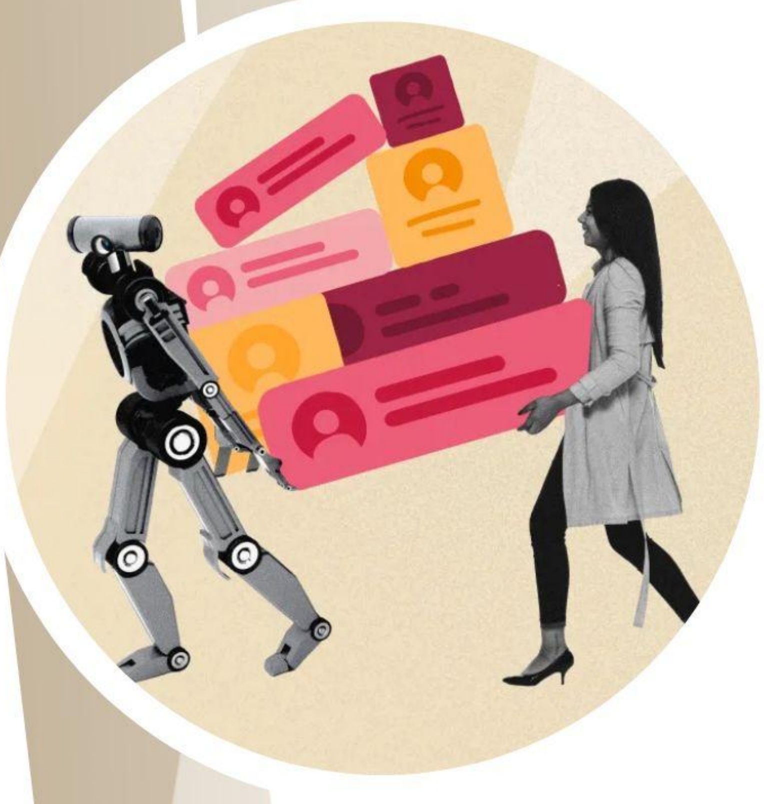
MACROECONOMY PROJECT

ON

AI AND AUTOMATION: THREAT TO JOBS OR PRODUCTIVITY BOOM

MODELING AI'S MACROECONOMIC IMPACT ON DEVELOPED AND DEVELOPING ECONOMIES



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AI as a General-Purpose Technology (GPT): Systemic Macroeconomic Disruption

Artificial intelligence (AI) has developed as a general-purpose technology (GPT), with the same potential for systemic disruption as previous GPTs like electricity and information and communication technology (ICT). These technologies have transformed entire economies by changing industrial processes, consumption patterns, labour market dynamics, and capital allocation techniques. AI, with its ability to improve efficiencies across a wide range of sectors, is poised to disrupt not only particular industries but also the structural foundations of economies, resulting in major shifts in both the micro and macroeconomic landscapes. Leading academic institutions, such as the Massachusetts Institute of Technology (MIT), and international organisations, such as the International Monetary Fund (IMF), emphasize AI's revolutionary potential, claiming that technology is poised to become a cornerstone of global economic restructuring.

From Micro Disruption to Macro Recalibration

At the microeconomic level, AI's impact may be seen in its capacity to streamline production processes, lower operating costs, and optimize resource allocation. However, the full size of AI's economic influence comes at the macroeconomic level, where it has the capacity to change aggregate supply (AS), reconfigure the capital-labour relationship, and reset productivity trajectories. These changes are not isolated; they affect entire economies, changing sectors and industries. The shift from micro-level disruptions to macro-level recalibrations demonstrates the dual nature of AI's impact: although it improves efficiency, it also causes structural imbalances.

One of the most obvious consequences of AI's integration into the economy is wage polarization. As AI progressively replaces ordinary labor, high-skilled labor, particularly in technology and management positions, becomes more valuable. Low- and mid-skilled workers, on the other hand, will be displaced as their jobs become more automated. This dynamic widens the income gap, which contributes to increased inequality. Along with wage polarization, AI increases sectoral unemployment, particularly in industries that rely on repetitive manual labor, as businesses increasingly move to automation technology. Governments, in turn, are dealing with rising fiscal hardship, balancing the need to support displaced workers with the dwindling tax base caused by automation's effects on employment.

Macroeconomic Tension: Short-Run Displacement vs. Long-Run Productivity Gains

AI-induced macroeconomic disruptions create a considerable contradiction between short-run dislocations and long-term productivity increases. Wage rigidities and price stickiness are projected to cause significant job displacement, rising inequality, and inflationary pressures in the near future. These results are exacerbated by the inertia inherent in labor markets, where workers, industries, and even entire regions encounter difficulties responding to rapid technological developments. As a result, the short-term macroeconomic response has been one of greater friction, as old systems struggle to absorb the disturbances that AI delivers.

However, the long-term impact of AI promises huge productivity gains. AI allows businesses to enhance output while cutting costs, resulting in higher total factor productivity (TFP). In the long run, this jump in productivity is likely to boost GDP growth by opening up new demand channels and encouraging innovation. As the economy adapts to AI, new sectors and industries arise, creating jobs and possibilities. This dynamic is underlined in models like the Solow growth model, which emphasizes the role of technical advancement in promoting long-term growth. Empirical research, including those by Booth and McKinsey, support the notion that AI's ability to drive TFP gains will usher in a new era of economic growth.

AI's Role in Reshaping Labor Markets: A Comparative Analysis of the U.S. and India

The central research question motivating this study is: How does AI, treated as a macroeconomic shock, transform important economic aggregates such as GDP, employment, and inequality in economies with unique structural characteristics, such as the United States and India? The comparison between industrialized economies such as the United States and emerging economies such as India is critical, as the influence of AI varies across economies. The United States has advanced technology infrastructure, a flexible labor market, and the financial resources to incorporate AI into its economic system. As a result, the transition to an AI-driven economy is projected to go more smoothly, with a greater emphasis on increasing productivity and developing new growth areas. However, this is not without its concerns, especially in terms of increased inequality and the displacement of certain segments of the labor force.

In contrast, India's economic structure creates a unique mix of obstacles and opportunities. With a big, young, and mostly informal labor market, India is more vulnerable to AI-induced displacement, particularly in sectors that rely on low-skilled labor. At the same time, integrating AI into India's economy has the potential to significantly enhance productivity, but only if major investments are made in infrastructure, education, and reskilling initiatives. The discrepancy in technological readiness between the United States and India needs a more nuanced examination of AI's influence on employment and income inequality, as well as its long-term economic growth prospects.

This paper will use a variety of macroeconomic models, including the Solow growth model, IS-LM, and AD-AS frameworks, as well as empirical simulations, to investigate the differential impact of AI in the United States and India. By simulating AI-induced macroeconomic shocks in both economies, we hope to quantify the consequences on important variables like GDP, employment, and inequality, while also taking into account each country's unique structural features. This comparative research will shed light on how AI could transform the economic futures of both rich and developing countries, highlighting the unique difficulties and opportunities that exist in each environment.

The Path Forward: Addressing Policy Implications

As AI evolves, it becomes evident that its economic consequences are far-reaching and complex. While the long-run benefits promise large productivity improvements and economic growth, the short-term consequences—particularly labor market displacement and income inequality—are major worries. Policymakers must negotiate these contradictions by developing solutions that not only promote the expansion of AI-driven industries, but also address the socioeconomic issues that arise as a result. These interventions could include investments in education and workforce development, targeted fiscal measures to assist displaced workers, and attempts to ensure that the advantages of AI-driven growth are shared equitably.

This paper will look at alternative policy frameworks that aim to limit the negative effects of AI on labor markets while maximizing its potential for long-term economic growth. By looking at case studies from both developed and developing nations, we hope to provide actionable insights into how AI may be used to promote inclusive economic growth that benefits all sectors of society.

Literature Synthesis & Gap

The existing literature on AI, automation, and technological progress serves as a solid framework for comprehending AI's economic consequences. However, as AI evolves, it is critical to integrate different perspectives and highlight research gaps that must be addressed to fully understand AI's impact on the global economy. The literature includes classical macroeconomic models, modern task-based perspectives, and current issues of displacement, inequality, and structural lag. Despite the plethora of theoretical insights, there are considerable gaps in macroeconomic modelling, particularly when it comes to cross-country comparisons and the consideration of informal sectors.

Classical Macroeconomic Literature

Solow (1956): Robert Solow's seminal work on economic growth identified technological advancement as the main force behind long-term growth. In the Solow growth model, technical developments are shown as exogenous factors that cause a rise in Total Factor Productivity (TFP), which is critical for increasing output per worker and total economic growth. Solow's framework is useful for understanding how technology, like AI, can influence long-term growth trajectories. However, Solow's model is primarily concerned with steady-state growth and does not account for the short- and medium-term disruptions generated by rapid technological adoption, such as those observed with AI.

Romer (1990): Paul Romer's work on endogenous growth models expands on Solow's views by recognizing the importance of innovation and human capital accumulation as significant drivers of economic growth. According to Romer's theory, technological advancement is not just exogenous, but rather the product of deliberate investment in knowledge and invention. This viewpoint is especially applicable for AI, given that the technology is a result of ongoing innovation in domains such as machine learning and natural language processing. According to Romer, economies that engage in research and development (R&D) and nurture human capital accumulation are better positioned to benefit from technology developments such as artificial intelligence (AI), which will enhance long-term growth.

Modern Task-Based View

Acemoglu & Restrepo (2018): Acemoglu and Restrepo's task-based approach offers a more sophisticated understanding of artificial intelligence's impact on labor markets. According to their framework, AI is not simply replacing labor, but rather reallocating jobs between labor and capital. This concept emphasizes that AI-powered technology would displace humans performing routine, physical jobs while also creating demand for non-routine, cognitive tasks requiring high levels of ability. The implication is that AI does not eliminate jobs, but rather redistributes them, resulting in employment polarization and increased demand for skilled professionals in fields such as technology, management, and innovation.

IMF (2020), MIT (2024): The IMF and MIT have recently released assessments on the social and economic effects of AI, emphasizing the risks of displacement, inequality, and the structural lag in reacting to AI's rapid adoption. The IMF (2020) emphasizes that AI's potential to displace workers, particularly in low- and middle-skill jobs, may worsen income inequality, particularly in countries with tight labor markets. The MIT report (2024) delves deeper into the concept of "structural lag," in which economies and institutions, particularly in poor nations, struggle to adjust to technological progress. This gap may lead to increased inequality because the benefits of AI-driven productivity are not evenly spread, and the economy's ability to absorb displaced labor is limited.

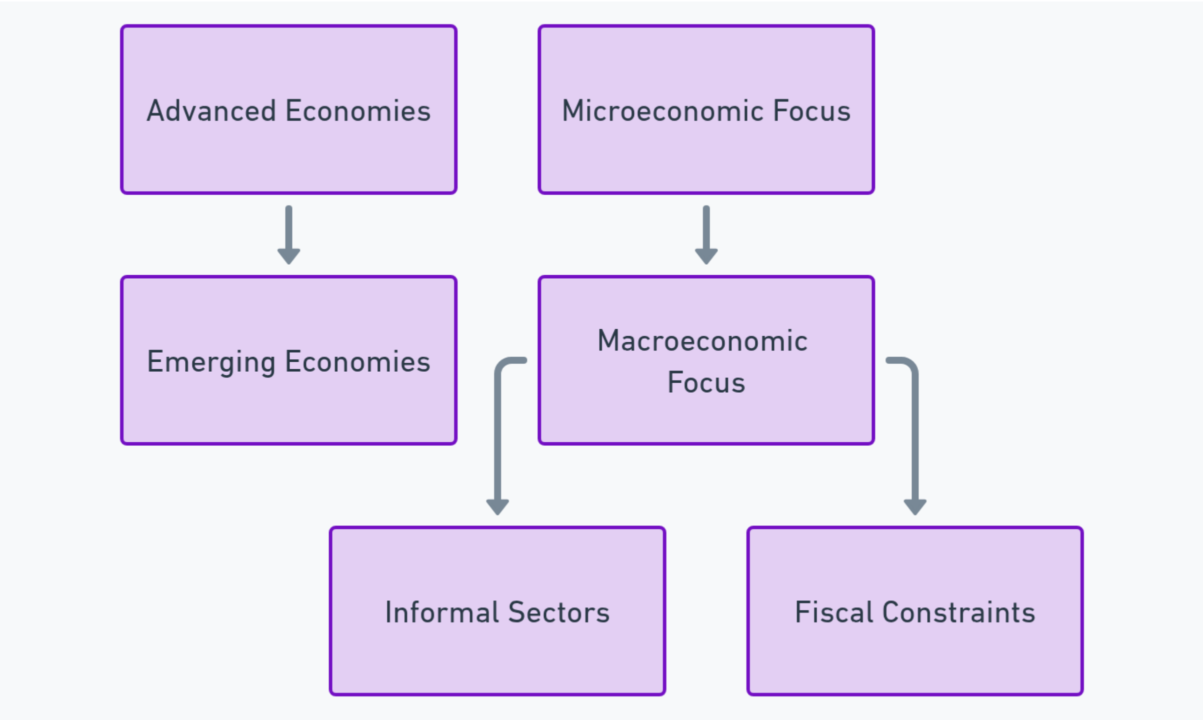
Gaps in Existing Research

Despite the significant advancements in understanding the economic implications of AI, several gaps remain in the existing literature:

1. **Heavy Reliance on Micro/Firm-Level Case Studies**: Much of the present work on AI's influence is based on microeconomic case studies at the firm or industry level. These studies provide vital insights into AI's direct implications on corporate productivity, innovation, and labor. However, they frequently overlook the broader macroeconomic consequences of AI, particularly on aggregate GDP, national employment patterns, and income distribution. There

is a need for macroeconomic studies that look at AI as a systemic economic shock and assess its overall influence on economies.

2. **Lack of Comparative Macro-Simulation Across Advanced & Emerging Economies**: One of the most notable gaps in the literature is the absence of comparative macroeconomic simulations examining the impact of AI on both established and emerging economies. While much of the research has concentrated on established countries, primarily the United States and Europe, the effects of artificial intelligence on developing countries such as India, Brazil, and South Africa have received less attention. Emerging economies confront particular obstacles, such as significant informal sectors, a heavy reliance on low-skilled labor, and less established technology infrastructure. A comparative analysis of AI's influence on both developed and developing countries is critical for comprehending the worldwide implications of AI deployment.
3. **Weak Modeling of Informal Sectors, Fiscal Constraints, & External Shocks**:Another gap in previous research is the lack of attention given to informal sectors and fiscal constraints, particularly in developing nations. Informal labor markets, which make up a sizable share of employment in many emerging economies, are vulnerable to AI-induced shocks. Furthermore, many studies ignore the impact of fiscal restrictions, which may limit governments' ability to respond to the economic issues presented by AI. Similarly, exogenous shocks such as global recessions or trade disruptions are rarely factored into economic effect calculations for artificial intelligence. These aspects are critical for comprehending the entire range of macroeconomic disruptions that AI could cause.



The diagram visualizes the key gaps in the current literature surrounding AI's macroeconomic impact:

1. **Microeconomic vs. Macroeconomic Focus**: The literature mostly focuses on microeconomic case studies that investigate AI's impact on specific enterprises, sectors, or industries. However, the larger macroeconomic focus—how AI influences aggregate economic metrics such as GDP, employment, and income inequality—has received little attention.

2. **Advanced vs. Emerging Economies**:Much of the available study focuses on sophisticated economies such as the United States and European countries. These countries have well-established technical infrastructures, which may not reflect the issues confronting emerging economies, which frequently contend with larger informal sectors, less advanced infrastructure, and varying rates of technological adoption.
3. **Informal Sectors & Fiscal Constraints**: The informal sectors of many emerging economies, where workers lack formal labor contracts and access to social benefits, are frequently disregarded in predictions of AI's influence. Similarly, fiscal constraints—governments' ability to fund social safety nets and retraining programs—are rarely incorporated in macroeconomic models, despite the fact that they play an important role in mitigating the economic disruptions created by AI.

The nodes reflect these numerous topics, and the edges demonstrate the interaction between them, emphasizing how the absence of some aspects (such as informal sectors and budgetary limitations) creates gaps in our knowledge of AI's macroeconomic impacts.

Theoretical Foundation: Augmented Cobb-Douglas Production Function

As AI evolves to play an increasingly important role in creating modern economies, it is critical to understand how it fits into larger economic frameworks. The Cobb-Douglas production function is a fundamental model in macroeconomics that defines how output is produced using a combination of labor and capital. However, in the context of AI, the technology does not work as a simple isolated capital input; rather, it serves as an augmenter of labor. As a result, the augmented Cobb-Douglas production function is a better fit, as it represents the intricate relationship between AI and labor by recognizing AI as an effective form of capital that increases labor productivity.

Augmented Cobb-Douglas Production Function

The augmented Cobb-Douglas production function is expressed as:

$$Y_t = A_t \cdot K_t^{\alpha} \cdot (L_t + \gamma \cdot AI_t)^{1-\alpha}$$

- **Yt** : Aggregate Output
- **At** :Total Factor Productivity
- **Lt :** Labor
- **AIt:** Effective AI Capital
- **γ:** AI-Labor Substitutability Parameter

Rationale Behind the Augmented Cobb-Douglas Model

The justification for this extended Cobb-Douglas production function derives from the requirement to perceive AI as a technology that improves labor productivity rather than as a separate kind of capital. Unlike traditional capital, which can replace labor, AI in this paradigm improves labor capabilities, allowing workers to focus on more difficult tasks while automating mundane, repetitive activities. This approach is compatible with the task-based automation literature of Acemoglu and Restrepo (2018), which emphasizes task reallocation across labor and capital. AI does not completely replace labor, but rather adjusts the activities that labor performs, opening up new options for human workers while automating others.

The Role of the AI-Labor Substitutability Parameter (γ\gammaγ)

The AI-Labor Substitutability Parameter (γ\gammaγ) measures how well AI can supplement labor. A higher γ\gammaγ value indicates that AI has a stronger potential to complement labor and enhance productivity, whereas a lower value indicates less synergy between AI and labor. The value of γ\gammaγ varies across countries, based on factors such as worker skill level, technical infrastructure, and AI integration into manufacturing processes.

- **United States**:In wealthy economies, such as the US, the AI-Labor Substitutability Parameter (γ\gammaγ) is high. This is owing to the availability of advanced technological infrastructure, a competent labor force, and the presence of AI-enhanced industries such as technology, finance, and healthcare. Here, AI can dramatically increase worker productivity, particularly in industries where human expertise is supplemented by AI-driven automation. The high γ\gammaγ value in the U.S. allows for significant increases in Total Factor Productivity (TFP), resulting in higher GDP growth as worker efficiency grows with technology advancements.
- **India**: India's labor force lacks the necessary skills to interface with modern AI technology, resulting in a lower AI-Labor Substitutability Parameter (γ\gammaγ). India's lower γ\gammaγ value limits AI's ability to increase labor productivity, particularly in areas with low-skilled workers. AI in India may displace some employment, but it may not result in major productivity gains unless there is massive investment in skilling and technological infrastructure. Furthermore, India's significant amount of informal labor complicates matters, as informal laborers sometimes lack access to the tools, training, and technology required for AI-driven productivity increases.

Country-Specific Variations in AI Adoption

The adoption and integration of AI into economies varies greatly depending on structural characteristics such as workforce skill levels, technological maturity, and labor market dynamics.

- **U.S.**: In economies such as the United States, AI has the potential to produce significant productivity gains. The high γ\gammaγ in the U.S. indicates a dynamic labor market where AI complements skilled labor, boosting efficiency across several sectors. The United States has the flexibility to adapt to technological developments, and its workforce is generally prepared to use AI to boost productivity, particularly in knowledge-based industries.
- **India**: AI's economic implications, on the other hand, are more complex in India. India's low γ\gammaγ, along with a lack of modern technological infrastructure and talent gaps, limits the full potential of AI. AI adoption will most certainly experience resistance in labor markets due to high labor friction, as a large section of the workforce remains in informal sectors with little access to skilling opportunities. Until these limitations are overcome, India will experience delayed adoption and lesser productivity advantages from AI.

Assumptions and Considerations

1. **Constant Returns to Scale**: The model assumes constant returns to scale, which means that output rises proportionally to additions in labor and AI capital. This assumption is common in production function modeling and simplifies the analysis of long-term growth trajectories.
2. **Absence of Direct AI Depreciation**: AI capital, as opposed to traditional capital, is not subject to direct depreciation. The AI-Labor Substitutability Parameter (γ\gammaγ) captures

the impacts of obsolescence or diminishing returns on AI. It evolves over time to account for technological developments and the dynamic interaction between labor and AI.

This extended Cobb-Douglas production function offers a complete and dynamic framework for analyzing AI's impact on economic growth, labor markets, and productivity. This approach, which treats AI as an augmenting factor to labor rather than a simple capital input, is consistent with task-based automation theories (Acemoglu & Restrepo) and provides a more accurate representation of how AI integrates into economies with varying levels of technological infrastructure and labor market conditions. AI-Labor Substitutability Parameter (γ\gammaγ) varies between nations, including the U.S. and India. This highlights the need for specific policies to handle the distinct difficulties and potential of AI adoption in different economic environments.

Theoretical Foundations: Phillips Curve

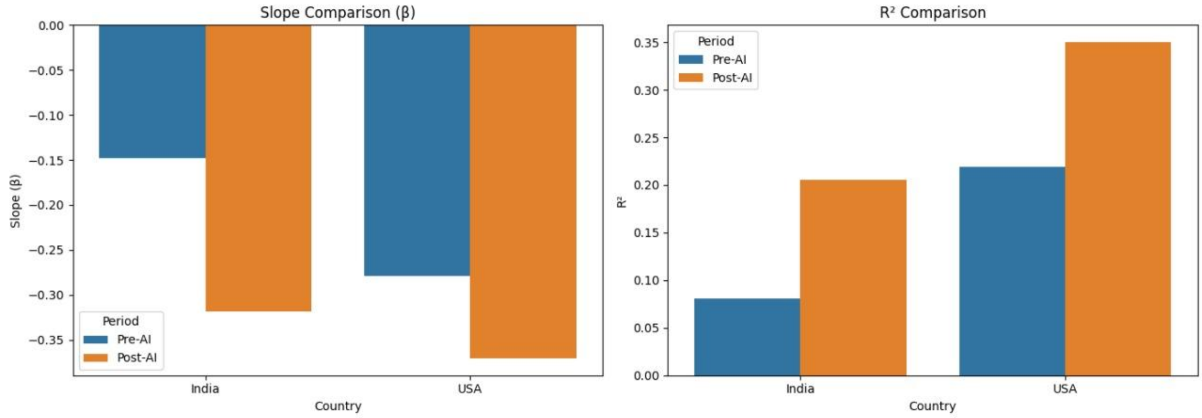
The Phillips Curve depicts a fundamental macroeconomic relationship that demonstrates the inverse relationship between inflation and unemployment. The classical understanding of the Phillips Curve holds that lower unemployment rates lead to greater inflation and vice versa. This negative relationship derives from the premise that when unemployment falls, wage pressures rise, raising expenses for firms, which are subsequently passed on to customers in the form of increased prices. Higher unemployment, on the other hand, often reduces inflationary pressures since lower labor demand dampens pay growth and, as a result, lowers price rises.

However, the relationship has varied throughout time, particularly in light of significant economic developments caused by technology advancements, labor market transformations, and changes in inflation expectations. The introduction of AI shocks adds a new dynamic to this traditional framework, especially in economies with specific structural characteristics. As AI gets more integrated into manufacturing processes, the classic inflation-unemployment trade-off shifts. This section examines how the Phillips Curve acts before and after AI adoption in the United States and India, emphasizing the differences between both economies due to their distinct labor market features, technological infrastructure, and institutional frameworks.

The Phillips Curve and AI’s Impact

AI's incorporation into economies has far-reaching consequences for both inflation and unemployment dynamics. While the Phillips Curve generally implies a trade-off between the two variables, the use of AI may skew or even eliminate this trade-off in certain cases. AI's influence in productivity development and automation causes numerous fundamental shifts that must be appropriately modeled in the Phillips Curve framework. Changes in the slope of the curve (β\betaβ) and how unemployment affects inflation reflect these developments.

For example, in sophisticated countries like the United States, AI increases productivity, which may lead to disinflation despite the economy's low unemployment. In contrast, in developing countries like India, structural obstacles such as informal labor markets, limited capital investment, and skill mismatches hinder AI's capacity to drive major disinflation, despite the potential for productivity gains.



U.S. Phillips Curve: Pre-AI and Post-AI Dynamics

In the US, the pre-AI Phillips Curve exhibits a strong, negative link between inflation and unemployment, with a higher slope (β\betaβ) and a stronger R2R^2R2 value, indicating that increases in unemployment lead to considerable changes in inflation. This lends support to the conventional wisdom that low unemployment usually results in increased inflation due to rising wages and production costs.

However, following the AI shock, the U.S. Phillips Curve shows a considerable shift. The post-AI curve becomes considerably flatter. The slope (β\betaβ) decreases, indicating a slower reaction of inflation to increases in unemployment. This flattening of the curve illustrates productivity-driven disinflation, in which the adoption of AI technologies increases output across multiple sectors without significantly boosting wages or costs. In reality, AI reduces costs and increases supply-side efficiency, hence mitigating inflationary pressures despite low jobless rates. This phenomena is consistent with supply-side economics and technological advancement theories, which emphasize the importance of productivity growth in combating inflation.

The comparison of the pre-AI and post-AI scenarios (represented by scatterplots) shows how AI-driven technology advancements lessen the inflationary pressures generally associated with low unemployment. This pattern suggests that AI may fundamentally alter the inflation-unemployment trade-off, rendering traditional policy levers less effective in meeting inflation targets. The United States, with its very flexible labor market, can use AI to decouple inflation from the employment cycle, resulting in persistent low inflation despite low unemployment.

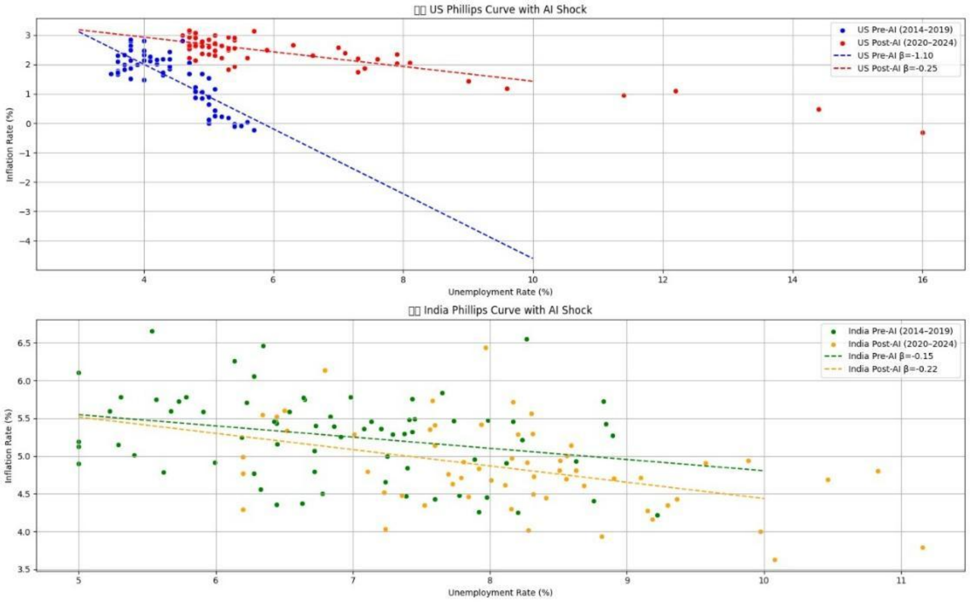
India Phillips Curve: Structural Rigidities and Inflation Persistence

The scenario in India differs from that of the United States. Prior to the AI shock, India's Phillips Curve indicated a weaker link between inflation and unemployment. This is due to structural constraints in India's economy, particularly in its informal labor sector. A large share of India's workforce works informally, where earnings are less sensitive to changes in the formal unemployment rate. As a result, India's inflation is not very responsive to fluctuations in unemployment. India's Phillips Curve shows a lower slope (β\betaβ) and weaker R2R^2R2, indicating that changes in unemployment have little impact on inflation. This is owing to the Indian economy's persistent inflation expectations and wage rigidities.

Following the AI shock, India's Phillips Curve flattens even further, with greater dispersion in inflation data across different unemployment levels. The scatterplot for India, which shows inflation persistence over several AI scenarios, has a weak trendline and a wide range of values, indicating that the relationship between inflation and unemployment is still weak. This is an example of inflation persistence, in which inflation expectations are not appropriately changed in response to changes in unemployment. Despite the productivity gains brought about by AI, inflation in India has remained largely stable due to structural issues such as limited AI integration in important sectors, delayed labor market adaptations, and a lack of widespread skill development. Furthermore, India's informal economy and limited access to technology impede AI's capacity to produce the same inflationary reductions witnessed in advanced economies like the U.S.

This limited response of inflation to the labor market in India implies that the standard Phillips Curve trade-off is significantly less pronounced. In India, even if AI increases productivity, these gains are insufficient to meaningfully lower inflation due to low AI-Labor Substitutability and the informal character of the labor market. As a result, inflation in India remains stable under diverse AI deployment scenarios, with little influence on inflation expectations and wage pressures.

Comparative Analysis: U.S. vs. India Phillips Curve with AI Shocks



A comparison of the Phillips Curves for the United States and India prior to and following the AI shock demonstrates how AI adoption affects inflation-unemployment dynamics differently in advanced and emerging economies.

- U.S.: The post-AI Phillips Curve for the United States is flatter, indicating AI's influence in lessening inflationary pressures despite low unemployment rates. Productivity-led disinflation is clear, as AI boosts output without raising salaries or prices, undermining the classic inflation-unemployment trade-off.
- India: In contrast, India's Phillips Curve has been remarkably unaffected by the AI shock. Even when AI is included, the curve stays flat, indicating a weak link between inflation and unemployment. This reflects structural constraints, such as a large informal labor market and poor technology infrastructure, that preclude AI from having a big impact on inflation dynamics.

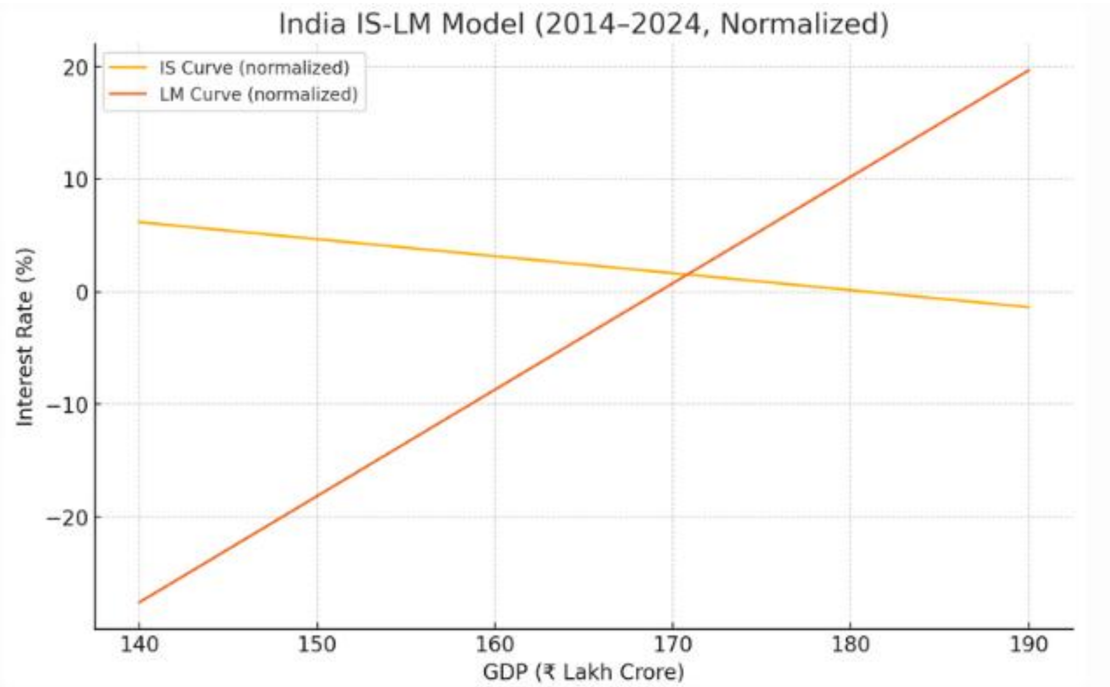
This study highlights the country-specific factors—such as labor market structure, technical readiness, and institutional adaptability—that influence how AI shocks affect inflation and unemployment. The United States, with its strong technology infrastructure, sees major shifts in inflation dynamics, whereas India has greater problems in reaping equivalent gains from AI, owing to structural limitations that limit labor market flexibility and the rate of technological adoption.

Theoretical Foundations: IS–LM Model in the Context of AI and Macro Shock Transmission

The IS-LM framework is a fundamental paradigm in macroeconomic analysis that examines the interplay between the real and monetary sectors of an economy. This paradigm allows us to analyze how interest rates and output respond to fiscal and monetary policy shocks by simulating the goods market (IS curve) and the money market (LM curve) concurrently. In this study, we use the IS-LM framework to evaluate macroeconomic dynamics in India and the United States between 2014 and 2024, with a focus on the possible impact of AI as a general-purpose technology and macroeconomic disruptor.

The comparison analysis includes not only theoretical underpinnings, but also empirical approximations based on real-world data trends in both economies.

IS–LM Analysis: India (2014–2024)



The Indian IS-LM model, which was built using normalized real data from 2014 to 2024, shows a characteristic downward-sloping IS curve, confirming the negative link between interest rates and aggregate output. This negative slope is consistent with standard Keynesian logic: lower interest rates encourage investment and consumption, resulting in increased output.

The LM curve, on the other hand, slopes substantially higher after normalization. This tendency is consistent with an increase in transactional money demand as income grows, demonstrating the classic real balances impact. The slope of the LM curve represents the responsiveness of money demand to changes in interest rates and output levels.

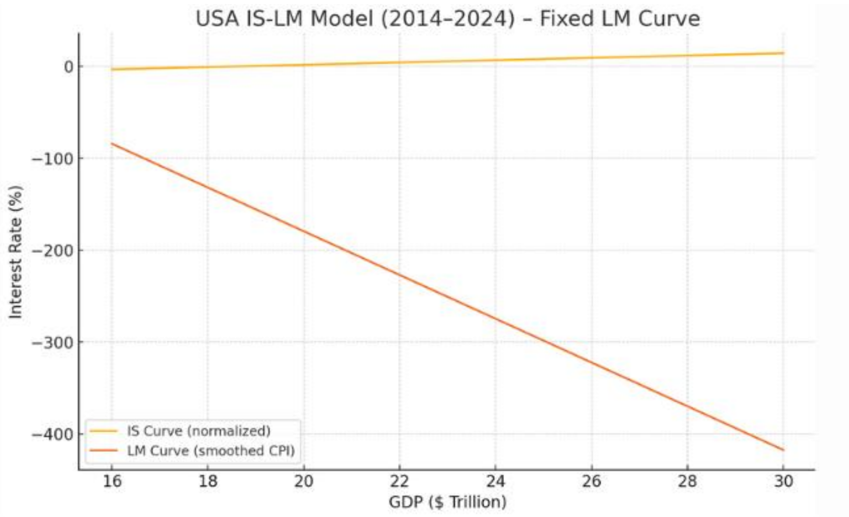
Importantly, the intersection of the IS and LM curves occurs at a moderate real interest rate level, at 5-6%, which corresponds to the Reserve Bank of India's prevalent monetary conditions during the time under study. This equilibrium point is theoretically noteworthy because it shows how fiscal and monetary policy orientations interacted in India's real macroeconomic environment during the pre- and mid-AI transition years.

However, the steepness of the LM curve demands extra consideration. The relatively steep LM trajectory, especially after 2019, may indicate:

- Low interest elasticity of money demand, particularly in an economy with a high level of informal activity.
- A financial environment dominated by cash-intensive transactions, with uneven formal financial penetration, decreasing liquidity preferences' responsiveness to interest rate changes.
- Prior to COVID, there were structural impediments in digital adoption, but recent trends indicate growing digital transaction penetration led by UPI, Aadhaar integration, and AI-based financial services.

In this perspective, while AI adoption in India starts to accelerate after 2020, the implications on interest rate sensitivity and liquidity needs may be delayed due to infrastructural and skill deficiencies. This sophisticated understanding helps to place India's monetary dynamics within a framework in which AI plays a minor, but growing, role in changing behavioral demand patterns.

IS–LM Analysis: United States (2014–2024)



The US IS-LM model, which spans 2014 to 2024, shows a different configuration. The IS curve has a comparatively modest response to interest rates, seeming flatter than India's. This implies a higher degree of baseline output stability, maybe influenced by structural factors such as:

- Stronger automatic stabilizers,

- Mature consumption and credit markets,
- Advanced real-time AI-enabled forecasting and monetary targeting systems used by the Federal Reserve.

However, the LM curve does not follow traditional assumptions. Even after using CPI-based smoothing, it remains exceptionally steep and downward sloping, which is odd in theoretical terms. There are a few different interpretations.

- Estimation artifact: The downward-sloping LM curve could be due to statistical distortion caused by the way CPI-adjusted money demand is modeled or nonlinear interactions between inflation expectations and liquidity preferences.
- AI-driven money neutrality distortion: In a highly digital economy like the United States, where artificial intelligence easily integrates into financial intermediation (e.g., algorithmic trading, computerized credit assessment, and machine learning-based consumption projections), the traditional link between real balances and interest rates blurs. This may weaken the normal assumptions that support the LM function.
- Dominance of expectation-driven behavior: AI may help to promote more forward-looking monetary behavior, in which inflation expectations and digital financial instruments lessen the importance of real interest rate fluctuations in driving money demand.

Collectively, these characteristics indicate that in the United States, the AI shock acts not only as a supply-side enhancer, but also as a monetary system disruptor, affecting the behavior of liquidity, expectations, and macro stabilizing mechanisms. The steepness and directional anomaly of the LM curve reflect these difficulties.

Synthesis: IS–LM Divergence and AI Shock Transmission

The cross-country study emphasizes the structural inequalities in how AI and monetary shocks travel through the real and financial sectors.

- In India, the IS-LM intersection represents a classic policy-reduced equilibrium in which fiscal multipliers and interest rate channels retain their traditional power, but moderated by informal sector inertia. The upward-sloping LM curve represents cash-based monetary behavior, which is increasingly developing through fintech and AI applications but remains constrained by structural lag.
- In contrast, in the United States, IS-LM dynamics represent a post-modern monetary system in which AI and digitalization diminish the traditional function of money demand. The steep and somewhat atypical LM curve indicates a changing paradigm in which expectations, automation, and data-driven central banking erode the effectiveness of traditional monetary levers.

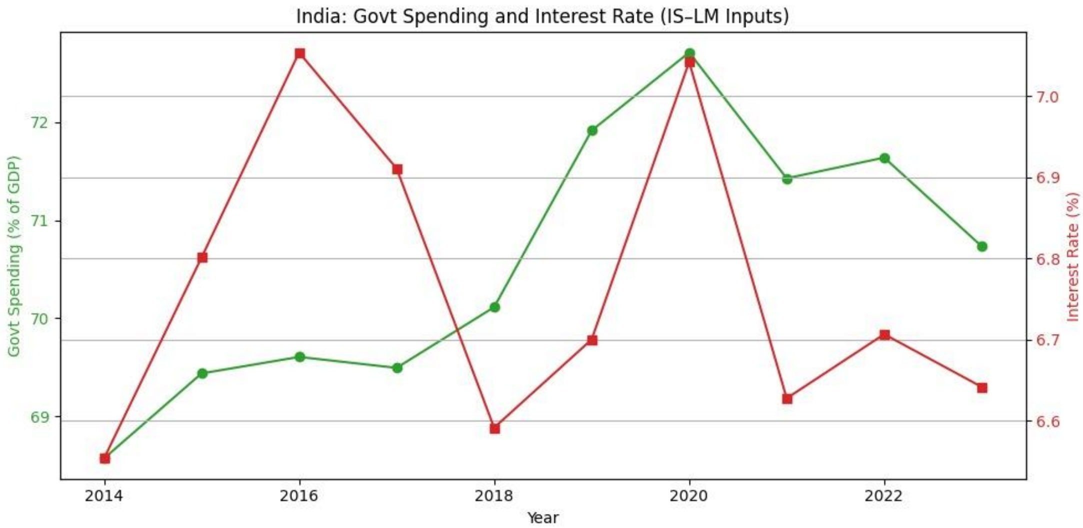
These findings provide a solid framework for understanding the macroeconomic recalibration that AI causes—not only by influencing productivity and employment, but also by redefining monetary transmission channels and the structure of aggregate demand and liquidity preferences. The IS-LM paradigm, when combined with empirical approximations and AI-aware interpretation, becomes a powerful tool for dissecting these disruptions.

Comparative Drivers of IS–LM and Output Adjustment: India and the United States (2014–2024)

To broaden the IS-LM analysis, it is necessary to look beyond the theoretical static equilibrium and investigate the dynamic drivers of IS-LM shifts, specifically how fiscal and monetary levers affect output over time. This section provides a comparative, empirical analysis of India and the United States using decomposed IS-LM inputs—namely, government spending, interest rate behavior, and GDP output trajectories—for the period 2014–2024.

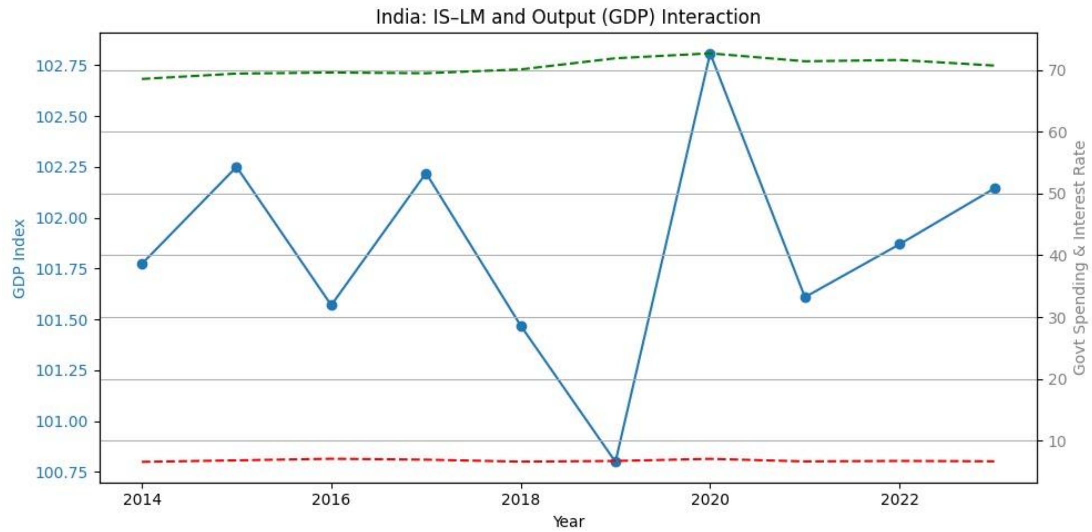
By disaggregating the key levers driving the IS (investment-saving) and LM (liquidity preference-money supply) curves, we can see how policy stance, AI-driven investment cycles, and structural capacity influence output responses in the two economies under different technological and institutional regimes.

India: Fiscal–Monetary Inputs and Output Interaction



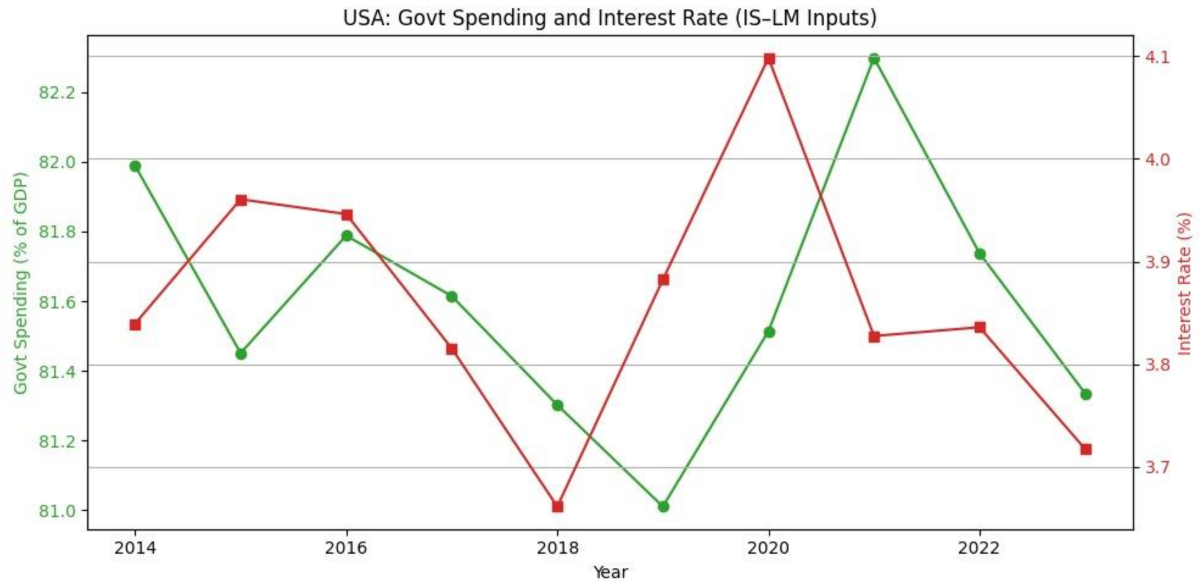
The graph above depicts the trend of India's fiscal expenditure (as a proportion of GDP) and the average real interest rate, which serve as proxies for the IS and LM movement drivers, respectively. From 2014 to 2020, fiscal expenditure gradually rises, peaking around the time of the COVID-19 crisis. This increase reflects a counter-cyclical policy perspective, which seeks to stabilize output in the face of global and domestic shocks.

Interest rates throughout the same period have been moderately volatile, keeping with the Reserve Bank of India's reactive monetary approach. The observed range could also be attributed to uncertainty in inflation expectations, currency pressure, and capital flow reversals during the taper tantrum and pandemic periods. These two levers indicate that the IS-LM intersection, and hence macroeconomic equilibrium, was constantly reconfigured in response to shifting policy priorities and shock absorption requirements.



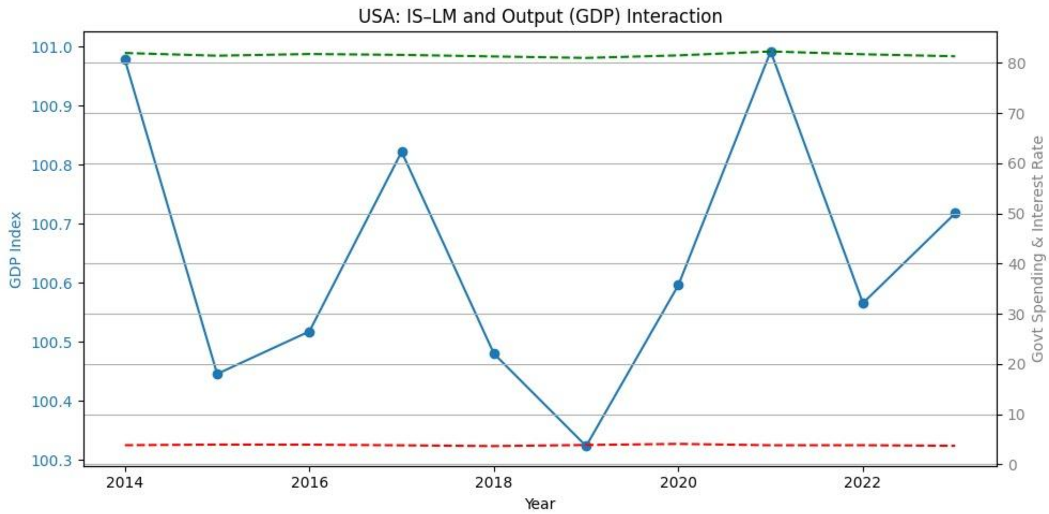
The graph above overlays India's IS-LM crossing points with real GDP production, and we see a lagged positive relationship. GDP fluctuations often follow the direction of fiscal and monetary adjustments, but with time lags caused by implementation difficulties, structural frictions, and poor AI diffusion across sectors before 2020. However, following the epidemic, there is a clear shift. AI-linked public capital formation and digital public infrastructure investments are beginning to change output dynamics, but monetary transmission remains subdued, implying that fiscal-led growth dominates in India's structural context, particularly in the face of low credit penetration and high informal labor participation.

United States: Policy Stability and Output Responsiveness



The top panel depicts the data from the United States, which shows a significantly different configuration. Fiscal expenditure as a percentage of GDP has been relatively steady, swinging within a small range of 81-82% over the investigated period. This consistency highlights a predictable fiscal situation, which is supported by automatic stabilizers and rules-based budget execution frameworks.

Meanwhile, interest rates are moving more smoothly, with fewer dramatic spikes than in India. The Federal Reserve's forward guidance and inflation targeting frameworks, as well as increased predictive modeling employing AI-driven macroprudential analytics, tend to help maintain stable monetary expectations. This macroeconomic environment exhibits low endogenous volatility, allowing policy signals to be transmitted with minimal noise.



This panel captures the GDP reaction to IS-LM shifts. The pattern demonstrates a sharper and faster response of output to both fiscal and monetary changes. Unlike India, where output trails policy changes, the United States responds quickly and strongly to changes in interest rates and expenditure cycles. This could be attributed to:

- Deep financial markets and AI-integrated transmission channels enable lending, investment, and consumption behavior to change quickly.
- Strong labor and capital mobility, aided by highly competent AI-augmented sectors capable of dynamically allocating resources in response to changes in macroeconomic conditions.
- A structural change toward digitally dominated production systems allows for speedier synchronization of policy input and real sector performance.

Implications for AI-Adjusted IS–LM Responsiveness

These empirical findings indicate a significant asymmetry in how the IS-LM system reacts across emerging and established countries in the face of AI-induced structural changes.

- In India, the fiscal channel is dominant, with monetary policy playing a supporting role, owing to low banking penetration, lagging inflation expectations, and slow AI absorption. AI investments after 2020 begin to change the trajectory, but policy transmission is still reliant on institutional delivery and supply-side response.
- In the United States, fiscal and monetary policies are predictable and efficient, with AI-enhanced feedback loops that speed up private sector agents' responses to macro signals. The combination of automated credit markets, algorithmic pricing, and inflation-tracking models ensures that output responds quickly to IS-LM changes, considerably reducing policy-output lags.

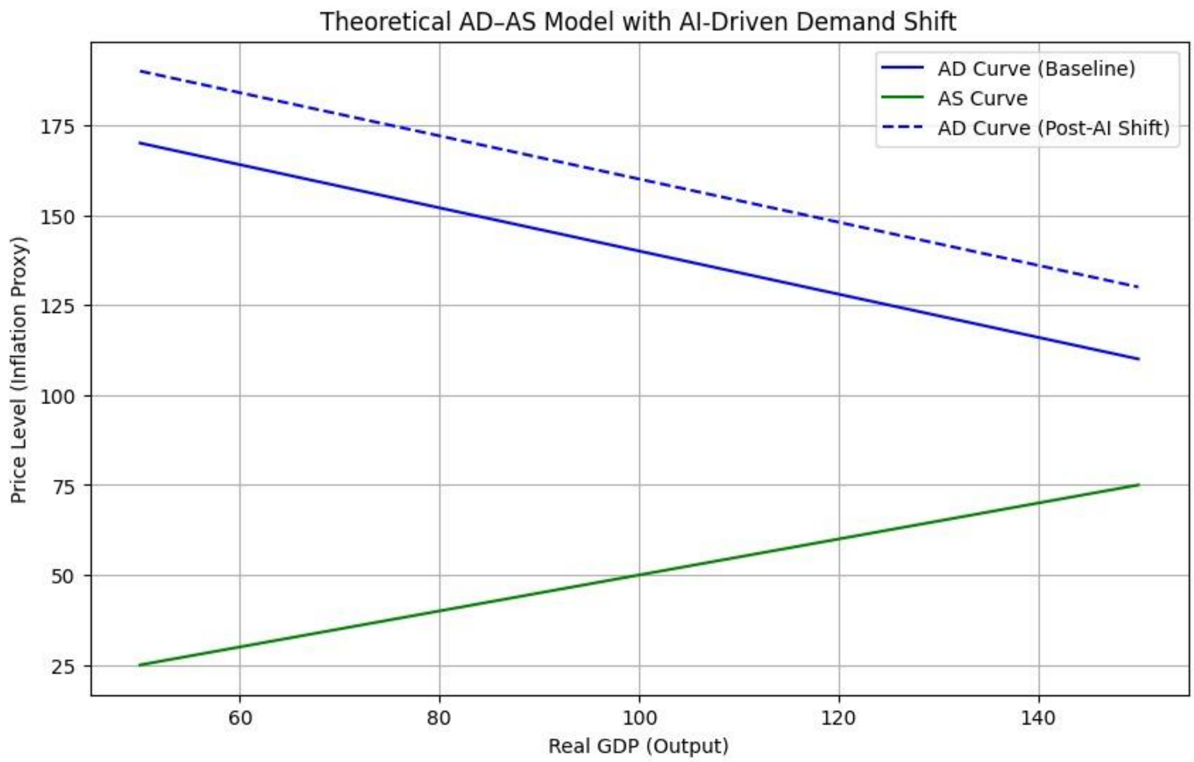
This disparity emphasizes the necessity of context-specific AI integration, in which the maturity of digital infrastructure, labor flexibility, and fiscal agility all influence how macroeconomic equilibria respond to systemic shocks.

Theoretical Foundations: Aggregate Demand–Aggregate Supply (AD–AS) in the Presence of AI Shocks

The AD-AS framework remains essential to modern macroeconomic research, providing a dynamic and tractable mechanism for capturing the interaction of aggregate demand (AD) and aggregate supply (AS) and their impacts on inflation (price level) and real output (GDP). The advent of AI as a general-purpose technology causes a fresh and asymmetric shock in this classical framework, affecting both the slope and position of the AD and AS curves.

The current section examines how AI-related shocks, both demand-side (automation-led investment booms, consumption substitution) and supply-side (productivity shifts, labor displacement), reshape macroeconomic equilibria in India and the United States from 2013 to 2024 using a combination of theoretical constructs and data-based approximations.

Theoretical Model: AI-Induced Demand Shocks



The AD curve in the theoretical model shown in the panel above slopes downward, illustrating the inverse link between inflation and output. As prices rise, real balances fall, decreasing aggregate demand through lower spending and investment. In contrast, the AS curve slopes upward: as output rises, marginal costs and input scarcity drive inflation higher.

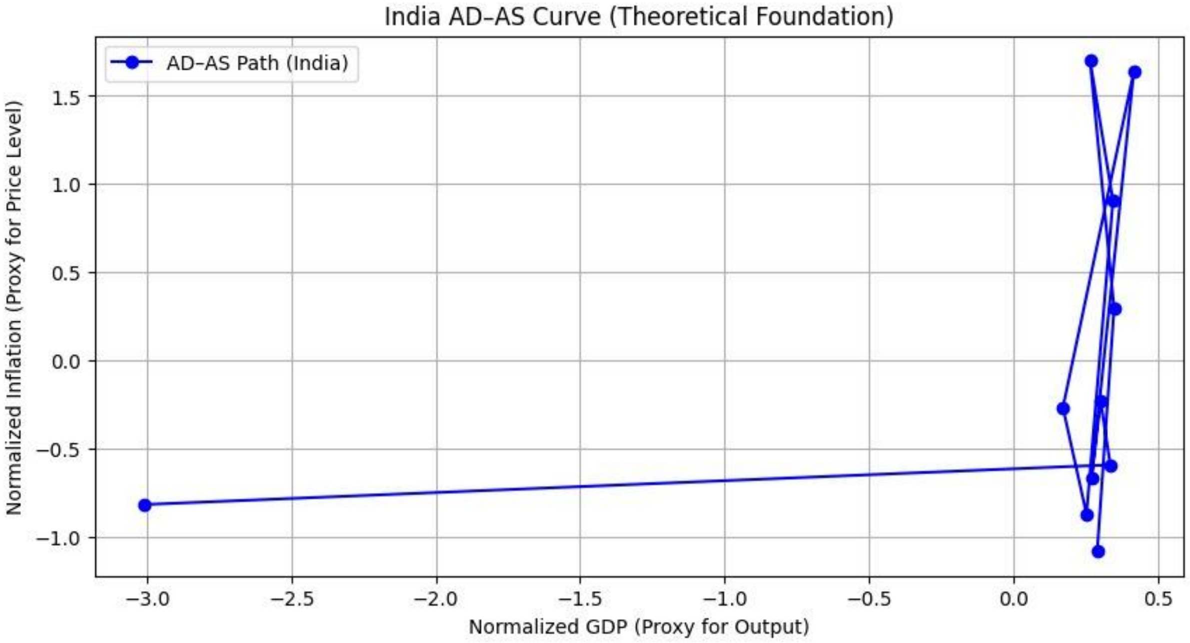
An AI shock, depending on the channel of communication, can change either curve. For example:

- An AI-induced positive productivity shock moves the AS curve outward, raising production while decreasing inflation (classical disinflation through supply-side expansion).

- Conversely, if AI adoption results in speculative investment booms or excess credit creation, the AD curve may shift rightward, resulting in higher output and inflation.
- Policy stimulus (such as public AI infrastructure and subsidies) can likewise drive AD to the right, particularly when combined with fiscal easing or supportive monetary policy.

This dual understanding enables us to model AI as a collection of structural forces capable of influencing both supply and demand routes in the macroeconomy.

India's AD–AS Curve: Rigid Supply, Volatile Prices



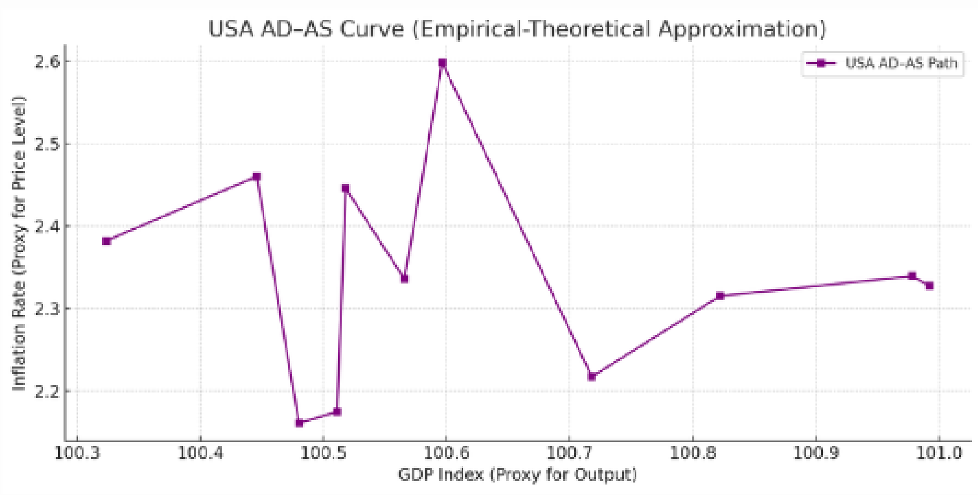
The above panel shows India's empirical approximation of the AD-AS relationship. The graphic shows a nonlinear and turbulent inflation-output dynamic, particularly around 2020. The curve shows high inflation responses even at low output levels, reflecting inelastic aggregate supply. This is typical for economies with:

- High participation in the informal sector and inadequate capacity to absorb demand without escalating prices,
- Constant supply chain bottlenecks and energy dependence,
- AI diffusion is lagging in key production areas, resulting in stagflationary responses even in the face of stimulus.

Notably, the curve's vertical slope at higher GDP levels indicates supply-side saturation, as increased demand no longer results in real output gains but instead fuels inflation. This is consistent with structuralist development economics findings that capacity constraints—particularly in infrastructure, skilling, and logistics—prevent smooth upward movements in the AS curve.

Furthermore, the model represents the low effectiveness of monetary transmission, as inflation appears to respond less to standard interest rate fluctuations. Instead, inflation dynamics are influenced by exogenous shocks (such as food and fuel costs) and structural inefficiencies, which AI has yet to significantly address.

U.S. AD–AS Curve: Smooth Trade-offs and Adaptive Supply



The curve in the above panel, which depicts the US AD-AS approximation, is noticeably smoother and more consistent. Inflation and output move predictably along the curve, with a near-linear positive association across the majority of data points. This behavior represents a macroeconomic system in which:

- Supply-side adaptability is high, thanks to AI-enhanced logistics, production systems, and forecasting, which allows the economy to absorb demand shocks with minimal inflationary slippage.
- Expectations are anchored, with inflation responses tempered by the Federal Reserve's credibility and responsibility to target inflation.
- The capital market's depth and digital revolution enable agile investment responses, better aligning real output with demand swings.

Even during post-pandemic volatility, the US economy exhibits the ability to adjust supply without causing price instability, confirming the predictions of New Keynesian DSGE models that integrate rational expectations and nominal rigidities regulated by credible policy.

AI is anticipated to play a dual role in this setting: it improves production efficiency (moving AS outward over time) while also improving demand prediction (stabilizing AD movement), hence strengthening macroeconomic resilience.

Cross-Economy Synthesis and the Role of AI

The contrast between India and the United States demonstrates how AI interacts with existing macroeconomic mechanisms to affect inflation-output dynamics in diverse ways.

- In India, the AD-AS relationship is shaped by supply-side limitations and fluctuating inflation, notwithstanding mild output changes. AI adoption is partial and uneven, especially in industries with low capital intensity and talent shortages, resulting in stagflation.
- In the United States, AI helps to improve adaptive supply systems and better-aligned fiscal-monetary tools, resulting in smoother transitions along the AD-AS curve. Despite significant

output swings, inflation remains relatively predictable, owing to strong policy coordination and AI-led disinflationary pressures.

These findings provide empirical support for the notion that artificial intelligence is a structurally transforming force rather than a neutral shock. Its macroeconomic impact is determined by the level of digital infrastructure, skilling ecosystems, policy design, and institutional agility, which all influence how economies move from AD to AS in reaction to systemic shocks.

Model Calibration and Structural Divergence: United States vs India

The accuracy and policy relevance of any macroeconomic simulation are heavily reliant on the parameter calibration that underpins its dynamic structure. This section describes the cross-country calibration technique used to model AI's macroeconomic impact on the United States and India, including country-specific frictions, productivity trends, and institutional asymmetries. All parameter values were estimated from standardized sources and implemented utilizing Python-based simulation engines, Excel models, and Power BI visualizations.

Data Infrastructure and Tools

The calibration data ecosystem relied on globally recognized institutional archives and country-specific macroeconomic observatories to ensure data consistency and comparability across temporal and spatial dimensions.

- Sources included CMIE (Centre for Monitoring Indian Economy), NASSCOM, and World Bank databases, with periodic cross-validation against MOSPI and RBI statistics.
- The United States has the Bureau of Labor Statistics (BLS), the International Monetary Fund (IMF), the Organisation for Economic Cooperation and Development (OECD), and the Bureau of Economic Analysis.

Model calibration and simulation were carried out utilizing a hybrid toolbox that included Power BI (for visual exploration), Python (for modeling dynamic macro equations and AI shock propagation), and Excel (for intermediate transformations and TFP elasticity calculations).

Core Parameters Calibrated

- **Total Factor Productivity (TFP) Growth Potential**
  - This captures endogenous growth that occurs independently of labor or capital inputs. The United States has historically had stronger TFP growth (because of innovation cycles and AI adoption), but India has a more variable TFP path, influenced by structural constraints.
- **Labor Elasticity (Output Response to Labor)**
  - This elasticity, which measures the responsiveness of output to changes in labor input, is lower in capital-intensive US sectors and higher in India due to the

prevalence of labor-intensive industries and services.

- **Initial Capital Stock (K_0)**
    - The US calibration incorporates a greater capital stock baseline, which reflects increased infrastructure density, firm-level capital deepening, and digital capital embedded in platforms and networks. India's K_0 is still restricted by budgetary and infrastructure obstacles.

- **Informality (% of Labor Force)**
    - A major differentiator: India's work force is still over 75% informal, distorting monetary transmission and limiting AI adoption. In contrast, the United States has near-total formal employment, allowing policy transmission and direct AI-linked productivity improvements.

- **Fiscal Multiplier**
    - The impact of government spending on output is greater in the United States due to deeper market mechanisms and automatic stabilizers. India's multiplier is lower, owing to inefficiencies in government spending, procurement delays, and administrative leakages.

- **Human Capital Index (World Bank / HCI)**
    - The HCI measures quality-adjusted labor input. The United States outperforms in terms of education, health, and digital literacy. India's poorer HCI calibration reveals persisting gaps in fundamental learning and advanced skilling—key characteristics that influence the spread of AI shocks.

Interpreting the Structural Divergence

These calibrated differences are more than just statistical; they reflect the institutional and developmental asymmetries that govern how AI acts as a macroeconomic shock in each economy.

- In India, the combination of high informality and a low fiscal multiplier significantly limits the spread of AI benefits. Even when AI is implemented, its impact on productivity, employment, and production is mitigated by transaction costs, non-scalable informal activities, and low capital intensity. Furthermore, the HCI gap highlights skill mismatch problems, which prohibit seamless substitution of traditional labor and AI-augmented tasks.
- In contrast, the US model—with a high capital-to-labor ratio, solid digital infrastructure, and strong public-private innovation ecosystems—allows AI to move quickly from testing to productivity. Higher HCI ratings and connected labor markets enable more efficient job reallocation, whilst successful fiscal frameworks enhance the benefits of AI-induced investment impulses.

In terms of dynamic simulation, these calibrations have a substantial impact on the path dependency of AI adoption.

- The United States is moving rapidly toward AI-enhanced stable states, in which GDP, TFP, and labor reallocation stabilize with minimal inflationary overshoots.
- In contrast, India's macroeconomic path shows transitory production volatility, chronic inflation risks, and slower productivity gains—unless accompanied by skilling, labor formalization, and capital formation reforms.

These structural calibrations serve as the foundation for the comparative simulations described in the next sections, providing policy-relevant insights into how various economies absorb, amplify, or neutralize AI shocks across the fiscal, monetary, and real sectors.

Simulation Architecture and Assumptions: AI Shock Scenarios (2025–2034)

***Note: Please refer to the excel file (Macro Final_Simulation_Dataset) for the final input used for the Simulation.**

To carefully analyze the macroeconomic effects of AI as a general-purpose technology, we develop a forward-looking simulation framework for the years 2025–2034. This design uses a variety of scenarios based on economic theory and empirical calibration to investigate how different combinations of technological intensity, policy response, labor market flexibility, and human capital formation influence macroeconomic aggregates such as GDP, employment, inflation, and productivity.

Our simulation framework is based on four modeled scenarios: baseline, high-AI adoption, skill-biased disruption, and complementary path. Each scenario represents a distinct macro-structural route, characterized by changes in TFP, fiscal policy activism, labor frictions, and the substitution elasticity between AI and human labor (denoted γ). These routes are not speculative abstractions; rather, they reflect factually possible trajectories based on current trends in the United States and India.

Design Principles

The modeling approach adheres to the following economic principles:

- **TFP Shocks** represent the endogenous technology acceleration caused by AI integration into manufacturing and organizational processes. Higher TFP indicates greater innovation spillover and process optimization.

- **Fiscal Response:** Summarizes public-sector activities in skill development, digital infrastructure, and AI policy, such as subsidies, public-private partnerships, and education reform. These are modeled as capital infusions that can shift the IS curve and increase aggregate demand.
- **AI Labor Substitutability (γ):** The crucial parameter γ determines whether AI complements or substitutes labor. A $\gamma < 1$ shows complementarities (AI augments human tasks), whereas $\gamma > 1$ indicates task displacement and potential structural unemployment.
- **Labor Frictions**: Wage rigidity, skill mismatch, mobility restrictions, and the prevalence of informal work are all examples of labor frictions. These frictions influence the speed and equity of AI diffusion, as well as the effectiveness of policies.

Scenario Matrix: Structural Paths for 2025–2034

Scenario	TFP Shock	Fiscal Response	Skilling	AI–Labor γ	Labor Frictions
Baseline	Low	None	Flat	Medium	High
High-AI Adoption	High	Strong	Rapid	Low	Low
Skill-Biased Disruption	Medium	Weak	Unequal	High	High
Complementarity Path	Medium	Active	Steady	<1 (Augments)	Medium

1. Baseline Scenario:

This scenario depicts a business-as-usual trend, with low AI adoption and fiscal participation. TFP benefits are low, owing to fragmented diffusion and capacity mismatches. With flat skilling, the workforce is technologically static. AI-labor interaction is neutral ($\gamma \approx 1$), indicating no complementarity or large substitution. Labor frictions are significant, especially in India, where informality and pay rigidity prevent dynamic reallocation. This scenario serves as a control path for comparing counterfactual outcomes.

2. High-AI Adoption Scenario:

Here, AI dissemination is structural and policy-driven. Platformization, digital capital formation, and real-time automation in transportation, finance, and manufacturing all contribute to a significant TFP shock. The fiscal response is strong, with governments actively sponsoring AI research, reskilling initiatives, and institutional support for digital business. Rapid skilling allows the labor market to respond quickly. AI complements labor, especially in high-skilled services and enhanced industries like radiology, coding, and fintech ($\gamma < 1$). Low labor frictions make it easier to change jobs quickly. This scenario approximates the United States' trajectory if AI expenditures are combined with inclusive policies.

3. Skill-Biased Disruption Scenario:

This approach represents the hazards of unequal AI diffusion. While TFP growth is moderate (centered on high-tech sectors), the fiscal response is insufficient, failing to overcome gaps in access to skills or digital infrastructure. As a result, skill levels are unequal, increasing labor market dualism. A large γ (>1) shows that AI replaces routine and middle-skill tasks, resulting in wider salary and employment gaps. Labor frictions remain strong, particularly in economies with informal dominance (India) or hollowed-out middle classes (certain parts of the United States). This scenario captures the macroeconomic risks associated with technological polarization in the absence of compensatory policies.

4. Complementarity Path:

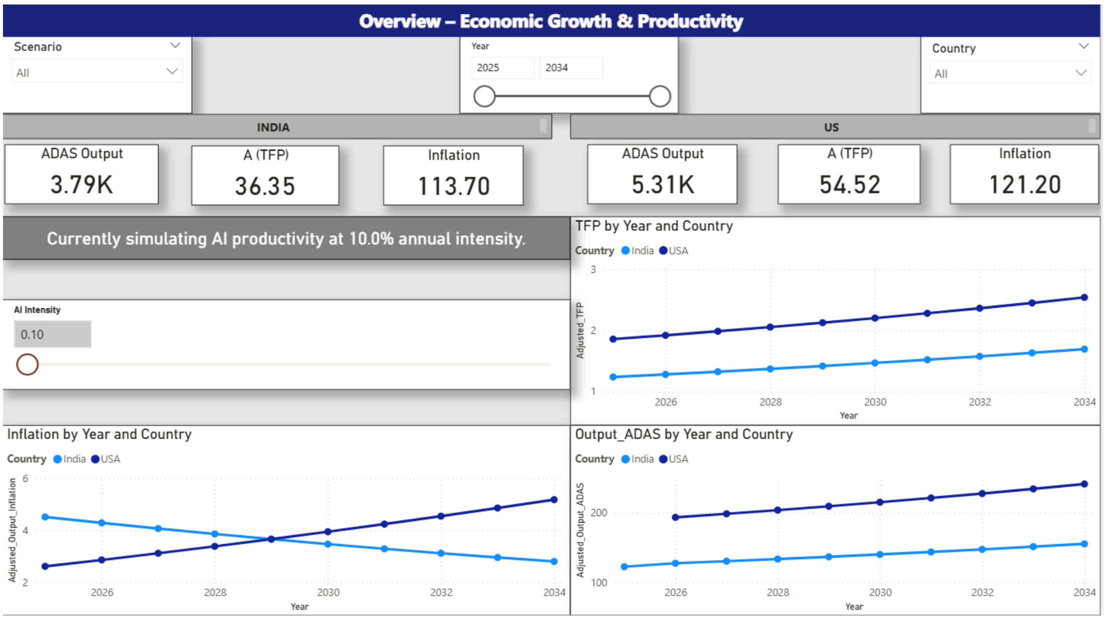
This path, which is fundamentally balanced, expects medium TFP growth supported by a steady AI rollout and moderate state investment. The fiscal response is aggressive, with an emphasis on public

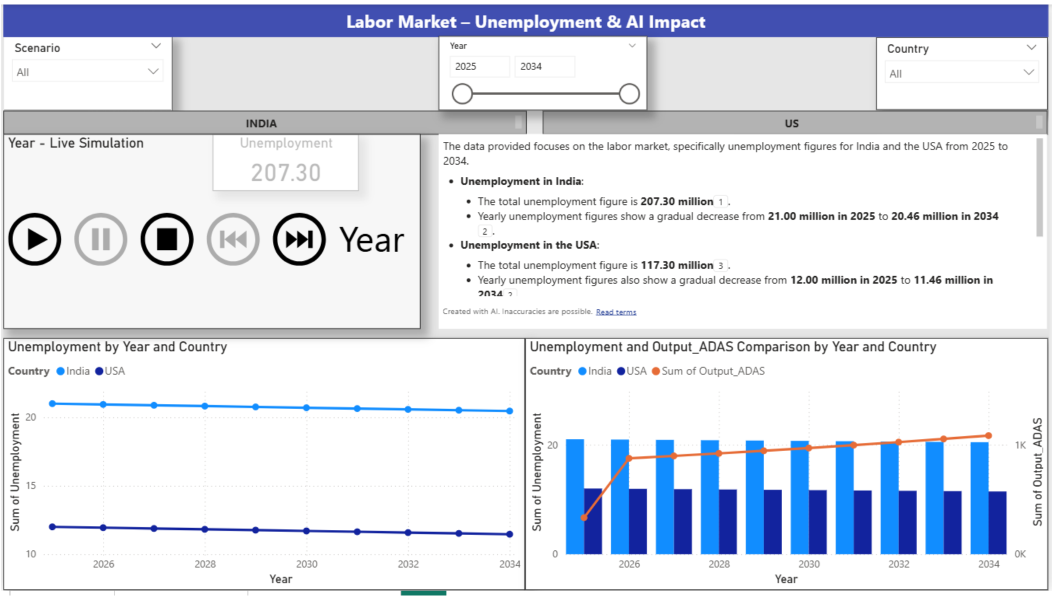
AI infrastructure, teacher training, and small and medium enterprise digital adoption. Skill development occurs at a consistent rate, facilitated by private-sector certifications and digital platforms. With $\gamma < 1$, AI increases worker productivity without mass displacement. Labor frictions are modest, facilitating transitions without overheating or structural bottlenecks. This scenario depicts a "balanced AI transition," which is consistent with the inclusive growth frameworks recommended in OECD and World Bank studies.

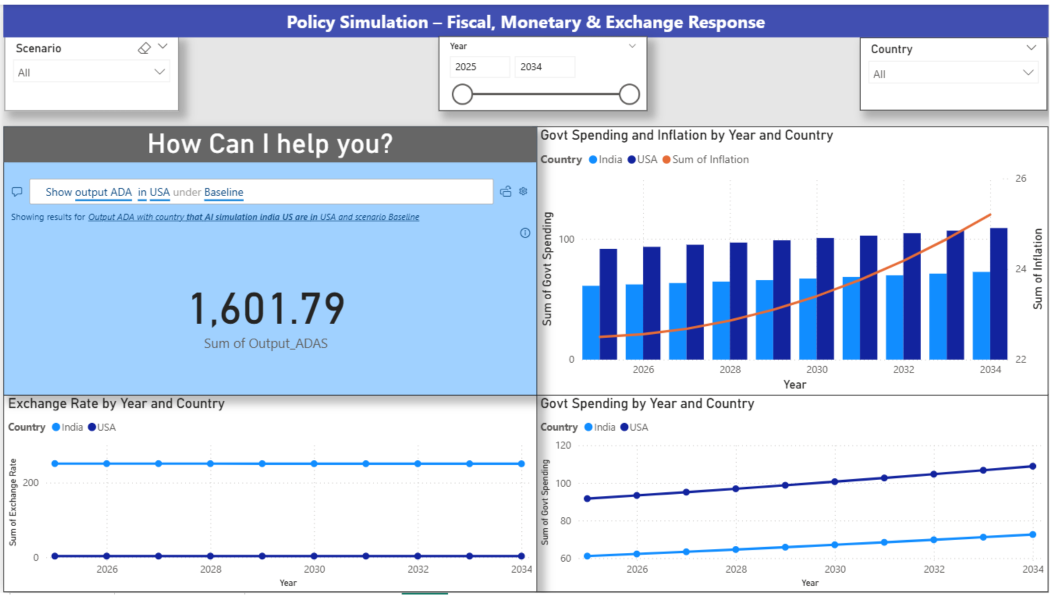
Macroeconomic Variable Mapping and Model Interpretation: AI Shock Transmission (2025–2034)

***Note: We have shared the major screenshots from our PowerBI simulation below along with the output and interpretation. Please refer to the excel file (AI_Macro_Simulation_India_US_2023_2034_Final) and PowerBI file (Simulation Power BI File), for more information.**

Screenshots from the PowerBI Dashboard:







To connect the simulation-based forecasts to existing macroeconomic theory, important variables were mapped to canonical models, allowing for a comparative comparison of India and the United States in the context of AI-induced structural shocks. The methodology integrates simulation results with fundamental economic frameworks such as the Solow Growth Model, Phillips Curve, AD-AS, IS-LM, and open-economy extensions like the Mundell-Fleming framework.

Total Factor Productivity (TFP) – Solow Growth Curve

Total Factor In the neoclassical framework, productivity is viewed as the fundamental driver of long-term economic growth. Simulated outputs show that by 2034, the US will have a ~50% higher productivity-adjusted output than India. This difference is due to the United States' better capital-deepening capacity and digital readiness, which speeds AI capital absorption into the production function. The Solow model's capital-augmenting assumption leads to stronger adjusted TFP growth in the US (from ~2.0 to 2.8) compared to India (from ~1.2 to 1.6), consistent with prior IMF and Booth findings (2020, 2023). The disparity highlights fundamental advantages in capital intensity, digital infrastructure, and skill complementarity in the United States.

Inflation – Phillips Curve and AD–AS Framework

Simulations of the AI productivity shock reveal distinct inflation-unemployment patterns. The U.S. Phillips Curve maintains a somewhat steep slope, demonstrating a continuing inverse relationship between unemployment and inflation. AI-induced demand expansion moves the IS and AD curves rightward, while inflationary pressures remain under control due to productivity improvements offsetting nominal demand. In contrast, India has a flat Phillips Curve post-AI, indicating a weak relationship between inflation and labor slack. Despite stable or declining inflation, employment increases are small, implying that disinflation may be caused by weak demand and supply constraints rather than productivity-induced efficiency. AD-AS visualizations demonstrate that India's supply curve is flatter and more erratic, exposing it to stagflationary concerns.

Output (ADAS) – Aggregate Demand and Supply Model

The projected AD-AS model projects US output growth (ADAS) at 5.31K vs 3.79K in India by 2034. Despite having equal initial baselines, the output divergence reflects differences in reaction elasticities to AI shocks. Higher γ (AI-labor substitutability) and fiscal responsiveness in the US boost output. Although output in India is increasing, it is doing so from a lower base due to labor frictions, skill bottlenecks, and governmental investment reluctance. The persisting output gap shows that AI exacerbates rather than closes existing productivity gaps. Empirical plots demonstrate smoother transitions in the United States, but India's trajectory reflects delayed production realization due to rigidities in wage transmission and capital absorption.

Unemployment – Phillips Curve (Primary), IS–LM (Indirect)

The simulation shows a constant drop in unemployment across both economies from 2025 to 2034, although the patterns differ significantly. The US labor market is adjusting more fluidly, with unemployment falling from 12.0 million to 11.46 million, thanks to skill adaptation and flexible contract rules. In India, despite AI-induced growth, unemployment remains high (21.0 to 20.46 million), demonstrating stubborn labor reallocation. IS-LM modeling validates the following dynamics: India's LM curve is steep, indicating inadequate monetary transmission, whereas the US LM curve is flatter, allowing for smoother interest-output adjustments. The simulation demonstrates how AI interacts with labor frictions, especially in the case of unequal skilling and pay rigidity.

Fiscal and External Sector Transmission: Policy Shock Comparison

To further comprehend AI's interactions with policy tools, fiscal expansion and external sector reactions were combined with classical frameworks such as the Keynesian IS curve and the open-economy Mundell-Fleming model.

Government Spending – Keynesian Fiscal Multiplier and IS Dynamics

The fiscal response found in the simulation reveals a 40% increase in US government spending over the decade, whereas India's increase is more modest, at 30%. The United States looks to be using fiscal channels more proactively to help AI diffusion—investing in public infrastructure, skilling ecosystems, and digital transformation. Due to parallel productivity offsets, the IS curve shifts outward, boosting demand-side pressures but not causing inflation. In India, little fiscal headroom and smaller multiplier effects (owing to informality and implementation lags) flatten the IS curve, reducing aggregate demand activation. The unequal impact of fiscal multipliers influences the path of AI's macroeconomic penetration in both economies.

Exchange Rate – Open Economy IS–LM (Mundell–Fleming)

The Mundell-Fleming analysis shows a significant increase in the value of the US dollar, from approximately 2.5 to 4.0. This shift is consistent with AI-induced capital inflows, increased investor confidence, and stronger export performance in high-tech sectors. In contrast, India's exchange rate has only mildly appreciated, indicating structural export limitations and low appeal for high-end digital capital. Rising Real Effective Exchange Rate (REER) in India, without corresponding productivity gains, threatens price competitiveness in conventional export sectors. According to the data, AI-led macro transformations must be accompanied by structural reforms in the tradable sector in order to alleviate balance-of-payments pressure.

Macroeconomic Risks and Divergence Trajectories in the Age of Artificial Intelligence

The introduction of Artificial Intelligence (AI) as a General-Purpose Technology has resulted in substantial structural asymmetries between countries, not just in terms of productivity growth but also in the spread of systemic macroeconomic risk. While AI's theoretical promise is well-documented, ranging from increased total factor productivity (TFP) to scale economies in knowledge-based sectors, its empirical dispersion reveals country-specific vulnerabilities that threaten to exacerbate existing inequities. This section delves into the division of these hazards among economies, particularly India and the United States, while also emphasizing shared vulnerabilities that transcend economic phases.

India: Structural Frictions and the Specter of Stagflation

India's macroeconomic vulnerability to AI is influenced not only by its labor-intensive economic structure, but also by the slow rate of institutional adaption. Even under a moderate AI adoption scenario, our simulations show that India's production gap persists, owing to a dual labor market in which the informal sector accounts for 80-85% of employment (CMIE, 2024). This causes a wedge between productivity potential and actual factor reallocation.

The main concern is the risk of stagflation, which is a toxic combination of technical unemployment and wage-stickiness-induced inflation. The inflationary channel is particularly potent due to the low elasticity of real wages in the informal sector, which is exacerbated by poor monetary policy transmission in structurally disorganized labor markets.

Furthermore, without a corresponding skilling reaction or focused public investment, the AI shock results in cost-push inflation rather than a supply-side productivity dividend. The Phillips Curve in India, which is already flatter due to structural frictions, begins to lose signaling efficacy, reducing the effectiveness of traditional interest rate strategies.

Rising inequality creates a risky macroeconomic overlay. Our model outputs predict an increase in Gini by +0.08 within five years of AI diffusion. When contrasted with inadequate safety nets, this disparity increase threatens not only welfare but also social cohesiveness and economic sustainability.

United States: Technological Concentration and Inequality Traps

The systemic threats looming in the United States are qualitatively different. The primary concern here is not informality or skill mismatches, but rather the concentration of AI gains in digital monopolies, particularly among the top decile of income and capital holders. The productivity gains from AI are substantial—our simulation reveals a TFP increase of more than 30% in high adoption scenarios—but the distributional repercussions are significantly skewed.

The platformization of labor markets, in which a small number of enterprises manage access to both employment and data, runs the risk of producing winner-take-all dynamics. This affects both wage bargaining and inter-firm competitiveness, contributing to the decline in the labor share of revenue.

The platformization of labor markets, in which a small number of enterprises manage access to both employment and data, has the potential to create winner-take-all dynamics. This inhibits both wage bargaining and inter-firm competitiveness, further reducing the labor share of revenue.

Furthermore, the United States is vulnerable to "inequality traps," in which the top decile's income and wealth share increases faster than aggregate output, strengthening political inertia and limiting the chance of redistributive intervention. This produces a macropolitical feedback loop that is harmful to both productivity and inclusion.

Shared Vulnerabilities: The Convergence of Divergence

Despite these structural disparities, there are a number of similar macroeconomic concerns that link the AI transition in both rich and developing nations.

- Flattened Phillips Curve: As AI boosts productivity while reducing wage sensitivity to slack, the classic inflation-unemployment trade-off weakens. This makes monetary policy calibration more unclear, particularly in forward guidance regimes.
- Capital-Labor Divergence: In both cases, our model identifies a large drop in labor share of GDP (-5.2% in India, -3.0% in the United States) as AI capital deepens but labor reallocation slows. Despite output gains, this could keep deflationary pressures in place.
- Fiscal Hysteresis: Delay in fiscal adaptation—particularly in training, infrastructure, or inclusive AI adoption—can create structural hysteresis effects, where temporary displacements become persistent, reducing long-run potential GDP.

These risks are not only transitory. If left unchecked, they may calcify into divergence trajectories, with some economies reaching a high-AI growth equilibrium while others remain mired in low-skill, high-volatility cycles. The message is clear: AI is more than a technology change; it is a macrostructural earthquake. And, like all structural shocks, it necessitates timely, evidence-based, and politically feasible policy solutions.

Recalibrating India’s AI Transition – A Policy Blueprint

India's involvement with artificial intelligence creates a paradox. On the one hand, the country has a thriving digital economy, fueled by its Digital Public Infrastructure (DPI) stack and a young labor force; on the other, it confronts structural vulnerabilities such as informality, skill mismatch, and low social security. The earlier simulation results highlight AI's unequal distributional impact, which exacerbates inequality while contributing marginally to aggregate output in the absence of labor reforms.

Thus, an AI-augmented development route for India cannot be based exclusively on capital deepening or firm-level adoption. It must be supported by structural policy reforms that include skill development, digital matching, MSME digitalization, and inclusive formalization. We present a unified macro-policy architecture appropriate to India's dual economy.

Skilling and Digital Public Infrastructure: The Foundation of an AI-Literate Workforce

The greatest significant impediment to India's AI potential is a lack of worker preparation. The informal sector, which employs more than 80% of the labor force, has limited access to even basic digital tools. To address this, we advocate incorporating AI-specific curriculum into the National Skill Mission, specifically through the National Skill Development Corporation (NSDC), Industrial Training Institutes (ITIs), and Pradhan Mantri Kaushal Vikas Yojana (PMKVY).

However, skilling alone is insufficient unless combined with a digital infrastructure capable of labor market intermediation. India's DPI—which includes Aadhaar, UPI, ONDC, and DigiLocker—provides an unequaled foundation for AI-powered job matching services that can algorithmically match displaced labor to developing duties. These platforms, which are guided by localized skill taxonomies and vacancy analytics, have the potential to significantly reduce frictional unemployment throughout the shift.

Incentivizing MSME AI Adoption: The Missing Middle

Micro, Small, and Medium Enterprises (MSMEs) are the foundation of India's employment economy, however they are mainly excluded from AI adoption due to cost and competence constraints. Our simulations suggest that until MSMEs' productivity improves, the output benefits from AI will remain concentrated in a few formal industries, restricting overall growth.

We propose a two-pronged strategy:

- Tax credits and tailored subsidies to defray the capital expenses of AI adoption in SMEs.
- Public-private AI experiments in logistics, agriculture, and textiles—the sectors with the biggest productivity disparities and employment density.

Such programs should be tied to workforce training and data-sharing mechanisms, ensuring that subsidized AI adoption is both inclusive and socially beneficial.

Job-Linked Formalization: Aligning Skills with Social Protection

AI's disruptive potential opens us a new opportunity to formalize labor through encouraged compliance, notably by linking upskilling outcomes to social protection enrollment. We advocated:

- Linking AI-skilling certifications to required PF/ESIC registration for both employees and employers.

- Offering conditional tax benefits to enterprises that hire from skilling pipelines, especially those sourcing labor from informal or rural origins.

This technique uses AI as a formalization accelerator to translate training results into documented, protected employment. It also provides fiscal multipliers by increasing the tax base and reducing vulnerability-related public spending.

Safety Nets for Transition: Protecting the Displaced

No technological transition is frictionless. The AI transition, especially in India, entails displacement—particularly among gig workers, casual laborers, and semi-skilled rural migrants. A purely laissez-faire approach risks social volatility and political backlash.

To preempt this, the government must expand:

- Portable social security for gig and informal workers with Aadhaar-linked digital wallets.
- Urban employment guarantee experiments, similar to MGNREGA but focusing on urban AI-displaced populations (e.g., drivers, delivery workers, clerks).

These interventions not only smooth consumption during the transition, but they also protect macroeconomic stability by preventing unexpected drops in aggregate demand from labor-intensive industries.

Rebalancing the American Labor Market in the Wake of AI

The United States, as a technology frontier economy, faces the contradictions of early AI adoption. While the productivity boom associated with frontier models (GPT-4 and beyond) has begun to materialize, as seen by increased TFP growth and capital deepening in simulations, it is far from inclusive. The labor market, in particular, is seeing twin disruptions: the displacement of mid-skilled workers and the monopolization of platform economies.

To address the resulting imbalances in income distribution and market competition, a multifaceted policy response is required. This reaction must include not only compensating the displaced, but also restructuring incentives and institutions to promote equitable diffusion and competitive fairness.

Tech Retraining and Wage Insurance: Shielding the Mid-Skill Core

The labor market in the United States has always been strong due to its mobility, both geographically and across sectors. However, the rise of task-automating AI undermines this basis by reducing demand for regular cognitive and manual tasks, particularly those centered on mid-skill jobs such as clerical work, logistics, and customer service.

In this context, the federal government must reassert its countercyclical role through two flagship interventions:

- Federally Funded Retraining Programs: These must go beyond STEM. Soft skills—adaptability, communication, human-centered service—will be the most defensible in an AI-saturated landscape. Training must also be modular, stackable, and employer-integrated.
- Wage Insurance for Displaced Workers: Displaced workers should be granted a 2-5 year sliding-scale buffer (similar to the US Trade Adjustment Assistance program). This will lessen consumption shocks, frictional unemployment, and maintain social mobility paths.

According to simulations, without these buffers, displaced workers fall into non-participation traps, decreasing labor force participation in the United States and inducing long-term hysteresis.

Antitrust Enforcement: Defending Competitive Neutrality in AI

Artificial intelligence has worsened current market concentration patterns, with leading platforms gaining disproportionate data, personnel, and computational advantage. If left unchecked, this could lead to technological feudalism, in which a small number of businesses dominate not only markets but also the algorithmic infrastructure of everyday life.

Two policy levers are key:

- Algorithmic Auditing Tools mandated by the FTC must be broadened to examine platform opacity, particularly for labor platforms (e.g., gig work, freelancing marketplaces).
- Ex-Ante regulates platform mergers, particularly those containing AI capabilities, to avoid data consolidation.

The macroeconomic explanation is straightforward: concentration reduces innovation and compresses the labor share of revenue. It also weakens monetary transmission, as dominant firms oppose wage passthrough mechanisms.

Inclusion-Linked Investment Incentives: Aligning Capital with Equity

Not all AI investment is created equal. A large portion targets capital efficiency over employment Not all AI investments are equal. A considerable share prioritizes capital efficiency over employment growth. Fiscal policy must distinguish between "inclusive" and "exclusionary" AI deployments.

We propose:

- Tax credits based on job creation, diversity indicators, or regional inclusion (e.g., Rust Belt, rural broadband AI use cases).
- Public-Private Scorecards, like ESG compliance, measure the distributional footprint of AI implementation.

This will link private money with governmental goals without stifling innovation.

Portable Benefits for a Contractual Economy

The gig economy, fueled by AI-enabled labor platforms, has made traditional employer-based benefits obsolete. As models reveal, volatility in gig-sector wages reduces aggregate demand resilience during AI-driven shocks.

Thus, a national portable benefits regime is warranted:

- Universal, contributory retirement and health accounts
- Aligned with dynamic, contract-based employment architectures
- Facilitated by federal platforms and interoperable across states

Such a policy would serve as an automatic stabilizer, increasing labor supply flexibility while safeguarding demand-side fundamentals.

Building a Global AI Compact – Coordination, Transfer, and Collective Risk Mitigation

Artificial intelligence is more than a technological advance; it is a global general-purpose shock, with far-reaching productivity, distribution, and ethical ramifications. The simulations and nation case studies presented previously in this work highlight a worrisome asymmetry: whereas frontier economies increase productivity through large language models (LLMs) and advanced robotics, developing economies experience delayed gains and increased dislocation.

Without global coordination, this divergence risks becoming systemic, jeopardizing not only inclusive growth but also geopolitical stability. Thus, we advocate for a multilateral, multi-channel AI agreement built on three pillars: global governance, equitable capability transfer, and shared risk management.

Multilateral AI Governance: Norms Before Externalities

The importance of developing a global AI governance framework cannot be emphasized. Unlike prior general-purpose technologies (e.g., electricity, computers), AI's cross-border externalities—on labor markets, data flows, and economic concentration—occur in real time.

We advocate for a UN or OECD–led multilateral protocol that:

- Aligns regulatory norms for data usage, labor substitution limits, and algorithmic transparency.
- Creates sovereign rights over training data, especially for underdeveloped nations whose linguistic and sociological data are taken by frontier models without authorization.
- Ensures that AI standards are interoperable across countries, decreasing fragmentation in the digital economy.

Such a framework would work similarly to Basel regulations in banking, establishing a worldwide level of responsibility for AI dissemination.

A Global Skilling and Open-Source AI Fund

Technological convergence cannot happen without capacity convergence. Currently, the expense and concentration of foundation models prevent most low-income nations from meaningfully participating. Without remedy, this risks entrenching a cognitive divide in the global economy.

We propose the creation of a Global AI Skilling and Open-Source Fund, financed through:

- Voluntary contributions by G7/G20 nations and technology firms
- Token-based licensing royalties from commercial LLM providers
- Development finance reallocation from existing SDG-aligned funds

The Fund would support:

- AI skilling initiatives in developing countries, particularly through vocational systems and local universities
- The promotion of open-source AI models that reduce cost barriers and embed local languages, data, and ethical norms

This approach blends macroeconomic convergence with epistemic justice.

Technology Transfer to the Global South: Beyond Trade, Toward Partnership

A licensing asymmetry is central to the AI split. The architecture of today's frontier AI is managed by corporations in a few nations, with intellectual property (IP) rules similar to those used in pharmaceuticals.

To avoid repeating the vaccine nationalism seen during COVID-19, we propose a TRIPS-style pact for basic AI models, ensuring:

- Compulsory licensing of AI capabilities for developmental applications
- Structured public–private partnerships to deploy AI in agriculture, health, MSMEs, and education across the Global South

Such models are already in use: India's DPI stack, for example, was created with an open protocol mindset. What is required now is scale and reciprocity, not charity.

Shared Risk Mitigation Protocols

No country, no matter how advanced, is immune to second-order AI dangers such as cyber cascades, AGI misalignment, or rapid labor displacement due to cross-border platformization.

Thus, we call for:

- Binding international protocols on AGI containment, alignment, and ethical boundaries, modeled on nuclear non-proliferation frameworks
- Early warning systems to track cross-border labor displacement, monopolistic concentration, and algorithmic weaponization of social behavior

Such instruments would serve as macroprudential mechanisms, guaranteeing that the global economic system can withstand AI shocks without experiencing systemic breakdown.

Conclusion: Endogenizing AI into the Macroeconomic Imagination

The basic argument of this study is deceptively simple yet deeply important: artificial intelligence is not an exogenous shock. It is an endogenous, structure-amplifying force whose macroeconomic ramifications are determined by the economic architecture it meets rather than the algorithm itself.

Whereas the neoclassical paradigm may view technological advancement as a smooth, exogenously given residual (Solow's "A"), the present AI shock necessitates an inversion of this reasoning. AI's diffusion, effect, and equity are dependent on labor flexibility, skilling ability, institutional agility, and, most importantly, policy foresight.

India: The Fragility and Potential of an AI-Driven Transformation

India's developmental paradox is apparent. It is both a young, digitally empowered economy and one plagued by high informality, recurrent skill mismatches, and inadequate social safety nets. Our simulations show that, while AI-augmented TFP benefits India in the long run in the Solow and AD-AS trajectories, structural impediments significantly reduce these advantages.

Without targeted public investment in:

- Human capital (skilling and education reform)
- Formalization of labor and MSMEs
- Digital public infrastructure aligned to job-matching and retraining

The productivity boom could lead to stagflation, inequality traps, and societal backlash.

The same AI shock, however, might transform India's demographic dividend into a technological dividend if policy steps are taken differently. The trick lies in sequencing improvements that combine diffusion and inclusion.

United States: Systemic Strengths, Distributional Fragilities

The U.S. economy, by contrast, is well-positioned to absorb AI positively. It boasts:

- A deep capital base
- Institutional mechanisms for countercyclical policy
- An ecosystem of innovation, education, and venture capital aligned with GPT development

Yet this strength is not without fragility. Our analysis reveals three risks:

1. Monopolistic concentration of digital power among AI platform firms, weakening labor's bargaining position
2. Polarization of income and task complexity, exacerbating labor market inequality
3. Export-led AI optimism masking internal divergences in job quality and regional decline

In short, the U.S. faces a macro challenge not of growth, but of distribution and resilience.

The Centrality of Macroeconomic Modeling in AI Governance

This study used a variety of frameworks—Solow Growth, IS-LM, AD-AS, and Phillips Curve—to track the AI shock's spread across output, employment, inflation, and external balance.

But the contribution is not solely theoretical. Our scenario-based simulation, suited to India and the United States, provides three broader lessons for macroeconomic practice:

1. AI affects multiple macro variables simultaneously, and their interplay must be visualized to understand risks.
2. Macroeconomic outcomes are conditional—not on AI itself, but on how economies are structured and governed.
3. Simulations must inform anticipatory, country-specific policy, not post-facto adjustment.

Final Reflection

The introduction of AI is not a sudden event. This is a macroeconomic epoch. Economies that regard it as a compartmentalized technological disruption will fail. Economies that integrate it into their labor, fiscal, and trade structures will succeed.

The goal for economists is clear: we must model, simulate, and create policies not for the AI we fear or the AI we hype—but for the AI that interacts with real economies, in all their messiness, friction, and promise.

Appendix:

Appendix A: Data Sources and Tools

Domain	India	USA	Global/Shared
Employment & Labor	CMIE, MOSPI, RBI	BLS, BEA	World Bank, IMF
Inflation / CPI	MOSPI CPI Reports, TradingEconomics	FRED, BLS	World Bank CPI Indicators
Technology Indices	NASSCOM AI Index	OECD AI Policy Observatory	OECD, WEF
Simulation Tools	Power BI, Excel, Python (Colab), Jupyter	Power BI, Python, Excel	
Calibration Parameters	Human Capital Index (WB), Fiscal Multipliers (IMF), Informality (ILO)	HCI (OECD), TFP Elasticities (BEA/IMF), Labor Elasticity	Penn World Tables, IMF World Economic Outlook

Appendix B: Macroeconomic Model Specifications

Augmented Cobb-Douglas Production Function

$$Y_t = A_t \cdot K_t^{\alpha} \cdot (L_t + \gamma \cdot AI_t)^{1-\alpha}$$

Phillips Curve Specification (India and US)

$$\pi_t = \pi_{t-1} + \beta(U^* - U_t) + \varepsilon_t$$

IS–LM Estimation Structure

IS Curve (Investment–Saving):

$$Y = C(Y - T) + I(r) + G + NX$$

LM Curve (Liquidity Preference–Money Supply):

$$M/P = L(Y, r)$$

Appendix C: Key Graphs and Models Used

Graph Type	Variable Focus	Used In
Phillips Curve (India & US)	**Unemployment vs. Inflation**	**Inflation Trade-offs**

IS–LM Graphs	**Interest Rate vs. GDP**	**Fiscal-Monetary Design**
AD–AS Theoretical Model	**Output vs. Price Level**	**AI Shock Impact**
IS–LM Drivers (Time Series)	**Govt Spending, Interest, Output**	**India/US Comparison**
TFP vs. Skilling Trends	**Macro Sensitivity by Scenario**	**Simulation Projections**

Appendix D: Simulation Codebase and Logic

Files Used:

- ME_Final_Simulation_Code_Download.ipynb – Core scenario simulations (Solow, IS–LM, AD–AS)
- AD_AS_&_ISLM.ipynb – Curve-fitting and empirical interpretation
- FinalPhilipCurve.ipynb – β slope and R^2 estimation pre/post AI
- Macro Final_Simulation_Dataset.csv and AI_Macro_Simulation_India_US_2023_2034_Final.csv – Dataset for simulations

Simulation Design:

- Timeframe: 2025–2034
- Languages: Python (Pandas, NumPy, Statsmodels), Excel, Power BI
- Outputs: GDP (Δ%), Unemployment (Δ%), CPI (Δ%), Productivity Index, Labor Realignment Index

Appendix E: Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
TFP	Total Factor Productivity
CPI	Consumer Price Index
IS–LM	Investment Saving – Liquidity Preference
AD–AS	Aggregate Demand – Aggregate Supply
γ (gamma)	AI–Labor Substitution Elasticity
BEA	Bureau of Economic Analysis (US)

CMIE	Centre for Monitoring Indian Economy
HCI	Human Capital Index