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From Econometrics to e.conometrics

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Abstract

Starting from the observation that econometric models have shown significantly degraded forecasting accuracy during structural breaks and crisis regimes, when past behavioural patterns can no longer serve as reliable guides for the future due to contextual changes (deglobalization, technological innovation, and reduced international cooperation), this paper examines models that have attempted to utilise nonlinear mathematics (such as that used by physicists), the related increasingly copious statistics and sentiments information that are accumulating, and Artificial Intelligence progresses. These models do not require a priori specification of structural economic equations as mandatory starting points and benefit from increasing computational power that machine learning techniques make better use of. In this framework, economic theory is not abandoned but repositioned: it enters as optional constraints, informed priors, or evaluation benchmarks rather than as the foundational architecture of the model. The paper provides a concise overview of the progress made in this domain and the results of initial experiments demonstrating the validity of AI methods in enhancing econometric forecasting.

Keywords

Econometric Models, AI Techniques, Econophysics, Data-Driven, Computational Power

1. Introduction

Never since Galileo's famous metaphor, reported in *The Assayer* (Galilei, 1623), has it been truer than nowadays that the world is an open book written in mathematics, indispensable for humans to understand it. The problem is in which specific mathematics was the world written. This was the question that Newton posed to himself when, seeing an apple fall, he wondered why it fell to the ground and not upwards. The solution lay in identifying the laws of gravity using the mathematics of physicists, that we call here for simplicity non-linear. Economists, benefiting from better computational tools (computers), used linear mathematics to certify their theories and forecast future economic behaviours of macro-variables (GNP, Consumption, Import & Export, etc.). For almost a century this was the Promethean dream of economists for harnessing the uncertainty of the future, decoding its hidden logic, and providing policymakers and market operators with a map to navigate the complex currents of the economy, that we call today econometrics. The dream was based on a premise as powerful as it is, in hindsight, fragile: that the future would behave according to the patterns of the past, and that these patterns could be distilled into a set of stable mathematical relationships, interpreted through hypotheses about the aggregate behaviour of economic agents.

For decades, in a world characterised by relatively stable economic policy trends and relatively uneventful technological innovation, this paradigm has provided very useful results, fostering confidence in an economic universe that adheres to a quasi-Newtonian order.

The end of political cooperation between global blocs, the deceleration of global trade, the explosion of finance, and an unrelenting technological revolution have introduced such radical uncertainty into the economy that it is no longer fully manageable with traditional econometric tools—particularly in macro nowcasting during sudden shocks, medium-horizon GDP forecasting during recessions, and structural model-based predictions—because this alters the very foundations of the system, making past behaviour an unreliable guide for the future.

Econometric models have begun to show predictions that are far from reality, especially in times of crisis and sudden transitions, creating a context from which Artificial Intelligence (AI) has emerged, with logical roots dating back to the distant past but performances matured over the last half century.

It is not simply "a new tool to add to the toolbox of the economist" of Robinsonian (Joan Robinson) memory but represents a "philosophical" paradigm shift. The AI approach does not begin with a strong theoretical hypothesis about how the economy works, like econometrics, but embraces the complexity and totality of the components of reality (the "data," i.e., statistics and information); it does not seek to impose an a priori order, but rather to discover the order emerging from a continuous flow of heterogeneous and unstructured data. This does not imply the absence of all modelling assumptions—every model embeds implicit choices in feature design, architecture, and training procedure—but rather that structural economic restrictions are no longer a prerequisite for the model to function.

Despite its popularity, it struggles to assert its "predictive" capabilities because, as Keynes taught us, in order to conceive new ideas, we must move beyond the old ones, while the world is still immersed in them (Keynes, 1936). AI does not "predict" the future in the classical econometric sense, rather provides a continuous, multidimensional forecast of reality, a very high-resolution snapshot of the economic system, which constantly adapts to ongoing evolutions. We believe that future developments in quantum computing and AI will be such that this limitation can also be overcome.

This work does not propose abandoning the mathematical rigor of econometrics, but rather enriching it, freeing it from axioms that are no longer tenable. The advanced AI frameworks discussed in this paper, inspired by the physics of complex systems, seek answers in a world that is no longer linear, stationary, or in equilibrium, if it ever was or even tends to be.

A new paradigm has emerged that does not seek a "one-size-fits-all" model, but rather a flexible framework that integrates economic theory with the power of modern computational approaches.

We define this framework as "e.conometrics." An approach qualifies as e.conometric—as distinct from a conventional econometric model augmented with more information, and machine learning—if it satisfies the following criteria: (i) it relies on non-linear, non-parametric, or data-driven modelling techniques that do not require the a priori specification of structural equations relating economic variables; (ii) it integrates alternative and/or high-frequency data sources beyond traditional macroeconomic aggregates into the forecasting pipeline. These criteria serve as the organizing principles for the methodological taxonomy presented in Section 3 and the empirical validation in Section 4.

2. The Classical Econometric Paradigm

We will not delve into the econometric models, which the readers of this Journal will certainly be familiar with, but we will briefly recall the logical tree (trunk, branches, twigs). The trunk is the CLRM (*Classical Linear Regression Model*), a theoretical framework whose parameters are typically estimated using the *Ordinary Least Squares* (OLS) method (Greene, 2012). It is a highly elegant mathematical tool that, under a well-defined set of assumptions, aims to estimate the strength and nature of the relationships between economic variables, providing a framework for testing hypotheses.

The idea is seductive: starting from a theoretical hypothesis about how the economy works, testing its components (consumption, investment, exports, etc.), and building an explanatory model in which the complex interaction between dependent and independent variables is captured by a matrix of coefficients of the estimated behavioural functions—that is, the main components of the vital tree.

The model was used since its inception to estimate causal relationships between variables, and, beginning in the 1920s, Ragnar Frisch and Jan Tinbergen used it to validate certain theoretical hypotheses on the functioning of the economy (Frisch, 1933, and Tinbergen, 1939). In 1944, Franco Modigliani developed a mathematical model of Keynesian interpretation according to the so-called neoclassical version (Modigliani, 1944). Following the computing power increase, in the 1960s, Modigliani himself, together with Frank de Leeuw, and Albert Ando launched the MIT-FED-PENN model, and from then on, econometric models became widely used (in Europe, with Bank of Italy's M1BI) (Ando & Modigliani, 1963).

Two main applied approaches branch off from the CLRM:

- *Time Series Analysis* focusing on the analysis of economic variables over time, starting from assumptions of stationarity and linearity. Standard models such as VAR (*Vector Auto-Regressive*) (Sims, 1980), BVAR (*Bayesian VAR*) (Litterman, 1986), and SARIMA (*Seasonal Auto-Regressive Integrated Moving Average*) derive from this. A critical assumption of the CLRM is homoskedasticity (constant variance). Violating this assumption (heteroskedasticity) led to a super-branch dedicated to volatility modelling, with ARCH (*Auto-Regressive Conditional Heteroskedasticity*) models (Engle, 1982), and their generalisation, GARCH (*Generalized ARCH*) (Bollerslev, 1986).

- *Structural Modelling* attempts to map the fundamental relationships of the economy based on equilibrium assumptions and rational agents. This branch includes the complex theoretical DSGE (*Dynamic Stochastic General Equilibrium*) models (Stiglitz, 2018) and, as a more specific application for very short-term forecasting (nowcasting), BE (*Bridge Equations*) (Giannone, Reichlin, & Small, 2008), which connect data at different frequencies. Their limitation is the aggregation of only traditional indicators, ignoring the wealth of signals coming from alternative data—that is, non-traditional, often high-frequency information sources not produced by official statistical agencies. For example, aggregated credit card transaction volumes can serve as a real-time proxy for household consumption, while tourism flow data can capture shifts in service-sector activity weeks before official GDP figures are released. These signals can provide a more accurate and timely view of the state of the economy.

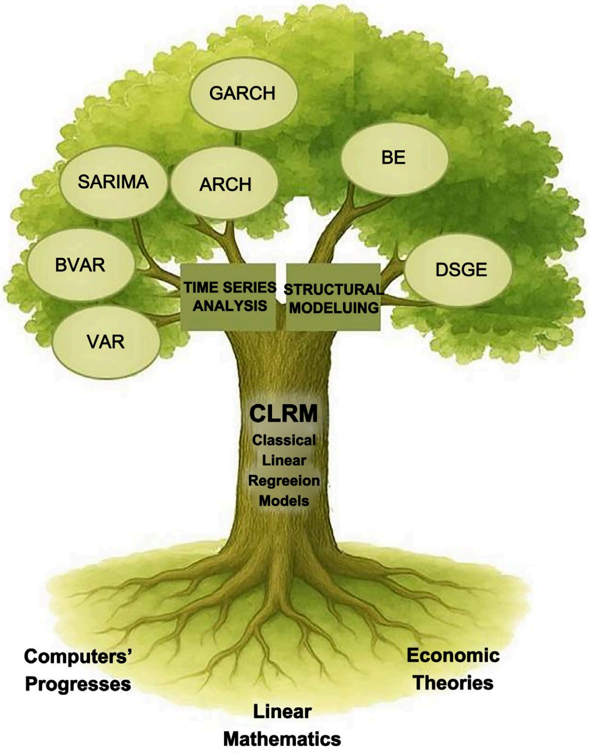

Figure 1. The logical structure of the classical econometric paradigm. (Roots: *Linear Mathematics*, *Economic Theories*, *Computers.* Trunk: *CLRM* (*Classical Linear Regression Model*). Left Branch: *VAR*; *BVAR*; *SARIMA*, up *ARCH*; *GARCH.* Right Branch: *DSGE*; *BE*)

This representation highlights the cornerstones of the growth of the AI shrub, rich in applications that mark the theoretical and practical progress with respect to the stages shown in **Figure 1**.

Despite significant mathematical refinements, econometrics has shown the weaknesses of its logical underpinnings, primarily during economic turning points—financial crises, pandemics, and geopolitical shocks—where structural breaks, non-stationarity, and omitted nonlinearities cause systematic forecast failures. In such regimes, it proves to be an imperfect tool for navigating the complexity of the modern world. Its assumptions, created to ensure mathematical tractability, have become shackles that limit its ability to see the world for what it is: nonlinear, unstable, interconnected, and dominated by emergent behaviours—that is, macroscopic regularities, such as volatility clustering in financial markets or power-law distributions in firm sizes, that arise spontaneously from the decentralised interaction of heterogeneous agents and cannot be deduced from any individual agent's behaviour alone.

Meanwhile, a new paradigm has emerged, which can be synthesised with the popular term *Artificial Intelligence* (AI).

3. The e.conometrics Framework

The structural changes in the global economy, discussed earlier, do not require simple incremental adjustments to existing models, but a fundamental paradigm shift. The limits of the classical paradigm, rooted in assumptions of linearity, stationarity, and optimizing rationality, make it inadequate for a world dominated by radical uncertainty, complex interconnections, and emergent behaviours (**Figure 2**).

His approach abandons the metaphor of the single, hierarchical, and *top-down* logical tree (the CLRM tree of **Figure 1**) in favour of a more organic and decentralized structure, akin to a "shrub" or a system of interconnected trees. This metaphor reflects a *bottom-up*, adaptive, and intrinsically multidisciplinary approach. The economic system is no longer seen as a Newtonian mechanism, but as an ecology or a complex adaptive system.

This new paradigm is not based on a single, all-encompassing theory, but on a set of interacting foundations and methodologies. As illustrated in **Figure 2**, the structure of e.conometrics can be taxonomized into foundational roots, two distinct but complementary methodological trunks (with their respective branches), and a crown representing the frontier of hybrid integration.

The shrub's roots are non-linear mathematics—more precisely that used by physicists, named *econophysics* (Mantegna & Stanley, 2000; Bouchaud & Potters, 2003)—higher computational powers—quantum computers in perspective—and Neurosciences (Rangel, Camerer, & Montague, 2008). Altogether they see the economy in general, and financial markets in particular, not as mechanisms, but as ecologies, that is, relationships between humans and the environment in which they live (Farmer & Axtell, 2025).

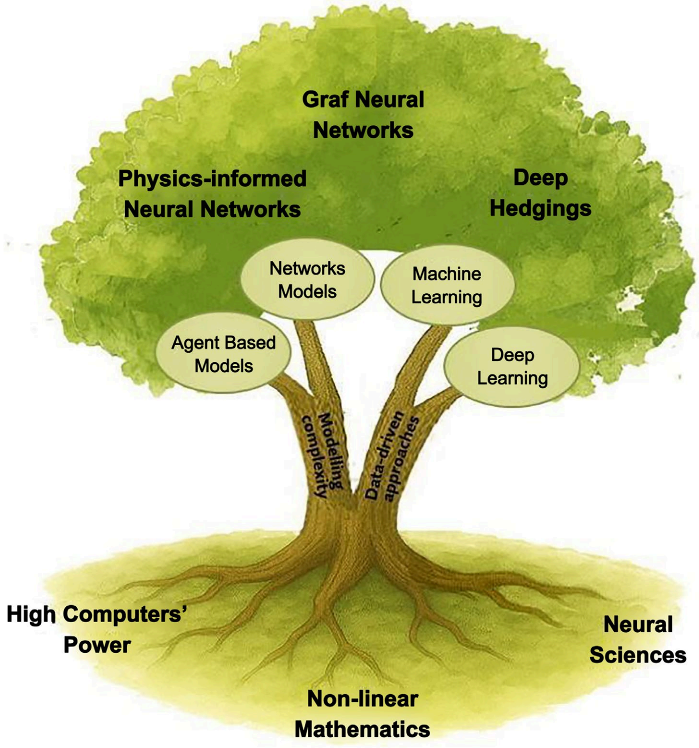

Figure 2. The interdisciplinary structure of the new e.conometrics Paradigm. (Roots: *Non-Linear Mathematics*; *High Computational Power*; *Neural Sciences*. Left Trunk: *Modelling Complexity*. Branch 1: *Agent Based Models*; *Networks Models.* Right Trunk: *Data-Driven Approaches.* Branch 2: *Machine Learning*; *Deep Learning.* Tree Crown: *Physics-Informed Neural Networks*; *Graph Neural Networks*; *Deep Hedging*)

Two trunks emerged as main approaches:

Modelling Complexity, with two branches: *Agent Based Models* (ABMs), and *Networks Models* (NMs).

Data-driven Analysis, with two branches: *Machine Learning* (ML), and *Deep Learning* (DL).

The shrub shows a crown: *Physics-Informed Neural Networks* (PINNs), *Graph Neural Networks* (GNNs), and *Deep Hedging* (DH)

In this context, econophysics plays a central role identifying universal statistical regularities, known as *stylized facts*, which act as the equivalent of physical laws for economic systems (Frisch, 1933). Pioneering work has provided a solid empirical basis for this approach, documenting robust and ubiquitous properties such as heavy-tailed return distributions, volatility clustering (the autocorrelation of absolute returns), and the leverage effect.

3.1. The Roots: The Foundations of the New Paradigm

The foundations of the old paradigm were Linear Mathematics and classical Economic Theory. The roots of the new paradigm are not only different but represent a liberation from the constraints imposed by those foundations. *E.conometrics* is made possible by three conceptual and technological "liberations": the liberation from linearity (Non-Linear Mathematics), the liberation from analytical tractability (High Computational Power), and the liberation from *homo economicus* (Neural Sciences).

3.1.1. Non-Linear Mathematics and Econophysics

While classical econometrics sought to force inherently non-linear economic phenomena into the tractable framework of linear mathematics, the first root of e.conometrics embraces this complexity, using econophysics, an interdisciplinary field that applies theories and methods from statistical physics to economic systems.

The fundamental contribution of econophysics is a shift in perspective: the so-called "stylized facts" (heavy-tailed return distributions, volatility clustering, leverage effects) are no longer seen as anomalies or violations of assumptions to be "corrected" (as attempted by ARCH/GARCH models in the old paradigm). Instead, they are recognized as the universal and fundamental statistical properties of a complex system composed of interacting agents. Seminal works like those of Mantegna and Stanley and Bouchaud and Potters (Mantegna & Stanley, 2000; Bouchaud & Potters, 2003) established the empirical foundations for this approach, demonstrating that these statistical regularities are the equivalent of physical laws for economic systems.

3.1.2. High Computational Power

If the first root provides the language (non-linear mathematics), the second provides the engine. Classical econometrics was itself a product of the first computational revolution: the advent of mainframe computers in the 1960s made large macro-econometric models like the MIT-FED-PENN possible (Modigliani, 1944). We are now living through the second computational wave, defined by widespread access to *High Performance Computing* (HPC) and *Graphics Processing Units* (GPUs).

This new class of computing power is the root that makes the other components of the paradigm practicable. Many of the theories of complexity and non-linear models had existed for decades but remained largely computationally intractable. It is the exponential increase in computing power that directly enables data-driven approaches (requiring the optimization of millions of parameters) and simulation-based approaches (requiring the simulation of millions of interacting agents) (Hamilton, 2006).

3.1.3. Neural Sciences

The third root provides the liberation from the most restrictive assumption of classical economics: the rational, optimizing agent, which forms the microeconomic foundation of the DSGE models criticized in Section 2. Neural Sciences, and in particular Neuroeconomics, provide an empirical and biologically plausible micro-foundation for economic behaviour (Rangel, Camerer, & Montague, 2008; Fehr & Camerer, 2007).

This field studies the neurobiological and computational bases of value-based decision-making, integrating methods from neuroscience, behavioural economics, and psychology. Neuroeconomic research conclusively demonstrates that human decision-making is not a unitary process of utility maximization, but the result of the interaction between multiple, often competing, systems that govern emotions, habits, heuristics, and cognitive biases. This understanding of "bounded rationality" provides the intellectual justification and behavioural foundations for building bottom-up, agent-based models, as we will see in the Left Trunk.

3.2. The Left Trunk: Modelling Complexity

This first trunk represents the generative and simulative approach to e.conometrics. Instead of starting from top-down aggregate equations (like the CLRM), this approach builds the system bottom-up. It defines the behavioural rules of heterogeneous agents (based on insights from Neural Sciences) and their modes of interaction; the macroscopic behaviour of the system (cycles, crashes, patterns) then *emerges* spontaneously from these micro-interactions.

3.2.1. Branch 1: Agent Based Models (ABMs)

ABMs are computational simulations that model a system as a collection of autonomous and heterogeneous agents (be they individuals, households, firms, or banks). These agents interact with each other and their environment according to adaptive, often sub-optimal, behavioural rules.

The primary function of ABMs is to act as "digital laboratories" to explore the dynamics of complex systems. They excel at explaining *emergent* phenomena—such as speculative bubbles, sudden crashes, and economic cycles—that classical equilibrium models, by their very nature, cannot predict (Farmer & Axtell, 2025; Wheeler & Varner, 2024; Biondo & Delli Gatti, 2024). They also allow researchers and policymakers to explore "counterfactual narratives" (e.g., "What would have happened if Lehman Brothers had been saved?") and to test the impact of policy interventions (like a fiscal stimulus or financial regulation) in a complex environment, capturing non-linear effects and distributional consequences. Recent reviews confirm that ABMs are "coming of age," moving from theoretical constructs to practical tools for policy and economic analysis.

3.2.2. Branch 2: Networks Models (NMs)

This branch complements ABMs by shifting the focus from the agents themselves to the connections between them. The modern economy, and particularly the financial system, is a complex *graph* of interdependencies: interbank networks, global supply chains, cross-credit exposures, and trade flows (de Paula, 2017; Jochmans, 2018). The analysis of these network structures is fundamental to understanding the system's resilience and fragility.

This methodological approach is the tool of choice for studying systemic risk, shock propagation, and financial contagion. It allows for the identification of "too connected to fail" institutions not based on their size, but on their centrality in the network. It is crucial to distinguish this branch (the *theory* and *econometric analysis* of networks) from its counterpart in the tree crown. *Networks Models* described here are the theoretical framework for describing and measuring the system's topology; *Graph Neural Networks* (Section 3.4.1) are the deep learning tool that learns and predicts the dynamics on that same structure.

3.3. The Right Trunk: Data-Driven Approaches

This second trunk represents the *predictive* and *theory-agnostic* approach. While classical econometrics (Section 2) starts from a strong theoretical hypothesis and uses data to estimate a pre-specified model, this approach inverts the process. Leveraging the High Computational Power root, it "lets the data speak", using statistical-computational methods to discover complex patterns and relationships without imposing a rigid a priori structure.

3.3.1. Branch 3: Machine Learning (ML)

Machine Learning (ML) offers a set of non-parametric statistical tools for the analysis of complex systems, focusing primarily on predictive accuracy. The adoption of ML replaces or supplements many steps of traditional econometric analysis (Mullainathan & Spiess, 2017; Ortiz & Rodrigo, 2025; Gogas, Papadimitriou, Goumenidis, Kontos, & Giannakis, 2025):

1) *Variable Selection*: Instead of relying on economic theory and (often problematic) p-values for variable selection, ML uses techniques based on regularization (like LASSO) or predictive importance, which effectively manage high dimensionality and collinearity.

2) *Unstructured Data*: Unlike econometric models, which require structured numerical data, ML models can natively ingest high-frequency alternative data, such as text (news articles, social media), through *embedding* techniques that transform qualitative information into dense numerical representations.

While classical econometrics is focused on parameter estimation and causal inference, ML is optimized for prediction.

3.3.2. Branch 4: Deep Learning (DL)

Deep Learning (DL) is a subclass of ML based on artificial neural networks with multiple layers (*deep neural networks*). These models have proven to be the most powerful tool for capturing extremely complex non-linear dependencies and long-term temporal patterns in data.

In e.conometric applications, architectures like *Long Short-Term Memory* (LSTM) (Hochreiter & Schmidhuber, 1997) or *Transformers* (Lim, Arik, Loeff, & Pfister, 2021; Zhou, Zhang, Peng, & Zhang, 2020) are the direct successors to the time-series models (VAR, SARIMA) criticized in Section 2. However, unlike their predecessors, DL models do not require rigid assumptions of stationarity or linearity and can simultaneously handle a vast number of time series.

Furthermore, DL models benefit from so-called *scaling laws* (Kaplan, McCandlish, Henighan, Brown, Chess, Child, & Amodei, 2020): unlike classical econometric models, which have a fixed number of parameters and quickly reach a performance plateau, DL models improve their predictive accuracy as computational power and, especially, the volume of training data increase. This makes them the technology of choice in the era *of big data.*

3.4. The Tree Crown: Hybrid Integration and the Frontiers

The true frontier of e.conometrics lies not in the choice between simulation (Left Trunk) and data (Right Trunk), but in their *synthesis*. The tree crown represents this hybridization: the use of data-driven models to calibrate and inform simulations, and the use of theoretical and simulative structures to constrain and guide data-driven models.

3.4.1. Graph Neural Networks (GNNs)

Graph Neural Networks (GNNs) represent the direct fusion of the Left Trunk (*Networks Models*) and the Right Trunk (*Deep Learning*). They are a deep learning architecture designed specifically to operate on graph-structured data (Zhou, Cui, Hu, Zhang, Yang, Liu, Wang, Li, & Sun, 2020).

While classical network analysis (Section 3.2.2) can describe the structure of a financial network, a GNN can learn the dynamics of shock propagation on that same network. In a systemic risk context, a GNN is trained to recursively aggregate information on the state of neighbouring nodes (other banks) and predict how the default or stress of one institution will propagate through the system, capturing non-linear contagion effects. Comprehensive surveys, such as that by Wu et al. (2020), have mapped the broad potential of these architectures for the non-Euclidean data typical of finance.

3.4.2. Physics-Informed Neural Networks (PINNs)

Physics-Informed Neural Networks (PINNs) fuse the Root (Non-Linear Mathematics/Econophysics) with the Right Trunk (*Deep Learning*) (Pateras et al., 2023; Brunton, Proctor, & Kutz, 2016). These models directly address the main problem of purely data-driven approaches: the "black box." A standard DL model, trained for pure predictive accuracy, might generate economically absurd or physically impossible results, such as violating the no-arbitrage principle.

PINNs solve this by incorporating theoretical knowledge—physical laws or, in our context, financial *Partial Differential Equations* (PDEs), like the Black-Scholes equation (Black & Scholes, 1973)—directly into the loss function of the neural network. As detailed in the seminal work of Raissi, Perdikaris, and Karniadakis (Raissi, Perdikaris, & Karniadakis, 2019), the network is trained simultaneously for two objectives: i) to minimize the error on observed data (market prices) and ii) to minimize the "residual" of the PDE, i.e., how much the network's solution violates the theoretical equation. This forces the neural network to learn solutions that are not only predictively accurate but also theoretically coherent.

3.4.3. Deep Hedging (DH)

Deep Hedging (DH) is perhaps the most sophisticated example of hybridization, blending simulation (Left Trunk) with *Deep Reinforcement Learning* (DRL), an advanced branch of Deep Learning (Right Trunk). This approach offers a radical departure from classical hedging models (like the delta-hedging derived from the Black-Scholes model).

The Black-Scholes model assumes perfect, complete, and frictionless markets. *Deep Hedging*, in contrast, does not seek an analytical solution. Instead, it trains a DRL "agent" to learn the optimal hedging strategy by interacting with a market simulator (often an ABM) that realistically incorporates real-world frictions: transaction costs, liquidity constraints, and market impact.

The main contribution on this was provided by Buehler et al. (2019). The agent is not trained to replicate a theoretical price, but to directly optimize a risk measure of the final *Profit & Loss* (*P&L*) *distribution*, such as the *Conditional Value-at-Risk* (CVaR). This leads to more robust, realistic, and economical hedging strategies, designed for incomplete and illiquid markets.

4. Summary, Empirical Validation, Conclusion

4.1. Summary

This work has traced the evolution from classical econometrics to *e.conometrics*. The logical tree of econometrics (**Figure 1**), based on linear mathematics and strong top-down theoretical assumptions (CLRM, DSGE), has demonstrated its fragility in the face of a non-linear, unstable, and shock-prone global economy.

The new e.conometrics paradigm (**Figure 2**) is not a single replacement model but a flexible, bottom-up framework that rests on multidisciplinary foundations (Roots): Non-Linear Mathematics (Econophysics), High Computational Power, and Neural Sciences. This framework integrates two main approaches: *Modelling Complexity* (Left Trunk), which uses simulation (ABMs) and network models (NMs) to understand emergent behaviours; and *Data-Driven Approaches* (Right Trunk), which use ML and DL to extract predictive patterns from large volumes of data.

The frontier of this field (The Crown) lies in the hybridization of these approaches—GNNs, PINNs, and DH—to create models that are simultaneously predictively powerful, theoretically grounded, and robust to real-world frictions.

4.2. Fast Data and Emerging Behaviors

A crucial element that distinguishes the new paradigm is the use of alternative, high-frequency data, capable of capturing dynamics that traditional macroeconomic datasets, with their slowness and rigidity, cannot grasp (Dvorak, 2023). Digital transactions, geolocalized mobility, satellite imagery, energy consumption, and textual or visual information extracted from the web represent a new information infrastructure.

These seemingly heterogeneous and noisy data take on predictive value when processed by machine learning architectures (Right Trunk) and linked to the world of econophysics (Root), capable of selecting, weighing, and integrating them with the constraints of economic theory (Crown). The output is not a deterministic forecast, but a multidimensional nowcast, an ultra-high-resolution snapshot of economic reality.

The most innovative aspect is the ability to capture emergent behaviours: phenomena that arise from the interaction of millions of agents (Left Trunk) and cannot be deduced from the sum of individual historical data. Power laws in firm distribution, volatility clusters in financial markets, and consumption patterns that change in real-time following exogenous shocks are examples of emergent regularities that become visible only through the combination of fast data and advanced computational power.

4.3. Empirical Validation: The IIEC "Econometric Accelerator" Project

The paradigm shift from econometrics to e.conometrics is not our mere theoretical proposal but is already being actively implemented in pioneering projects. A significant example is the ongoing research named "Econometric Accelerator," conducted by the Italian International Economic Center (IIEC, 2025) and the LUISS Quantum & AI Lab at Luiss Guido Carli University, with the computational support of CINECA.

This project embodies the principles of e.conometrics: it moves away from monolithic, theory-heavy models (like those in Section 2) to employ a dynamic, multi-model system that integrates Artificial Intelligence (Right Trunk) with econophysics principles (Root) and the use of a vast array of alternative and high-frequency data (Section 4.2).

The experimental setup can be summarised as follows. The target variable is the Italian real GDP quarter-on-quarter growth rate (year-over-year). The dataset comprises more than 50 variables at mixed frequencies (daily, monthly, and quarterly), sourced from official providers (ISTAT, OECD, Banca d'Italia, ECB), financial data vendors (Bloomberg, Refinitiv), and alternative data sources including electronic payment transactions, energy consumption, tourism flows, and sentiment indicators. The time series span from 1980Q1 to 2024Q4. Mixed-frequency data are aligned to quarterly frequency through a preprocessing pipeline that combines deterministic aggregation with Bayesian imputation. Model validation follows an Expanding Window Rolling Forecast strategy, ensuring strict temporal separation between training and test sets to prevent data leakage. The forecasting architecture is based on a dynamic ensemble combining time-series foundation models, gradient boosting regressors, and tabular foundation models, with model selection optimised independently for each forecast horizon (1 to 4 quarters ahead). The institutional forecasts shown in **Figure 3** (grey lines) correspond to publicly available projections issued by major Italian and international institutions over the same period.

The effectiveness of this approach, particularly in tackling periods of extreme volatility, is illustrated by the model's performance during the COVID-19 crisis. Figure 3 shows an out-of-sample forecast of the Italian GDP growth rate, comparing the IIEC's AI-driven estimate (blue line) with the actual growth rate (orange line) and the forecasts of various institutions relying on traditional econometric models (grey lines) (Simeone, Simeone, & Teza, 2025).

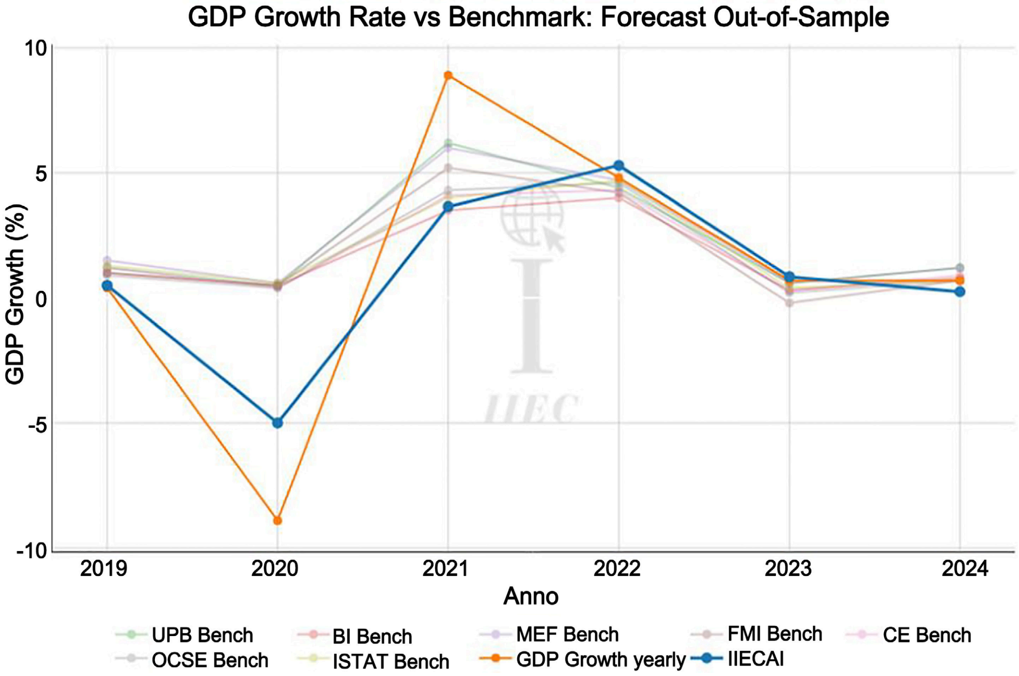

Figure 3. A comparison between the actual Italian GDP growth rate (orange line) and out-of-sample forecasts over the 2019-2024 period.

As is evident, the sudden and severe economic shock of 2020 caused a dramatic plunge in GDP, followed by a strong rebound in 2021. The traditional models (grey lines), calibrated on decades of relative stability and bound by linear assumptions, failed to capture the magnitude of this non-linear event.

In contrast, the IIEC model (blue line), by leveraging its ability to process real-time data and adapt to structural breaks (principles of the Right Trunk), tracked the real economic trajectory with notably greater precision. Figure 4 provides the quantitative validation of this observation.

If we observe the Median Absolute Percentage Errors (MdAPEs or Median MAPEs), Symmetric Median Absolute Percentage Errors (SMdAPEs or Median SMAPEs), and Root Median Squared Errors (RMdSEs or Median RMSEs), in each case, a lower dark bar signifies a smaller forecast error and thus higher accuracy of results.

At this stage, the aim is to demonstrate that the methodology is consistent with the e.conometric paradigm and capable of delivering more accurate economic predictions than the baselines described above.

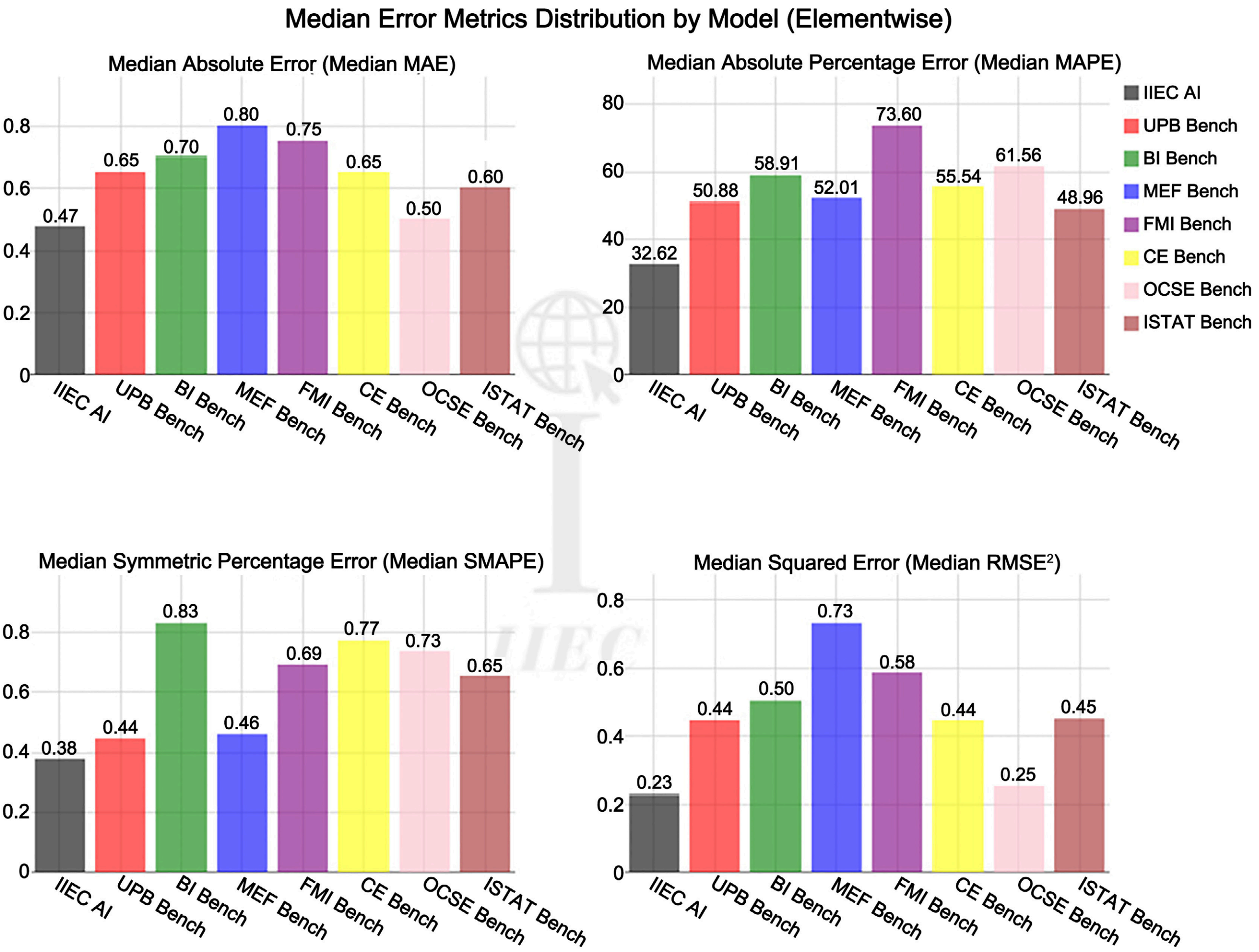

Figure 4. Quantitative performance analysis of forecast errors.

This preliminary result provides compelling evidence that the assumptions of linearity and stationarity underlying classical econometrics (Section 2) are inadequate for today's volatile world (Simeone, Simeone, & Teza, 2025).

The statistical basis, while adequate for a preliminary validation, was more limited than the researchers would have desired, owing in part to difficulties in accessing proprietary data sources for research purposes—a challenge that would benefit from a clearer legal framework distinguishing research use from commercial exploitation.

4.4. Conclusion

The preliminary empirical validation of the AI Econometric Accelerator project demonstrates that e.conometrics can provide more resilient and reliable tools for navigating and understanding the modern economy.

The weaknesses of the old models have real costs. Fiscal policies, which use econometric forecasts to draft public budgets, often mask forecasting errors behind complex political needs. Monetary policies, on the other hand, are paying a high cost in the form of losing their *forward guidance* function, applying a logic of *data-driven methods* on past data, that arrives late and often relies on personal judgments rather than robust e.conometrics models.

In this context, the real economy suffers while virtual finance thrives, fueled by the same uncertainty that the old models cannot tame. Embracing complexity, harnessing diverse data sources, and integrating the advanced computational methods described in the e.conometrics tree (**Figure 2**) is not just an academic exercise but a necessity for policymakers and market operators.

4.5. Limitations

While the e.conometrics framework represents a step forward in forecasting methodology, some limitations of the current work should be noted.

These constraints primarily relate to the present scope of the application, which serves as a preliminary proof of concept for the broader e.conometrics architecture. Future research will aim to extend this model to a wider array of macroeconomic indicators and diverse geographic regions, thereby enhancing the framework's robustness across varied and heterogeneous economic landscapes. There is also significant room to further optimize the synergy between the different structural layers of the e.conometrics "crown", particularly in refining how advanced computational power interacts with hybrid modeling frameworks to handle increasingly complex datasets. Additionally, while the current approach effectively integrates various information streams, subsequent iterations will focus on the continuous refinement of data acquisition techniques, especially concerning high-frequency and alternative sources that are essential for navigating periods of structural change and high uncertainty. Such developments will facilitate the evolution of the methodology into a more versatile and adaptive tool, capable of providing deeper insights for decision-makers and stakeholders operating within an ever-shifting global economic environment, ultimately bridging the gap between theoretical modeling and real-world operational needs.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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