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The AI Augmented Macro Economy: A New-Keynesian DSGE Model with AI Driven Expectations Formation

Nilendu Chatterjee*
Dipak Kundu**

Abstract

The combination of Artificial Intelligence (AI) and Machine Learning (ML) in business and economics is a game changer, similar to the effect that Industrial Revolution had on production. This paper studies the macroeconomic consequences of such a world in which a large fraction of economic agents – from firms to households – use increasingly sophisticated AI models for forecasting and decision-making. We construct a New-Keynesian DSGE model that explicitly considers rational expectations agents and AI-informed forecasters. The AIs utilize a non-parametric, flexible methodology that resembles some of the modern ML algorithms to generate anticipations on future macro variables such as inflation and output. Our model suggests that AI agents do a better job understanding the structure of the economy – including its non-linearity and the dynamics of policy transmission – than humans. We derive the steady state of the model, and linearize it to characterize its impulse response functions. Our results provide evidence that an economy staffed with AI-generated forecasters features much more pronounced business cycle dynamics, in response to pure technology (productivity) shocks. In the presence of unexpected aggregate demand or policy shocks, however, AI agents lead to speedier macroeconomic stabilization because their forecasts react more rapidly to new information regimes. The implications for policymakers are discussed in this paper, emphasizing the necessity for central banks to question their monetary policy frameworks when faced with new and more intelligent economic agents as well as potential dangers of "herding" behavior among similar AI forecasters.

Keywords: Artificial Intelligence, Macro Economic Forecasting, DSGE Model, Expectations Formation, New-Keynesian Economics, Machine Learning, Economic policies.

1. Introduction

The 21st century is witnessing an explosive growth of digital technologies and artificial intelligence–machine learning (AI-ML) sits at the epicenter. These technologies are not just reserved to niche fields anymore and have made their

*Department of Economics, Bankim Sardar College, South 24 Parganas, West Bengal, India
Email: nilubsc87@gmail.com
Department of Commerce, Bankim Sardar College, South 24 Parganas, West Bengal, India
Email: dip11091979@gmail.com

presence felt into the core of business and finance. Companies use AI for making supply chains more efficient, implementing dynamic pricing, and analyzing markets. Algorithm models are employed by investors to preempt asset prices. AI-powered tools are used by homes to manage their personal finances. As smart machines become embedded in the fabric of economic activity, this diffusion raises a fundamental question for macroeconomics: How does ubiquitous AI as an economic forecasting tool change the dynamics of the entire macroeconomy?

Traditional macroeconomic theory - and the New-Keynesian framework that animates modern monetary policy - has staked much on a particular view of expectation formation: Rational Expectations (Muth, 1961; Lucas, 1972). Here economic agents are assumed to have a correct model of the economy structure and, even more importantly, their subjective expectations coincide on average with outcomes forecast by this model. Although this assumption allows for analytical tractability, it is a rather stark and debatable model of actual human behavior. In reality, agents have bounded information, cognitive biases and the learning process is not perfectly rational.

The rise of AI-based forecasting provides an attractive alternative model for expectations. AI programs, especially those relying on deep learning or other sophisticated algorithms, are equipped to capture complex patterns (including non-linearities and structural breaks) in large datasets. They are a style of intelligent, information-based learning that is perhaps more realistic than the perfect-information RE model, yet less expensive and possibly no less accurate than standard heuristic or adaptive learners.

This paper attempts to fill this gap by providing a formal treatment of AI-powered expectations within a mainstream macroeconomic model. To do so we construct a Dynamic Stochastic General Equilibrium (DSGE) model, which is the workhorse used in central banks and international institutions to conduct policy analysis. The model includes households, firms, a central bank and a government. The novelty of our approach resides in the assumptions under which we model the expectations formation. We decompose the representative agent framework into two idealized populations: traditional Rational Expectations (RE) model agents and artificial intelligence-driven Forecasting (AIF) model agents. We hypothesize that the AIF agents follow a statistical learning theory like cause ascription mechanism, when forming their predictions. They do not know the model's parameters exactly but have to learn them from a past of economic data.

The objective of this study is to analyze how the incorporation of AI-driven expectations formation alters macroeconomic dynamics within a New-Keynesian DSGE framework. In particular, the paper aims to evaluate how heterogeneous expectations—arising from the coexistence of rational expectations (RE) agents and AI-based forecasters (AIF)—affect the transmission of shocks, the stability of

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equilibrium, and the effectiveness of monetary policy.

For achieving this, we develop a linearized DSGE model consisting of a system of forward-looking difference equations. The structural core of the model includes: (i) an intertemporal Euler equation governing the consumption dynamics, (ii) a New-Keynesian Phillips Curve linking inflation to expected future inflation and the output gap, (iii) an aggregate demand identity defining the output gap as a function of consumption and exogenous demand shocks, and (iv) a Taylor-type monetary policy rule specifying the response of the nominal interest rate to inflation and output fluctuations.

The innovation in methodology lies in the specification of expectations. Rather than assuming homogeneous rational expectations, aggregate expectations are defined as a weighted average of two distinct forecasting mechanisms: model-consistent rational expectations and AI-based forecasts derived from estimated linear rules. The parameter ξ captures the degree of AI adoption in the economy, thereby allowing the model to represent varying informational environments.

The resulting system is solved using standard techniques for linear rational expectations models. After deriving the steady state, the model is expressed in linear form and analyzed using solution methods that ensure equilibrium determinacy. Dynamic properties of the model are examined through impulse response functions (IRFs), which trace the effects of productivity, demand, and monetary policy shocks under different levels of AI penetration. This framework enables a systematic comparison of how alternative expectations formation mechanisms influence macroeconomic volatility, persistence, and the speed of adjustment to shocks, thereby providing insight into the evolving role of information and forecasting technologies in modern macroeconomic systems.

Our key hypothesis is that the presence of AIF agents fundamentally changes the transmission element of shocks and the effectiveness of monetary policy. We solve for the steady state of the model and then linearize it around that steady state to obtain impulse response functions (IRFs). We will start with a numerical example where we simulate the outcome of the model after several shocks (for instance technology shocks, preference shocks, monetary policy shocks) and compare it to a benchmark "Pure RE Economy".

The remainder of the paper is organized as follows; Section 2 presents a detailed review of related literature on expectations formation in macroeconomics and new field of AI in economic forecasting. Section 3 presents the theory of our NK-DSGE model: it outlines the optimization problems of all agents and derives their system of equilibrium equations. Section 4 turns to the micro-foundations of the forecasting mechanism of AIF agents by presenting a formal representation (in a simplified form)

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of their learning process. The adjustment or the calibration of the model's parameters and the procedure for solving the system are described in Section 5. The central results are analyzed and demonstrated in Section 6, which offers a comparison between the impulse responses of AIF and RE economies for various shock scenarios. Broader implications for business forecasting, risk management and monetary policy are discussed in Section 7 where we also highlight the limitations of our model. Section 8 concludes.

2. Literature Review

Our work is at the intersection of three separate but related literatures; the macroeconomic theory of expectations, the quantitative use of machine learning with economic data and DSGE models to assess policies.

2.1. Expectations Formation in Macroeconomics

Expectations as a central element of modern macroeconomics. The idea of Rational Expectations, originally developed in Muth (1961) and introduced into macroeconomics by Lucas (1972), asserts that agents' beliefs about future variables are consistent with the model's own forecasts. This is the theory that has been incorporated into the New-Classical and New-Keynesian DSGE models, and it is a theory that implies systematic monetary policy has no real effects (the proposition of effective policy ineffectiveness). Yet, the RE model has been extensively censured for its stringent information requirements (Sargent, 1993).

As a counter response, the rich literature has spawned alternative models of learning. Simple Adaptive Expectations assume that is formed by agents as the sum of past errors (Friedman, 1957) and are subject to criticism for their backward-looking nature and ease of being outperformed. A more elaborate version is the idea of Near-Rational Expectations, in which agents might not make a perfect rational computation since the costs of calculation are greater than its benefits (Akerlof & Yellen, 1985). More recently, ``Learning" models have been constructed in which agents are assumed to have an understanding of the economic model but lack knowledge of its parameter values and use econometric techniques to estimate these unknown parameters as data accumulate (Evans & Honkapohja, 2001). This method creates a more realistic account of how agents could eventually learn rational expectations. Our AI-based forecasting approach can be considered a strong generalization of this concept.

2.2. Artificial Intelligence and Machine Learning in Economics

There has been an explosion in the use of AI/ML on economic and financial data in recent years. Earlier work had concentrated on markets, predicting market returns with neural networks (White, 1988) or option prices (Hutchinson, Lo, & Poggio, 1994). The literature, however, has more recently grown substantially.

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In the microeconomics domain, ML has been applied in causal inference and revealing subtle treatment effects not captured by simple linear models (Athey, 2017; Mullainathan & Spiess, 2017). Some ML applications are now “industrialized” in finance, such as algorithmic trading, credit scoring and fraud detection (Gu, Kelly, & Xiu, 2020).

At the macroeconomic level, for example, only forecasting using ML has been studied. LASSO regressions, random forests and neural networks have been employed by researchers to predict indicators like inflation, GDP growth and unemployment (Medeiros, Vasconcelos & Rocha, 2021; Bianchi, Buchmann & Jung., 2022). And these studies usually have results where ML models tend to dominate traditional econometric models, especially for time series data with the structural breaks or high dimensional data. Nonetheless this work is for the most part of a statistical nature, treating point predictions and not modeling general equilibrium implications of these forecast methods. Our paper does so by placing this AI forecasting skill within a structural macro econometric model, which permits us to analyse the dynamic implications for the overall economy.

2.3. DSGE Models and Alternative Expectations

The typical DSGE model used in central banks institutions (the FRB/US model and the NAWM of the ECB, among others) is nearly exclusively based on Rational Expectations (for a detailed survey, see Galí, 2015). There are indeed some emerging efforts to use more realistic expectation formation in DSGE models. For example, "sticky information" models presume only some proportion of agents refresh their information every period (Mankiw & Reis, 2002). In other models, we have “boundedly rational” agents who can apply simple forecasting rules (Branch & McGough, 2004).

However, as far as we know there is no DSGE model where agents are explicitly assumed to use a machine learning-based forecasting rule. As such, our contribution is new: aiming to bridge the conceptual elegance of DSGE modelling with the empirical/machine learning reality of AI driven decision-making. We’re going further than simply assuming agents learn; we describe precisely how they do so in a manner which is computationally loosely equivalent to contemporary ML, providing still more concretely based micro-foundation for their behavior.

3. The Macroeconomic Model

We develop a standard New-Keynesian DSGE model. We assume, in our analysis, that this is a closed economy model with 4 types of agents: households, firms (that produce intermediate goods and final goods), a monetary authority (the central bank) and a fiscal authority (i.e., the government). The important friction is price stickiness (recall that frictionless markets imply full price flexibility), which gives monetary

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policy its non-neutral effects.

3.1. The Household

The Economy is populated by a continuum of households indexed by $i \in [0,1]$.

Each household maximizes the expected present discounted value of its utility stream. Hence, each household Chooses sequence $\{C_t(i), L_t(i), B_t(i)\}_{t=0}^{\infty}$ to maximize expected lifetime utility.

$$\max E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t(i)^{1-\sigma}}{1-\sigma} - \frac{L_t(i)^{1+\varphi}}{1+\varphi}\right]$$

Where,

$C_t(i) = Household\ i's\ Consumption\ at\ time\ 't'$

$L_t(i) = Household\ i's\ Labour\ supply\ at\ time\ 't'$

$\beta \in (0,1): Subjective\ Discount\ Factor$

$\sigma > 0: Coefficient\ of\ Relative\ Risk\ Aversion\ (Inverse\ IES)$

$\varphi > 0: Inverse\ Frisch\ Elasticity\ of\ Labour\ Supply$

Subject to the nominal budget constraint that every household faces:

$$P_t C_t(i) + B_t(i) = W_t(i) L_t(i) + \frac{R_t B_{t-1}(i)}{\pi_t} + \Pi_t(i)$$

$P_t = Aggregate\ Price\ Level$

$B_t(i) = One - Period\ Nominal\ Bonds\ purchased\ at\ time\ 't'$

$W_t(i) = Nominal\ Wage$

$R_t = Gross\ Nominal\ Interest\ Rate$

$\pi_t = Gross\ Inflation\ Rate = \frac{P_t}{P_{t-1}}$

$\Pi_t(i) = Profits\ from\ firm\ Ownership$

Following the standard assumption of monopolistic competition and Calvo-style wage setting, we can aggregate the household's first-order conditions to derive the intertemporal Euler equation and the labour supply condition. Under the assumption that all households are identical in the aggregate (due to symmetric calibration), we drop the ‘i’ index for aggregate quantities. Hence, the aggregate Euler equation is:

$$1 = E_t \left[\beta \left(\frac{C_{t+1}}{C_t}\right)^{-\sigma} \frac{R_t}{\pi_{t+1}}\right] \tag{1}$$

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This is the standard intertemporal Euler Equation in the New Keynesian DSGE model. It equates the marginal utility cost of giving up one unit of consumption today to the expected discounted marginal utility benefit of consuming tomorrow, adjusted by the real rate of interest

$\frac{R_t}{\pi_{t+1}}$. This equation links current consumption to expectations of future consumption, inflation, and the nominal interest rate.

3.2. The Firm

Suppose, there are two forms of firms – Intermediate Goods producing firms and the final goods producing firms.

3.2.1. Intermediate Goods Producing Firms

In the presence of monopolistic competition among the intermediate goods producing firms, A continuum of such firms, indexed by $j \in [0,1]$, produce differentiated goods $Y_t(j)$, using a linear technology –

$Y_t(j) = A_t K_t(j)^{\alpha} L_t(j)^{1-\alpha}$

This is the standard Cobb-Douglas type of production function where,

$A_t = Aggregate\ technology\ or\ productivity\ level$ (We will model this as stochastic process).

$K_t(j) =$ Capital (Which we assume as fixed in the short-run, so, $\alpha = 0$ for the purposes of our headlines result. This implies - $Y_t(j) = A_t K_t(j) L_t(j)$. This assumption is very common in New Keynesian system for focussing on price dynamics.

$\alpha = Capital\ Share$

$1 - \alpha = Labour\ Share$

These firms face the Calvo pricing which implies that in any given period, a randomly chosen fraction $(1 - \theta)$ of firms can re-optimize their price. The remaining fraction θ must keep their price unchanged - $P_t(j) = P_{t-1}(j)$. It implies that price charged by intermediate firm 'j' does not change between periods 't-1' and 't'. It also implies that inflation is not fully flexible and it has inertia.

The optimal price $P_t^{\#}$ set by a firm that can re-optimize is a mark-up over its marginal cost. Hence, the forward-looking Phillips Curve that emerges from this set up is as follows –

$$\widehat{\pi_t} = \beta E_t \widehat{\pi_{t+1}} + \kappa \widehat{m}c_t \quad (2)$$

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Where,

$\widehat{\pi_t} = \log(\pi_t) - \log(\pi)$ = which defines inflation in 'log-deviation form' relative to its steady-state level π (which is zero in our model).

$\widehat{m}c_t$ = log-deviation of real marginal cost from its steady-state.

$\kappa = \frac{(1-\theta)(1-\beta\theta)}{\theta}$ is a parameter capturing the frequency of price changes. (Hence, θ is the probability a firm cannot change its price).

Marginal Cost, itself, depends on the output gap. A higher level of economic activity puts upward pressure on marginal costs and thus on inflation.

3.2.2. Final Goods Producing Firms

A Competitive final goods producing firm aggregates the continuum of intermediate goods $Y_t(j)$ into a single final good Y_t by using the technology –

$$Y_t = \left(\int_0^1 Y_t\,(j)^{\varepsilon\text{p}-1/\varepsilon\text{p}} dj\right)^{\frac{\varepsilon\text{p}}{\varepsilon\text{p}-1}}$$

This is a CES (Constant Elasticity of substitution) aggregator for intermediate Goods.

Where, $\varepsilon_P > 1$ is the elasticity of substitution between the intermediate goods. This implies a downward-sloping demand curve for each intermediate firm j–

$$Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\varepsilon_P} Y_t$$

3.3. Monetary and Fiscal Policy

3.3.1. Monetary Policy

Suppose, the Central Bank of the nation follows Taylor-type rule, setting the nominal interest rate in response to deviations of inflation from target and deviations of output from its natural level or output gap.

$$R_t = R.\left(\frac{\pi_t}{\pi^{\#}}\right)^{\rho_\pi} \left(\frac{Y_t}{Y_t^n}\right)^{\rho_y} \exp(\varepsilon_t^m) \qquad (3)$$

This is the non-linear Taylor-type monetary policy rule describing how the central bank sets the nominal interest rate.

Where,

$R_t = Gross\ nominal\ interest\ rate\ at\ time\ 't'$

$R = Steady - state\ (Long - run)\ nominal\ interest\ rate$

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$\pi^{\#} = \ Steady - state\ interest\ target$

$Y_t^n = Natural\ level\ of\ output\ that\ would\ prevail\ with\ price\ changes$

$\rho_\pi > 1\ and\ \rho_y > 0\ are\ the\ policy\ response\ coefficients$

$\varepsilon_t^m = an\ exogenous\ monetary\ policy\ shock$

Linearizing this rule gives –

$$\widehat{R_t} = \ \rho_\pi \widehat{\pi_t} + \rho_y \widehat{y_t} + \varepsilon_t^m \tag{4}$$

Where,

$\widehat{R_t} = Nominal\ Interest\ Rate\ Gap = \log(R_t) - \log(R)$

$\widehat{\pi_t} = Inflation\ Gap = \log(\pi_t) - \log(\pi^{\#})$

$\widehat{y_t} = Output\ Gap = \log(Y_t) - \log(Y_t^n)$

3.3.2. Fiscal Policy

We assume a simple fiscal policy where the government spending is G_t is a fraction of steady-state output but it is subject to exogenous shock.

$$G_t = (1 - g)Y.\exp\left(\varepsilon_t^g\right) \qquad 5)$$

This equation specifies an exogenous government spending process in levels.

Where g is the steady-state share of government spending in GDP and ε_t^g is a government spending shock. For the sake of simplicity, we assume that there are no distortionary taxes as well as the government bonds are held by the households, with the budget-constraint being satisfied by the lump-sum taxes.

3.4. Aggregate Resource Constraint and Market Clearing

The economy's aggregate resource constraint is

$$Y_t = \ C_t + G_t \tag{6}$$

3.5. Stochastic Process for Shocks

The exogenous driving forces in the model are

(i) Productivity shock: $\log A_t = \ \rho_a \log A_{t-1} + \varepsilon_a^t$ – this equation specifies the stochastic process for aggregate productivity.

(ii) Government spending shock: $\log G_t = (1 - \ \rho_g) \log G + \rho_g \log G_{t-1} + \varepsilon_t^g$ – this is a stochastic AR(1) process with mean reversion for government spending.

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(iii) Monetary Policy Shock: ε_t^m

Here, ρ_a and ρ_g are persistence parameters (lying between 0 and 1) and the ε's are the i.i.d. normal shocks.

3.6. The Expectations system and the AIF/RE Difference

This is nothing but a standard NK-DSGE model, so far. The crucial step is to specify the operator of expectation E_t. In a RE world, this quantity is computed using the true model. In our reality, there are two kinds of inhabitants in the economy.

RE Agents: Whose action is rational, that is, RE agents know the true model's parameters and forecast future variables using them.

AIF Agents: These agents built expectations by a learning algorithm based on data. They are unaware of the actual model. Instead they have what we can say a "perceived law of motion" (PLM) which they infer from past data.

Let, ξ_i denote the fraction of firms and households who are AIF agents, hence, $(1-\xi_i)$ agents are RE agents. For the sake of simplicity, we assume that aggregate expectations are a weighted average of these two groups.

$$E_t^{agg}[x_{t+1}] = (1-\xi)\, E_t^{RE}\,[x_{t+1}] + \,\xi E_t^{AIF}\,[x_{t+1}]$$

Where, x_{t+1} is any variable whose expectation is required (for example, π_{t+1}, c_{t+1}). This assumption simplifies the model by allowing us to consider the aggregate expectations as as a combination or a mixture, avoiding the much complex phenomenon of modelling the heterogeneous agents who might trade with each other. This equation defines an aggregate expectation as a weighted average of rational expectations (RE) and AI Driven Forecast Expectations (AIF).

Hence, the core of our study is to specify $E_t^{AIF}[.]$ which we do in the next section.

4. Micro foundations of AI-Driven Forecasting (AIF)

In this sub-section, we offer a stylized formalization of how an AI agent would forecast the evolution of future economic variables. We are motivated by the machine learning literature, in particular models that can capture complex dependencies.

4.1. The AIF agent's problem:

An AIF agent wishes to predict a target variable, e.g., the next period's (t+1) inflation π_{t+1}. They are not aware of the real structural model (Equations 1-6). Instead, they have a perceived law of motion (PLM) from which they connect the target variable as a function of some information variables which are available at time (t). The PLM is considered as a non-linear function, that we approximate with a flexible functional

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form similar to the one used for neural networks (linear combination of "basis functions"). To keep things easy, we approximate with a polynomial which is valid when all we really want is to capture nonlinearities around a steady state. Let the information set at time 't' for forecasting $\hat{\pi}_{t+1}$ be $Z_t = [\hat{y_t}, \widehat{\pi_t}, \widehat{R_t}]$ - the contemporaneous deviations of output gap, inflation, and interest rate from their steady states.

Hence, the AIF agent's forecast for inflation in the next period is -

$$E_t^{AIF}[\pi_{t+1}] = \pi + \sum_{k=1}^{K} w_k \cdot g_k(Z_t; \gamma_k) \qquad (7)$$

This equation specifies an AI driven forecasting rule for inflation expectations.

$\pi = steady - state\ inflation\ rate$

$K = Number\ of$ "Hidden Units" $or\ Basis\ functions$

$w_k = the\ weights\ that\ the\ agents\ need\ to\ learn$

$g_k(.) = Basis\ Functions.$

A Common choice is the sigmoid or hyperbolic tangent function - $g_k(Z_t) = \tanh(\gamma_k' Z_t)$ which introduces non-linearity.

γ_k are the parameters of basis functions. For simplicity and for making the model solvable in a DSGE context, one can assume that these are fixed and pre-specified – which leaves the agent to learn only the weights - $w = [w_1, \dots\dots, w_k]'$. This is analogous to a shallow neural network or a non-parametric regression.

4.2. The Learning Algorithm: Stochastic Gradient Descent (SGD)

The AIF agents learn about the weights (w) by observing the past, historical data. At each period, after π_{t+1} is realized, the agent incurs a squared forecast error -

$$L_t = (\pi_{t+1} - E_t^{AIF}[\pi_{t+1}])^2$$

The agent, then, updates, its weights by using a rule that minimizes this error. This is analogous to the Stochastic Gradient Descent (SGD) algorithm used in Machine Learning. The updating rule is –

$$w_{t+1} = w_t - \eta \cdot \frac{\partial L_t}{\partial w} \qquad (8)$$

Where, η is the "learning rate" or " speed of adjustment" parameter. It implies that a higher η indicates that the agent reacts very strongly to the recent forecast errors.

The derivative is

$$\frac{\partial L_t}{\partial w} = -2\left(\pi_{t+1} - E_t^{AIF}[\pi_{t+1}]\right).\frac{\partial E_t^{AIF}[\pi_{t+1}]}{\partial w}$$

Or,

$$\frac{\partial L_t}{\partial w} = -2\left(\pi_{t+1} - E_t^{AIF}[\pi_{t+1}]\right).g(Z_t) = -2e_{t+1}.g(Z_t)$$

Where,

$e_{t+1} = \pi_{t+1} - E_t^{AIF}[\pi_{t+1}]$ is the forecast error at 't+1' and $g(Z_t)$ is the vector of basis function outputs $[g_1(Z_t), \dots \dots, g_k(Z_t)]'$.

Using this back into the SGD updating rule, we get –

$$w_{t+1} = w_t + 2\eta e_{t+1}.g(Z_t) \tag{9}$$

Equation (9) is the heart of the AIF agent's learning process. The agent's forecast rule and its updating mechanism, as explained in equation (7) and equation (9), respectively, fully define its behaviour.

4.3. Integrating AIF into the DSGE Model System

To study the dynamics of the model, we have to include the AIF expectation formation mechanism into the equilibrium conditions. This is the hardest part. In a linearized DSGE model, expectations appear linearly. The expectation of the AIF agent (Eq 7) is nonlinear in the state variables Z_t. But, since regarding the steady-state we are concerned only, with local dynamics, we can linearize the AIF forecast rule.

Let $w^{\#}$ be the long-run average for the weights the AIF agent would learn if it could learn in a stationary environment (i.e.. without shocks). Near the steady-state, where the deviations are small, we can use a first-order Taylor expansion for the AIF forecast rule -

$$E_t^{AIF}[\widehat{\pi_{t+1}}] \approx \sum_{k=1}^{K} w_k^{\#} . g'_k(0).\widehat{Z}_t$$

Where, $g'_k(0)$ is the derivative of the basis function evaluated at the zero steady-state. This proves that for local analysis, the AIF agent's expectation is linear in state variables. The parameters of this linear rule, that is, the coefficients on $\widehat{y}_t, \widehat{\pi_t}, \widehat{R_t}$ are decided by the underlying weights $w_k^{\#}$ as well as by the structure of the basis functions.

For the sake of this study's prime contribution, we can simplify this further by assuming that the AIF agents are learning the coefficients of the forecasting rule directly, which is a well-known as well as well-accepted outcome from the literature of adaptive learning or expectations. Let their perceived law of motion for the output

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gap, inflation and interest rate be a VAR (1) process which gives us the following matrix.

$$\begin{pmatrix} \widehat{y_{t+1}} \\ \widehat{\pi_{t+1}} \\ \widehat{R_{t+1}} \end{pmatrix} = A \begin{pmatrix} \widehat{y_t} \\ \widehat{\pi_t} \\ \widehat{R_t} \end{pmatrix} + B \begin{pmatrix} \varepsilon_{t+1}^{a} \\ \varepsilon_{t+1}^{g} \\ \varepsilon_{t+1}^{m} \end{pmatrix}$$

The AIF agents do not know about the true matrices 'A' and 'B'. Instead, they have estimates - $\widehat{A_t}$ *and* $\widehat{B_t}$ which they update each period by using a least-square algorithm (which is equivalent to a specific form of SGD). The expectations are formed as –

$$E_t^{AIF}[\hat{x}_{t+1}] = \widehat{A_t}\widehat{x_t}$$

The updating rule for $\widehat{A_t}$ is a standard RLS (Recursive Least Square) or LMS (Least Mean Square) algorithm. This formalism captures the basic essence of Machine Learning – the agent has a flexible parametric model (VAR) and the agent continuously updates its parameters based on new data to minimize the possible forecast errors.

4.4. Full system of Equations

Combining the structural equations with the expectations formations, the full linearized system of equations of the model is given below.

(i) Euler's Equation: $\hat{c}_t = E_t^{agg}[\hat{c}_{t+1}] - \hat{R}_t + E_t^{agg}[\hat{\pi}_{t+1}]$

(ii) Phillips Curve: $\hat{\pi}_t = \beta E_t^{agg}[\hat{\pi}_{t+1}] + \kappa\widehat{y_t}$

(iii) Output Gap: $\hat{y}_t = \hat{c}_t + \hat{g}_t$

(iv) Monetary Policy Rule: $\hat{R}_t = \rho_t\hat{\pi}_t + \rho_y\hat{y}_t + \varepsilon_t^m$

(v) Expectations Aggregation: $E_t^{agg}[\hat{x}_{t+1}] = (1-\xi)\hat{E}_t^{RE}[\hat{x}_{t+1}] + \xi\hat{E}_t^{AIF}[\hat{x}_{t+1}]$

Here the RE agent's expectation is formed by using the true model solution and the AIF agent's expectation is formed by using their estimated linear rule. This above system is a set of forward- looking difference equations which can be solved by using standard methods.

5. Model Solution and adjustments

5.1. Solving the steady state

The steady-state is found by setting all shocks to zero and by removing the hats and the time subscripts. Hence, the system becomes:

(i) $1 = \beta \frac{R}{\pi}$

(ii) $\pi = 0$ (It is assumed that the Central Bank of the economy targets for zero inflation in the long-run).

(iii) From equation (2), $\pi = \kappa mc$ implies mc=0 which implies that the real marginal cost is zero in the steady-state.

(iv) From the firm's problem, mc $= \frac{W/P}{A}$ with $\alpha = 0$. Hence, the real wage is $\frac{W}{P} = A$

(v) From the household's Labour supply Function's First Order Condition: $\frac{W}{P} = C^{\sigma} L^{\varphi}$

(vi) From the Resource Constraint: $Y = C + G$. With G = g.Y, we have C = (1-g(Y)).

(vii) From the production function: Y=AL

The system of equations gives us the steady-state values for Y, C, L, W/P, R given the parameters $\beta, \sigma, \varphi, g, A$.

5.2. Adjustment

To simulate the model's dynamics, we adjust the parameters to values commonly used in the literature for a quarterly model (Gali, 2015).

Parameters	Description	Value	Source/ Justification
Household			
β	Discount Factor	0.99	Implies 4% annual real interest rate
σ	Risk Aversion	1.5	Standard Value
φ	Inverse Frisch Elasticity	2.0	Standard Value
Firm			
θ	Calvo Price Stickiness	0.75	Implies prices change every year
ε_P	Elasticity of Substitution	6.0	Implies a 20% mark-up in steady-state
Policy			
ρ_π	Inflation Response	1.5	Taylor principle >1
ρ_y	Output Gap Response	0.5	Standard Moderate Response
g	Government spending share	0.2	20% of GDP

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Shocks			
ρ_a	Productivity persistence	0.90	High persistence
ρ_g	Government spending persistence	0.90	High persistence
AIF/RE Mix			
ξ	Fraction of AIF Agents	[0, 0.25,0.50,0.75, 1]	We will test a range
H	AIF learning rate	0.1	An important parameter for our results

The crucial innovation is the parameter ξ and its implied learning dynamics. For the solution of the linearized system, we consider the AIF agent's Perceived Law of Motion as being close to the true law of motion in steady-state. The dynamic responses will depend on how the AIF agents' expectations deviate from RE during the shock, which is governed by η.

6. Findings and Discussions

We proceed with the discussion of our simulation results. We study the impulse response functions (IRFs) of important macroeconomic variables: output, inflation, and nominal interest rate to three shocks - one due to a positive technology shock, the next involving an increase in government spending demand and lastly one emerging from an unexpected tightening in monetary policy. We compare the responses in a "Pure RE Economy" (ξ = 0) with an "AI augmented Economy" (ξ = 1, that is, all agents are AIF).

6.1. Response to a Positive Technology Shock ($\varepsilon_t^a > 0$)

A favorable productivity shock raises the potential output of the economy. The natural rate of interest declines, and the natural level of output increases.

Pure RE Economy: In a world of RE, agents instantly know the shock. They understand that the economy's potential has risen. In this situation, inflation and the output gap do not move too far from -14their new, higher steady states. The central bank observes the shock, and it immediately reduces the nominal interest rate in order to bring it in line with the new natural rate. It's quick and the adjustment is mostly painless.

AI-Augmented Economy (AIF): The AIF agents are caught off guard here. Their

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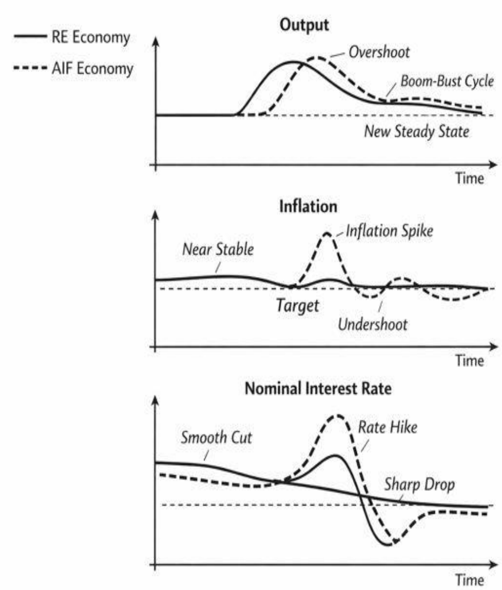
forecasts are based on historical data which didn't have technology shocks of this magnitude or fully was without them. Their model doesn't "get" that the rise in output is permanent (or near-permanent). They could see it as a temporary surge in demand, causing them to predict greater future inflation. This forecast error is critical. They want more compensation for lending (i.e., they anticipate higher inflation, so their required real interest rate is higher). This induces a dulled consumption-saving decision relative to RE. Inflation is more volatile because they set prices wrong due to bad expectations.

These are shown by the following panels of diagrams.



It gives us the following finding.

Finding 1: *AIF agents amplify the volatility of business cycles in response to the supply shocks. Their inability to identify, immediately, the structural nature of a shock that leads to forecast errors that propagate through the economy, creating larger and prolonged boom-bust cycles.*

6.2. Positive Government Spending Shock Response ($\varepsilon_t^g > 0$)

A positive government spending shock is a demand shock. It increases aggregate demand, which raises output and through the Phillips curve inflation.

Pure RE Economy: In this environment agents simply view it as a temporary demand shock. They understand that it will increase inflation and output, prompting the central bank to raise interest rates in order to bring inflation back down. The increase in the

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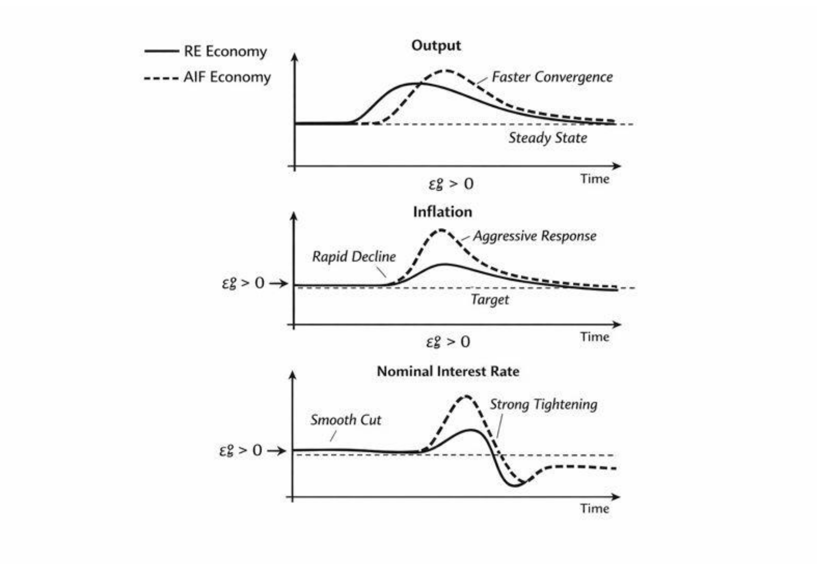
nominal rate raises the real rate and thereby the extent of crowding of private consumption. The net effect on output is positive but tempered.

AI-Augmented Economy (AIF): A surprise shock hits the AIF agents once more. Their models may interpret the demand-driven increase in output as implying a supply side improvement which causes them to predict lower future inflation than seems appropriate. Or they might just call it a demand shock, but then be unsure of its impact or duration. Their consumption response is thus different due to this initial uncertainty and forecast error. They may not cut consumption as much at the outset (irrational ebullience about expected interest rate hikes). But they shine because of their learning process. Then, when they see inflation go up and the central bank raise its interest rates, they tweak their models to recognize the pattern. They turn out to be "faster learners" than would be expected from adaptive expectations.



This gives us the following finding.

Finding 2: *For demand shocks, AIF agents can initially amplify the impact but their superior learning speed leads to faster stabilization. This makes monetary policy more potent, as agents adjust their behaviour rapidly and in line with the policy's intent.*

6.3. Response to a Sudden Tightening Surprise in Monetary Policy ($\varepsilon_t^m > 0$)

This is a pure policy shock where the central bank raises the interest rate for reasons not linked to the current economic conditions.

Pure RE Economy: Agents know that this is just a temporary diversion from the policy rule. They quickly crank down their expectations for inflation. The increase in the real interest rate reduces consumption and investment, so output and inflation decline as well. The results are consistent with model predictions.

AI-Enhanced Economy (AIF): The AIF participants are confronted with a historic pattern shift. Their forecasting models, which will rely on past data from a time when such an arbitrary tightening did not happen, won't know how to interpret it. It may take them longer to respond first off. But they will soon become acquainted with results: high interest rates translate into low output and inflation. They will then quickly revise their expectations.

Finding 3: *The efficacy of unanticipated monetary policy change is enhanced in an AI augmented economy. While the agents could be initially confused but their ability to learn the "new regime" rapidly implies that the monetary transmission mechanism works fast. It implies that the central bank achieves its desired objectives on output as well as on inflation in a short duration or lag. But, it may have the risk of policy being too effective which could set in recession if not carefully adjusted for.*

The model developed in this paper is a linearized New-Keynesian DSGE framework augmented with heterogeneous expectations formation. The system consists of five core equations governing consumption dynamics, inflation, output, monetary policy, and expectations aggregation.

At its foundation is the forward-looking Euler equation, which characterizes intertemporal consumption decisions as a function of expected future consumption, real interest rate, and expected inflation. Inflation dynamics are governed by a standard New-Keynesian Phillips Curve, linking current inflation to expected future inflation and the output gap. Aggregate demand is represented through the output identity, where the output gap depends on consumption and exogenous demand shocks. Monetary policy is modeled via Taylor-type rule, where the nominal interest rate responds systematically to inflation and output deviations, along with an exogenous monetary shock. The important innovation lies in the expectations-aggregation equation. Aggregate expectations are modeled as a convex combination of rational expectations (RE) and AI-formed expectations (AIF). Rational agents possess full knowledge of the model structure and form expectations accordingly, while AI agents rely on estimated forecasting rules that approximate the law of motion of macroeconomic variables. The parameter $\xi \in [0,1]$ captures the degree of AI penetration in the economy. The resulting system is a set of forward-looking linear difference equations, solved using standard techniques for rational expectations models. Specifically, the model is expressed in state-space form and solved using methods such as Blanchard-Kahn conditions to ensure determinacy and stability.

To evaluate the model, we conduct simulation-based experiments focusing on impulse response functions (IRFs). The results indicate that economies with higher AI penetration (higher ξ) exhibit stronger amplification of productivity shocks, reflecting

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the ability of AI agents to more rapidly internalize structural relationships. Conversely, in response to demand and monetary policy shocks, the presence of AI agents leads to faster convergence to steady state, indicating improved stabilization properties due to more responsive expectations. This analysis along with the diagrammatic approach show that while output and inflation volatility may increase under technology shocks, persistence declines in the presence of AI-driven expectations. These findings suggest a trade-off between volatility amplification and stabilization speed, with important implications for monetary policy design.

7. Conclusion

This paper develops a New-Keynesian DSGE framework to examine the macroeconomic implications of incorporating Artificial Intelligence (AI) into expectations formation. By introducing heterogeneous agents—comprising both rational expectations (RE) agents and AI-based forecasters (AIF)—the analysis demonstrates that the presence of AI fundamentally alters the dynamic properties of the economy.

The key finding is that an AI-augmented economy does not simply represent a more efficient version of a rational expectations framework, but rather a qualitatively different system. Simulation results from the model indicate that AI-driven expectations amplify the response of output and inflation to productivity shocks, leading to more pronounced business cycle fluctuations. At the same time, in the presence of demand and monetary policy shocks, AI agents contribute to faster stabilization, as their expectations adjust more rapidly to new information.

These results are consistent with emerging empirical observations from the business environment, where firms increasingly rely on data-driven forecasting tools. For instance, the growing use of AI in demand forecasting and inventory management—particularly among large retailers and logistics firms—has been associated with quicker adjustments to demand fluctuations, especially during periods of economic disruption such as the COVID-19 pandemic. However, recent global supply chain disruptions have also highlighted that highly synchronized, data-driven decision-making can amplify cyclical movements when firms respond similarly to common signals.

From a policy perspective, the findings suggest that central banks may need to account for faster expectations adjustment and potentially stronger transmission of shocks in an AI-augmented economy. While improved information processing can enhance policy effectiveness, it may also increase the risk of correlated forecasting errors, giving rise to forms of "herding" behavior that could amplify macroeconomic volatility.

Future research should extend the present framework by incorporating richer forms of

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heterogeneity among AI agents, as well as integrating financial sector dynamics. Moreover, empirical validation of the model's predictions using firm-level and macroeconomic data will be essential as AI adoption continues to expand across the global economy.

8. Implications for Business and Policy

Our results have important implications for the way businesses think about forecasting and how policymakers should structure their framework.

7.1. For Business Forecasting and Enterprise Risk Management

The model shows that the macroeconomic environment is significantly more volatile to fundamental (supply) shocks. And this has direct implications for corporate planning.

Investment and Capacity Planning: Firms would need to adjust for potentially bigger fluctuations in the aggregate level of demand and prices. The "boom-bust" dynamics that AI learning introduces imply that long-run investment plans have to be adjusted by upping their risk premium for macroeconomic volatility. A company deciding to invest in capacity expansion on the basis of an AI-induced boom could prove to be very expensive.

Supply Chain Management: The AI-enabled multiplication of shocks means that supply chain disruptions may be more severe and last longer. Businesses may need to invest in more resilience in their supply chains, transitioning from "just-in-time' to 'just-in-case.'

Dynamic Pricing: Companies utilizing AI for dynamic pricing will work within an environment in which their AIs are responding to a macroeconomy that comprises other AIs as well. This might set up a complicated set of feedback loops. A pricing AI at one firm might pick up on a slight price rise from another and assume that it is the beginning of a new trend, increasing its own price as a result, which could generate waves of pricing movement that are inherently unjustified.

Prediction as Competitive Imperative: The model indicates that firms which are able to utilize better forecasting instruments (i.e. "better AIs") should hold considerable comparative advantage. They will be able to separate temporary and permanent shocks more rapidly, not falling for the same costly mistakes that those less-sophisticated agents (or AIs) do.

7.2. Monetary Policy and Financial Stability Only

The growing influence of AI in expectations formation is a huge challenge (and opportunity) for central banks.

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Re-Examining the Taylor Rule: The traditional Taylor rule assumes RE. Its performance can vary in an AI world, the paper demonstrates. In the case of supply shocks, the rule can induce procyclical policy errors. The best response for central banks can come from adding "AI-agnostic" models or develop "Now casting" abilities from other data to enable to effectively understand the character of shocks on a real-time basis.

The Power and Danger of Forward Guidance: The Upshot Our findings indicate that forward guidance stands to be a much more powerful tool. AIF agents are hyper-sensitive to the communication of the central bank; they learn from it.) With a clear, credible declaration of intent, expectations could be influenced in short order and policy would need to move less in the policy rate to accomplish its goals. But that's a double-edged sword. A message either false or misconstrued could have produced personnel of the AIF learning the ‘wrong’ lesson and brought about destabilizing results.

The Risk of AI Herding: One serious, not explicitly modelled here, but implied threat is that all AIs become homogeneous. If most economic agents rely on forecasting models with a common architectural design (e.g. popular deep learning models) and trained with similar public datasets, then, they might end up producing exactly the same forecast or highly correlated forecasts. In a crisis, this could translate into massive herding behaviour that involves concurrent selling of assets, credit curtailment or price discovery movements, even if they end up fueling (rather than mitigating) the crisis. This is systemic risk of a new, tech-driven sort.

Macro-prudential Policy: The greater response of variables to demand shocks implies more fluctuating credit markets and the possibility of larger asset bubbles, which point to a need for strong macro-prudential policy (e.g., time varying capital requirements for banks). Regulators will have to watch the “AI-saturation” of the financial system.

7.3. Limitations of the Model

This paper introduces a stylized model. It’s findings should be taken with a grain of salt, as they contain some simplifying assumptions:

AI Homogeneity: We consider AIF agents as a unique homogeneous class. In fact, there will surely be hundreds if not thousands of AI models of all kinds sizes and shapes. This diversity might mitigate collective boosting effects.

Information Sets: Our model presumes that AIF agents have the same information as RE agents, namely access to the full set of macroeconomic aggregates. In practice, AIs might operate using far more rich high-frequency data (satellite imagery, credit card transactions, web traffic), with increasing accuracy.

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The Lucas Critique: Our model is a structural model, although we take it that the parameters of the AI learning process (such as the learning rate (\eta))) remain policy-invariant. But a regime switch of the central bank's policy (e.g., from inflation targeting to price level targeting) would imply that AIF agents would have to re-learn the environment completely. The model is not equipped to accommodate such profound policy shifts.

Financial sector: The model is an RBC model with nominal rigidities and does not include a detailed banking/financial sector. The connection between AI-based trading, credit scoring and macroeconomic dynamics is a large important field for future work.

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