Fusing Multi-agent Reinforcement Learning and Fiscal Theory for Crisis Management

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Abstract. In this research, we enhance the AI-Economist framework to better analyze economic dynamics during the COVID-19 pandemic using the fiscal theory of price level. We have added new features that allow for more assertive economic interventions by a federal planner, enabling detailed exploration of decisions like subsidy implementation and interest rate adjustments in a fiscally tight environment. Additionally, the utilization of multi-agent reinforcement learning and simulation-based policy analysis frameworks play a pivotal role in enriching our framework's capabilities to address complex economic scenarios. Our improved model provides insights into managing future global crises by simulating policy responses, highlighting the trade-offs and impacts of various policy options to aid real-world decision-making.

Keywords: multi-agent reinforcement learning · simulation-based policy · fiscal theory of price level · monetary policy · fiscal policy

1 Introduction

The AI-Economist paper [5] presents a two-level deep reinforcement learning (RL) framework that trains both agents and a social planner who co-adapt [4]. This framework provides a tractable solution to the highly unstable and novel two-level RL challenge, serving as a powerful policy and mechanism design tool [4]. It overcomes limitations such as a lack of counterfactual data, simplistic behavioral models, and limited opportunities to experiment with policies and evaluate behavioral responses. Moreover, the AI-Economist's AI-driven economic simulations capture real-world economic features without relying on hand-crafted behavioral rules or oversimplifications [5]. The framework's dual-level approach enables the learning of optimal policies at both the individual agent and social planner levels, making it particularly valuable in contexts such as mechanism design, principal-agent problems, and systems regulation where agents may have misaligned incentives. One of its significant strengths is addressing the Lucas critique [5], which argues that historical data might not adequately capture behavioral responses to policy changes.

However, in the context of COVID-19, the model exhibits several limitations:

1. **Lack of Comprehensive Economic Modeling:**
   - The AI-Economist primarily focuses on the impact of lockdowns implemented by state governments, thereby neglecting the broader macroeconomic consequences of federal stimulus spending.
   - The model does not account for federal monetary policy, such as interest rates set by the Federal Reserve, which significantly influenced the fiscal environment during the pandemic.
2. **Neglect of Long-Term Economic Consequences:**
   - The model is more suited to analyzing short-term economic outcomes rather than long-term effects. It fails to consider the potential long-term consequences of government spending, debt accumulation, and inflation—factors essential to understanding the broader economic impact of the pandemic.

In this work, we address these limitations by integrating the Fiscal Theory of the Price Level (FTPL) into the AI-Economist framework, thereby significantly enhancing its capability to simulate and analyze the macroeconomic effects of various federal policy decisions. Our key contributions include:

- **Enhanced Economic Modeling:** By incorporating FTPL, our model robustly captures the interplay between fiscal policy and price levels, enabling the simulation of long-term impacts such as inflation dynamics, debt sustainability, and economic growth.
- **Expanded Policy Toolkit for the Federal Planner:** We extend the original action space by empowering the federal planner with a broader set of tools—including setting interest rates, implementing tax cuts or hikes, and adjusting federal spending on welfare and defense. This enhancement allows for a more comprehensive representation of federal-level decision making.
- **Addressing Long-Term Consequences:** Our integration of FTPL ensures that the model now accounts for the long-term effects of government actions, such as sustained deficits, debt accumulation, and inflationary pressures, thereby offering a more realistic simulation of economic outcomes during crises.

Consequently, the enhanced AI-Economist framework is better equipped to provide insights into how federal-level decisions might mitigate or exacerbate economic conditions during crises such as the COVID-19 pandemic, ultimately leading to more informed and effective policy recommendations.

2 Overview

2.1 Multi-agent Reinforcement Learning on Policy Simulation

Multi-agent reinforcement learning (MARL) is a specialized sub-field of reinforcement learning concerned with learning optimal policies among multiple agents interacting in an environment [7]. Unlike single-agent RL, where focus lies on one agent's behavior, MARL must handle cooperation, competition, or both [8], leading to more complex learning dynamics. MARL's diverse applications include robotics [9], traffic control [10], financial markets [11], and social policy simulations [12, 13], especially where emergent behaviors arise from agent interactions.

Government institutions have investigated MARL for macroeconomic scenarios, as in [6], which examined RL agents within a real business cycle setting. Recent surveys [14] highlight achievements such as Hinterlang and Tänzer (2022) [36], who used deep RL to refine interest rate policies in a New Keynesian framework by estimating IS-LM, Phillips curve, and central bank reaction functions [37]. Castro et al. (2022) [38] employed RL to optimize liquidity policies in high-value banking systems. Other research has focused on microeconomic settings: in [30], MARL agents learned resource accumulation, exchange, and consumption under spatial constraints, revealing behaviors aligned with supply-demand theory. Jirnyi and Lepetyuk (2011) [29] applied RL to liquidity-constrained markets; Covarrubias (2022) [39] analyzed oligopolistic structures in monetary policy transmission; and Calvano et al. (2020) [28] demonstrated how RL-driven sellers could collude, posing regulatory challenges for competition policy.

2.2 Modern Macroeconomic Theory

Modern macroeconomic theory, grounded in diverse schools of thought, explores government intervention and the broader macroeconomic environment. Central to this field are New Keynesian economics, New Classical economics, Monetarism, and the Fiscal Theory of the Price Level, each providing distinct insights into how policies influence economic outcomes.

New Keynesian economics refines the ideas of John Maynard Keynes by addressing critiques from New Classical economists who emphasize flexible wages and prices [42]. New Keynesians highlight price and wage stickiness, arguing that short-run fluctuations and involuntary unemployment arise when these rigidities slow adjustments to economic shocks. Concepts such as menu costs and coordination failures underscore why firms may not rapidly change prices, reinforcing the importance of active monetary policy to stabilize output.

In contrast, New Classical Macroeconomics, championed by Lucas, Sargent, Wallace, and Prescott, posits that economic agents are rational optimizers forming expectations based on available information [43]. Business cycles are seen as rational responses to technological or policy shocks, and systematic monetary interventions are deemed largely ineffective once anticipated. Lucas's policy non-invariance critique contends that changing policy rules alters economic behavior, challenging the predictive power of traditional econometric models.

The Quantity Theory of Money (QTM) underscores the relationship between the money supply and the price level: if velocity (V) is relatively stable, changes in money (M) lead to proportional changes in price (P) or output (Q) [45]. Monetarism, influenced by Friedman, Schwartz, Brunner, and Meltzer, further develops QTM's tenets by arguing for long-run monetary neutrality but acknowledging short-run non-neutrality [44]. Monetarists distinguish between real and nominal interest rates, emphasize managing monetary aggregates like M1 and M2, and favor monetary policy over fiscal measures for stabilizing the economy. Friedman's proposal for a constant-money-growth rule, while influential, sparked debates as velocity proved less stable than initially assumed.

The Fiscal Theory of the Price Level (FTPL) broadens the analysis by integrating government fiscal positions into price level determination [41]. It stresses that the real value of nominal government debt must be supported by the present value of expected fiscal surpluses. If persistent deficits are not offset by future surpluses, the price level may adjust to ensure the intertemporal government budget constraint holds. Active versus passive policy interactions become critical: fiscal authorities can influence inflation if their policies shift the balance of expected surpluses and deficits, while central banks often respond by adjusting the money supply or interest rates. Recent policy debates, such as student loan forgiveness proposals, illustrate the FTPL's relevance by linking future fiscal shortfalls to potential inflationary pressures.

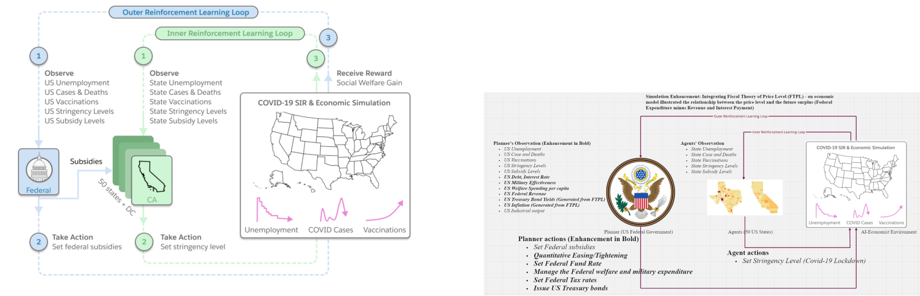
3 Method

3.1 Improving the COVID-19 Simulation from the AI-Economist framework

First, we adopt a two-tiered multi-agent reinforcement learning structure [1], akin to the original AI-Economist framework, with emphasis on the enhancements of the planner's capabilities to influence the macroeconomic environment. In this hierarchy, the planner agent embodies the combined US Government and the Federal Reserve, observes the macroeconomic condition effected by the state agents' policies into consideration, thus tackling the economic ailments via monetary instruments and fiscal firepower, while the governments of the 50 US states and the District of Columbia - represented by the state agents - address the COVID-19 crisis via stringency policies.

State space $\mathcal{S}$. The state space encompasses the signals originating from the environment, observable from the agents' perspective. These features include:

1. *Epidemiology Model:* An SIR-model [15] is used to track the evolution of the pandemic, considering the effects of vaccines. The model operated effectively for the first 500 days of the simulation, considering that the model only represents one variant of COVID-19 and vaccine effectiveness is considered constant. The infection rate within each US state is a linear function of that state's stringency level, meaning stricter measures lead to lower infection rates.
2. *Economic Model:* US State economic output is the sum of incoming subsidies T and the net production from the private sector. The federal output is the sum of the state outputs minus the borrowing costs for subsidies and the financial burden of taxation [31]. Unemployment is modeled using a time-series approach based on the historical stringency levels (fetched from Oxford COVID-19 Government Policy Tracker [25]) - let S denote the stringency of



(a) The previous AI-Economist's Covid-19 policy simulation [1]

(b) Enhanced policy simulation for managing the Covid-19 pandemic.

Fig. 1: Side-by-side comparison of the AI-Economist policy simulations.

policy measures. The higher the stringency level, the lower the economic output.

Action space $\mathcal{A}$. The action space $\mathcal{A}$ defines the set of possible interactions between the agents and the environment at time t.

1. *Agents' Policies (State-Level):* Each U.S. State agent sets a pandemic management strategy via a stringency level from 1 (minimal) to 10 (maximal restrictions).
2. *Planner's Policy (Federal-Level):*
   – *Subsidy:* The federal government provides subsidies up to \$20,000 per capita for a certain period [21], denoted as $T_{i,t}^{state}$.
   – *Taxation policy:* The planner adjusts the taxable portion of GDP (Tax_r). In 2019, the U.S. tax revenue was about 16% of GDP [23]; the planner can tweak this by 0.1% increments.
   – *Monetary policy:* The planner initiates quantitative easing or tightening by buying or selling long-term bonds (to finance deficit spending), controls the balance sheet Re_t^r, and sets the federal fund target i_t [22].
   – *Social Security, Medicare, Medicaid, Income Security, Defense Spending:* Funding is adjusted in \$100 billion increments. Initial data references come from the CBO and other institutions [17, 19, 20].

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Reward function $\mathcal{R}(s, a, s')$. The reward function measures how well action a transitions the system from state s at time t to s' at time $t+1$. Adapting the AI-Economist framework [3], state governments update lockdown levels while the federal government conducts budget-balancing, monetary, or subsidy policies. The final reward functions are:

$$\mathcal{R}_i = SW_i, \quad \mathcal{R}_p = SW_p + Pov_t + Def_t \tag{1}$$

1. *Social Welfare (Planner and State Agents)* SW combines a health index H and an economic index E:

$$SW_i = \alpha_{EH} \sum_{i=1}^{N} \Delta H_{i,t} + (1 - \alpha_{EH}) \sum_{t=1}^{T} \Delta E_{i,t} \tag{2}$$

$$\Delta H_{i,t} = \frac{\Delta D_i^{\min} - \Delta \tilde{D} i, t}{\Delta D_i^{\min} - \Delta D_i^{\max}}, \quad \Delta E i, t = \frac{crraP_{i,t} - crraP_i^{\min}}{crraP_i^{\max} - crraP_i^{\min}} \tag{3}$$

The health score inversely relates to COVID-19-related deaths D_i, and the economic score E depends on productivity, unemployment, and federal subsidies. For the planner:

$$SW_p = -\alpha_{EH} \sum_{i=1}^{N} \Delta D_{i,t} + (1 - \alpha_{EH}) \cdot \Delta E_{p,t}, \quad \Delta E_{p,t} = ccra \frac{\sum_{t=1}^{T} P_{i,t} - Cost}{\sum_{t=1}^{T} P_{i,0}} \tag{4}$$

$$Cost = (1 + i_t) \cdot Re_t^r + (T_t^i - Re_t^r) \cdot r_t^n + Tax_r \cdot c \tag{5}$$

2. *Defense Index / Poverty Alleviation Index (Planner)*: Def_t measures defense spending D_t relative to a maximum level D^* of 1.2 trillion USD. Pov_t captures the effectiveness of social programs in alleviating poverty based on per-beneficiary spending and inflation π_t:

$$Def_t = \frac{D_t}{D^*} \cdot Def^*, \quad Pov_t = \frac{S_t}{B_t} \cdot \frac{1}{\bar{I}_{social} \cdot (1 + \pi_t)} \tag{6}$$

The Fiscal Theory of Price Level. John H. Cochrane's model [2] provides a comprehensive framework for how the price level responds to changes in government debt and deficits. Inflation emerges when markets expect insufficient future surpluses, prompting reliance on seigniorage (printing money) rather than spending cuts or tax increases. [2].

In the following, Cochrane has delivered the fiscal model:

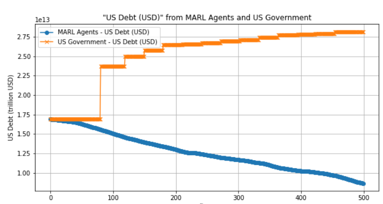
$$x_t = E_t x_{t+1} - \sigma (i_t - E_t \pi_{t+1}) \tag{7}$$
$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t \tag{8}$$
$$E_t r_{t+1}^n = i_t \tag{9}$$
$$r_{t+1}^n = \omega q_{t+1} - q_t \tag{10}$$
$$i_t = \theta_{i\pi} \pi_t + \theta_{ix} x_t + u_t^i \tag{11}$$
$$s_{t+1} = \theta_{s\pi} \pi_{t+1} + \theta_{sx} x_{t+1} + \alpha v_t^+ u_{t+1}^s \tag{12}$$
$$\rho v_{t+1} = v_t + r_{t+1}^n - \pi_{t+1} - s_{t+1} \tag{13}$$
$$0 = \lim_{T \to \infty} \rho^T E_t v_{t+T} \tag{14}$$
$$u_{t+1}^i = \rho_i u_t^i + \varepsilon_{t+1}^i \tag{15}$$
$$u_{t+1}^s = \rho_s u_t^s + \varepsilon_{t+1}^s \tag{16}$$

Core Equations. Equations (7)–(8) resemble standard IS-Phillips relations, linking the output gap x_t to nominal interest rates i_t and capturing the feedback of expected future inflation on current inflation. Equations (9)–(10) relate government debt returns r_t^n to bond prices q_t. The Taylor rule in (11) sets interest rates based on inflation π_t, output gap x_t, and monetary shocks u_t^i, while the surplus process in (12) includes fiscal shocks u_t^s, reflecting how inflation, output, and debt v_t shape fiscal outcomes. Equation (13) ties government debt to changes in inflation and surpluses, with (14) imposing the long-run condition that debt must be backed by future surpluses. Lastly, (15)–(16) define the autoregressive structures of monetary and fiscal disturbances.
AI-Economist Integration. In the AI-Economist framework, these equations are calibrated on an annual timescale, with fiscal shocks ε_t^s reflecting surplus-to-GDP ratios, and monetary shocks driven by changes in the federal funds rate and reserve balances. By combining shocks from subsidies, tax cuts, interest rate adjustments, and quantitative easing, this setup models how macroeconomic indicators (e.g., government debt, inflation, bond yields) evolve under different policy interventions.

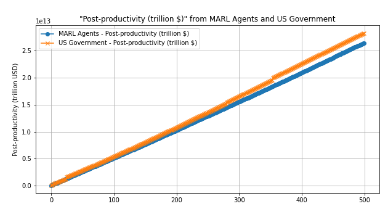
$$\varepsilon_t^s = \frac{s_t}{G_{t-1}}. \tag{17}$$

4 EXPERIMENTAL EVALUATION

4.1 Experimental Setup



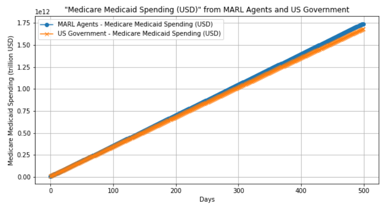
(a) Federal debt comparison metrics



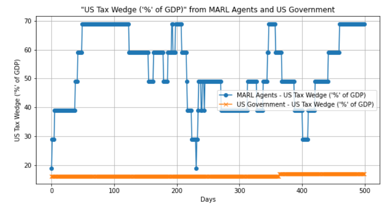
(b) Post-productivity comparison metrics.

Fig. 2: Comparison metrics from the AI-Economist MARL (blue graph) and the real-life US Government (yellow graph), starting from March 22, 2020.

In our research, we analyze two distinct scenarios to understand the dynamics of policy coordination: This scenario involves collaboration between the agents and the planner over the first 500 days to explore policy coordination. The focus is on the interplay between fiscal, monetary, and COVID-19 policies at both federal and state levels. The scenario uses data [24] [25] from 2020 to 2021, calibrated until January 2021, with validation completed by June 2021.

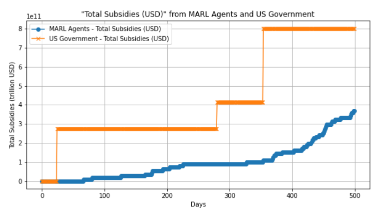


(a) Medicare-Medicaid Spending comparisons.

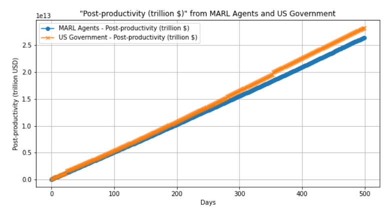


(b) US Taxation rates in GDP Percentage.

Fig. 3: Federal Welfare Expenditure and Tax rate in GDP Percentage from the AI-Economist MARL (blue graph) and the real-life US Government (yellow graph), starting from March 22, 2020.



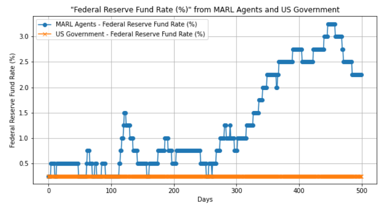
(a) Direct federal subsidies comparisons.



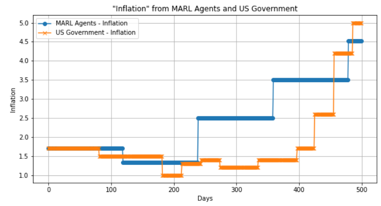
(b) Post-productivity comparison metrics.

Fig. 4: Subsidies and Productivity from the AI-Economist MARL (blue graph) and the real-life US Government (yellow graph), starting from March 22, 2020.

For the implementation of the scenarios, the Proximal Policy Optimization (PPO) algorithm - known for its efficiency and stability [26] - is employed, leveraging its default implementation from the Ray RLlib library [27]. In the examined scenarios, the planner and state actors demonstrate considerable effectiveness in navigating the COVID-19 crisis, evidenced by lower inflation rates and decreased subsidy costs. In a departure from real-world strategies, the planner adopts a proactive role by advocating for interest rate hikes to control inflation while also seeking to boost government revenue. This approach stands in contrast to the current real-world situation, where the Federal Reserve's monetary policy of increasing rates and tapering quantitative easing seems to be at odds with a less coordinated fiscal policy. Although the government is looking to implement strategies like the Inflation Reduction Act to reduce the deficit, other legislative actions such as the CARES Act, the American Rescue Plan, and the Infrastructure Investment and Jobs Act contribute to an increased deficit, perpetuating the underlying issue of fiscal imbalance [32] [33] [34] [35].



(a) Federal Reserve Fund Rate comparisons.



(b) Inflation comparison metrics.

Fig. 5: Federal Reserve Fund Rate and Inflation from the AI-Economist MARL (blue graph) and the real-life US Government (yellow graph), starting from March 22, 2020.

4.2 Conclusion

Our enhanced AI-Economist framework, which integrates the Fiscal Theory of the Price Level (FTPL) into the original model, offers a more comprehensive tool for crisis management. The empirical evaluation demonstrates several key outcomes when comparing the performance of the Multi-agent Reinforcement Learning (MARL) approach to actual US government policies during the COVID-19 crisis:

- **Inflation Control:** The MARL simulation achieves slightly lower inflation levels than those observed under US government policies, highlighting the effectiveness of our integrated fiscal-monetary dynamics in mitigating inflationary pressures.
- **Monetary Policy Aggressiveness:** The simulation exhibits a federal funds rate averaging around 3.0 percentage points, which is significantly higher than the 0.25 percentage points observed in real-world policies. This more assertive monetary stance demonstrates the model's capability to leverage higher interest rates for economic stabilization.
- **Fiscal Strategy – Taxation:** Our framework adopts substantially higher tax rates, peaking at approximately 50% of GDP compared to the 25% peak under actual US government policies. This aggressive fiscal approach is designed to balance the budget and reduce the reliance on deficit spending.
- **Economic Output:** Despite the differences in policy measures, the overall productivity levels in the simulation remain near identical to those observed in reality, confirming that assertive fiscal and monetary interventions need not compromise economic performance.
- **Subsidy Expenditure:** The MARL-driven approach results in federal subsidies that are approximately 4 trillion USD lower than those administered by the US government, indicating a more fiscally conservative strategy that potentially reduces long-term economic burdens.

Key Contributions: Beyond these performance metrics, our work makes several methodological advancements:

1. **Fiscal Integration:** By incorporating FTPL into the AI-Economist framework, we enhance the model's ability to simulate the long-term macroeconomic impacts of fiscal policy, particularly regarding inflation dynamics and government debt sustainability.
2. **Expanded State and Action Spaces:** We extend the original model by integrating additional economic indicators (e.g., unemployment, productivity) and by broadening the federal planner's action space to include a diverse array of fiscal and monetary policy tools. This enables a more nuanced exploration of policy coordination and its effects.
3. **Innovative Reward Function Design:** Our novel reward functions, which combine public health metrics with economic performance indicators, allow the simulation to effectively balance the trade-offs between crisis management and fiscal stability.

In summary, our enhanced framework not only produces improved crisis management outcomes—demonstrated by lower inflation, more aggressive monetary and fiscal interventions, and reduced subsidy expenditures—but also contributes significant methodological innovations. These advancements provide valuable insights for policymakers seeking to achieve economic stability during crises while addressing the challenges of fiscal imbalances in the long term.

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