsh (1995)), which is not the case in the framework we consider. Furthermore, in our model, households do not rely on interest rate changes to forecast inflation in the absence of an explicit inflation target, so that we cannot address the so-called opacity bias (see Walsh (2010)). In such settings, transparency is moreover likely to coordinate inflation expectations (the so-called *coordination effect*, see Hellwig (2002)). While in our model coordination is not made attractive as such, because the utility function depends only on consumption, households' expectations indirectly influence other households' consumption[14]. They have therefore a collective interest in coordinating their inflation expec-

[12] We could have considered a noisy target but our focus is on credibility issues of the announcement and the way the CB can use it to manage expectations, that is why we do not want to add issues of clarity, which have been tackled in Salle et al. (2013).

[13] Since the CB does not directly use ζ in this case, this variable becomes in fact a characteristic of the households' expectation process. We have chosen to keep the same variable in both cases, in order to limit the number of variables.

[14] For instance, if most agents anticipate a rise in inflation, actual inflation will rise next period through the expectations channel. Agents who did not expect that rise may lose purchasing power, both through a misassessment of the real rate of return of their savings and an underindexation of their reservation wage.

tations. By the way, coordination could be assessed with respect to the performance of agents' learning. As strategies γ^w and γ^k are directly related to individual inflation expectations, one could expect that the social learning mechanism will yield better performances if it takes place in an environment where agents hold comparable beliefs on the future. Coordination could thus favor learning.

We now turn to the description of the firm's behavior and learning.

2.3 The firm

In our model, as in the baseline NK one, labor is the only input; there is no capital. We assume here a monopoly producing a perishable good, but that discrepancy with the usual monopolistic competition assumption of the NK framework turns out to be a minor one. The NK framework involves many firms, but they are identical (they share the same production function and the same mark-up on the marginal cost), and the analysis does only consider a symmetric equilibrium. In such a context, considering a single firm is not really restrictive, given the objective we give to our model. It should be noted that macroeconomic ABMs commonly make that assumption: for example, in Raberto et al. (2008).

Production, price and profit When the labor demand of the firm (resulting from its learning process, see below) meets the labor supply of the households on the labor market (see section 2.5), the rationing mechanism determines the actual quantity of labor (H_t) that the firm hires, and the corresponding wages that it pays to the hired households. The firm uses that quantity to produce the good, through a standard production function (see, for example, Gali (2008)):

$$Y_t^s = A_t H_t^{1-\alpha} \tag{7}$$

where $\alpha \in [0, 1[$ encompasses decreasing returns, A_t is the technology factor[15]. The only production costs of the firm result from the wage bill:

$$\Psi(Y_t^s) = \sum_{i=1}^{n} h_{i,t} w_{i,t} \tag{8}$$

and we can compute the nominal aggregate wage level, as a weighted average of individual wages, i.e. $W_t \equiv \frac{\Psi(Y_t^s)}{H_t}$.

Thanks to its market power, the firm sets its price P, according to a mark-up μ on the

[15] We assume a deterministic natural production level, we set $A_t = 1$, $\forall t$ (the long run value of the technology assumed by Woodford (2003*b*, p. 225)).

marginal cost given by:

$$\Psi'(Y_t^s) = \frac{W_t}{(1-\alpha)} \frac{Y_t^s}{A_t}^{\frac{\alpha}{1-\alpha}} = \frac{\Psi(Y_t^s)}{(1-\alpha)Y_t^s} \tag{9}$$

The resulting price is:

$$P_t = \frac{(1+\mu)}{(1-\alpha)} \frac{\Psi(Y_t^s)}{Y_t^s} \tag{10}$$

and it is an increasing function of the production Y^s as soon as $0 < \alpha < 1$.

The rationing mechanism on the good market (see section 2.5) determines the quantity that the firm does actually sell to the households (Y_t), which gives the corresponding profit of the firm:

$$\Pi_t = P_t Y_t - \Psi(Y_t^s) \tag{11}$$

As for households, the firm has only a limited knowledge of the problem it faces: notably, it does not know the aggregate demand on the good market it is confronted with, because it is not capable of anticipating all the individual demands $c_{i,t}^d$. We assume that the good is perishable. Consequently, the firm has to learn to set its labor demand facing a three-fold constraint: on the labor market, the total amount of labor supply is limited to n units (one per household), the reservation wages can become quite high, and, on the good market, the firm can be constrained by demand.

Adaptation of the good supply The firm behaves in an adaptive way, and updates, each period, its labor demand strategy H_t^d.[16] As we assume a single firm, it cannot benefit from social learning and can only learn through an individual learning process. We consider a simple adaptive mechanism, much in the spirit of gradient ascent learning (see for example Leijonhufvud (2006, p. 1631-32) or Delli Gatti et al. (2005)). As the firm's profit is increasing in the quantities of the good sold (as soon as $\alpha \neq 0$) and decreasing in case of remaining stocks, the firm raises its labor demand when its real profit is above its trend $\tilde{\Pi}_t$. Therefore, we specify the rule:

$$\text{If } \frac{\Pi_t}{P_t} \geq \tilde{\Pi}_t \text{ then } H_{t+1}^d = H_t \times (1+\epsilon) \tag{12}$$

$$\text{If } \frac{\Pi_t}{P_t} < \tilde{\Pi}_t \text{ then } H_{t+1}^d = H_t \times (1-\epsilon) \tag{13}$$

where $\epsilon > 0$ is a parameter which denotes an adjustment rate.

[16] If we overlook potential rationing, having a labor demand or a good supply strategy is equivalent from the firm's point of view, as labor is the only input (see Equation (7)). Through the mark-up price setting (10), adjusting price is also equivalent to adjusting quantities, so that the firm has actually only one decision-making variable, expressed here in terms of labor demand.

It should be finally noted that our framework implies price stickiness: The firm does not necessarily adjust, in each period, the good supply, and hence the price, when aggregate demand changes. We show in Salle et al. (2013) that the Philips curve in our ABM can be expressed as :

$$\pi_t = \frac{\sum_{i=1}^{n} \Delta w_i h_{i,t-1}}{\Psi_{t-1}} + \sum_{i=1}^{n} \frac{\Delta h_i}{H_{t-1}} \left(\frac{w_{i,t-1}}{W_{t-1}} + \alpha - 1 \right) \tag{14}$$

where ΔX stands for the variation of the variable X between $t-1$ and t. In our setting, the Phillips curve (14) does incorporate nominal rigidities, allowing for real effects of monetary policy in the short run.[17].

2.4 Monetary authority

Apart from its communication strategy (*i.e.* announcing or not the target and the radius), the CB reacts to both inflation and the level of activity, and sets the nominal interest rate i_t according to a non-linear Taylor (1993) instrumental rule[18]

$$1 + i_t = (1 + \pi^T)(1 + r^n_{t-1}) \left(\frac{1 + \pi_{t-1}}{1 + \pi^T} \right)^{\phi_\pi} \left(\frac{1 + u^*}{1 + u_{t-1}} \right)^{\phi_u} \tag{15}$$

where π^T stands for the inflation target, u^* for the natural rate of unemployment and $\phi_\pi > 0$ and $\phi_u > 0$ are the reaction coefficients to inflation and unemployment rates. The rule incorporates the unemployment rate, as we are able to explicitly derive it from the model (see also Orphanides & Williams (2007)).

2.5 Aggregation and dynamics

We do not assume that markets necessarily clear. Notably, price and wage setting strategies are not set *a priori* so as to make agents' strategies mutually consistent. Markets instead confront aggregate supply and aggregate demand according to rationing mechanisms that we structure by replicating as much as possible the characteristics of the markets in the original NK model, in order to keep our results comparable with the static equilibrium of the NK model.

[17]It can also be noted that this Phillips curve depicts a positive relationship between inflation and expected inflation (through the wage indexation process) as in the expectation-augmented Phillips curve of the NK framework

[18]We consider the non-linear form of the rule rather than the log-linearized version, given the non-linear dynamics of our framework, see Ashraf & Howitt (2012) for a comparable specification.

Labor market Aggregate demand for labor is the firm's strategy H_t^d, while aggregate supply is given by:

$$H_t^s = \sum_{i=1}^{n} h_{i,t}^s = n \quad (16)$$

Both are matched according to a process that is designed to be consistent with the fact that the firm aims at minimizing its production costs, and favors the less demanding consumers first: the firms hires the households in an order that corresponds to increasing reservation wages. The aggregate hired labor is then set as:

$$H_t = \min(H_t^d, n) = \sum_{i=1}^{n} h_{i,t} \quad (17)$$

The corresponding unemployment rate is computed as $u_t = \frac{n-H_t}{n}$. The real wage rate is given by $\omega \equiv \frac{W_t}{P_t} = \frac{(1-\alpha)}{(1+\mu)} H_t^{1-\alpha}$, decreasing with H and reaching a minimum $\frac{(1-\alpha)}{(1+\mu)} n^{1-\alpha}$ when full employment prevails.

Good market Actual aggregate labor (17) yields aggregate good supply Y_t^s through the production function (7), and the aggregate good demand is given by the sum of individual ones (see Equation (2)). Both are confronted according to an efficient rationing mechanism: households are ranked by decreasing good demand, so that the firm first faces the highest demand. That mechanism stands for the counterpart of the standard assumption of households aiming at maximizing their utility, derived from their consumption. If a household is rationed, it buys bonds b with its remaining cash. Inflation π_t is computed as $\pi_t = \frac{P_t - P_{t-1}}{P_{t-1}}$. A special case can be observed when full-employment is reached, and the firm can sell all the production (corresponding to the equilibrium on both markets). In that case, the rate of profit reaches a (maximum) static equilibrium level equal to $\frac{(\alpha+\mu)}{(1+\mu)} n^{1-\alpha}$.

We now present the simulation protocol that we use, before introducing our results.

3 Calibration and validation

The outcomes of the model are analyzed through computer simulations. Appendix A gives the model calibration, which is the same under IT and non-IT, and details the full simulation protocol. Values of structural parameters are set according to standard values in the NK literature (see, notably, Woodford (2003*b*)). We focus on the interaction between the learning environment, which determines the level of endogenous variability in the model (through parameters σ_d and σ_w), and the monetary policy strategy (through parameters ϕ_π, ϕ_u, π^T and ζ), and we analyze how that interaction affects economic performance under both regimes. We first define a `baseline` scenario by choosing a set of parameter values which allows to reproduce empirical regularities that are relevant for the purpose of the model. We then launch a set of simulations designed to give some intuitive insights into the way the model globally works under various configurations of learning and monetary policy parameters. These experiments test values of 8 parameters – *window*, the coefficients of the Taylor rule ϕ_π and ϕ_u, the radius ζ as well as the learning parameters σ_d, σ_w, P_{mut} and P_{imit} (see Table 4 in Appendix 3).

3.1 Empirical validation

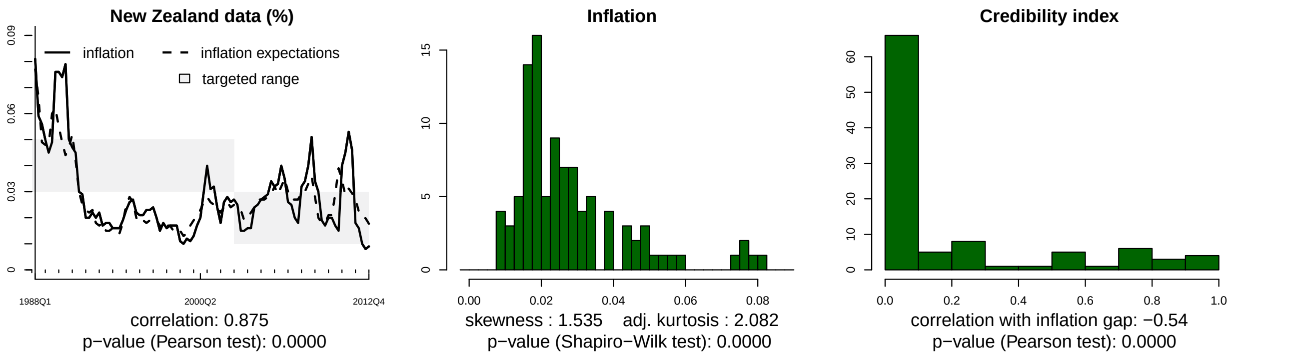
In line with recent developments in agent-based modeling[19], we define and specify the `baseline` scenario by confronting the model's dynamics to related empirical regularities (see Table 5, in Appendix A). As the paper focuses on the interplay between inflation expectations, CB's credibility and macroeconomic stabilization, we consider the following empirical features. Figure 1 displays the joint evolution of inflation and inflation expectations, and statistical properties of inflation distribution in New Zealand between 1988 and 2012, and in UK between 1997 and 2013. Those countries have been chosen because they have been pioneers in inflation targeting (implemented in 1989 in New Zealand and in 1992 in UK[20]), and they have been conducting surveys of inflation expectations since then (we use the J6 survey of inflation expectations available on the RBNZ website and the GfK NOP Inflation Attitudes survey available on the Bank of England's website). Three stylized facts are particularly relevant for our purpose. First, inflation and inflation expectations are strongly and positively correlated, suggesting the predominance of the expectations channel (see also Woodford (2003*b*)). Second, inflation is characterized by a non-normal distribution with fat tails: the distribution displays excess kurtosis, indicating that values far from the mean are more frequent than under a normal distribution, and the distribution is right-skewed, meaning that inflation rates are more often strongly higher than strongly lower than the average (see also De Grauwe (2012) for a comparable analysis). Third, we compute an index of inflation target credibility for those two countries, in line with Faust & Svensson (2001)'s definition of credibility as negatively related to the distance between agents' inflation expectations and the CB's announced target[21]. In the ABM, credibility is modeled as

[19] See, notably, Dosi et al. (2010), Lengnick (2013).

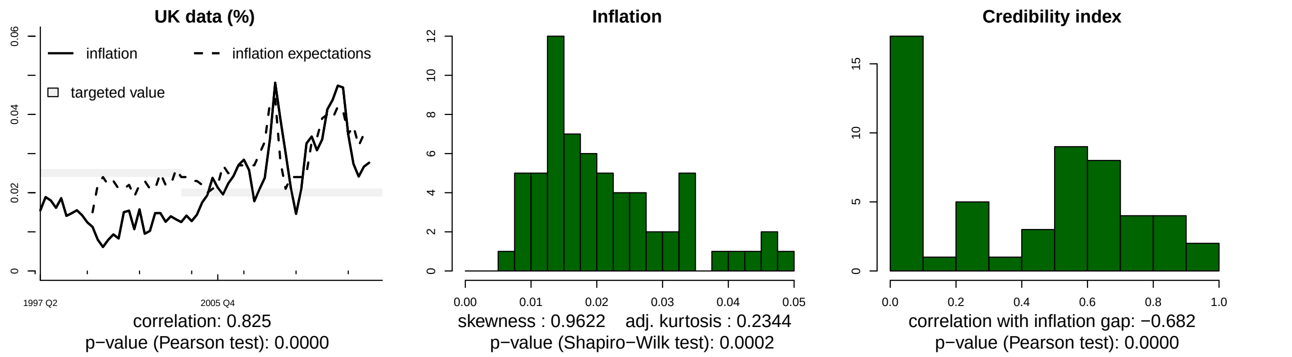
[20] An inflation target were first announced in September 1992 in UK, but the operational responsibility, which implies greater independence and credibility has been given to the Bank of England in May 1997.

[21] Precisely, we use de Mendonca (2007)'s credibility index, which accounts for the range of tolerance around the target:

$$\text{credibility index } = \begin{cases} 1 & \text{if } E(\pi) = \pi^T \\ 1 - \frac{E(\pi)-\pi^T}{\rho} & \text{if } \pi^T - \rho \leq E(\pi) \leq \pi^T + \rho \\ 0 & \text{if } E(\pi) > \pi^T + \rho \text{ or } E(\pi) < \pi^T - \rho \end{cases} \tag{18}$$



(a) New Zealand over 1987Q1-2012Q4. Left panel: evolution of inflation and inflation expectations, middle panel: inflation distribution (source: RNBZ), right panel: credibility index distribution (authors' calculation).



(b) United Kingdom over 1997Q2-2013Q1. Left panel: evolution of inflation and inflation expectations, middle panel: inflation distribution (source: Bank of England), right panel: credibility index distribution (authors' calculation).

Figure 1: Empirical data of two inflation targeting countries.

		$cor(\pi, \pi^e)$	skewness (π)	kurtosis (π)	$cor(\text{credibility}, \pi - \pi^T)$
ABM (`baseline` scenario)	mean	0.911	0.587	2.066	-0.362
	t-test, H_0 :	mean > 0			mean < 0
	p-value	0.0000	0.0000	0.0119	0.0000
UK (1997Q2-2013Q1)		0.825	0.9622	0.2344	-0.682
NZ (1987Q1-2012Q4)		0.875	1.535	2.082	-0.54

Table 1: Simulated data statistics, average over 100 runs, 800 periods, discarding the 100th first periods (in order to rule out the effects of initialization).

the fraction of agents who believe that inflation will be contained in the range, and is not directly comparable to the values of de Mendonca (2007)'s index. Nevertheless, both measurements have the same interpretation: credibility varies between 0 (no credibility) and 1 (full credibility), and they are sufficient to highlight the third empirical regularity under interest: credibility and inflation performances appear highly correlated, lower credibility leading to a higher inflation gap.

We apply the same index to both countries to make the comparison easier, although the UK does not announce a range around the target. However, an implicit range of ±1% may prevail, as the Governor is held to account through an open letter to the Chancellor if the target is missed by more than 1%.

We then run 100 replications of the baseline scenario, whose calibration is given in Table 5. Results are reported in Table 1. Well in tune with the previous empirical findings, our model significantly reproduces the correlation between expectations and inflation, and the non-normal distribution of inflation, both excess kurtosis and right-skewness. Importantly, we are able to provide a comprehensive explanation to these findings within the model, all the more as this model is also able to account for the strong negative correlation between inflation target credibility and inflation gap.

Finally, it should be noted that non-normality is an emergent property of the model, we do not assume it. In our model, volatility results from the learning shocks, which are obtained using normal draws, but the non-linear and decentralized nature of our model leads to non-linear aggregate dynamics following these normal disturbances.

We conclude that our ABM is able to account for stylized facts that are central to the analysis that we aim at performing. We now highlight the main lines of the latter by focusing on the underlying mechanisms that shape the role of monetary policy in our framework.

3.2 Overview of the model outcomes: learning, credibility loops, and macroeconomic performance

As we mentioned, the simulation protocol aims at analyzing the interaction between the learning environment and the monetary policy strategy that prevails in the different economies we simulate. Those interactions rest on two sequences of actions, the interplay of which fundamentally underlies the working of the model in each period, and the ensuing dynamics.

The first sequence goes from the learning and expectations formation by the agents to the determination of aggregate, macroeconomic outcomes. The households decide over the level of both their desired consumption and reservation wage using the related rules of thumb, and their inflation expectations. Together with the price formation process implemented by the firm, those decisions lead to the determination of the individual and aggregate levels of consumption, unemployment and output, after the matching processes have operated on the labor and good markets.

The second sequence works in the reverse way, going from the macroeconomic outcomes to the learning behavior, and the expectation formation process by the agents. Consumption and wage indexation heuristics are updated by the households through a social learning process. Accordingly, the individual consumption levels observed in the population do feed back into the evolution of the behavioral rules of the agents (learning by adaptation). Simultaneously, under IT, inflation expectations are revised by taking into account the degree of credibility that is

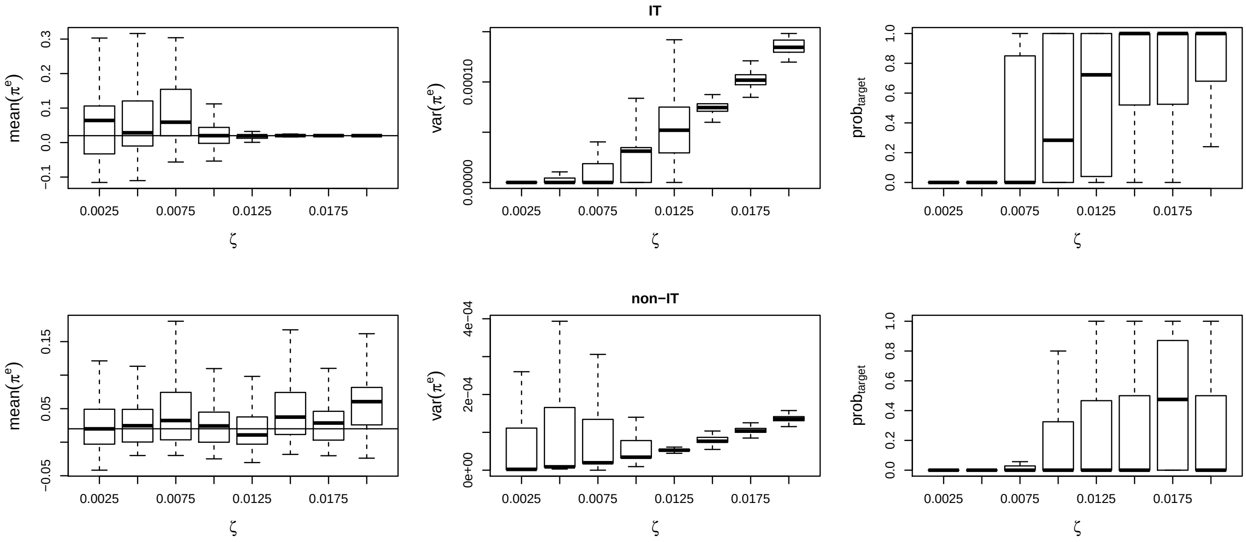


Figure 2: The role of the radius around the inflation target under both regimes

Boxplots depict the distribution of the average inflation expectations among households ($mean(\pi^e)$), their variance ($var(\pi^e)$) and the credibility measure P_{target} over the whole simulations ($33 \times 30 = 990$ runs per regime). Each one is measured every 50 periods, i.e. $t = 100, 150, ..., 750, 800$.

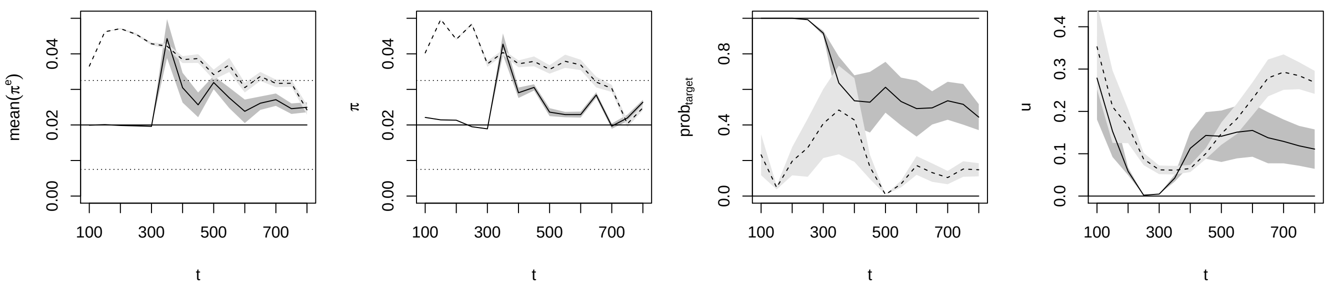
assigned to the CB.

Monetary policy, by which we mean both the setting of the interest rate and the communication strategy of the monetary authorities, does interact with both aforementioned sequences. On the one hand it affects the determination process of the aggregate outcomes through the consumption and expectation channels; on the other hand, the formation of inflation expectations rests partly upon the communication strategy of the monetary authorities, through the reference points that the latter provide under IT.

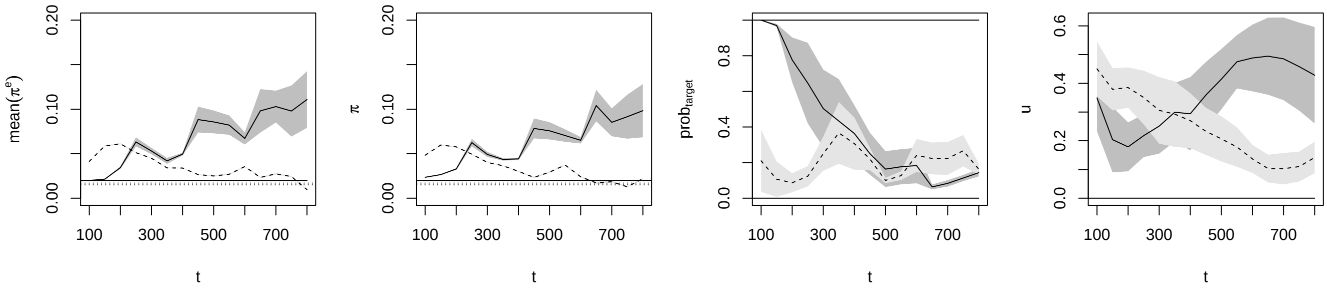
The main purpose of the simulations that we perform is then to assess whether distinctive features emerge from the dynamic interplay we just described and what role is played in that respect by the learning environment and/or the dimensions of the monetary policy conduct.

Overall, the results provide some evidence about the impact of the announcement of the inflation target under IT. Whether that impact is significant (compared to the case of a non-IT regime), and whether it provides an efficient anchoring of the expectations, and brings about positive stabilization properties depends, however, on the scenarios under concern, and thereby, on different parameter values of the model.

In particular, and as in Demertzis & Viegi (2008), we find that the radius ζ that refers to the tightness of the range around the inflation target plays an ambiguous role under IT. Figure 2 (upper panel) displays the trade-off that emerges under IT between providing a clear signal in order to coordinate heterogeneous individual expectations (with a narrow range), and allowing



(a) Experiment 16



(b) Experiment 30

IT ——— median ■ +/- std. dev. **non-IT** - - - median ■ +/- std. dev.

Figure 3: Dynamics in chosen experiments.

for a less tightly defined target to be met (with a wide range). That trade-off does not stand out as strictly under non-IT (see Figure 2, bottom panel).

The anchoring device property of IT goes through the emergence of a credibility / success loop. This loop allows the CB to achieve an effective coordination of individual inflation expectations on the target and thereby a favorable stabilization record regarding the inflation rate, which does, in turn, sustain the credibility of the monetary authorities. That virtuous circle can be illustrated using a selected experiment from the simulation exercise. Experiment 16 (see Table 4 in Appendix A and Figures 3 - panel (a) for illustration) refers to a context where (1) the structural parameters are close to the middle of their variation domain (and thus refer to a more or less stable learning environment) (2) a wide range around the target is considered ($\zeta = 1.50\%$), leading to a weaker trade-off regarding the magnitude of this bandwidth. We observe that, under IT, inflation expectations are contained in the range, even after a peak around the 300th period. This peak results in a credibility loss and an increase in unemployment, that dampens over time. The economic situation is worse under non-IT, however. In that case, the current inflation rate provides a moving anchor to the formation of expectations, which prevents the CB from taking advantage of the credibility/success loop. The probability (measured through P_{target}) of getting close to the target remains much lower than under IT[22]. It ensues that the stabilization of inflation into the targeted range appears, under such circumstances more costly in terms of unemployment.

The benefits of committing to an explicit inflation target should not be overvalued however and depend, among others, on the learning environment. In that respect, experiment 30 illustrates a case of a cumulative credibility loss process in a context where (1) the objective is tightly defined ($\zeta = 0.75\%$) and (2) the environment exhibits a significant heterogeneity in the learning behavior of households that leads to strong inflation volatility ($\sigma_w = 0.33$). Inflation expectations get unanchored, and feed back into the inflation process, which puts the CB into a reverse credibility loop, leading to adverse macroeconomic outcomes. On the contrary, the pursuit of an implicit target (under non-IT) allows for containing inflation expectations quite close to the objective and favors macroeconomic stabilization, especially as far as the unemployment is concerned.

Finally, we observe that inflation expectations and inflation appear to be highly and positively correlated across the different scenarios, suggesting that the expectations channel is predominant in the determination of inflation in the model.

On the basis of the previous results, the next section aims at tackling more precisely how the nature of the learning environment influences the impact of an inflation target announcement, and looks at the dimensions that an optimal monetary policy could take on accordingly.

4 Optimal monetary policy under IT

As we have seen, ranges of values for parameters σ_d and σ_w can be used to characterize various (learning) environments in terms of macroeconomic volatility. We define first a *stable environment* by setting $\sigma_d = \sigma_w = 0.05$. We then consider a scenario with high model uncertainty, by setting $\sigma_d = 0.4$, and a scenario with strong inflation variability, by setting $\sigma_w = 0.4$ (under the last two scenarios, when unchanged, the other parameters are kept at their "stable" values). Subsection 4.1 derives the optimal monetary policy rule under those three scenarios for both regimes – IT and non-IT, while subsection 4.2 carries the same analysis when partial announcements are considered.

For each set of simulations, we consider a standard loss function as a measurement of CB's

[22]The computation of P_{target} that is used on Figure 3 under non-IT is based on the deviation of inflation from the target, while P_{target} that is used in the updating process of inflation expectations under the same regime (see Sub-section (2.2.3)) is computed on the basis of the deviations from average inflation over the last *window* periods.

effective performance:

$$\mathcal{L}(\pi, u) = (\pi - \pi^T)^2 + u^2 \tag{19}$$

where the inflation rate π_t and the unemployment rate u_t are measured for each run as the average over the whole simulation, discarding the first 100th periods[23]. The entire methodology we use to map the loss function values to the monetary policy parameters in our non-linear ABM is detailed in Appendix B, and is based on Roustant et al. (2010).

4.1 Transparency, variability and optimal monetary policy rule

We first characterize, both under IT and non-IT, the best monetary policy configutations (coefficients ϕ_π and ϕ_u) prevailing in the stable scenario, and in the alternative configurations of shocks. In each of these configurations, we alternatively retain two radius levels, which correspond to either a price stability objective as a single point ($\zeta = 0.1\%$), or as a range ($\zeta = 1\%$). Tables 5 and 6 in Appendix A give the values taken by the other parameters. Table 8 in Appendix B reports the details of the estimation of the kriging models, that underlie our quantitative analysis . Table 2 shows the optimal coefficients ϕ_π^* and ϕ_u^* as well as the corresponding minimum estimated loss L^*, and investigates the sensitivity of the results to a change in the inflation target.

In the stable environment, an IT regime with a relatively broad range ($\zeta = 1\%$) outperforms a non-IT strategy. In the absence of adverse shocks, the CB may hence benefit from the credibility/success loop and better stabilize inflation expectations and inflation. As, in those conditions, the anchoring of expectations favors the achievement of the price stability objective, the CB can focus its monetary policy actions on the stabilization of unemployment, what reflects the relative values of the reaction coefficients in the optimal rule. Nevertheless, with a very tight objective ($\zeta = 0.1\%$), credibility and success cannot be ensured, and the IT regime looses its attractiveness. The benefit that can be reaped from announcing a vague objective have been notably emphasized by Stein (1989) and Garfinkel & Oh (1995), but in a theoretical framework that incorporates time inconsistency issues. In such a setting, the CB can create surprise inflation by announcing a wide range, which allows to depart from the target without loosing its credibility, even when a low inflation objective is officially followed. In our model, the CB has no incentive to create inflation surprises but the learning environment may cause deviations of inflation and unemployment from their targets and put the CB's credibility at risk.

High σ_d – led variability moves the economy away from the stable case. Whatever the configuration of the monetary policy regime, this environment leads the CB to optimally adopt

[23] That is necessary to rule out the effects of random initialization of the model and to allow the learning process to make consistent behaviors emerge.

a one-sided reaction, either based on inflation($\phi_u^* = 0$) or on unemployment ($\phi_\pi^* = 0$). We interpret this result as indicating that this configuration does not introduce any trade-off for the CB between its objectives, which would then lead to react to both inflation and unemployment deviations. If the signal is very precise ($\zeta = 0.1\%$), the optimal rule prescribes to react only to inflation. As previously mentioned, in that case, the credibility/success loop hardly arises, and inflation expectations are more likely to get unanchored, feeding back into the inflation process. On the contrary, with a less tightly defined objective, inflation expectations are better stabilized and the CB has only to react to deviations of unemployment. However, a non-IT regime outperforms an IT strategy, suggesting that the virtuous circle provided by IT could barely work when confronted to a high degree of uncertainty concerning the transmission channel of monetary policy. Raising the inflation target (4%) strongly improves macroeconomic stabilization whatever the regime while a non-IT strategy almost insulates the economy from the uncertainty shocks in this case. It has to be noted on this point, that the economic configuration we tackle with the scenario we consider here shares some common features with the current economic situation where, following the global crisis of 2007/2008, financial dislocation is impairing conventional monetary transmission (Minegishi & Cournède (2009)). In recent debates on the design of post-crisis monetary policy facing such challenges, Blanchard et al. (2010), among others, call for a rise in the inflation target in such a context, from 2 to 4%. Our analysis supports such a proposal.

Under high σ_W – led variability (inflationary shock dominance), macroeconomic outcomes strongly deteriorate, while a trade-off between the CB objectives arises. Accordingly, optimal monetary policy implies, in all but one of the regimes considered, a strong reaction to both inflation and unemployment. As explained in Subsection 2.2.3 (see, also, Equation (14)), this kind of volatility does directly lead to variability in the inflation process. The CB is therefore highly likely to miss its inflation objective and hence, to lose its credibility. Expectations get unanchored, all the more as the noise ξ is related to the variability level σ_W. Inflation gets then mostly driven by these erratic expectations and is no more in line with the aggregate demand stance. This phenomenon creates a trade-off between the CB objectives. Here again, the benefits from an IT strategy through the loop between credibility and success are not robust to the introduction of a volatile learning environment. By the way, the losses that are incurred under an IT regime (compared to non IT) are fairly equivalent across the values of ζ. As noticed by Demertzis & Viegi (2009) in the conclusion of their article, in such an environment, not announcing at all the target is a better strategy than choosing to publicize a price stability objective with a broad range under IT. Moreover, and by contrast with the preceding scenario, rising the inflation target increases the loss level, and is not an desirable strategy under inflationary shock dominance.

	$\zeta = 0.001$ – IT	$\zeta = 0.01$ – IT	$\zeta = 0.001$ – Non-IT	$\zeta = 0.01$ – Non-IT
Stable scenario: $\{\sigma_w, \sigma_d\} = \{0.05, 0.05\}$, $\pi^T = 0.02$				
ϕ^*_π	0	0.34	1.31	0
ϕ^*_u	0.65	1	1	1
L^*	0.077	0.0334	0.0486	0.0551
Model uncertainty: $\{\sigma_w, \sigma_d\} = \{0.05, 0.4\}$, $\pi^T = 0.02$				
ϕ^*_π	1.4	0	2	0
ϕ^*_u	0.14	1	0	1
L^*	0.0897	0.0786	0.0343	0.0543
Model uncertainty: $\{\sigma_w, \sigma_d\} = \{0.05, 0.4\}$, $\pi^T = 0.04$				
ϕ^*_π	0.31	0.3	2	0
ϕ^*_u	1	1	0	1
L^*	0.0273	0.0458	0.0241	0.0094
Inflationary shocks: $\{\sigma_w, \sigma_d\} = \{0.4, 0.05\}$, $\pi^T = 0.02$				
ϕ^*_π	0	2	1.34	2
ϕ^*_u	0.89	1	0.66	1
L^*	0.2111	0.18	0.0962	0.0877
Inflationary shocks: $\{\sigma_w, \sigma_d\} = \{0.4, 0.05\}$, $\pi^T = 0.04$				
ϕ^*_π	0	2	2	2
ϕ^*_u	0	1	1	1
L^*	0.318	0.176	0.148	0.117

Table 2: Optimal monetary policy (ϕ^*_π, ϕ^*_u) and associated minimum loss L^*, based of the optimization of the kriging model of the CB's loss as a function of ϕ_π and ϕ_u.

In all the cases we have considered, we note that the optimal monetary policy rule is always an aggressive one. This result goes along the lines of previous statements about optimal monetary policy under uncertainty (see Schmidt-Hebbel & Walsh (2009) for a review). Model uncertainty, that is to say uncertainty concerning the parameters which depict the transmission mechanisms of monetary policy, characterizes our environment. It is a multiplicative uncertainty case. There is no consensual answer to the question of optimal monetary policy in such a context. The conservatism principle first established by Brainard (1967) prescribes a moderate rule. However, when shocks and parameters are correlated, as it is the case in our model, the Brainard principle does not hold anymore. Other contributions call for an aggressive rule under other cases of "Brainardian" uncertainty, for example when the CB cannot accurately estimate how inflation responds to inflation expectations (see Söderström (2002)). Moreover when radical uncertainty surrounds the economic model, and is tackled through the tools of robust control theory, optimal monetary policy rules are hawkish ones (Giannoni (2007)), especially when the CB cannot identify which parameters are uncertain (Tetlow & von zur Muehlen (2001)). We also conclude in favor of aggressive rules under model uncertainty, which primarily stems, in out case, from learning.

4.2 Can partial announcements overperform pure IT or non-IT regimes?

Some contributions to the debate about the optimal degree of transparency have emphasized the role of partial announcements (see, among others,Cornand & Heinemann (2008) and Walsh (2009)). In those works, it is assumed that only a fraction $P \in [0,1]$ of agents receives the CB's signal, i.e. the so-called "degree of publicity" P can be lower than one. According to Cornand & Heinemann (2008) this is the case if the CB chooses to provide news only in certain communities, or in a language that is understood only by some. Furthermore, public announcements are in general released through media, but each agent acknowledges a certain medium only with some probability, so that a CB can choose the degree of publicity by selecting appropriate media for publication. Agents may also have limited ability to process information, or may face costs to acquire it, so that an immediate release does not necessarily turn out to be incorporated into all agents' decisions. Partial dissemination of precise public information may be an optimal communication strategy in combining the positive effects of valuable information for the agents who receive it with a confinement of the threat of overreaction by limiting the number of receivers (Cornand & Heinemann (2008)). Walsh (2007*b*) also shows that the optimal degree of economic transparency is affected differently by the existence of cost-push or, alternatively, demand shocks.

In the same vein as those authors, we introduce partial dissemination of CB's announcement by defining the degree of publicity of the inflation target as the share of agents ($P \in [0,1]$) who learn the target, and use it to forecast inflation (*see* the mechanism depicted in Sub-section 2.2.3). Conversely, a share $1 - P$ of agents forms inflation expectations in the same way as under non-IT. Following Demertzis & Viegi (2009), we also include in our experiments different values of the radius ζ around the target. We thus obtain a four-dimensional monetary policy strategy $(P, \phi_\pi, \phi_u, \zeta)$, and derive the optimal one in the stable scenario, and in the two volatility scenarios we consider. Result are reported in Table 3, and details of the estimations in Table 9 in Appendix B.

In the stable scenario, a pure non-IT regime (i.e. $P = 0$) is optimal. However, the minimum loss obtained fairly equals the one obtained under a pure IT regime (*i.e.* when $P = 1$, see Table 2). As a conclusion, we confirm the result of Demertzis & Viegi (2009): the publicity of the target is superfluous in a weakly volatile environment. This result is in line with what has been observed during the *Great Moderation* period, where developed countries, either under IT and non-IT, have experienced a low macroeconomic variability (Geraats (2009)). The performance of IT in these countries appear, thus, at the most, "non-negative" (Walsh (2009)).

On the contrary, in front of adverse shocks, partial announcements turn out to minimize the

	$(\sigma_w, \sigma_d) = (0.05, 0.05)$	$(\sigma_w, \sigma_d) = (0.05, 0.4)$	$(\sigma_w, \sigma_d) = (0.4, 0.05)$
ϕ_π^*	0	0	0
ϕ_u^*	1	0.43	1
ζ^*	0.008	0.01	0.006
P^*	0	0.24	0.5692
L^*	0.0363	0.0271	0.0718

Table 3: Optimal monetary policy with partial announcements – $\pi^T = 2\%$.

expected loss of the CB. In case of model uncertainty (high σ_d – led variability), the CB has to release its target only to a small part of the agents composing the economy (25%). This strategy overperforms a pure IT or a pure non-IT regime. Note that, this results contradicts Walsh (2007a), which establishes that complete transparency is optimal in front of demand shocks. These demand shocks are assimilable to the disturbances associated with a high level of σ_d in our model: in both frameworks, they correspond to the control error of the CB on the demand through the nominal interest rate. However, the two models work differently. In Walsh set-up, transparency on the target allows firms to infer the kind of shocks (demand or supply) that the CB is expecting while, in case of opacity, firms set their forecasts using the CB's instrument only, and the so-called opacity bias arises. As firms only adjust their prices in reaction to supply shocks, demand shock contaminates inflation if firms misinterpret the change in the interest rate in reaction to a demand shock, as a change in response to a supply shock. In our model, the gain (or the loss) of being transparent comes from the gain of being credible (or the loss of having lost its credibility). Credibility, in turn, anchors the heterogeneous private inflation expectations, and reduces macroeconomic volatility. Partial dissemination of the target then limits the risk of losing its credibility, while maintaining a partial anchorage in case of success. In that respect, the optimal range around the target is relatively high, close to 1%. That result indicates that the insurance against a credibility loss turns out to be the primary concern of a CB facing high model uncertainty, in comparison with to the need of providing a clear focal point to coordinate expectations.

When facing inflationary shocks, partial announcements lead to the minimum loss, which is obtained with a rather high degree of publicity ($P = 0.57$). This strategy seems to provide an efficient management of inflation expectations and, hence, a reduction in inflation volatility, so that the CB can focus on the stabilization of the level of activity ($\phi_\pi^* = 0$, $\phi_u^* = 1$). As a consequence the trade-off between both objectives that this kind of disturbances lead to is significantly weakened. A mitigate dissemination of the target balances the risk of loosing credibility in front of inflation variability and the gain from the coordination of inflation expectations at the targeted level. A higher degree of publicity is required when inflationary shocks are concerned, than when model uncertainty is dominant. Intuitively, the anchoring of expectations through a clear focal point obtained via a precise signal is of critical importance when the expectation channel of monetary policy is highly volatile so as not to add to the volatility implied by the learning environment. On the other hand, the insurance against the loss of credibility becomes crucial when the effect of monetary policy on aggregate activity is uncertain. In that respect, the optimal band width is higher in the latter case.

5 Conclusion

The main objective of this paper has been to revisit the benefits and costs of transparency for an inflation targeting central bank using an agent-based modeling framework for that purpose. By transparency, we mean the announcement of the numerical value of the inflation target together with a range around it. In so far as we fully address, in the first place, the case for heterogeneous agents and bounded rationality, the features of this agent-based model offer a comprehensive and original way to analyze how credibility, coordination between agents and learning issues interfere with each other and affect the performances of the inflation targeting regime. In our setup, the benefit from announcing the target arises from the emergence of a loop between credibility and success for the monetary authorities. According to this virtuous circle, inflation expectations may remain anchored at the CB's inflation target and as a result, inflation may be stabilized around the target. The trade-off that the CB faces between the inflation objective and the level of activity may be loosened, and monetary policy can focus on the stabilization of unemployment at a lower cost in terms of inflation variability. Our results confirm that those mechanisms prevail in a rather stable environment. However, those outcomes are not robust to the introduction of uncertainty affecting the (real) interest rate transmission channel of monetary policy, nor to the existence of a volatile wage indexation process.

The first of these unstable environments can be faced with a higher and mostly implicit inflation target: the insurance against the loss of credibility appears a priority when the effect of monetary policy on aggregate activity is highly uncertain and volatile. Recent debates on central banking, notably those pointing to the potential benefit from raising the inflation target, have taken place after the crisis (*see* Blanchard et al. (2010), among others). Our results go along the lines of that suggestion.

The second environment type we consider produces disturbances in the way inflation expectations feed the inflation dynamics and volatility, potentially giving rise to a self-reinforcing mechanism. That vicious circle makes the trade-off between the level of activity and inflation steeper. In that case, a partial dissemination of the target in association with a rather narrow radius minimizes the CB's loss. Hence, providing a clear signal to anchor inflation expectations on one part of the public, while allowing for a less tightly defined objective for the remaining part achieves a best management of expectations when inflation and inflation expectations display high degree of volatility. In addition, achieving a better control of expectations loosens the trade-off that the CB faces between its objectives. Overall, our results provide a new and alternative theoretical support to the lack of robustness that a transparent inflation targeting regime would suffer from under unstable and volatile economic environments.

Several extensions to our agent based model can be considered. We can introduce a more sophisticated and richer learning/expectations mechanism, allowing the agents to generalize, and therefore to adopt a more forward-looking behavior (as in (Yıldızoğlu et al. 2012)). Using such a learning framework, we can moreover account for other aspects of CB communication, such as interest rates projections, guidance on future paths of relevant economic variables, and their role in expectation formation. These aspects are left for further research.

References

Arifovic, J. (1995), 'Genetic algorithms and inflationary economies', *Journal of Monetary Economics* **36**(1), 219–243.

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.

Blanchard, O., Dell'Ariccia, G. & Mauro, P. (2010), Rethinking Macroeconomic Policy. IMF Staff Position Note, janvier.

Blinder, A. (1998), *Central Banking in Theory and Practice*, MIT Press. Cambridge.

Brainard, W. (1967), 'Uncertainty and the Effectiveness of Policy', *American Economic Review Papers and Proceedings* **57**, 411–425.

Branch, E. & Evans, G. (2006), 'Intrinsic heterogeneity in expectation formation', *Journal of Economic Theory* **127**(1), 264–295.

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.

Brock, W. & Hommes, C. (1997), 'A Rational Route to Randomness', *Econometrica* **65**(5), 1059–1096.

Canzian, J. (2009), Three essays in agent-based macroeconomics. Doctoral Thesis, University of Trento CIFREM.

Cioppa, T. (2002), Efficient nearly orthogonal and space-filling experimental designs for high-dimensional complex models. Doctoral Dissertation in philosophy in operations research, Naval postgraduate school.

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.

Cornand, C. & Heinemann, F. (2008), 'Optimal degree of public information dissemination', *The Economic Journal* **118**(528), 718–742.

De Grauwe, P. (2011), 'Animal spirits and monetary policy', *Economic Theory* **47**, 423–457.

De Grauwe, P. (2012), *Lectures on Behavioral Macroeconomics*, Princeton University Press.

de Mendonca, H. (2007), 'Towards credibility from inflation targeting: the Brazilian experience', *Applied Economics* **39**, 2599–2615.

Delli Gatti, D., Gaffeo, E., Gallegati, M. & Palestrini, A. (2005), 'The Apprentice Wizard: Monetary Policy, Complexity And Learning', *New Mathematics and Natural Computation (NMNC)* **1**(01), 109–128.

Demertzis, M. & Viegi, N. (2008), 'Inflation Targets as Focal Points', *International Journal of Central Banking* **4**(1), 55–87.

Demertzis, M. & Viegi, N. (2009), 'Inflation targeting : a framework for communication', *The B.E. Journal of Macroeconomics* **99**(1), 44.

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.

Eusepi, S. & Preston, B. (2010), 'Central bank communication and expectations stabilization', *American Economic Journal: Macroeconomics* **2**(3), 235–271.

Evans, G. W. & Honkapohja, S. (2001), *Learning and Expectations in Macroeconomics*, Princeton University Press.

Faust, J. & Svensson, L. (2001), 'Transparency and Credibility: Monetary Policy with Unobservable Goals', *International Economic Review* **42**(2), 369–397.

Gaffeo, E., DelliGatti, D., Desiderio, S. & Gallegati, M. (2008), 'Adaptive Microfoundations for Emergent Macroeconomics', *Eastern Economic Journal* **34**(4), 441–463.

Gali, J. (2008), *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework*, Princeton University Press.

Garfinkel, M. & Oh, S. (1995), 'When and how much to talk, credibility and flexibility in monetary policy with private information', *Journal of Monetary Economics* **35**(2), 341–357.

Geraats, P. (2002), 'Central Bank Transparency', *The Economic Journal* **112**(483), 532–565.

Geraats, P. (2009), 'Trends in Monetary Policy Transparency', *International Finance* **12**(2), 235–268.

Giannoni, M. & Woodford, M. (2004), Optimal Inflation-Targeting Rules, *in* 'The Inflation-Targeting Debate', University of Chicago Press, chapter 3, pp. 93–172.

Giannoni, P. (2007), 'Robust optimal monetary policy in a forward-looking model with parameter and shock uncertainty', *Journal of Applied Econometrics* **22**(1), 179–213.

Hellwig, M. (2002), 'Public Information, Private information and the Multiplicity of Equilibria in Coordination Games', *Journal of Economic Theory* **107**(2), 91–222.

Holland, J., Goldberg, D. & Booker, L. (1989), 'Classifier Systems and Genetic Algorithms ', *Artificial Intelligence* **40**, 235–289.

Honkapohja, S. & Mitra, K. (2006), 'Learning Stability in Economies with Heterogeneous Agents', *Review of Economic Dynamics* **9**(2), 284–309.

Leijonhufvud, A. (2006), Agent-based Macro, *in* L. Tesfatsion & K. Judd, eds, 'Handbook of Computational Economic, vol. 2', North-Holland, chapter 36, pp. 1625–1646.

Lengnick, M. (2013), 'Agent-Based Macroeconomics: A Baseline Model', *Journal of Economic Behavior & Organization* **86(C)**, 102–120.

Matheron, G. (1963), 'Principles of geostatistics', *Economic Geology* **58**(8), 1246–1266.

Mebane, W. J. & Sekhon, J. (2011), 'Genetic Optimization Using Derivatives: The rgenoud Package for R', *Journal of Statistical Software* **42**(11), 1–26.

Melecký, M., Palenzuela, D. R. & Söderström, U. (2009), Inflation target transparency and the macroeconomy, *in* K. Schmidt-Hebbel & C. Walsh, eds, 'Monetary Policy under Uncertainty and Learning', Vol. 13, Central Bank of Chile, chapter 10, pp. 371–441.

Minegishi, M. & Cournède, B. (2009), The Role of Transparency in the Conduct of Monetary Policy, OECD Economics Department Working Papers 724, OECD Publishing.

Morris, S. & Shin, H. (2002), 'Social value of public information', *American Economic Review* **92**(5), 1521–1534.

Oeffner, M. (2008), Agent-Based Keynesian Macroeconomics – an evolutionarymodel embedded in an agent-based computer simulation. Doctoral dissertation, Bayerische Julius - Maximilians Universität, Wurzburg.

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.

R Development Core Team (2009), *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0.
URL: *http://www.R-project.org*

Raberto, M., Teglio, A. & Cincotti, S. (2008), 'Integrating Real and Financial Markets in an Agent-Based Economic Model: An Application to Monetary Policy Design', *Computational Economics* **32**, 147–162.

Roger, S. (2009), Inflation Targeting at 20: Achievements and Challenges, IMF Working Papers 09/236, International Monetary Fund.

Roos, M. W. & Schmidt, U. (2012), 'The importance of time series extrapolation for macroeconomic expectations', *German Economic Review* **13**(2), 196–210.

Roustant, O., Ginsbourger, D. & Deville, Y. (2010), 'DiceKriging, DiceOptim: Two R packages for the analysis of computer experiments by kriging-based metamodeling and optimization', *Journal of Statistical Software* **VV**(II).

Rudebusch, G. & Williams, J. (2008), Revealing the Secrets of the Temple: The Value of Publishing Central Bank Interest Rate Projections, *in* J. Y. Campbell, ed., 'Asset Prices and Monetary Policy', NBER Chapters, 5373, University of Chicago Press, chapter 6, pp. 247–284.

Sacks, J., Welch, W., Mitchell, T. & Wynn, H. (1989), 'Design and analysis of computer experiments', *Statistical Science* **4**(4), 409–423.

Salle, I. & Yıldızoğlu, M. (2012), Efficient Sampling and Metamodeling for Computational Economic Models, Cahiers du GREThA 2012-18, Groupe de Recherche en Economie Théorique et Appliquée.

Salle, I., Yıldızoğlu, M. & Sénégas, M.-A. (2013), 'Inflation targeting in a learning economy: An ABM perspective', *Economic Modelling* . forthcoming.

Salle, I., Zumpe, M., Yıldızoğlu, M. & Sénégas, M.-A. (2012), Modelling Social Learning in an Agent-Based New Keynesian Macroeconomic Model, Cahiers du gretha, no. 2012-20, Groupe de Recherche en Economie Théorique et Appliquée.

Sanchez, S. (2005), Nolh designs spreadsheet . Software available online via http://diana.cs.nps.navy.mil/SeedLab/.

Sargent, T. (1993), *Bounded Rationality in Macroeconomics*, Oxford University Press.

Schmidt-Hebbel, K. (2009), Inflation Targeting Twenty Years on: Where, When, Why, With what Effects, What lies ahead?, Documentos de Trabajo 360, Instituto de Economia. Pontificia Universidad Catholica de Chile.

Schmidt-Hebbel, K. & Walsh, C. (2009), Monetary Policy under Uncertainty and Learning: An Overview, *in* K. Schmidt-Hebbel, C. E. Walsh & N. Loayza, eds, 'Monetary Policy under Uncertainty and Learning', Vol. 13 of *Central Banking, Analysis, and Economic Policies Book Series*, Central Bank of Chile, chapter 1, pp. 1–25.

Söderström, U. (2002), 'Monetary Policy with Uncertain Parameters', *Scandinavian Journal of Economics* **104**(1), 125–145.

Stein, J. (1989), 'Cheap talk and the Fed: A theory of imprecise policy announcements', *American Economic Review* **79**(1), 32–42.

Svensson, L. (2008), Beyond Rational Expectations : Practical Policy Considerations – comment on Sims, *in* 'BIS Annual Conference'. Luzern, Switzerland, June 26-27 juin.

Svensson, L. (2009), 'Transparency under Flexible Inflation Targeting: Experiences and Challenges', *Sveriges Riksbank Economic Review* **1**, 5–44.

Svensson, L. E. (2010), Inflation Targeting, *in* B. M. Friedman & M. Woodford, eds, 'Handbook of Monetary Economics', Vol. 3 of *Handbook of Monetary Economics*, Elsevier, chapter 22, pp. 1237–1302.

Taylor, J. (1993), 'Discretion versus policy rules in practice', *Carnegie-Rochester Conference Series on Public Policy* **39**(1), 195–214.

Tetlow, R. J. & von zur Muehlen, P. (2001), 'Robust monetary policy with misspecified models: Does model uncertainty always call for attenuated policy?', *Journal of Economic Dynamics & Control* **25**, 911–949.

van Beers, W. & Kleijnen, J. (2004), *Kriging interpolation in simulation : a survey*, R .G. Ingalls, M. D. Rossetti, J. S. Smith, and B. A. Peters, eds, chapter Computer experiments. In Handbook of Statistics.

Walsh, C. (1995), 'Optimal contracts for central bankers', *American Economic Review* **85**(1), 150–67.

Walsh, C. (2007*a*), 'Optimal Economic Transparency', *International Journal of Central Banking* **3**(1), 5–36.

Walsh, C. (2007*b*), Transparency, Flexibility and Inflation Targeting, *in* F. Mishkin & K. Schmidt-Hebbel, eds, 'Monetary Policy under Inflation Targeting', Vol. 11 of *Central Banking, Analysis, and Economic Policies Book Series*, Central Bank of Chile, chapter 7, pp. 227–263.

Walsh, C. (2008), 'Announcements and the Role of Policy Guidance', *Federal Reserve Bank of St. Louis Review* **Jul**, 421–442.

Walsh, C. (2009), 'Inflation targeting : what have we learned?', *International Finance* **12**(2), 195–233.

Walsh, C. (2010), Transparency, the Opacity Bias and Optimal Flexible Inflation Targeting. mimeo, Nov.

Woodford, M. (2003*a*), Imperfect common knowledge and the effects of monetary policy, *in* P. Aghion, R. Frydman, J. Stiglitz & M. Woodford, eds, 'Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps', Princeton University Press.

Woodford, M. (2003*b*), *Interest and Prices : Foundations of a Theory of Monetary Policy*, Princeton University Press.

Woodford, M. (2005), Central bank communication and policy effectiveness, *in* 'The Greenspan Era: Lessons for the Future', Federal Reserve Bank of Kansas City, Kansas City, pp. 399–474.

Yıldızoğlu, M., Sénégas, M.-A., Salle, I. & Zumpe, M. (2012), 'Learning the optimal buffer-stock consumption rule of Carroll', *Macroeconomic Dynamics* . forthcoming.

A Parameters setting

Each configuration is repeated 30 times as the model is not deterministic.

Moreover, we set $\sigma_\xi \equiv \frac{\sigma_W}{40}$, meaning that the variance of the noise ξ is related to the variance of the proxy for supply shocks σ_W (where 40 is a scaling parameter). This is a rather intuitive modeling device: the more unstable the economy is (i.e. the bigger the shocks affecting the inflation rate are), the further from the objective the inflation rate is likely to be and the more difficult it is to stabilize inflation expectations. That is also assumed for the sake of parsimony in the parameters set.

We use a *design of experiment* (DoE, hereafter)[24] to cover the space of parameters. Large sampling methods such as Monte Carlo simulations come at a computational cost if we aim at considering the effects of numerous parameters with large experiment domains. DoE allows to minimize the sample size under constraint of representativeness. We use the design proposed by Cioppa (2002) and provided by Sanchez (2005), which efficiently combines space-filling properties and parsimony.

exp.	*window*	σ_d	σ_W	ϕ_π	ϕ_u	P_{mut}	P_{imit}	ζ (en %)
1	40.00	0.08	0.20	0.40	0.90	0.07	0.19	1.00
2	35.00	0.40	0.09	0.80	0.50	0.03	0.20	0.75
3	35.00	0.20	0.37	0.30	0.00	0.06	0.19	0.25
4	25.00	0.36	0.40	0.80	0.90	0.02	0.21	0.25
5	40.00	0.06	0.21	0.40	0.70	0.07	0.13	1.25
6	40.00	0.38	0.16	0.60	0.40	0.03	0.08	1.75
7	30.00	0.21	0.39	0.50	0.00	0.07	0.13	1.75
8	25.00	0.29	0.38	0.70	0.90	0.03	0.09	2.00
9	30.00	0.14	0.13	1.10	0.70	0.04	0.05	0.50
10	30.00	0.28	0.15	1.40	0.20	0.06	0.07	1.00
11	30.00	0.13	0.31	1.90	0.30	0.02	0.08	0.50
12	30.00	0.30	0.28	1.90	0.80	0.10	0.14	1.00
13	25.00	0.10	0.12	1.10	0.60	0.02	0.24	1.50
14	35.00	0.26	0.18	1.80	0.20	0.06	0.24	1.50
15	25.00	0.12	0.35	1.80	0.40	0.01	0.18	1.50
16	35.00	0.27	0.26	2.00	0.80	0.09	0.16	1.50
17	25.00	0.23	0.23	1.00	0.50	0.06	0.15	1.25
18	5.00	0.37	0.25	1.60	0.10	0.04	0.11	1.25
19	10.00	0.05	0.36	1.30	0.50	0.08	0.10	1.50
20	10.00	0.25	0.08	1.70	1.00	0.05	0.11	2.00
21	20.00	0.09	0.05	1.20	0.10	0.09	0.09	2.00
22	5.00	0.39	0.24	1.60	0.30	0.04	0.17	1.00
23	5.00	0.07	0.29	1.40	0.60	0.08	0.22	0.50
24	15.00	0.24	0.06	1.50	1.00	0.04	0.18	0.50
25	20.00	0.16	0.07	1.30	0.10	0.08	0.21	0.25
26	15.00	0.31	0.32	0.90	0.30	0.07	0.25	1.75
27	15.00	0.17	0.30	0.60	0.80	0.05	0.23	1.25
28	15.00	0.32	0.14	0.10	0.70	0.09	0.23	1.75
29	15.00	0.15	0.17	0.10	0.30	0.01	0.16	1.25
30	20.00	0.35	0.33	0.90	0.40	0.09	0.06	0.75
31	10.00	0.19	0.27	0.30	0.80	0.05	0.06	0.75
32	20.00	0.33	0.10	0.20	0.60	0.10	0.12	0.75
33	10.00	0.18	0.19	0.00	0.20	0.02	0.14	0.75

Table 4: Design of experiments (near-orthogonal latin hypercube) with 8 parameters – (subsection 3.2).

[24]See, for example, Salle & Yıldızoğlu (2012) for a pedagogical statement. That method is widely used in computer simulations in areas such as industry, chemistry, computer science, biology, etc. To our knowledge, Oeffner (2008) and Yıldızoğlu et al. (2012) are the only applications in economics.

n	T	P_{imit}	P_{mut}	σ_d	ϕ_π
500	800	0.1	0.02	0.15	1.5
ϵ	α	μ	$window$	σ_W	ϕ_u
0.01	0.25 (Woodford (2003*b*))	0.1 (Woodford (2003*b*))	20	0.15	0.2

Table 5: Model calibration under the `baseline` scenario.

DoE (estimation, Sanchez (2005))			Additional points (external validation)		
exp.	ϕ_π	ϕ_u	exp.	ϕ_π	ϕ_u
0	0.60	1	0	1.73	0.38
1	0.10	0.30	1	1.25	0.87
2	0.30	0.40	2	0.27	0.62
3	0.40	0.60	3	0.75	0.13
4	1.50	0.90	4	1.96	0.65
5	2.00	0.30	5	0.04	0.35
6	1.30	0.20	6	0.71	0.98
7	1.10	0.90	7	1.29	0.02
8	1.00	0.50			
9	1.40	0.00			
10	1.90	0.80			
11	1.80	0.60			
12	1.60	0.40			
13	0.50	0.10			
14	0.00	0.70			
15	0.80	0.80			
16	0.90	0.10			

Table 6: Design of experiments (orthogonal latin hypercube) with 2 factors (subsection 4.1)

DoE (estimation, Sanchez (2005))					Additional points (external validation)				
exp.	P	ζ	ϕ_π	ϕ_u	exp.	P	ζ	ϕ_π	ϕ_u
1	0.30	0.010	0.80	0.30	1	0.67	0.001	1.33	0.44
2	0.10	0.003	1.10	0.00	2	0.89	0.004	0.22	0.11
3	0.10	0.005	0.50	0.60	3	0.33	0.002	1.78	0.56
4	0.20	0.007	2.00	0.60	4	0.56	0.005	0.44	1.00
5	0.80	0.009	0.30	0.30	5	0.78	0.008	2.00	0.22
6	1.00	0.004	1.60	0.10	6	0.44	0.006	0.00	0.67
7	0.60	0.003	0.60	0.90	7	0.00	0.003	0.67	0.00
8	0.60	0.009	1.90	0.80	8	0.11	0.009	0.89	0.33
9	0.50	0.006	1.00	0.50	9	1.00	0.01	1.11	0.89
10	0.70	0.001	1.30	0.80	10	0.22	0.007	1.56	0.78
11	0.90	0.008	0.90	1.00					
12	0.90	0.006	1.50	0.40					
13	0.80	0.004	0.00	0.40					
14	0.30	0.002	1.80	0.70					
15	0.00	0.007	0.40	0.90					
16	0.40	0.008	1.40	0.10					
17	0.40	0.002	0.10	0.20					

Table 7: Design of experiments (orthogonal latin hypercube) with 4 factors (subsection 4.2)

B Technical appendix : kriging metamodeling

B.1 Principle

Let $D \equiv [0,2] \times [0,1] \in \mathbb{R}^2$ and $x \equiv (\phi_\pi, \phi_u) \in D$ the two factors. Let the loss function (19) be the response-variable $\mathcal{L} : x \in D \rightarrow \mathcal{L}(x) \in \mathbb{R}$. Kriging model aims at optimally forecasting, for each point $x \in D$, the variable $\mathcal{L}(x) \in \mathbb{R}$ through a stochastic process $L : x \in D \rightarrow L(x) \in \mathbb{R}$, called a *metamodel*[25]. This metamodel is obtained through a linear combination of the $n = 17$ observations of $\mathcal{L}$ over D, denoted by $\{\mathcal{L}(\mathbf{x}_1), ..., \mathcal{L}(\mathbf{x}_{17})\}$[26]:

$$L(x) = \mu(x) + Z(x) \tag{20}$$

where $\mu : x \in D \rightarrow \mu(x) \equiv \sum_{j=1}^{l} \beta_j f_j(x) \in \mathbb{R}$, $l > 0$, f_j are fixed functions and β_j are unknown coefficients to be estimated, and Z is a stochastic process with zero mean and covariance $C : (u,v) \in D^2 \rightarrow C(u,v) \in \mathbb{R}$.

Kriging has the following properties: it is an exact interpolator (i.e. $L(\mathbf{x}) = \mathcal{L}(\mathbf{x})$), it is global (i.e. L is defined over the whole domain D) and it is spacial: indeed, contrary to LS fitting, in order to determine L at a point $x \in D$, kriging models put more weight on observations of $\mathcal{L}$ at points $\mathbf{x}$ in the neighborhood of x. That is why kriging needs a DoE with good space-filling properties to give accurate estimations.

We use the Matérn $v = \frac{5}{2}$ covariance function, which is the default one in `DiceKriging`-package of R Development Core Team (2009):

$$C(x_i, x_j) = \sigma_L^2 \prod_{g=1}^{k} \left(1 + \frac{\sqrt{5}|x_i - x_j|}{\theta_g} + \frac{5(x_i - x_j)^2}{3\theta_g^2}\right) \exp\left(-\frac{\sqrt{5}|x_i - x_j|}{\theta_g}\right) \tag{21}$$

with $k = 2$ as we have two factors ϕ_π and ϕ_u. It is a continuous Gaussian process which is twice differentiable and therefore gives more accurate estimations. Parameters θ, which stand for the relative weight of each factor, and σ_L^2, the estimated variance of L process, are estimated using maximum of likelihood. As simulations are stochastic, we integrate $\mathcal{L}$ variance across the 30 runs at each of the 17 points into the covariance matrix C (see Roustant et al. (2010)).

We have to choose the trend μ (i.e. to specify functions f_j). With two factors, we define four specifications[27]:

$$\mu(x) = \beta_0 \tag{I}$$

which is a single trend (called ordinary kriging), a first order polynomial:

$$\mu(x) = \beta_0 + \beta_{\phi_\pi}\phi_\pi + \beta_{\phi_u}\phi_u \tag{II}$$

to which we add second-order interactions:

$$\mu(x) = \beta_0 + \beta_{\phi_\pi}\phi_\pi + \beta_{\phi_u}\phi_u + \beta_{\phi_\pi\phi_u}\phi_\pi\phi_u \tag{III}$$

and a full second-order polynomial:

$$\mu(x) = \beta_0 + \beta_{\phi_\pi}\phi_\pi + \beta_{\phi_u}\phi_u + \beta_{\phi_\pi\phi_u}\phi_\pi\phi_u + \beta_{\phi_\pi^2}\phi_\pi^2 + \beta_{\phi_u^2}\phi_u^2 \tag{IV}$$

We successively estimate each specification and discriminate between them with external validation. It is indeed preferable to other techniques such as cross-validation, based on the existing sample and leave-one out estimation, all the more that we have few observation. We randomly add validation points to the design and compute the root mean square error (RMSE) between these additional observations

[25] This kind of models originally comes from geostatistics (see Matheron (1963)). See Sacks et al. (1989) for a complete treatment. We use packages `DiceKriging`, `DiceEval` and `DiceOptim` of R Development Core Team (2009) to perform all kriging estimations (see Roustant et al. (2010)).

[26] We have $n = 17$ observation points of $\mathcal{L}$ over D (see DoE 6, Appendix A). As the model is stochastic, we repeat each 30 times. The kriging estimation has then to be performed in averaging $\mathcal{L}$ values over the 30 repetitions (van Beers & Kleijnen (2004)). This results in $n = 17$ observations of $\mathcal{L}$ over D.

[27] More complex forms would involve more parameters to be estimated, besides σ_L^2, θ_{ϕ_π} and θ_{ϕ_u}. With only 17 points, we have to avoid overfitting the model. For that reason, we only estimate forms (I) and (II) in subsection 4.2 as the kriging model involves 4 parameters, which gives 6 parameters to estimate for the form (I) and 10 for the form (II). Moreover, these specification already cover a wide range of relation between ϕ_π, ϕ_u and $\mathcal{L}$.

and the estimated one for each of the 4 above specifications (reported in appendix B.2) and choose the one which minimizes this figure.

As soon as we have a satisfying metamodel L, we determine the pair (ϕ_π^*, ϕ_u^*) which minimizes the estimated value of loss L, denoted by L^*. This is done through the packages `rgenoud` (*R-GENetic Optimization Using Derivatives*, see Mebane & Sekhon (2011)) and `DiceOptim` (see Roustant et al. (2010)) provided by R Development Core Team (2009). This is a quite powerful optimization function that efficiently combines evolutionary algorithm methods for global purpose with a derivative-based (quasi-Newton) method for local search of optima.

B.2 Kriging models reports

β_0	β_{ϕ_π}	β_{ϕ_u}	$\beta_{\phi_\pi\phi_u}$	$\beta_{\phi_\pi^2}$	$\beta_{\phi_u^2}$	θ_{ϕ_π}	θ_{ϕ_u}	σ_L^2
$\{\sigma_W, \sigma_K\} = \{0.05, 0.05\}$								
IT, $\zeta = 0.1\%$, $\pi^T = 2\%$								
RMSE: 0.033 (I) - 0.0282 (II) - 0.0283 (III) - **0.0249 (IV)**								
0.129	-0.009	-0.18	0.034	0.004	0.147	0.027	0.733	0.0006
IT, $\zeta = 1\%$, $\pi^T = 2\%$								
RMSE: 0.029 (I) - **0.02 (II)** - 0.022 (III) - 0.023 (IV)								
0.093	0.034	-0.038				0.084	2.00	0.0007
Non-IT, $\zeta = 0.1\%$, $\pi^T = 2\%$								
RMSE: 0.03 (I) - **0.019 (II)** - 0.03 (III) - 0.027 (IV)								
0.0902	-0.0242	0.0012				0.088	2.00	0.0002
Non-IT, $\zeta = 1\%$, $\pi^T = 2\%$								
RMSE: 0.042 (I) - 0.04 (II) - **0.039 (III)** - 0.041 (IV)								
0.05	0.015	0.004	-0.006			0.048	1.47	0.0002
$\{\sigma_W, \sigma_K\} = \{0.4, 0.05\}$								
IT, $\zeta = 0.1\%$, $\pi^T = 2\%$								
RMSE: **0.031 (I)** - 0.032 (II) - 0.032 (III) - 0.032 (IV)								
0.24						0.555	0.266	0.0008
IT, $\zeta = 1\%$, $\pi^T = 2\%$								
RMSE: **0.015 (I)** - 0.029 (II) - 0.015 (III) - 0.021 (IV)								
0.23						2.608	0.154	0.0028
Non-IT, $\zeta = 0.1\%$, $\pi^T = 2\%$								
RMSE: 0.073 (I) - 0.067 (II) - 0.066 (III) - **0.051 (IV)**								
0.332	0.085	-0.539	-0.05	0.044	0.457	4.00	0.022	0.002
Non-IT, $\zeta = 1\%$, $\pi^T = 2\%$								
RMSE: **0.013(I)** - 0.016 (II) - 0.014 (III) - 0.013 (IV)								
0.1607						1.667	0.821	0.001
IT, $\zeta = 0.1\%$, $\pi^T = 4\%$								
RMSE: 0.06 (I) - 0.059 (II) - 0.054 (III) - **0.038** (IV)								
0.3183	0.0631	-0.1242	-0.0949	-0.0039	0.2268	0.012	0.7110	0.0005
IT, $\zeta = 1\%$, $\pi^T = 4\%$								
RMSE: 0.042 (I) - 0.034 (II) - **0.024 (III)** -0.048 (IV)								
0.2620	0.0239	0.0830	-0.0961			0.012	1.322	0.0014
Non-IT, $\zeta = 0.1\%$, $\pi^T = 4\%$								
RMSE: 0.066 (I) - **0.017 (II)** - 0.052 (III) - 0.04 (IV)								
0.2261	-0.0018	-0.1033				4.00	0.05	0.0027
Non-IT, $\zeta = 1\%$, $\pi^T = 4\%$								
RMSE: 0.058 (I) -0.04 (II) - 0.045 (III) - **0.033 (IV)**								
0.275	-0.005	-0.523	-0.045	0.017	0.456	1.847	0.046	0.0023
$\{\sigma_W, \sigma_K\} = \{0.05, 0.4\}$								
IT, $\zeta = 0.1\%$, $\pi^T = 2\%$								
RMSE: 0.03 (I) - **0.029 (II)** - 0.035 (III) - 0.034 (IV)								
0.1191	0.0063	-0.0027				0.1441	0.3744	0.0006
IT, $\zeta = 1\%$, $\pi^T = 2\%$								
RMSE: 0.0289 (I) - **0.023 (II)** - 0.023 (III) - 0.024 (IV)								
0.0932	0.0428	-0.0246				0.2002	1.2596	0.0014
Non-IT, $\zeta = 0.1\%$, $\pi^T = 2\%$								
RMSE: 0.026 (I) - **0.024 (II)** - 0.028 (III) - 0.033 (IV)								

0.0856	-0.0094	0.0014				2.0340	0.1409	0.0008
Non-IT, $\zeta = 1\%$, $\pi^T = 2\%$								
RMSE: 0.028 (I) - 0.027 (II) - 0.027 (III) - **0.023 (IV)**								
0.0223	0.0044	0.1637	0.0218	-0.1176	-0.0483	0.0024	0.2587	0.0004
IT, $\zeta = 0.1\%$, $\pi^T = 4\%$								
RMSE: 0.037 (I) - **0.036 (II)** - 0.039 (III) - 0.04 (IV)								
0.17	0.006	-0.033				0.01	0.78	0.0009
IT, $\zeta = 1\%$, $\pi^T = 4\%$								
RMSE: 0.041 (I) - **0.039 (II)** - 0.039 (III) - 0.042 (IV)								
0.0926	0.0156	-0.0138				0.121	0.001	0.0012
Non-IT, $\zeta = 0.1\%$, $\pi^T = 4\%$								
RMSE: 0.022 (I) - 0.024 (II) - **0.018 (III)** - 0.028 (IV)								
0.11	-0.022	-0.109	0.067			0.01	0.189	0.0004
Non-IT, $\zeta = 1\%$, $\pi^T = 4\%$								
RMSE: 0.024 (I) -0.021 (II) - **0.017 (III)** - 0.02 (IV)								
0.109	-0.025	-0.11	0.076			0.964	0.263	0.0004

Table 8: Kriging models reports – 2 parameters (subsection 4.1)

β_0	β_{ϕ_π}	β_{ϕ_u}	β_ζ	β_P	θ_{ϕ_π}	θ_{ϕ_u}	θ_ζ	θ_P	σ_L^2
$\{\sigma_W, \sigma_K\} = \{0.05, 0.05\}$									
RMSE: 0.031 (I) - **0.026** (II)									
0.102	0.021	-0.08	-1.867	0.035	3.014	0.003	0.004	2.00	0.0004
$\{\sigma_W, \sigma_K\} = \{0.4, 0.05\}$									
RMSE: **0.026** (I) - 0.029 (II)									
0.223					1.689	0.398	0.018	0.744	0.002
$\{\sigma_W, \sigma_K\} = \{0.05, 0.4\}$									
RMSE: 0.0386 (I) - **0.034** (II)									
0.065	0.005	-0.023	-0.199	-0.001	4.00	0.16	0.017	0.346	0.0004

Table 9: Kriging models reports – 4 parameters (subsection 4.2)