Modern Economy, 2026, 17(9), 1238-1253
https://www.scirp.org/journal/me
ISSN Online: 2152-7261
ISSN Print: 2152-7245

From Econometrics to E.conometrics: Models, Forecasting, and Conditions of Validity

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How to cite this paper: La Stella, L. (2026). From Econometrics to E.conometrics: Models, Forecasting, and Conditions of Validity. *Modern Economy, 17,* 1238-1253.
https://doi.org/10.4236/me.2026.179059

Received: June 18, 2026
Accepted: September 21, 2026
Published: September 24, 2026

Abstract

The transition from econometrics to e.conometrics proposed by Antonio Simeone, Marco D'Ambra and Paolo Savona on this Journal arises from the need to model economic systems characterised by nonlinearity, interdependence, shocks, emergent behaviour and increasingly rich, high-frequency information. This paper develops the concepts of controlled epistemological circularity, dynamic validity, and algorithmic reflexivity to distinguish forecasting from explanation and intervention. The paper argues that stronger predictive systems must state their uncertainty, applicability conditions, and limitations when informing economic-policy decisions.

Keywords

E.conometrics, Economic Forecasting, Economic Epistemology, Artificial Intelligence, Validation, Controlled Epistemological Circularity, Algorithmic Reflexivity, Economic Policy

1. Introduction

What does it mean to forecast? The question appears purely technical only as long as the forecast is treated as an output separate from the reality upon which it acts. For the economist, forecasting means constructing models capable of drawing inferences, on the basis of available information and identified relationships, about the future evolution of selected variables. Yet when relationships change, agents react to information, and decisions alter the context from which the data are generated, forecasting also becomes a question about the epistemic status of the model and the limits of the knowledge it produces.

It is at this threshold that the proposal by Simeone, D'Ambra and Savona (2026) is situated. The transition from econometrics to e.conometrics does not simply consist in adding artificial intelligence to the economist's toolkit. The authors start from an economic world that cannot be assumed to be necessarily linear, stationary or convergent towards equilibrium, and identify three "liberations": from linearity, from the limits of analytical tractability, and from homo oeconomicus. The resulting framework integrates nonlinear mathematics, econophysics, agent-based models, networks, machine learning, artificial intelligence and alternative data.

For the purposes of this paper, e.conometrics is defined more narrowly than the generic use of machine learning in econometrics. Following Simeone, D'Ambra and Savona (SDS hereinafter), an approach is e.conometric when it combines modelling techniques that need not begin from a pre-specified system of structural economic equations as traditional econometrics typically does with the systematic integration of alternative and/or high-frequency information, within an adaptive framework in which models, data sources and validation procedures can be compared and revised. E.conometrics is therefore not synonymous with machine-learning econometrics, agent-based modelling, or nowcasting: machine learning is one possible predictive component; agent-based and network models provide complementary representations of interaction and emergence; nowcasting concerns timely estimation of the present. Its distinctive claim lies in their possible integration within a plural, adaptive and explicitly validated architecture.Related recent treatments include Gaillac and L'Hour (2025) and Kreinovich et al. (2024).

Starting from forecasting also helps to avoid a misunderstanding. E.conometrics is not examined here as a chapter in the history of artificial intelligence applied to economics, but as a proposal that requires a reconsideration of several categories of economic knowledge. The aim is therefore not to reconstruct a complete genealogy of model theory, but to isolate those passages in which technical innovation changes the content of the concepts being used. In this sense, the analysis is logical-semantic: it asks whether there is continuity or discontinuity of meaning between econometrics and e.conometrics, and whether apparently identical terms continue to designate the same epistemic operations.

The question is whether we are dealing merely with a more powerful toolkit or with a transformation in the way the model itself is conceived. Caution is required: a new technology does not, by itself, constitute a new paradigm. However, when the relationship between theory and data, the meaning of forecasting, the status of error, and the conditions of validity all change together, the issue becomes epistemological and, even before that, semantic. It is not enough to ask whether a model forecasts better; we must clarify what we mean by "model", "data", "forecast" and "validity" within the new inferential environment. In Kuhn's terms, a change of instruments is not by itself a paradigm change; the stronger claim becomes meaningful only if the shared problems, admissible methods and standards of validation of the field are also transformed[1]. This methodological framing fol-

[1]On the distinction between technical innovation and a change in the standards that define a scientific paradigm, see Kuhn, T. S. (1962), *The Structure of Scientific Revolutions*, University of Chicago Press.

lows Kuhn (1962).

This paper follows the structure suggested by that problem. It begins with the encounter between model and reality, moves to the relationship between top-down and bottom-up approaches, and then addresses the distinction between forecasting and explanation. The conclusions return to the applied dimension: if forecasting errors affect monetary policy, public budgets, expectations and the real economy, the quality of knowledge cannot be separated from responsibility for its use.

2. Scope, Method, and Type of Contribution

This paper is conceived as a conceptual and epistemological inquiry into the methodological implications of e.conometrics. Its purpose is to examine the conditions under which the model proposed by SDS may acquire epistemic significance for economic modelling, forecasting and decision-making. The method is analytical: it reconstructs the methodological claims of the e.conometric proposal, distinguishes the meanings assigned to model, data, forecast, explanation, intervention and validity, and derives operational conditions under which those concepts can be used consistently. The empirical material reported by SDS is used as a published test case for this epistemological argument. The paper's specific contribution is to formulate and delimit three analytical concepts—controlled epistemological circularity, dynamic validity and algorithmic reflexivity—and to specify their implications for model validation and policy use.

3. When the Model Meets Reality: From the Crisis of Econometrics to the E.conometric Proposal

The problem from which e.conometrics begins is not that classical econometrics ignored uncertainty. Probability and statistics are precisely the instruments through which uncertainty entered econometric formalisation. The question is different: what happens when instability is no longer merely a disturbance around relatively persistent structures, but affects the structures themselves?

A model can incorporate an error term distributed according to specified assumptions; it is more difficult to incorporate a transformation in the conditions that give variables their meaning and relationships their stability. In this sense, the three "liberations" proposed by Simeone, D'Ambra and Savona also have semantic significance. To free a model from an assumption does not mean declaring that assumption originally false. Linearity, analytical tractability and homo oeconomicus may have been heuristically fruitful abstractions; they become limiting when treated as necessary properties of a system that exhibits nonlinearity, heterogeneity, networks and emergent behaviour.

The shift from the isolated agent to the agent in relation is particularly significant. In network systems, some economically relevant properties do not belong to the agent considered separately, but emerge from its position, interactions and systemic feedback. The move beyond homo oeconomicus can also be read in this perspective: not as the replacement of one anthropology by another, but as recognition of the limits of a representation that separates the agent too sharply from the relationships within which decisions are made. With the necessary caution, this issue meets a more general insight from contemporary physics: representing the isolated element may be insufficient when observable properties depend on relationships. This does not mean transferring quantum mechanics to economics; it means treating relation as an epistemological problem.

This approach also helps clarify the meaning of "crisis". The crisis of a model does not necessarily demonstrate that the model was useless. An abstraction may have performed a decisive epistemic function and later become insufficient when the field of observed phenomena changes or when new tools make previously intractable relationships visible. The issue, therefore, is not to oppose "false" modelling to "true" modelling, but to understand when a simplification shifts from being a condition of intelligibility to becoming a constraint that prevents economically relevant properties from being represented.

Analytical tractability provides a clear example. A substantial part of economic modelling has required the selection of functional forms and assumptions that made a model solvable. The growth of computational capacity changes this constraint: systems that could not previously be treated analytically can now be simulated, explored numerically or learned through algorithmic procedures. Yet liberation from the limits of tractability does not mean liberation from the discipline of modelling. The ability to compute a larger number of configurations increases, rather than reduces, the need to determine which are economically interpretable and under what conditions the results can be generalised.

The same applies to nonlinearity. Its significance does not lie in replacing linear functions, as a matter of principle, with more complex structures, but in making it possible to represent dynamics in which small changes can produce disproportionate effects, interactions can generate aggregate properties that cannot be deduced from individual components, and stability can depend on network configuration. In this framework, econophysics and agent-based models matter not as decorative imports from other disciplines, but as tools for investigating phenomena in which heterogeneity and interdependence are part of the economic problem itself.

The third liberation, from homo oeconomicus, completes the movement. The point is not to deny the usefulness of the rational-agent abstraction, but to avoid turning it into an exhaustive description of behaviour. The contemporary economic agent operates in complex information environments, responds to signals produced by other agents and algorithmic systems, is subject to cognitive and emotional constraints, and participates in networks in which individual decisions may generate feedback effects. In this sense, the shift from the isolated agent to the agent in relation becomes part of the transformation of the model, rather than an anthropological addition external to econometrics. This qualification is also consistent with the behavioural-economics tradition, in which decision under risk departs systematically from the fully rational benchmark. The behavioural-economics reference is Kahneman and Tversky (1979).

The empirical test proposed through the Econometric Accelerator should be read within this framework. Its interest lies not only in the comparison of forecasting errors, but also in the system's attempt to combine different models, frequencies and information sources. Under conditions of high uncertainty, robustness may depend less on selecting a single "best" model than on comparing models built on different assumptions. Plurality thus becomes a robustness mechanism: convergence among representations may strengthen confidence, whereas divergence may itself become information, signalling sensitivity to assumptions or a current regime that is not adequately represented by historically learned relationships.

E.conometrics thus shifts attention from the quantity of data to the structure of knowledge. Big Data do not automatically imply better knowledge. More information becomes scientifically relevant when it makes it possible to identify configurations, interactions and transformations that an overly rigid structure could not represent, without confusing the ability to detect regularities with the ability to assign meaning to them. The point also recalls Hayek's argument that economically relevant knowledge is dispersed and never simply given in its totality to a single decision-maker: greater data availability changes the scale of the problem without abolishing the problem of selection and interpretation. The point concerning dispersed knowledge refers to Hayek (1945).

The empirical example used in this paper is taken from SDS, rather than independently re-estimated here. Their Econometric Accelerator application targets Italian real GDP and uses a mixed-frequency information set of more than 50 variables, with daily, monthly and quarterly inputs drawn from official, financial and alternative-data sources. The underlying time span reported by the authors is 1980Q1-2024Q4 (180 quarters for the quarterly span), while the out-of-sample comparison displayed for the crisis and post-crisis period covers 2019-2024 (24 quarters). Mixed-frequency inputs are aligned to quarterly frequency through deterministic aggregation and Bayesian imputation, and validation follows an expanding-window rolling-forecast design with temporal separation between training and test information. The architecture is a dynamic ensemble combining time-series foundation models, gradient-boosting regressors and tabular foundation models, with model selection differentiated by forecast horizon from one to four quarters ahead. The published comparison uses institutional forecasts as benchmarks and reports forecast-error measures based on median absolute percentage error (MdAPE), symmetric median absolute percentage error (SMdAPE) and root median squared error (RMdSE). Since the present analysis relies on the empirical evidence reported in SDS, no additional p-values, confidence intervals or statistical-comparison tests are introduced here. As the authors clearly state, these results should be treated as preliminary evidence; broader quantitative and qualitative validation is required before predictive performance can support stronger methodological or policy conclusions. Their purpose is to open a debate on economic prediction after a long period of inaccurate forecasts and the related policy choices.

This caution is methodologically essential. Better predictive performance in a single case does not establish the general superiority of a new framework. At least three levels must be distinguished: the predictive effectiveness of the individual model, the validity of the methodology that produces it, and the epistemological soundness of the framework within which that methodology acquires meaning. A model may forecast better under certain conditions without thereby proving the truth of the theory supporting it; conversely, a theory may have explanatory power without being the most accurate predictive instrument in every circumstance.

The distinction between risk and uncertainty also remains relevant. Knight (1921) distinguished risk, which is amenable to probabilistic treatment, from uncertainty that cannot be reduced in the same way to a known distribution. Greater computational capacity and very large datasets can greatly extend the domain of tractable risk, but they do not automatically turn every possible future into a calculable probability. Novel events, institutional changes and regime breaks may not belong to a sufficiently homogeneous class of past cases. E.conometrics should therefore not be conceived as the progressive absorption of uncertainty into calculation, but as a form of knowledge capable of distinguishing what can be modelled from what continues to exceed the model.

The first question can therefore be stated precisely: if linearity, stability and optimising rationality are insufficient to represent complex economic systems, are we facing only a crisis of certain models, or a transformation in the very conception of the model? In the latter case, the model is no longer merely a relatively stabilised representation, but tends to become an adaptive inferential system. If it learns from data and continuously modifies its representation, the decisive question becomes: what guarantees the validity of its inferences when the conditions under which they were learned change?

4. From Top-Down to Bottom-Up? Theory, Data, and the Circularity of Knowledge

One of the most important aspects of the e.conometric proposal concerns the relationship between theory and data. Traditional econometrics proceeds predominantly from a priori theoretical hypotheses, translating them into formalised relationships to be subjected to empirical testing. Data-driven approaches appear to reverse the direction: they start from a multiplicity of data in order to identify regularities and configurations that need not have been predetermined by theory.

The transformation is real, but it requires semantic clarification. Data do not "speak" autonomously. They become information within a process that already involves selection, measurement, classification, coding and interpretation. Even when an algorithm identifies correlations that were not hypothesised in advance, the nature and quality of the available data, the architecture employed, the objective function and the evaluation criteria remain determined upstream. A weaker a priori theoretical constraint therefore does not imply an absence of assumptions.

Breiman's (2001) distinction between two cultures of modelling clarifies the issue. One culture assumes an explicit stochastic model of the data-generating process and estimates its parameters; the other uses algorithmic models and evaluates primarily their ability to transform inputs into outputs with high predictive accuracy. E.conometrics, however, does not appear simply to abandon the first culture in favour of the second. Its most interesting frontier lies in hybridisation: data-driven approaches allow non-predetermined structures to emerge, while economic theory and plausibility constraints return to prevent predictive performance from being confused with economic meaning.

The semantic point can be stated more precisely. "Bottom-up" does not mean that knowledge begins with theory-free data, just as "top-down" does not mean that data are irrelevant. The two expressions instead indicate a different distribution of the initial constraint. In the first case, the researcher allows greater scope for configurations to emerge from the data; in the second, the structure of the relationships to be estimated is specified more directly. In both cases, however, the result must return to a question of economic meaning. An algorithmically identified correlation becomes knowledge only when we know what it represents, within which domain it operates, and which observations could call it into question.

It is precisely here that circularity must be distinguished from mere technical updating. Updating parameters after new data arrive does not necessarily imply epistemological revision. Circularity becomes significant when confrontation with evidence can modify not only estimated values, but also the choice of variables, the form of the model, validation criteria and, where necessary, the theoretical categories through which the phenomenon was defined. A system can be said to learn from reality only if it preserves the possibility that its own representational scheme may need to change.

This approach avoids two extremes. The first is theoretical dogmatism, in which evidence is forced into a structure that cannot genuinely be challenged. The second is algorithmic dogmatism, in which high performance is treated as a sufficient guarantee of knowledge. In the first case, the model risks failing to see what is new; in the second, it risks detecting regularities without understanding their stability or meaning. E.conometrics becomes epistemologically interesting precisely insofar as it can keep the tension between these two risks open.

Validation must therefore be conceived on several levels. This includes statistical-predictive validation, which measures the system's ability to generalise; economic validation, which examines the plausibility and coherence of the relationships; temporal validation, which tests the model's resilience when regimes change; and decision validation, which considers the effects of using the forecast. These levels should not be conflated. Excellent performance on the first may be insufficient on the others, especially when the model is used for high-impact interventions. In this sense, operational usefulness cannot be separated from the epistemic governance of the model: the conditions of the estimate, its principal sources of uncertainty, its sensitivity to alternative assumptions and the signals of regime change are part of the quality of the decision itself.

The relationship between mathematical form and economic content thus takes on a new configuration. Formal power makes it possible to explore much wider spaces of relationships, but it does not remove the problem of correspondence between what is optimised and what is economically relevant to know. An algorithm may be internally coherent and statistically effective with respect to an objective function that does not coincide with the relevant institutional or economic question. The semantics of the model also concerns this correspondence: what are we actually asking the system to do when we ask it to "forecast"? This tension between formal structure and economic content has a long-standing place within economics itself; Debreu distinguished the mathematical form of theoretical models from the economic content that gives their formal relations substantive meaning. The distinction between mathematical form and economic content is discussed by Debreu (1986).

The movement is therefore not a simple replacement of "theory → model → data" by "data → algorithm → forecast". It takes a recursive form: theory → data → learning → inference → validation → revision → renewed interrogation of the data. The endpoint of one cycle changes the conditions of the next.

To describe this configuration, we propose the notion of controlled epistemological circularity. "Controlled" is the decisive term. A system that continuously adapts to data may improve its ability to reproduce the past without increasing its ability to know new phenomena. Revision must therefore remain exposed to data not used in training, out-of-sample tests, robustness analysis, comparison with alternative models, and checks of economic plausibility.

Controlled epistemological circularity is intended here as an analytical framework, not merely as a descriptive label for iterative model development. Its minimum operational criteria are: 1) temporal separation between information used for learning and information used for evaluation; 2) the possibility that evidence can trigger revision not only of parameter values but also of variables, model form or theoretical constraints; 3) systematic comparison with alternative specifications or model classes; 4) explicit checks of economic plausibility in addition to predictive performance; 5) reporting of uncertainty and of the domain within which the model has been validated; and 6) pre-specified signals that trigger revalidation, model revision or abstention. Circularity is therefore epistemologically controlled only when feedback from outcomes can modify the representational scheme while the revised scheme remains exposed to independent empirical challenge. Its requirement of independent empirical challenge is also consistent with Popper's (1959) criterion that scientific claims remain open to refutation.

Validation thus becomes a permanent function of the inferential system. Data quality, stability of relationships, robustness, consistency with relevant theoretical constraints, uncertainty associated with the output, and domain of applicability must all be assessed together. Three criteria must coexist: accuracy, coherence, and correspondence with reality. Their relationship is not self-evident: a more accurate model is not necessarily more interpretable; a theoretically elegant model is not necessarily the most predictive; and a system that performs well on construction data must still demonstrate its capacity to generalise.

This also changes the meaning of "model". In the e.conometric environment, the term may designate not only a single mathematical structure, but a system comprising multiple models, different frequencies, heterogeneous data, learning procedures, simulations, theoretical constraints, and validation criteria. Mathematical form remains indispensable, but internal coherence cannot substitute for comparison with economic content and with the changing conditions under which the model is applied.

Circularity therefore does not reduce the role of theory; it changes its position. Theory is not only what precedes the data, but also what returns after inference to interrogate the meaning of the relationships that have emerged. Data, in turn, do not merely confirm or refute an already formulated hypothesis: they may force a revision of the categories through which the phenomenon was observed. Knowledge becomes a process of mutual correction, without either theory or data claiming self-sufficiency.

5. Forecasting Is Not Explaining: The Epistemological Status of Prediction

If the relationship between theory and data changes, so does the meaning assigned to forecasting. Econometrics and machine learning pursue at least partly different objectives: the former has traditionally placed particular emphasis on parameter estimation and inference, while the latter often privileges predictive accuracy. The difference concerns the question addressed to the model: what will happen, or why does it happen? The two questions may intersect, but they are not semantically equivalent.

Shmueli (2010) showed particularly clearly that explanation and prediction are often conflated even though they involve different objectives and criteria. A system may identify, with high accuracy, a configuration associated with an outcome without having identified the causal mechanism that produces it. A fundamental caution follows: accuracy does not automatically imply truth, correlation does not automatically imply causation, and prediction does not automatically imply explanation.

This distinction does not diminish the operational value of machine learning. A forecast may be useful even when the causal explanation is incomplete. But it is necessary to state what kind of knowledge is being produced and what kind of decision it can support. The problem becomes more demanding when moving from forecasting to intervention. As Guala (2006) observes, economics does not merely anticipate future phenomena: theories and models are also applied to guide interventions. The question then shifts from "what will happen?" to "what would happen if we intervened in the system?”

The distinction between prediction and explanation also has institutional significance. In a purely predictive exercise, quality can be measured by comparing output with observation. In an economic-policy decision, by contrast, the output is only one element of judgement. The decision-maker must consider asymmetric error costs, irreversibility, timing, distributional effects, and possible reactions by agents. Predictive accuracy remains necessary, but it does not exhaust decision reliability.

Nowcasting intensifies this tension by bringing observation and decision closer in time. Greater timeliness can be decisive during periods of discontinuity, but it also increases the risk of reacting to transitory signals or to data that have not yet sufficiently stabilised. Knowing the present sooner does not necessarily mean understanding it better. The quality of a nowcast depends on the ability to distinguish noise, temporary variation and structural change, and on the possibility of updating the degree of confidence assigned to the representation.

From this perspective, abstention may itself have informational value. A mature system should not be assessed only by how often it produces an answer, but also by its ability to signal when the available information does not support a sufficiently reliable forecast. Declaring high uncertainty, widening the range of possibilities, or withholding a recommendation does not necessarily amount to failure: it may be the most rigorous response when the system recognises that it is operating outside its validated domain.

Nor is error neutral in the way it is communicated. A point forecast may convey a degree of certainty that the model does not possess. Making intervals, scenarios, sensitivities and invalidation conditions explicit turns the communication of uncertainty into an integral part of the model. This is especially important for institutions, because the form in which a forecast is communicated may alter expectations and behaviour as much as its numerical content.

Causality here acquires a practical function. Knowing that two variables are associated is not enough when the decision changes the conditions under which that relationship was observed. Central banks, governments, supervisory authorities, banks, firms and market participants use forecasts to make decisions, and those decisions alter the reality on which the forecasts were based. The linear relationship “reality → forecast” thus tends to become recursive: reality → data → forecast → decision → new reality → new data.

We may define algorithmic reflexivity as the situation in which human behaviour, the algorithmic representation of that behaviour, and behaviour modified by that representation enter the same circuit. An inflation forecast may affect expectations; a recession forecast may influence investment and consumption; a monetary-policy decision changes the conditions under which expectations will subsequently form. The decision-maker is therefore not necessarily external to the observed system. The more predictive outputs are incorporated into decisions and disseminated across institutions and markets, the more necessary it becomes to assess their endogenous and second-order effects: a forecast may alter the very dynamics it seeks to anticipate.

Nowcasting makes this transformation even more apparent. Digital transactions, mobility, energy consumption, satellite imagery, and information extracted from the web reduce the time lag between the occurrence of a phenomenon and the possibility of representing it. In traditional forecasting, the process can be schematised as past → model → future; in AI-assisted nowcasting, it becomes closer to data stream → updating → representation of the present → new stream → new representation. Better forecasting may therefore mean, in some cases, knowing the present sooner.

The metaphor of a continuously updated multidimensional snapshot, used in the e.conometric proposal, can be taken further: what we have is closer to a dynamic map than to a photograph. Comparison with reality does not occur only at the end, but enters into the operation of the system itself: observation → inference → forecast → comparison → error → updating → new inference. Error thus changes status. It is not merely the residual of failure; it can become information.

A distinction must nevertheless be drawn between error due to estimation and error that signals a change in the data-generating process. Structural breaks, forecast failure and distribution shift show that a model may be adequate for one regime and lose reliability when relationships, institutions, expectations or transmission mechanisms change. A large volume of past data may represent with precision a world that no longer operates in the same way.

Validity must therefore be understood dynamically. The question is not only how accurate the model is, but under what conditions it is accurate and which signals indicate that those conditions are ceasing to hold. An epistemically robust system should make at least four dimensions explicit: observed performance, uncertainty associated with the output, domain of applicability, and signals of deteriorating reliability. This transparency is particularly important when the output enters public or financial decision-making. Public decision-making must therefore distinguish historical accuracy from prospective reliability: the relevant institutional question is not only which model forecast yesterday more accurately, but which system can recognise more quickly that yesterday's conditions no longer hold.

6. Predictive Validation, Causal Identification, and Policy Evaluation

Three forms of validation must be kept distinct when a forecast is used to support intervention. Predictive validation asks whether a model generalises to unseen observations and how forecast errors behave out of sample. Causal identification asks whether a change in one variable can legitimately be interpreted as producing a change in an outcome, rather than merely predicting it through association. Policy evaluation asks a further question: what consequences follow when an intervention is implemented in a system whose agents, institutions and expectations may respond to the intervention itself? A forecast can therefore be predictively accurate without identifying a causal mechanism, and a causally credible estimate can still be insufficient for policy if distributional effects, behavioural responses, implementation constraints or asymmetric losses are ignored. The use of an e.conometric forecast for policy consequently requires a validation chain rather than a single performance criterion: out-of-sample predictive evidence, a defensible causal argument when intervention is contemplated, and an explicit assessment of policy consequences and feedback. Recent work at the intersection of causal inference and machine learning likewise reinforces the need to distinguish predictive performance from the identification assumptions required for causal and policy claims[2]. Related discussions include Cartwright (1989) on causal capacities and Yuksel and Aydede (2026) on causal inference and machine learning.

7. Structural Breaks, Noise, Data Quality, and the Decision to Revise

A model should not interpret every forecast error as evidence of structural change. Before revising its specification, the diagnostic sequence should first exclude data-quality problems—missing observations, revisions, coding changes, measurement errors or abnormal release lags—and assess whether the deviation is compatible with the model's ordinary forecast-error distribution. A structural-break hypothesis becomes more credible when forecast deterioration is persistent rather than isolated, appears across more than one model or information set, is accompanied by parameter-instability or change-point evidence, and is economically consistent with an identifiable institutional, technological, behavioural or policy discontinuity. Conversely, a transient error that disappears as data are revised or that remains within historically expected uncertainty should not automatically trigger structural redesign.

Operationally, the distinction should therefore combine statistical and substantive diagnostics: data-integrity checks; comparison of realised errors with the model's historical error distribution; rolling or recursive stability analysis; comparison across alternative models; and external evidence on regime change. The purpose is not to create an automatic rule that declares a break, but to define a threshold for revalidation. When several independent signals deteriorate together, the appropriate response may be to widen uncertainty intervals, reduce decision weight, compare alternative specifications, or temporarily abstain before revising the model. This is consistent with the forecasting-under-breaks literature (Clements & Hendry, 2006; Castle, Clements, & Hendry, 2016): model revision should be evidence-driven and should distinguish a change in the data-generating process from noise or defective data. See also Hendry (1995) on dynamic econometric modelling and model stability.

[2]For a recent treatment of the relationship between causal inference and machine learning across economics and the social sciences, see Yuksel, M. and Aydede, Y. (2026), *Causal Inference and Machine Learning: In Economics, Social, and Health Sciences*, Chapman & Hall/CRC.

8. Conclusions: Open Knowledge, Validity, and Responsibility in Decision-Making

When the transition from econometrics to e.conometrics is not confined to its technical aspects, it opens questions that exceed the scope of this paper and require further development: the nature of decision-making in the light of neuroscience and emotion; the relationship between determinism, possibility and the capacity to alter trajectories through intervention; the transition from predictive to generative intelligence; and the movement from the isolated element to relation. There is no need here to reconstruct a history of these problems. It is sufficient to identify the underlying idea that connects them: economic knowledge increasingly confronts systems in which subject, model and reality cannot be treated as definitively separate terms. Broader reflections on digital transformation and the changing representation of the human subject are also developed by de Kerckhove (2025) and Ferrari (2012).

Any reference to contemporary physics must likewise remain confined to this epistemological level. The economy is not a quantum system, and no analogy can substitute for verifiable formalisation. What matters here is the limit of representing the isolated element when properties depend on relations and conditions of observation. In complex economic systems, networks, heterogeneous agents and feedback make this issue directly relevant to modelling without authorising unwarranted transfers between disciplines. The reference to contemporary physics may be situated, at the historical level, in relation to Bohr (1928).

Generative intelligence adds a further layer. A system may produce new scenarios, hypotheses and combinations, but the production of output does not automatically amount to the production of knowledge. Its scientific value depends on whether what it generates can be brought back to criteria of control, comparison and validation. AI may expand the space of hypotheses; it does not eliminate the need to return to reality.

From this perspective, the e.conometrics proposal may be regarded as a promising but still open stage in a research programme, rather than as the completed proclamation of a new paradigm. Its significance lies in the possibility of bringing together different instruments—econometrics, high-frequency data, agent-based models, networks, machine learning and artificial intelligence—without exempting them from testing the conditions under which their results remain valid. In this respect, the language of a "research programme" is used in the Lakatosian sense: methodological innovation becomes scientifically progressive insofar as it generates new, empirically assessable content rather than merely accommodating anomalies retrospectively[3]. The expression "research programme" is used in the methodological sense of Lakatos (1978).

The notion of open knowledge can now be specified more precisely. "Open" does not mean indefinite, relativistic or devoid of criteria. It means knowledge

[3]The expression "research programme" is used here in the methodological sense developed by Lakatos, I. (1978), *The Methodology of Scientific Research Programmes*, Cambridge University Press.

that preserves, as a methodological principle, the possibility of correction. Its strength lies not in being immune to change, but in making observable the conditions under which revision becomes necessary. In this sense, openness and rigour are not opposites: rigour includes the discipline of declaring the limits of validity.

It is precisely the return to reality that brings the discussion back to economic and policy questions. Savona (2024) has emphasised that errors in econometric models have acquired practical as well as theoretical significance, particularly when they affect monetary-policy choices and the ability to guide expectations. Forecasting errors are not neutral: they can be transmitted to public budgets, decisions by authorities, the behaviour of economic agents and, through these channels, the real economy.

The problem can now be stated more precisely. Forecasting is not explaining; but neither is forecasting an activity external to the world being forecast. When a forecast enters a decision and the decision contributes to changing the system, knowledge takes on a circular structure. The initial distinction between the predominantly top-down orientation of econometrics and the predominantly bottom-up orientation of e.conometrics therefore does not lead to a simple reversal of direction: theory and data enter a relationship of mutual determination in which the outcome of one cycle changes the conditions of the next. This is why circularity must remain controlled: the model must continue to expose itself to new data, independent tests, the possibility of error, and revision of its own assumptions.

From this perspective, a plurality of models may also acquire institutional value. When representations built on different assumptions converge, convergence may strengthen confidence in the output; when they diverge, dispersion may instead signal high structural uncertainty and the need for decisions to incorporate alternative scenarios. The Econometric Accelerator is particularly interesting if it is also interpreted as a device capable of making this plurality visible. Its multi-model architecture is therefore relevant not because plurality guarantees truth, but because controlled comparison among competing representations can itself become a source of information about robustness.

Knowledge therefore remains open not because it abandons rigour, but because it abandons the claim to unconditional validity. Openness means being able to recognise structural breaks, distribution shift, anomalies and regime changes; it means reporting, together with the forecast, the degree of uncertainty, the domain in which it has been validated, and the conditions that could make it unreliable.

It is precisely at this threshold that the epistemological problem becomes a problem of economic policy. The greater the capacity of algorithmic tools to anticipate, update and guide, the more the reliability of the model must be accompanied by responsibility for its use. Greater predictive capacity changes the quality of the information available to decision-makers, but it does not eliminate the need for judgement. The decision-maker's responsibility does not arise from the expectation that an infallible forecast should be available, but from the need to understand the quality and limits of the information on which action is based, to know when further validation or comparison with alternative models is required, and to recognise when residual uncertainty is still too great to support a sufficiently well-founded choice.

E.conometrics can offer economic policy not the illusion of a definitively calculable future, but tools that are more responsive to change and more capable of recognising their own limits. In an economy that changes while we attempt to understand it, the quality of forecasting is also measured by the ability to recognise when a forecast is not yet sufficient to ground a decision. The openness of knowledge thus becomes a condition of responsibility: it does not suspend decision-making, but makes it more aware of the conditions that make action possible and of the consequences that action itself helps to produce.

Conflicts of Interest

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

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