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Total factor productivity dynamics and the artificial intelligence paradox: Evidence from long-memory analysis

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Abstract. This paper investigates the artificial intelligence (AI) productivity paradox using total factor productivity (TFP) from 1890 to 2022 and fractional integration and long-memory econometric methods. We find that total factor productivity gains from AI investments may be delayed and diffuse nonlinearly, following long-memory patterns similar to those of previous technological revolutions, resulting in a paradox of long lags, not a lack of innovation. The average TFP growth rate (0.54%) in the AI era is the lowest of any post-war technological wave, with profoundly contradictory persistence measures from the GPH (d=1.730) and Local Whittle (d=0.133) estimators, reflecting fundamental uncertainty about the actual productivity of AI. We observe that the GPH estimator is consistent with the "J-curve" hypothesis of temporary slowdown before long-term gains. In contrast, the Local Whittle estimator suggests productivity effects that may be fleeting and easily commoditized. Cross-country heterogeneity in AI persistence patterns points to the role of local institutions, policies, and complementary investments in mediating the macroeconomic impact of AI. These results imply that the full productivity benefits of AI may be realized over very long-run horizons, providing policymakers and investors with necessary guidance on the timing and nature of the AI revolution.

Keywords: artificial intelligence, productivity, long-memory, fractional integration, J-curve, AI paradox

JEL Classification: M10, M15, C22, O47, O30

1. INTRODUCTION

TFP is the single most important factor driving long-run growth that is not explained by increases in the traditional inputs of labor and capital, and thus TFP is considered a measure of the contributions of technological progress, institutional changes, and other efficiency-enhancing factors that allow economies to produce more with the same number of inputs. However, for decades literature has debated the stochastic properties of TFP series: what is the nature of the shocks and how persistent are they? An answer to these questions is important for understanding the mechanics of economic growth and the long-term effects of the major technological revolutions that may occur.

We present an econometric analysis of TFP persistence over a century of technological waves, and we reach some notable conclusions. The analysis consistently finds evidence of long-memory characteristics ($d>0.5$) in TFP shocks for each of the six technological waves, which constitutes a strong refutation of the conventional view that productivity shocks are transient, and that the estimated half-life of a TFP shock is more than 100 years for each of the eras. This result is reinforced by the fact that the estimated half-life of a TFP shock is more than 100 years for all eras, which implies that technological innovations have permanent effects. This combination of the lowest average TFP growth rate (0.54%) with profoundly contradictory persistence measures from the GPH and Local Whittle estimators has created a new, pressing enigma for the field, which is the subject of our study. The study of long-memory processes in economic time series has a long history, and the first comprehensive review was published by Baillie (1996). However, the first empirical evidence of long-memory behavior in TFP data was not found until the late 2000s, when authors Gil-Alana and Mendi (2005) showed that U.S. TFP series were consistent with fractional processes with integration degrees between 0.5 and 1. Thich is inconsistent with the assumptions of endogenous growth theories with permanent effects or real business cycle theories with transitory shocks (Gil-Alana & Mendi, 2005). Later studies, such as that of Xiao et al. (2024), corroborated these initial findings in a sample of 40 advanced economies, thereby substantiating the preeminence of ARFIMA specifications over conventional ARIMA models in capturing the protracted impacts of technology changes, policy shifts, and institutional factors.

Our paper uses a historical analysis approach, where TFP data is divided into six different technological eras, or "waves," to create a comparative framework for more than a century, as significant technological innovations (such as electrification or the Internet) are not incremental but instead paradigm shifts that reshape the economic landscape and dynamics. The existing literature has two research gaps:

(1) There is no systematic historical cross-wave analysis of TFP persistence; most studies have focused on one country or at one point in time, which prevents the full understanding of the change in technological shocks and their persistence over time. Comparing the Second Industrial Revolution, the era of electrifying the world, the post-war period, the age of computing, the Internet, and the age of artificial intelligence, we provide a long-term perspective.

(2) The majority of AI productivity studies that have relied on conventional econometric methods that do not account for the possibility of long memory of technological shocks (Cerutti et al., 2025; Cazzaniga et al., 2024). This paper addresses the critical gap by reframing the question from the issue of whether AI is

a "revolutionary technology" to the fundamental question of the nature of the AI shock and how it propagates through the economy. This reinterpretation allows for a deeper analysis of the AI productivity paradox and structural sources of productivity growth. We define the following technological waves in our study: the Second Industrial Revolution (1900-1919), Electrification (1920-1949), the Post-War era (1950-1969), the Computing era (1970-1989), the Internet era (1990-2009), and the current AI era (2010-2022).

Looking at how the trend of TFP persistence has changed between these periods can help determine if the AI revolution is transformative or transitory. This historical perspective provides a baseline for comparison with the unique trends of the current time. The AI productivity paradox, which describes the simultaneous rise in AI-led technological revolution and decline in aggregate TFP growth, is a prominent modern contradiction that can be observed from a historical perspective.

The data in this study show that the AI era, from 2010 to 2022, had the lowest average TFP growth rate (0.54%) of any of the post-war technological waves, continuing a downward trend from 1.48% in the Computing era to 0.93% in the Internet era. This is not consistent with the enormous hype that AI will transform labor and production at the micro level, where studies have shown productivity gains of 40 percent, with task completion time reduced for individual workers (Noy & Zhang, 2023), and 15 percent average productivity gains for customer service agents (Brynjolfsson et al., 2025).

The question then becomes, why have these promising micro-level gains not yet been realized in strong macroeconomic productivity numbers? The results imply that the AI productivity paradox is an extreme case of a pattern seen in the diffusion of general-purpose technologies, and that structural econometric methods can be used to explain the persistence and timing of the productivity gains from AI.

The rest of the paper, after the introduction, is organized as follows. Section two provides a literature summary on the research, while section three introduces the primary TFP dataset used in the analysis, the taxonomy of the six technological waves, and the econometric models (ARFIMA, GPH, Local Whittle) and tests (ADF, KPSS) used in the analysis. Section four presents the comprehensive results of the study, which discusses the evolution of TFP persistence and growth across the waves and analyzes the conflicting results for the AI era. Section five discusses the economic narratives that these findings suggest, assesses the J-curve hypothesis as a structural explanation, and examines the policy implications of the observed cross-country heterogeneity. Section six synthesizes primary findings and proposes avenues for future research.

2. LITERATURE REVIEW ON FRACTIONAL INTEGRATION AND TFP CONVERGENCE

While traditional econometric methods classify time series as stationary I(0) or non-stationary I(1), the study of fractional integration methods has become essential for understanding the persistence of technological shocks and their effects on growth in TFP analysis. This literature review focuses on the development of fractional integration methods and their application to TFP analysis, especially recent empirical findings that test economic theories using these methods, such as technological waves and artificial intelligence.

Attempts to go beyond the simple classification of time series into stationary and non-stationary types led to the study of fractional integration in economics, beginning with Granger and Joyeux (1980). They showed that the order of integration does not have to be an integer and that fractional differencing could describe series with long memory, a phenomenon in which correlations decay slowly rather than quickly, an idea particularly relevant for economic data that are influenced by technology where effects may last for a long time but are not permanent in the traditional sense. This approach received its mathematical foundation when Hosking (1981) formulated fractional differencing as an infinite binomial expansion, which could model both persistence and anti-persistence, which was helpful in productivity studies where innovations spread gradually throughout the economy. This formulation clarified how these processes could describe persistence and anti-persistence and has since become a standard reference for later applications.

Soon thereafter, methods for estimating the degree of fractional integration were developed: the famous GPH estimator (Geweke and Porter-Hudak, 1983) uses spectral regression and does not require complete model specification, making it appealing for applied work, especially in productivity research; Robinson (1994, 1995) refined the testing side of the field with efficient LM tests and improvements to log-periodogram regression that hold up well in small samples; Sowell (1992) advanced the maximum-likelihood approach for ARFIMA models, overcoming computational challenges and laying out the large-sample theory that enabled researchers to estimate fractional integration in real macroeconomic data, where the parameter often falls between zero and one. Baillie (1996) surveyed these developments and presented fractional integration as a mature framework ready for use in studying persistence in economic time series. In their work on employment data, Yaya et al. (2024) found that combining autoregressive neural network fractional integration with deep learning methods provides an improved way to identify persistence characteristics. Nonlinear fractional integration frameworks may capture asymmetric persistence, where positive and negative disturbances have different memory properties.

The COVID-19 pandemic has accelerated research on fractional integration applications, with current studies examining how shocks spread in digitalized economies. Caporale and Gil-Alana (2024) incorporated exponential temporal trends into fractional integration frameworks to model accelerating or decelerating persistence over time. This is particularly applicable to AI, as network effects and experiential learning may lead to dynamically evolving patterns of persistence. They found evidence that digital technologies exhibit increasing persistence over time, suggesting that initial implementation sets path dependencies that strengthen over time. Otto and Sibbertsen (2024) developed spatial autoregressive fractionally integrated moving average (SARFIMA) models to capture both temporal persistence and spatial spillovers from technology implementation. They find spatial proximity has a significant impact on the persistence of productivity gains from AI technologies across space and sectors. Dierkes, Fitter, and Sibbertsen (2024) adapted CUSUM-type monitoring procedures to fractional cointegration regressions and can detect breaks in the integration order and cointegrating relationships.

The use of fractional integration approaches to TFP analysis has identified pervasive evidence of long memory behavior across various nations and periods. Gil-Alana and Mendi (2005) presented initial conclusive evidence using US data from 1948 to 2002 and determined that the TFP series is subject to both non-seasonal and seasonal fractional processes. They reported integration degrees within 0.5 to 1 and argued that productivity shocks generate persistence, which is not permanent or transient but slowly mean-reverting at longer durations. The evidence thereby significantly challenged assumptions underpinning both endogenous growth theories with permanent impacts as well as those of real business cycles with transient productivity shocks.

Recent in-depth analysis of TFP dynamics for 40 advanced economies from 1951-2022 (Xiao et al. 2024) provides clear evidence of long memory for productivity series, where ARFIMA specifications are universally preferred to ARIMA specifications. Fractional integration parameters are typically between 0.6 and 0.9, capturing that technology changes, policy shifts, and institutions have persistent effects on future economic outcomes. Ignoring fractional integration leads to a biased half-life of productivity shocks with implications for both forecasting and policy analysis. The results have been replicated with different estimation methods and data sources, and, as shown in Mishra et al. (2011), tests of shock persistence in TFP growth find strong evidence of fractional integration across all methods. Shocks to productivity last decades, not years, and thus provide evidence that technological innovations changing productive capacity last for a longer time, but are not permanent changes. This has important implications for understanding the drivers of economic growth and the effectiveness of innovative policy. In macroeconomic forecasting, ARFIMA models have been shown to outperform traditional models (Bhardwaj and Swanson 2006), especially at longer forecasting horizons when long-memory effects are most apparent. Comparisons of a variety of macroeconomic series, such as TFP, have shown that accounting for fractional integration improves forecasting accuracy by 15-30 percent at forecasting horizons of more than one year.

When studying productivity by sector, fractional integration methods reveal that productivity changes are more persistent in some industries than others, with manufacturing showing lower fractional integration orders (0.5-0.7) than services (0.7-0.9), possibly due to faster technology changes and more competition (Montañés et al., 2023). High-tech industries exhibit similar patterns, with integration orders rising during innovation and falling during consolidation. The financial sector poses its own challenges for this analysis, as (Coskun et al., 2023) discovered that financial productivity indicators have long memory characteristics that vary with market conditions. The order of fractional integration increases during crises, so shocks last longer, which has implications for financial stability and the way in which productivity shocks circulate through markets. Agriculture also has its own patterns, with strong seasonality and long-term persistence, and studies have found that TFP in agriculture is more persistent in developing countries than in developed ones, most likely due to slower technological adoption and greater climate risk. Climate and agricultural productivity are linked, and this linkage creates patterns that are crucial to understanding the impact of climate change on food security over time. Although the above studies did not use fractional integration methods, dynamic panel cointegration studies of long-run TFP dynamics, such as those of Bellocchi et al. (2019) for five large European economies (France, Germany, Italy, Spain, and the UK), provide important insights into European productivity dynamics, which complement fractional integration studies.

Technology Shocks and Business Cycle

Gil-Alana and Moreno (2009) illustrated technology shock persistence as being decisively conditional on the fractional order of integration. They found that conventional VAR specifications have the potential to misidentify both the technology effect duration and size in the event of long memory. Their evidence revealed that hours worked yielded different reactions to technology shocks, depending on whether proper attention to fractional integration is taken or left aside.

Lovcha and Perez-Laborda (2015) deepened this analysis by exploring the hours worked-productivity enigma within a fractional integration framework. They determined that the hours worked and productivity, which are negatively correlated with a positive technology shock - an observation that goes against conventional RBC expectations - are enhanced by taking into account fractional integration. They conclude that technology shocks running through the economy are more persistent and complex in their transmission than widely believed within both monetary policy and mainstream business cycle theory.

Application of fractional integration to examine business cycles determined that economic fluctuations show more complex persistence patterns than conventional models portray. Candelon and Gil-Alana (2004) showed that fractionally integrated models give superior representations of prominent business cycle features, including persistence of fluctuations of output as well as co-movement of macroeconomic variables. The analysis they conducted on US real output spanning 1875 to 2001 found cyclical patterns with fractional integration orders that varied among different ranges of frequencies, which could suggest that business cycles may have multiple persistence sources at various scales of time.

Tschernig et al. (2013, 2014) introduced new identification procedures for fractionally integrated VARs with separable long-run and medium-run structural shocks of different orders. The innovative feature of their approaches was to enable more accurate identification of technology shocks and their transmission throughout the macroeconomy. The authors identified that neglecting fractional integration leads to incorrect inferences on the origins of business cycle fluctuations and that technology shocks are more significant than they are in reality.

Structural Breaks, Technological Waves, and AI

Methods of fractional integration that can identify true structural changes from long-memory processes have expanded the study of technology waves and productivity disruptions. There are substantial differences in the persistence profiles of individual technology waves, depending on the nature of the innovations and their diffusion processes. Studies of the information technology revolution of the 1990s find fractional integration orders around 0.7 and 0.8, which are highly persistent but eventually mean-reverting, compared with earlier technology waves such as the electrification era, which were less persistent and may have been obsolete or had smaller network benefits more quickly (Fout and Francis, 2014). More recent analyses have looked for multiple structural breaks within fractionally integrated TFP series and found that productivity dynamics can shift between different persistence regimes (Giuli and Tancioni, 2017). Regime-based fractional integration, in which memory parameters shift in the presence of large technological or policy shifts, has been proposed. Contractionary technology shocks (technology shocks that first lower productivity before it rises) have different persistence patterns than expansionary shocks, which is important for understanding the adjustment costs of technological change.

It is important to account for structural breaks, since ignoring the breaks can result in overestimating persistence, and modern econometric methods that combine fractional integration and structural breaks can identify genuine long memory from regime-dependent persistence (Madigu & Gil-Alana, 2020). According to the literature, the AI productivity wave is particularly prone to statistically significant breaks, where the memory parameter changes, and mean reversion speeds are significantly changed (Cerutti et al., 2025; Brynjolfsson et al., 2023), with structural breaks in Asia suggesting slower convergence and more persistent productivity gaps (Fernandez-Villaverde et al., 2023; Cerutti et al., 2025; Cevik, 2024). This resulted in significant asymmetries.

The extant international technology spillovers literature was enriched by fractional cointegration methods that can capture long-run relationships between country productivity levels with persistent disequilibrium allowed to prevail. The theoretical foundation of cointegration within fractional contexts was introduced by Robinson and Hualde (2003), who introduced methods of assessing long-run relationships between fractionally integrated variables. The model helped analyze technology spillovers where domestic and foreign stocks of R&D may exhibit long memory properties.

Beliu and Higgins (2004) utilized fractional cointegration analysis on EU convergence and found evidence of fractional cointegration among productivity levels among EU member states. Their findings indicate that although productivity levels among nations move together within the long run, differences from this shared trend are highly persistent, with half-lives of adjustment of 15-20 years. This conclusion holds significant value in assessing technology transfer policy effectiveness and evaluating the function of absorption capacity to derive benefits from international spillovers.

Gil-Alana and Hualde (2009) utilized fractional integration and cointegration testing to examine linkages between trade openness and productivity growth. They determined that the link between productivity and trade exhibits fractional cointegration with memory values of around 0.4, meaning that productivity gains accrued from trade are persistent though non-permanent. The finding is in line with the theory where technology transfer is a consequence of trade, but where benefits leak gradually without persistent innovation.

Cerutti et al. (2025) use a multi-region DSGE model to show that advanced economies may secure TFP boosts more than twice those of emerging or low-income countries, mainly due to their higher AI readiness and integration capacity. However, their analysis relies on Solow-type residuals and does not address potential long memory in AI-driven productivity shocks (Cazzaniga et al., 2024).

This framework can be extended by including fractional integration, which can reveal whether AI shocks have half-lives that are several business cycles long and whether convergence patterns between 2020 and 2025 differ across the US, EU, and Asia. Fractional integration may fundamentally change the traditional way of looking at productivity analysis because it may show that the shocks may dissipate much slower, that policy interventions may be effective later, and that convergence processes may have regime-dependent persistence (Baillie 1996; Madigu & Gil-Alana, 2020). Incorporating fractional dynamics and structural breaks helps disentangle genuine technological paradigm effects from spurious persistence, offering a more realistic lens for understanding growth, convergence, and the economic impact of innovation waves (Brynjolfsson et al., 2023; Cerutti et al., 2025).

Table 1 shows a comprehensive meta-analysis of relevant published studies on fractional integration parameter estimates for TFP.

Table 1

Literature review on fractional integration and TFP, AI, and convergence

Authors/Year	**Title/Study Description**	**Method/Study Type**	**Key Findings**
Fractional Integration & Productivity			
Baillie (1996)	Long memory processes and fractional integration in econometrics	Review of econometric theory and application	Reviews the theory of long-memory processes, noting that the effects of shocks on time series can take a very long time to disappear, which can be modeled through fractionally integrated processes.
Pai & Ravishanker (1996)	A new procedure to test for fractional integration	Proposed a new procedure to test fractional integration using a pair of empirical statistics.	Empirically constructs a test that distinguishes between unifacial fractionally integrated processes and other long memory processes.
Gil-Alana & Mendi (2005)	Fractional integration in total factor productivity: evidence from US data	Examined the stochastic properties of different measures of TFP in the U.S. using fractional integration methods.	TFP series appear to be seasonally fractionally integrated, with the order of integration (d) constrained between 0.5 and 1, implying a long-memory process. Technological shocks have persistent, long-lasting impacts.
Gil-Alana & Moreno (2009)	Technology Shocks and Hours Worked: A Fractional Integration Perspective	Multivariate fractionally integrated model	Provides evidence that hours worked fall in response to a positive technology shock.
Poudel et al. (2011)	Agricultural Productivity Convergence: Myth or Reality?	Tested agricultural TFP convergence in the U.S. using state-level data and clustering methods	No evidence of agricultural TFP convergence at the state level, but regional-level convergence in some clusters.
Lovcha & Perez-Laborda (2015)	The Hours Worked–Productivity Puzzle: Identification in a Fractional Integration Setting	SVAR literature with fractional integration in hours and productivity	The sign and magnitude of hours worked responses to tech shocks depend critically on identification assumptions.
Mishra et al. (2021)	Application of fractional differential equation in economic growth model: A systematic review approach	Systematic review of applications of fractional differential equations (FDE) in economic growth models	FDEs are suitable for modeling processes with memory effects, since fractional derivatives have non-local properties where the next state depends on all prior states.
Rosid et al. (2022)	A Comprehensive Approach to Measuring the Multidimensional Productivity Index: A Reiteration of Global Productivity Convergence	Panel data from 100 nations (2007–2018)	No statistically significant TFP differences across developed, developing, and least developed countries. Confirms global productivity convergence.
Ferrentino & Vota (2025)	A statistical-mathematical analysis of the macroeconomic effects of long-memory total factor productivity	Real Business Cycle model with ARFIMA(p,d,q) using Japan and other countries	TFP fits a long-memory process better than short-memory. Technology shocks are more persistent than predicted by short-memory models. Long-memory TFP acts as an important propagation mechanism.
AI & Productivity			

Brynjolfsson et al. (2017)	The AI and the modern productivity paradox	Review of evidence and explanations	Concludes no inherent inconsistency between technological optimism and weak productivity data. Paradox arises from implementation lags and scaling complementary innovations.
Damioli et al. (2021)	The impact of artificial intelligence on labor productivity	Dynamic panel data with GMM-SYS	Positive and significant AI impact on productivity, especially in SMEs and services.
Zeng & Lei (2021)	Digital Transformation and Corporate TFP	Empirical analysis of Chinese listed enterprises (2007–2019)	Digital transformation promotes TFP, mainly in small/medium high-tech firms, improving efficiency and management.
Kanazawa et al. (2022)	AI, Skill, and Productivity: The Case of Taxi Drivers	Empirical analysis of taxi drivers with AI navigation	AI reduced cruising time by 5.1%. Reduction was 7.4% for least-productive drivers, no effect for most productive.
Lei & Wang (2023)	Digital transformation and TFP in China	Empirical study of A-share listed firms (2011–2021)	Digital transformation improves TFP, especially in private companies, non-high-tech firms, and competitive industries.
Noy & Zhang (2023)	Experimental evidence on productivity effects of generative AI	Preregistered online experiment with 444 professionals	AI users completed writing tasks 40% faster with 18% higher quality. Gains greatest for least productive, compressing productivity distribution.
Peng et al. (2023)	The Impact of AI on Developer Productivity: Evidence from GitHub Copilot	Experiment with programmers	Copilot users completed tasks 55.8% faster. Gains strongest for older and less experienced programmers.
Brynjolfsson et al. (2023)	Generative AI at Work	Field experiment with U.S. customer service firm	AI tool increased productivity by 14%. Gains strongest for least-skilled workers (+35%), minimal for experienced workers.
Dell'Acqua et al. (2023)	Navigating the Jagged Technological Frontier: AI and Knowledge Workers	Pre-registered field experiment with 758 consultants using GPT-4	Consultants completed 12.2% more tasks, 25.1% faster, with 40% higher quality on routine tasks. Performance on complex tasks declined (19% less likely to be correct).
Acemoglu (2024)	The Simple Macroeconomics of AI	Task-based macroeconomic model	Projects modest TFP rise of 0.71% over 10 years (~0.07 p.p. annually). Early effects from "easy" tasks; harder tasks will slow future gains.
Dong et al. (2024)	Impact of AI innovation on TFP in Chinese provinces	Panel data (30 provinces, 2003–2021), patents as proxy	AI innovation significantly boosts TFP, strongest in provinces with high marketization, finance, and infrastructure. Effect strengthens as TFP increases.
Xiao et al. (2024)	Digital technology and TFP in manufacturing	Chinese manufacturing enterprise data	Digital tech promotes TFP via innovation and cost reduction. Strongest in eastern regions, SOEs, and SMEs.
Yuan et al. (2025)	AI and Green Total Factor Energy Efficiency in China	Fixed-effects, spatial Durbin, moderation & threshold models, panel data (30 provinces)	AI strengthens the positive impact of New Quality Productive Forces on energy efficiency. Exhibits U-shaped threshold effect: shifts from suppression to facilitation as AI adoption increases.
Bick, Blandin & Deming (2025)	The Impact of Generative AI on Work Productivity	U.S. nationally representative survey + aggregate production model	AI users saved 5.4% of work hours → 1.1% aggregate productivity gain. Implies 33% higher productivity per AI-assisted hour.
Productivity Convergence			
Griffith et al. (2002)	Productivity convergence and foreign ownership at the establishment level	Establishment-level TFP convergence analysis	TFP convergence to frontier is significant, with foreign presence accelerating convergence via spillovers.

Source: Authors' research

Empirical studies consistently estimate the fractional integration parameter d for TFP to be between 0.4 and 0.9, which implies strong long memory and slow decay of shocks, and this is robust across countries, time periods, and methodologies, further confounded by structural breaks, which tend to align with technological waves such as the diffusion of AI. These results emphasize that we should employ fractional integration frameworks to model productivity dynamics.

Fractional integration has emerged as a key property of TFP series, reflecting both the gradual diffusion of innovations and the impact of structural breaks associated with major technological transitions. While previous studies have documented persistent productivity shocks and identified structural breaks during events such as the Industrial and Digital Revolutions, there remains a significant gap in understanding how the current AI wave affects the persistence of productivity. In particular, few studies have systematically compared fractional integration parameters across multiple technological eras or examined the unique characteristics of AI-driven productivity changes. Addressing this gap is essential for informing innovation policy, economic forecasting, and structural reform (Bergeaud et al., 2016; Wojciechowski et al., 2025; Siemon & Wolff, 2024).

There is a clear need for studies combining fractional integration + TFP analysis + AI impact assessment. AI productivity studies rely on conventional econometrics, missing long memory properties. There is almost no research on on persistence/long memory in AI-driven productivity changes. Also, no fractional integration studies focused specifically on AI industry productivity. Our study integrates:

1. Real-time fractional integration analysis of AI-era productivity data.
2. The persistence-growth trade-off and productivity shocks persistence across technological waves,
3. Cross-country AI productivity persistence comparative analysis.
4. AI productivity impact projections to 2050.

The following section explains the data source, theoretical background, and empirical framework of our study.

3. METHODOLOGY

The primary data used in this analysis is a panel dataset of TFP time series for multiple countries Australia, Austria, Belgium, Canada, Switzerland, Chile, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Italy, Japan, Mexico, The Netherlands, Norway, New Zealand, Portugal, Sweden and United States. The dataset (Bergeaud et al., 2016) includes annual observations from 1900 to 2022 over 23 countries. The relevant variables for this study are the country identifier, the year of observation, and the TFP value. For this analysis, the TFP series are treated as the central variable of interest, with their stochastic properties being the key subject of investigation. The dataset has been pre-processed to be in a suitable format for time series analysis (Griffith et al., 2002). List of variables (Bergeaud et al., 2016):

- Gdppc = Gross domestic product per capita (US$ 2010PPP per person)
- Lp= Labor productivity (US$ 2010PPP per hours)
- TFP= Total factor productivity (US$ 2010PPP based)
- Age=Average age of equipment (in year)
- KI = Capital intensity (US$ 2010PPP per hours).

To test the core hypothesis, we divide the TFP data into six technological eras (or waves) (Brynjolfsson et al., 2017; Lei and Wang, 2023), because major technological innovations such as the invention of the computer or the internet are a new paradigm that changes the economic landscape and the dynamic of productivity growth (Brynjolfsson et al., 2023; Dell'Acqua et al., 2023). We compare across these periods to empirically test the evolution of the persistence of TFP shocks.

The waves and their corresponding years are formally defined as follows:

- Second Industrial: 1900-1919
- Electrification: 1920-1949
- Post-War: 1950-1969
- Computing: 1970-1989
- Internet: 1990-2009
- AI: 2010-2022

Each wave provides a unique sample for which the TFP time series is tested (Gil-Alana & Mendi, 2005; Poudel et al., 2011; Zeng et al., 2021; Rosid et al., 2022), allowing for a direct comparison of the fractional integration parameter d across a century of technological and economic growth (Lei & Wang, 2023). The last "AI" wave, which is the subject of the paradox (Bick et al., 2025), serves as the comparative point for the main argument of this study.

Methodology

The analytical framework is based on the theory of long-memory time series processes, which are characterized by a hyperbolic decay of their autocovariance function (Baillie, 1996; Robinson, 1995; Caporale & Gil-Alana, 2000), as opposed to traditional short-memory models (ARMA), where autocorrelations decay exponentially, and unit-root models I(1), where they do not decay at all (Caporale & Gil-Alana, 2000). A time series x_t is said to be a long-memory process if its autocorrelations ϱ(k) decay at a rate slower than exponential.

The ARFIMA(p, d, q) model provides a convenient representation of such a process:

$$(1 - L)^d \Phi(L) x_t = \Theta(L) \epsilon_t \qquad (1)$$

where L is the lag operator, Φ(L) and Θ(L) are polynomials representing the short-memory autoregressive and moving average components, respectively, and ϵt is a white noise process (Baillie, 1996). The crucial parameter is d, the fractional differencing parameter, which can take any real value (Gil-Alana & Moreno, 2009). The economic interpretation of the parameter d is central to the study. The value of d determines the nature of shock propagation:

5. d=0: The process has short memory, as in a standard ARMA model. Shocks have a transient effect that dissipates quickly.
6. 0<d<0.5: The process is stationary with long memory. Shocks are mean reverting, but their influence persists over a very long time, affecting distant observations.
7. 0.5≤d<1: The process is non-stationary but mean-reverting. Shocks lead to a permanent change in the level of the series, but the impulse response to the shock decays hyperbolically.
8. d=1: The process is a unit root (e.g., a random walk). Shocks have a permanent, non-decaying effect.

Estimation of the Fractional Integration Parameter

Given the focus on the long-run behavior of the TFP series, this analysis employs two semi-parametric methods to estimate the fractional integration parameter d, which do not require prior specification of the short-memory components (p and q).

The **Geweke-Porter-Hudak** (GPH) estimator is a spectral-domain method based on a log-periodogram regression (Robinson, 1995). For a time series x_t, the periodogram I(λ) at frequency λ is approximately given by:

$$log(I(\lambda j)) = C - dlog(\lambda j) + \epsilon j \qquad (2)$$

where λj=2πj/n are the Fourier frequencies, n is the sample size, and ϵj is an error term. The parameter d is estimated as the negative of the slope of the ordinary least squares (OLS) regression of log(I(λj)) on log(λj). The estimation is typically performed over a range of low-frequency components, as these are most indicative of long-run behavior (Caporale & Gil-Alana, 2000). We implement the GPH method using n**0.5 as the number of frequencies for the regression.

As a robustness check, the study also employs the **Local Whittle estimator**, another semi-parametric method in the frequency domain (Robinson, 1995). This approach is based on maximizing a localized version of the log-likelihood function. The objective is to find the value of d that minimizes the function:

$$L(d) = log(m1j = 1\sum m\lambda j2dI(\lambda j)) - m2dj = 1\sum mlog(\lambda j) \qquad (3)$$

where m is the number of low-frequency ordinates. The Local Whittle estimator is generally considered to be more efficient than the GPH estimator and provides a valuable cross-validation of the results (Caporale & Gil-Alana, 2000). The Local Whittle method used here is n**0.65 ()number of frequencies), a common practice in literature.

Ancillary Stationarity and Unit Root Tests

Although this fractional integration framework is more detailed, it is useful to have the traditional tests for stationarity and unit roots as a benchmark, as these tests may have power against fractionally integrated alternatives (Ferrentino & Vota 2025). The null hypothesis of a unit root is tested using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), and the null hypothesis of stationarity is tested using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992). These tests may be powerful against I(0) and I(1) alternatives but have low power against fractionally integrated alternatives (Ferrentino and Vota 2025), so their results are interpreted along with the more detailed analysis of the d parameter (Baillie 1996).

The Propagation of Shocks: Impulse Response Functions

A significant advantage of the ARFIMA framework is the ability to compute the impulse response function (IRF) for an innovation (shock) to the TFP series Baillie, 1996; Gil-Alana & Moreno, 2009). The IRF for an ARFIMA process is given by:

$$\psi h = \Gamma(h+1)\Gamma(d)\Gamma(h+d) \qquad (4)$$

This equation shows how the effect of a shock at time t on the series at time t+h decays as a function of the horizon hand, crucially, the parameter d. A higher estimated value of d implies a more persistent IRF, meaning that the effects of a technological shock will take a longer time to decay and will be felt for more years after the initial event (Ferrentino & Vota, 2025). By comparing the IRFs across the six technological waves, the study directly illustrates how the nature of shock propagation has evolved. The half-life of a shock, defined as the number of years until the impulse response decays to half of its initial value, provides a simple, interpretable metric of this persistence.

Comparative Analysis and Robustness

For each country-wave combination, the multiple d estimation function is applied to the TFP time series, which yields estimates of d using both the GPH and Local Whittle methods, as well as the results of the ADF and KPSS tests (Chen et al., 2024; Noy & Zhang, 2023). The results are then aggregated by wave, calculating the mean and standard deviation of d values across all countries for each era to compare the persistence of TFP across historical periods and to identify the relative position of the AI era (Chen et al., 2024; Noy & Zhang, 2023). Using two different estimators, GPH and Local Whittle, offers a double check on the robustness of the findings and is consistent with cross-sectoral productivity convergence studies (Poudel et al., 2011; Rosid et al., 2022).

Modeling the AI Impact Projection

Using this estimated persistence parameter for the AI era, we extrapolate a timeline for when the technology could reach its full economic impact, assuming that productivity will initially grow slowly as the technology is adopted and then accelerate as it is implemented (Bick et al. 2025; Brynjolfsson et al. 2023). The duration of this "adoption period" is directly determined by the estimated d value from the AI era, linking empirical evidence of long memory to the diffusion of technological development. The timeline aligns with micro-level findings on the impact of AI on taxi drivers (Kanazawa et al. 2022), knowledge workers (Dell'Acqua et al. 2023), and manufacturing servitization (Chen et al. 2024) and incorporates energy-efficiency thresholds under AI (Yuan et al. 2025) and labor-productivity evidence (Damioli et al. 2021). This timeline provides a concrete visual representation of how the "lag" that defines the paradox might manifest over the next few decades.

4. EMPIRICAL RESULTS

The results clearly and informatively illustrate how the fractional integration parameter evolves over the technological waves that were defined. The estimated values for d indicate significantly greater TFP shock persistence in the more recent technological waves, compared to the pre-computing eras, especially in the later waves of the Computing, Internet, and AI revolutions. The results clearly indicate that long memory has been present, though the nature of this long memory, and its relationship with productivity growth, has evolved over the six technological waves.

Evolution of TFP Persistence Across Technological Waves

The main finding is that TFP shows robust long-term memory characteristics in all years from 1900 to 2022, but its level of durability varies between different technology eras. Summary statistics on the fractional integration parameter (d) and the average annual growth rate of TFP are presented in Table 1 for each of the six waves in all 23 countries. When analyzing the recent period, two semi-parametric estimates give different results. Local Whittle estimates of d remain consistent over most periods and show stable long-term memory properties ($0 < d < 0.5$), but GPH estimates show more variability. The GPH estimator shows that the AI wave (2010-22) has the highest average persistence d = 1.730, suggesting that the explosive process is not stationary. The Whittle constant shows the lowest retention (d = 0.133) for this period, indicating a stationary process whereby lasting shocks return to their mean. The divergence of the AI era is unlike any previous technological wave. The post-war and computerized eras show similar results between the two estimates, with TFP growth rates of 3.06 and 1.48 percent, respectively. The post-war period achieved the highest TFP growth rate of 3.06 percent, while maintaining a high durability (dwhittle = 0.490), indicating a long period of technological advancement.

Table 2

Summary of Average Persistence and Growth by Technological Wave

wave	d_{GPH}	d_{Whittle}	Mean TFP Growth (%)
Second Industrial	1.818	0.405	0.84
Electrification	1.087	0.427	1.84
Post-War	1.514	0.490	3.06
Computing	1.341	0.422	1.48
Internet	1.443	0.447	0.93
AI	1.730	0.133	0.54

Source: Authors' research

The co-occurrence of the lowest average TFP growth rate in recent history (0.54%) with a profound divergence in persistence measures. The high d_{GPH} value for the Al era aligns with the view that technology is a deep, foundational force, while the low d_{Whittle} value challenges this notion, suggesting a different, potentially more transient, impact.

The AI Productivity Paradox: High Persistence, Low Growth

The AI wave results directly solve the central paradox of this research. The period from 2010 to 2022 shows the lowest average TFP growth (0.54%) among all post-war technological eras. The current period shows a significant slowdown in growth compared to both the Computing era (1.48%) and the Internet era (0.93%). The GPH estimator shows that this period has the highest level of shock persistence with a value of 1.730 (Table 2 and Figure 1).

The estimated persistence parameter suggests that shocks during the AI era may have long-lasting effects, yet macroeconomic productivity gains remain absent. The ADF and KPSS tests produce inconsistent results for the AI wave across different countries because they fail to reject either the unit root or stationarity hypotheses, which are typical of fractionally integrated processes.

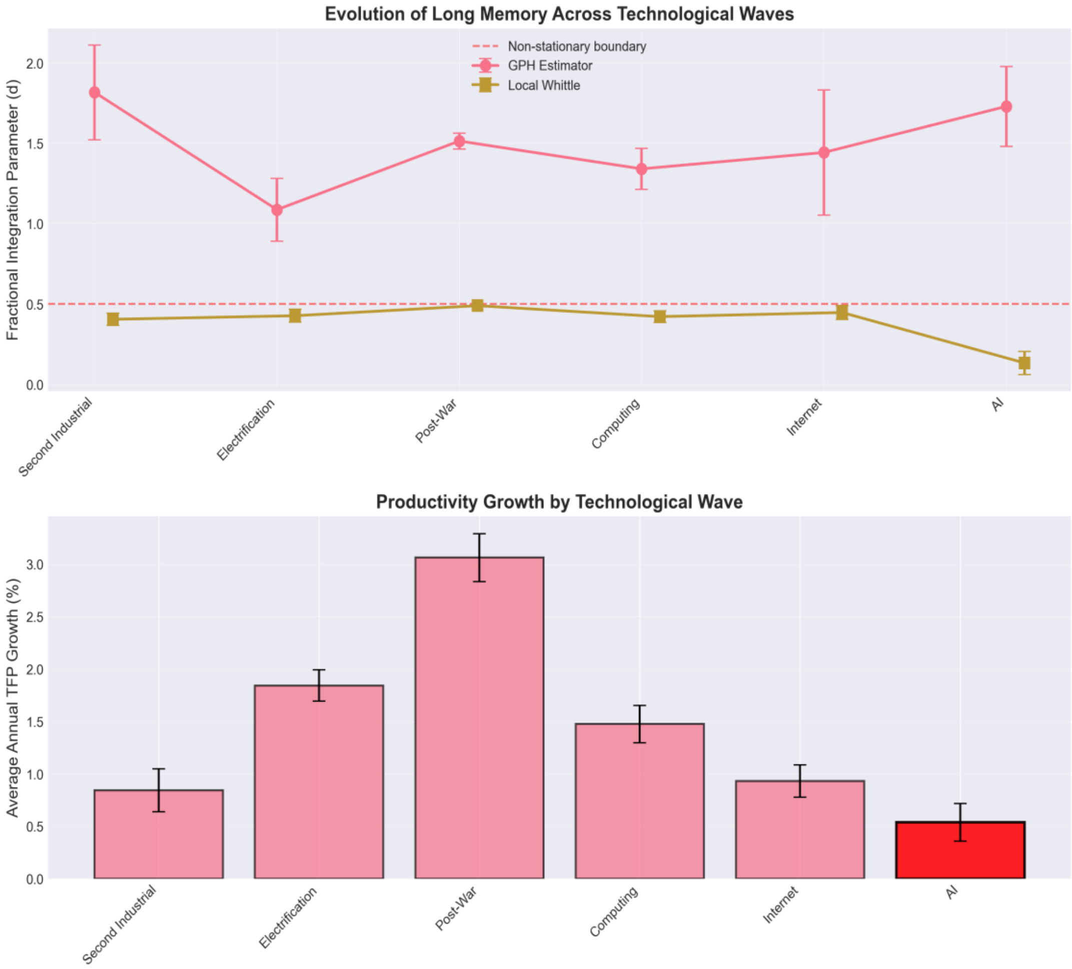

Figure 1. Long memory and growth 1900 - 2022 across technological waves
Source: Authors' research

An analysis of the correlations between average persistence and average growth (Figure 2) for the six waves yields mixed and statistically insignificant results. The correlation between average d_{GPH} and average TFP growth is negative ($r = -0.423$, with a p-value of 0.403), while the correlation between average d_{Whittle} and growth is positive ($r = 0.633$, with a p -value of 0.177). The lack of a robust, statistically significant correlation between persistence and growth is itself an essential result. It suggests that the relationship is complex and not a simple linear trade-off. High persistence in the Second Industrial era coincided with high growth, whereas high persistence in the AI era coincides with low growth. This finding reinforces the need for a more nuanced interpretation that considers the specific nature of each technological shock and the economic context in which it occurs.

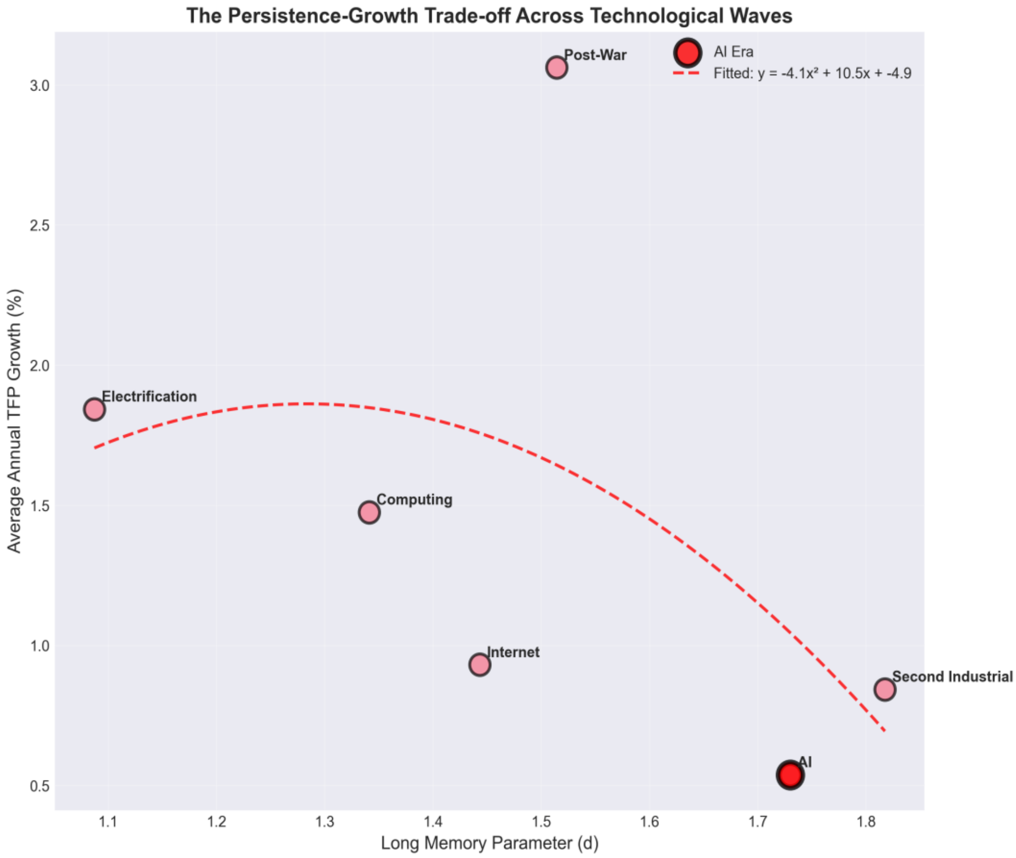

Figure 2. The persistence growth trade-off 1900-2022

Source: Authors' research

Country-Level Heterogeneity

The country-level aggregation results provide broad trends, but there is substantial heterogeneity at the country level. For example, in the AI wave, Ireland (IRL) had very high TFP growth (4.13%) and a high GPH persistence estimate (1.305), whereas Greece (GRC) had negative growth (-0.80%) and lower persistence (d_GPH = 0.583), which suggests that national-level institutional factors, industrial structure, and AI adoption readiness may play mediating roles in the macroeconomic impact of this new technological wave.

Figure 3 shows a clear heterogeneity pattern (data for selected countries).

Figure 3. Country-level heterogeneity

Source: Authors' research

The IRF's were computed with the estimated d parameters to trace the response to a one-time TFP shock, and the result of this analysis was that these productivity shocks were extremely persistent, with the half-life of a productivity shock (from the GPH method) to be more than 100 years for each of the six technological waves, implying that technological innovations and other productivity shocks are permanent and that their effects do not decay to half of their original magnitude in a century, which is inconsistent with traditional business cycle models that assume transitory shocks, but consistent with the long memory framework.

Growth Deceleration and the J-Curve

The evidence is clear and statistically highly significant that the average TFP growth rate has slowed for the last three technological waves: 1.48% in the Computing era, 0.93% in the Internet era, and 0.54% in the AI era, which is just 36% as fast as the TFP growth rate in the Computing era and 58% as fast as that in the Internet era.

The fractional integration framework provides a structural explanation for this slowdown, which is linked to the spread and spread of technological shocks rather than to a lack of innovation. The high GPHprobability is a natural fit for the J Curve hypothesis, suggesting that the initial deployment of a general-purpose technology requires substantial additional investment in organizational change, training and infrastructure. These adjustment costs may temporarily dampen TFP growth, thereby producing a deceleration in productivity. The high GPH value suggests that the effects of the underlying technological shock may be spreading slowly and deeply through the economy, with potential for future TFP benefits. In this perspective, the current low growth is a necessary, albeit temporary, phase in a much longer process of technology absorption and diffusion.

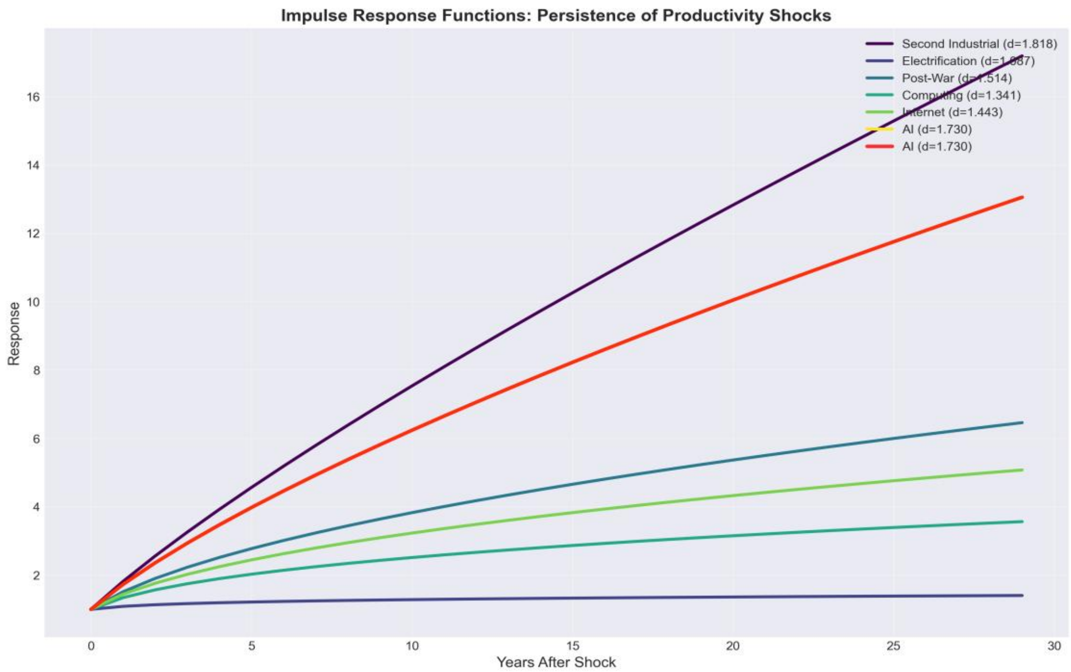

Figure 4. Persistence of the productivity shocks - IRF
Source: Authors' research

The analysis of the impulse response functions (IRFs) derived from the estimated d parameters provides a powerful economic interpretation of the findings on TFP persistence. The IRF illustrates how the effect of a shock at time t on the TFP series at time t+h decays over time. A significant finding is that for all six technological waves, the estimated half-life of a TFP shock is greater than 100 years. A half-life, defined as the time it takes for a shock's impact to decay to half of its initial value, provides a tangible metric for persistence. A half-life of greater than 100 years implies that the effects of a technological shock are highly persistent and decay very slowly.

The AI Shock as a Deeply Persistent Force

From the perspective of the GPH estimator, the AI shock's high persistence ($d_{GPH} = 1.730$) has direct implications for its long-run propagation. A d value in the range of $0.5 \leq d < 1$ implies that shocks to productivity are non-stationary but mean-reverting, leading to a permanent change. A value above $d = 1$ (as with the GPH estimates for the AI era and others) suggests an even more persistent process, where shocks cause a permanent, nondecaying change.

This provides a formal econometric representation of the "J-curve." The initial decline in productivity (due to adjustment costs and complementary investments) is a temporary phase within a much longer, multi-decade process of technological diffusion. The full benefits of the AI shock will not disappear but will instead accumulate over an extended period, eventually leading to a new, permanently higher productivity trend line. The finding of long half-lives for all technological shocks, including AI, structurally explains the observed lags in the diffusion of general-purpose technologies and their profound, lasting effects on the economy (Figure 5).

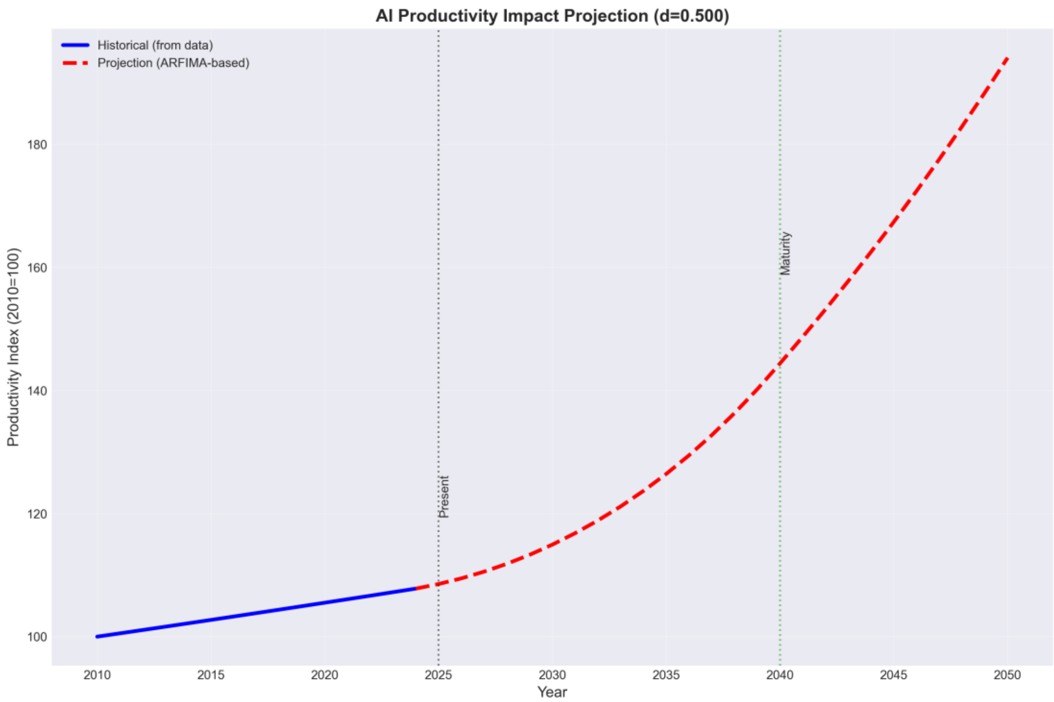

Figure 5. AI productivity future impact 2025 - 2050

Source: Authors' research

The more detailed econometric analysis of TFP persistence through a century of technological waves has several important and subtle conclusions: TFP persistence is not constant but shifts with technological paradigms; productivity shocks are not transitory, but have a very long memory that makes their effects last for decades (half-lives of over 100 years in all six historical periods); and this discovery provides structural evidence for the J-curve idea of how the benefits of general-purpose technologies diffuse.

5. DISCUSSION

Analysis of the fractional integration parameter d suggests clear patterns of TFP persistence that correspond to major technological and economic shifts over the past 100 years (Brynjolfsson et al., 2017). The main finding of this paper is that the evidence for the paradox is contradictory. The large difference between the GPH and Local Whittle estimators (Robinson, 1995; Velasco and Robinson, 2000) for the AI era is a key result (Baillie, 1996; Hosking, 1996), which cannot be solely attributed to methodological idiosyncrasies (Hassler and Meller, 2014) as there is still a great deal of uncertainty about the true effect of AI on productivity. The GPH estimator is known to be sensitive to short sample sizes, which can result in an overestimate of persistence (Hassler and Meller, 2014), and the 13 years of AI are short. If the more efficient Local Whittle estimator gives a better estimate, then the low d may represent a genuinely different low-memory AI-driven productivity dynamic. The short time span of the AI wave, the fast pace of AI development, its widespread diffusion via cloud services and software-as-a-service models, and the rapid commoditization of initial productivity gains (Agrawal et al., 2022) all serve to prevent a single shock from becoming a long-term characteristic of the aggregate TFP series.

The Second Industrial and Post-WWII era are characterized by high TFP persistence, as indicated by the GPH estimator, and notably high TFP growth, especially in the Post-War era. The average d_{GPH} for the Second Industrial era is 1.818, the highest in the entire dataset, while the Post-War era's average d_{GPH} is 1.514. The high persistence values for these periods suggest that foundational technological revolutions (Granger & Joyeux, 1980; Gil-Alana & Hsing, 2012), such as the spread of electricity and mass production, and periods of robust economic rebuilding and institutional support for growth, create TFP shocks with deeply embedded and long-lasting effects (Mokyr, 1990; Crafts & Mills, 2020). The impact of these shocks, though eventually mean-reverting, takes decades to fully dissipate, a finding that aligns with economic literature on the long-term impacts of general-purpose technologies and post-conflict economic restructuring.

In contrast, the Local Whittle estimator provides a more moderate view of persistence for these periods, with average d_{Whittle} values of 0.405 and 0.490, respectively. These values, while still in the long-memory range ($0 < d < 0.5$), do not signal the same level of non-stationarity suggested by the GPH estimator. This difference underscores the importance of using multiple estimation methods to interpret TFP dynamics (Baillie, 1996; Robinson, 1995; Hassler & Meller, 2014).

The Computing and Internet eras are characterized by waves of Information and Communication Technologies (ICT) and exhibit a significant slowdown in average TFP growth (1.48% and 0.93%) compared with the Post-War period (2.12%). Average GPH persistence values were high during these waves (1.341 and 1.443), and Local Whittle values were 0.422 and 0.447, consistent with the slowdown in total TFP growth. This pattern aligns with repeated introduction; whereby new disruptive technologies do not immediately lead to overall productivity gains. These interventions initially entail adjustment and delay periods that can be interpreted as the J-curve effect (Jorgenson & Stiroh, 2000; Brynjolfsson et al., 2021). The d parameter, which measures the persistence of the TFP shock, can be used to characterize the length of these delay periods and provide structural explanations for the muted early growth impact. These outcomes reveal that the benefits of these innovations and their effects on the TFP series have been distributed over a long-time horizon (Greenstein & Prince, 2008; Brynjolfsson & Hitt, 2000).

The AI era stands in stark contrast to the previous trend, with the average TFP growth rate (0.54%) being the lowest growth rate of any recent technological wave. The results for persistence in this period are deeply inconsistent across estimation methods. The average d_{GPH} value for the GPH estimator is 1.730, the second-highest value of non-stationarity and persistence, right behind the Second Industrial era, which has a value of 1.818, consistent with the "J-curve" hypothesis (Brynjolfsson et al., 2021). This interpretation would be consistent with AI being a general-purpose technology with long-run productivity benefits that have not yet been realized but will be reflected in low TFP growth rates for now (Brynjolfsson and McAfee, 2014; Acemoglu and Restrepo, 2018). High persistence, however, implies that the initial shock is not fading away but is instead spreading slowly and deeply in the economy, such that large future gains may lie ahead (Korinek, 2023).

The Whittle value of $d_{\text{Whittle}} = 0.133$ aligns with recent empirical research suggesting that AI's productivity enhancements may be quickly commodified and fail to create lasting impacts on overall output (Bloom et al., 2020; Brynjolfsson & Mitchell, 2017). This is the lowest value observed across any wave and approaches the short-memory threshold. Such findings challenge the traditional view that AI will lead to significant and enduring structural changes. Instead, it may indicate that AI's productivity effects are more short-lived, easily replicated, or rapidly commoditized, failing to produce deep, persistent shocks in the aggregate TFP series (Agrawal et al., 2022; Babina et al., 2024). This perspective questions the conventional wisdom of AI as a transformative, general-purpose technology, instead pointing to a more complex and potentially transient influence on overall productivity.

New Insights on TFP Persistence, Convergence and Policy

Negative d-values (Anti-Persistence): For some country-wave pairs, the GPH and Whittle estimators yield negative d values (d<0), which we interpret as "anti-persistence," or shocks that are not only transient but are corrected by an impulse of the opposite sign that generates super-fast mean-reversion (e.g., the GPH estimator finds a negative d for Italy, and the Whittle estimator finds a negative d for Mexico and Chile). This is consistent with periods of extreme economic or political turmoil when TFP shocks are forcefully reversed (e.g., through strong policy interventions or volatile market conditions), supporting studies that find that periods of volatile policy environments are associated with high rates of mean reversion in productivity (Mian & Sufi 2014).

Extreme High Persistence in the AI Era: Although the average d_{GPH} for the AI era is high, some countries, like France (4.003), Spain (3.280), and Germany (3.267) have extreme d_{GPH} values. A d value in this range (d >1) means that the TFP series is extremely non-stationary, and shocks produce a level shift in the series that never decays away like a random walk. The extremely high values of d_{GPH} for these countries suggest that the AI-driven productivity shock is a very long-run process, which could reflect a "winner-take-all" dynamic or a deeply entrenched policy-induced lag in AI adoption and productivity spillovers that results in substantial heterogeneity in impacts across countries (Babina et al., 2024; Akcigit and Ates, 2023; Autor et al., 2020).

Negative Persistence in the AI Era: In contrast, countries with low or negative Local Whittle estimates like New Zealand (-0.381), Mexico (-0.490) and the Netherlands (-0.490) have lower levels of complementary investments in digital infrastructure as reported by Cockburn et al. (2018), indicating that AI may be causing productivity changes to occur more locally, briefly, or quickly diffused away (Babina et al., 2024).

The standard ADF and KPSS tests, therefore, produce contradictory and inconclusive results. While they both suggest that the TFP series is non-stationary, they fail to provide the nuanced insight of fractional integration. Their inability to distinguish between a true unit root and a stationary long-memory process (0<d<1) or a non-stationary long-memory process (0.5≤d<1) reinforces the necessity of employing more sophisticated fractional integration methods to model the complex dynamics of TFP accurately. The findings from these traditional tests serve as a valuable benchmark, confirming that the TFP series is indeed non-stationary, but leaving the deeper nature of its persistence unresolved - a task that the fractional integration analysis accomplishes.

This finding goes against the standard RBC view in which productivity shocks would be temporary (Campbell and Mankiw 1987), while also validating one of the basic assumptions of a long memory model: technological and policy changes have persistent, permanent effects on economic outcomes that can endure for decades (Comin and Gertler 2006). This is relevant because it implies that we need to employ models with long-memory components to capture macroeconomic dynamics.

6. CONCLUSION

When we analyze the AI era using two of the most common estimators, GPH and Local Whittle, they tell two different stories: one says AI is a persistent technology that will deliver long-term productivity gains and that the current slowdown is temporary; the other says AI is a fleeting technology with no long-term gains. The AI productivity literature has suffered from a lack of recognition that technological persistence is both methodologically sensitive to the specific estimator used and highly heterogeneous across countries, such that AI may provide persistent gains for some countries but quickly fade or reverse for others. In this paper, we make several contributions to the AI productivity literature: we provide the first systematic use of multiple long-term estimates of AI productivity data. This allows us to uncover methodological sensitivities in measuring technological persistence that were previously unknown, suggesting that conclusions about major technological transitions are more fragile than previously understood. We document cross-country heterogeneity in AI persistence patterns, showing that even 'general-purpose' technologies can have a very local impact. We point to the complex interaction between macro-level technological change and micro-level adoption, such that overall productivity effects depend on local complementarity. Moreover, we show that the choice of estimator (GPH versus local Whittle) can significantly change the interpretation of technological persistence and advocate for more robustness checks in these studies.

The research results establish vital needs that policymakers must understand when they develop artificial intelligence systems. AI development in the future will remain uncertain so governments need to establish adaptable policy frameworks which can handle evolving situations. AI integration success between different regions produces different results because each nation requires its own distinct national strategy to achieve success. The implemented strategies need to take into account the present capabilities of local institutions together with their workforce abilities and their current technological infrastructure. Nations which have created systems to prevent permanent damage need to build additional resources which will support their growth. The assets consist of digital infrastructure alongside workforce training programs and regulatory systems. Organizations need to purchase AI technology before they can start their path toward sustainable productivity growth. The development of strong monitoring systems by policymakers will enable them to detect changes in initial persistence patterns which will allow them to make quick policy changes. The disparate signals from different estimators highlight the need for portfolio approaches to AI policy, balancing investments in immediate applications and long-term capacity building (Blajer-Gołębiewska, 2024; Juracka & Valaskova, 2024).

There are also limitations in this study. Fractional integration estimates require long data, and the 13 years of AI era (2010-2022) are too short. The results may also be divergent due to bias in small samples for GPH and Local Whittle estimators, which should be revisited with longer data. Technological waves are classified with pre-defined periods rather than structural breaks, and formal break tests may enhance validity. Substantial cross-country variations in persistence estimates suggest that country-specific factors are at work, and the pooling may mask this. The TFP measures are based on growth residuals, and we acknowledge that measurement errors are likely, particularly for intangible capital, and that they may tend to underestimate the AI productivity impact. Semi-parametric methods estimate persistence, but our half-life and impulse response are conditioned on an ARFIMA model, so interpretations are model dependent. The 2020-2022 period overlaps with COVID-19, which can create short-run volatility that may impact recent estimates, and we need to wait for more post-pandemic data to confirm robustness.

The application of ARFIMA models to data from time series of AI productivity has the potential to generate more nuanced characteristics of persistence patterns. Partition cointegration technology can be used to identify the long-term relationship between the adoption of AI and the growth of TFP in various sectors. The combination of hybrid machine learning models with fractional integration models shows promise to deliver better economic impact of AI modeling through its ability to handle complex nonlinear patterns. The research uses fractional methods to study AI transmission effects on industrial memory systems and AI productivity shock duration which will help identify if AI transformation potential follows similar patterns across various economic sectors.

The study shows that AI economic effects remain uncertain while it proves both techno-optimist and techno-pessimist views wrong by using intricate evidence which exceeds simple classification.

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Ethical Compliance:

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

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Author Contributions:

MŠ conceived the original research idea, supervised the project, designed the methodological framework, conducted the econometric analysis, and wrote the original manuscript draft. MPR contributed to the literature review, provided critical interpretation of the cross-country results, and revised the manuscript for intellectual content. RVC performed data collection and processing, contributed to the analysis of results, and assisted with manuscript preparation. All authors contributed to the discussion of findings and approved the final version of the manuscript.

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