Scientific Research Publishing

Theoretical Economics Letters, 2025, 15(6), 1365-1375
https://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

Unitary Economic Entities: A Theoretical Framework for Economic Analysis and Measurement

Vítězslav Budnikov

Independent Researcher, Holany, Czech Republic
Email: budnikov@apit.cz

How to cite this paper: Budnikov, V. (2025). Unitary Economic Entities: A Theoretical Framework for Economic Analysis and Measurement. *Theoretical Economics Letters, 15,* 1365-1375.
https://doi.org/10.4236/tel.2025.156075

Received: May 19, 2025
Accepted: November 9, 2025
Published: November 12, 2025

Abstract

This paper introduces the concept of *Unitary Economic Entities* (UEE) as a formal analytical framework for understanding, modelling, and measuring economic processes at their most elementary level. UEE are defined as the smallest indivisible units of economic activity, each characterised by an input, an activity, an output, and a consumption. The framework provides a bridge between micro-process modelling and macro-level economic interpretation. It extends classical production theory by introducing an atomic structure of activity, allowing efficiency and transformation intensity to be measured at unprecedented granularity. The paper develops the mathematical structure of UEE, discusses hierarchical composition, and demonstrates applicability through an illustrative production example. It argues that UEE can serve as a universal analytical foundation for empirical research, process management, and economic system modelling.

Keywords

Unitary Economic Entities (UEE), Economic Analysis, Production Models, Process Management, Efficiency, Consumption, Economic Systems

1. Introduction

Traditional economic analysis captures behaviour at aggregated levels—firms, sectors, or nations—using indicators such as GDP, productivity, or total factor efficiency. While powerful for macro-diagnostics, these measures conceal the fine-grained processes that create economic value. Each organisation, whether private or public, operates through numerous micro-activities that transform resources into outcomes.

Despite advances in econometrics and information systems, economics still lacks a universal formalism for describing those activities in a consistent, measurable way. The *Unitary Economic Entity* (UEE) fills that gap by defining the smallest transformation that preserves economic meaning.

The guiding idea is simple: any economic process, however complex, can be decomposed into a finite set of atomic transformations. Each UEE captures one such transformation through its inputs, consumptions, and outputs. The system of all UEE then represents the entire economy as a structured network of interdependent functions.

The objective of this paper is to establish the theoretical consistency of the UEE framework, derive its mathematical properties, and outline its relevance for empirical research and digital measurement. By linking functional analysis with information theory and process modelling, UEE offer a unified grammar for describing how economies actually work—one transformation at a time.

2. Theoretical Context and Relation to Existing Models

The UEE approach stands at the intersection of several traditions in economic thought.

2.1. Classical Production Theory

Cobb and Douglas (1928) expressed production as

$$Q = A \times K^{\alpha} \times L^{\beta}$$

linking aggregate inputs of capital (K) and labour (L) to output (Q).

Although elegant, such models treat firms as homogeneous producers, masking the micro-mechanics of transformation.

2.2. Input-Output Analysis

Leontief (1936) introduced a matrix representation of inter-industry dependencies. This allowed researchers to model how outputs from one sector become inputs to another. The UEE framework inherits this logic but applies it at a much finer scale-each element of the matrix may itself consist of hundreds of UEEs describing individual actions within firms (Leontief, 1936).

2.3. Micro-Productivity and Information Theory

Modern research (Syverson, 2011; Bartelsman & Haltiwanger, 2019) reveals that firm-level productivity dispersion is largely driven by micro-level heterogeneity. Information-theoretic models (Villas-Boas & Judge, 2013) view economies as systems processing information and energy. UEE extend these perspectives by providing a formal unit compatible with both deterministic and stochastic representations.

These findings are consistent with the broader literature using microdata to study structural transformation and firm-level heterogeneity (Lagakos, 2023). Earlier work also examined how information and decision value can be quantified at the microeconomic level (Alpar, 1990), anticipating later developments in data-driven productivity modelling.

2.4. Methodological Position

In methodological terms, UEE combine the deductive precision of mathematical economics with the descriptive richness of systems engineering. The framework can be viewed as a bridge between *process theory* in management science and *production theory* in economics, offering a formal foundation for measuring activity in digital economies and automated systems.

3. Definition of a Unitary Economic Entity

A Unitary Economic Entity is the smallest indivisible process of transformation within an economic system.

It is defined by four core elements:

- **Input (*I*)**—resources entering the process (labour, materials, energy, data, capital).
- **Activity (*A*)**—the operation transforming inputs.
- **Output (*O*)**—the result, tangible or intangible.
- **Consumption (*C*)**—resources expended during transformation (time, depreciation, energy, overhead).

The fundamental relationship is:

$$O = f(I, C)$$

where f is the transformation function.

For multiple inputs and consumptions:

$$O = \sum w_i \times f_i(I_i, C_{ij})$$

with weighting coefficients w_i representing relative contributions.

Inputs represent external resources entering the transformation, whereas consumptions denote internal use of these resources during activity (e.g., materials vs. energy).

Each UEE thus constitutes a self-contained, measurable function. In digital environments-production sensors, ERP systems, or service logs-each task recorded can correspond directly to a UEE instance.

4. Mathematical Structure and Internal Properties

The power of the UEE concept lies in its formal generality. The transformation function f can assume various forms-linear, non-linear, or stochastic-depending on the process.

Mathematically, UEEs constitute a family of mappings $f: I \times C \to O$ that share several properties valuable for theoretical and computational economics.

4.1. Elasticities and Efficiency

Local elasticities describe the sensitivity of output to marginal changes in inputs or consumptions:

$$\varepsilon_i = (\partial O/\partial I)\times(I/O)$$

$$\varepsilon_c = (\partial O/\partial C)\times(C/O)$$

These provide atomic-level measures of efficiency and can be aggregated across entities to produce system-wide indices.

4.2. Compositional Structure

Where O_1 from one entity becomes I_2 in another, composition is expressed as:

$$f_{12}(I_1, C_1, C_2) = f_2(f_1(I_1, C_1), C_2)$$

This recursive form enables modelling of entire production chains.

4.3. Conservation and Balance Principle

For a closed system of n entities:

$$\sum I_i = \sum (O_i + L_i)$$

where L denotes losses.

This expresses a conservation of economic matter-inputs transformed, outputs produced, resources consumed.

4.4. Linearity and Non-Linearity

In basic processes such as mechanical assembly or energy conversion, f may be approximated as linear:

$$O \approx \alpha \times I - \beta \times C$$

However, in complex systems-innovation, service delivery, information processing—relationships become non-linear and often exhibit diminishing returns.

Non-linearities allow the model to capture real-world phenomena like learning curves, congestion effects, or synergy among inputs.

4.5. Stochastic Behaviour

Real processes are subject to randomness—errors, delays, quality variation. Introducing a stochastic term ε gives:

$$O = f(I, C) + \varepsilon, \text{ with } E(\varepsilon) = 0$$

The variance Var(ε) then measures process volatility. Aggregating such entities yields macro-level uncertainty akin to business-cycle fluctuations.

4.6. Efficiency and Entropy

Information-theoretic interpretation treats C as "energy" dissipated to maintain transformation. Minimising C for given O maximises efficiency and reduces system entropy.

Hence, total system efficiency η can be defined as:

$$\eta = \sum O_i / \sum C_i$$

This links UEE analysis to thermodynamic analogies used in ecological and industrial economics.

Aggregated efficiency assumes a common valuation basis (e.g., cost or energy units). Weighted normalisation allows combining heterogeneous outputs.

5. Hierarchical Composition and Systemic Modelling

Economic activity rarely occurs in isolation. Every production system can be viewed as a hierarchy of Unitary Economic Entities.

At the micro-level, UEEs describe individual tasks; at the meso-level, they form modules such as departments or production lines; and at the macro-level, aggregated UEEs represent firms, sectors, or even national industries.

Each level follows the same functional logic. If the output of one entity serves as the input of another, a hierarchical relationship emerges:

$$\mathrm{UEE}_{k+1} = f_{k+1}\left(O_k, C_{k+1}\right)$$

Iterating across k entities forms a chain that can be represented as a directed network.

Such hierarchies are fractal: the same principles of transformation and consumption apply at every scale.

This property allows UEEs to bridge micro-based modelling with macro-economic analysis—something neither classical equilibrium theory nor purely statistical macro-models achieve easily.

Digital production systems increasingly mirror this structure. Sensors and enterprise resource-planning software already record data compatible with UEE definitions—inputs, energy use, time, and outputs—making empirical reconstruction of hierarchical matrices feasible.

6. Illustrative Example: Preparation of a Meal

To visualise the analytical mechanism, consider a restaurant preparing a meal consisting of meat, vegetables, and sauce.

Each component requires distinct inputs, consumptions, and transformations.

Input	Quantity	Unit Cost (€)	Main Consumption	Transformation
Meat	0.2 kg	15.00/kg	Time (5 min), Gas (0.1 m^3)	Cooking
Vegetables	0.15 kg	6.00/kg	Time (3 min)	Chopping
Sauce	0.03 kg	6.50/kg	None	Ready-made

Each sub-process is a UEE with its own transformation:

$$O_i = f_i\left(I_i, C_i\right),\ i = 1,2,3$$

Overall output:

$$O = \sum w_i \times O_i$$

Aggregating them yields the finished dish.

By altering the consumption parameters—time, gas, or labour—the model quantifies marginal effects on cost and output quality.

When scaled up to an entire kitchen or restaurant chain, the UEE approach allows identification of inefficiencies, comparison of branches, and forecasting of resource use. It exemplifies how even qualitative processes (taste, presentation) can be linked to measurable inputs and consumptions.

6.1. Model Structure of the Example

The process of meal preparation can be formalised as a miniature production system composed of three primary UEEs—meat processing, vegetable preparation, and sauce application.

Each UEE is a transformation function that converts inputs into partial outputs while consuming resources.

Formally, let each transformation be expressed as

$$O_i = f_i\left(I_i, C_i\right), \text{ for } \ i = 1,2,3$$

where I_i represents the physical input (e.g., meat, vegetables, sauce), and C_i denotes the consumptions required for that transformation—such as time, energy, or labour.

The resulting overall dish output O is obtained as the aggregation of the weighted partial outputs:

$$O = \sum w_i \times O_i$$

The weights w_i capture the relative contribution of each sub-process to the final product, which may depend on material cost, labour time, or qualitative importance (for example, the meat component may dominate the total value).

This formal decomposition ensures that every part of the cooking process can be represented as a measurable transformation—precisely what defines a Unitary Economic Entity.

For example, a line assembling 100 units with 10 kWh energy and 5 h labour yields η = 20 units/kWh or η = 20 units/h.

6.2. Interpretation and Scaling of Results

The example of meal preparation illustrates how the UEE model allows a process to be expressed numerically.

By assigning measurable parameters to each UEE—such as labour minutes, material quantities, or energy use—every transformation can be converted into comparable units of cost or efficiency.

Aggregating these measurements produces a matrix of micro-productivity, where each cell corresponds to a specific action or transformation.

The matrix can be scaled upward in several ways:

- Horizontally, by summing across similar UEEs to obtain process-level indicators (e.g. average cost per dish type).
- Vertically, by summing through hierarchical levels to obtain department- or firm-level indicators.

- Temporally, by comparing the same UEE over different periods to identify learning or efficiency gains.

Such scaling transforms the qualitative description of an activity into a quantitative framework compatible with economic modelling.

When linked to digital data streams—such as production logs or sensor readings—the resulting dataset can feed directly into productivity, forecasting, or cost-allocation analyses.

6.3. Comparative Perspective with Production Functions

Traditional production functions such as Cobb-Douglas, Leontief, or translog focus on aggregated factors of production.

Their functional forms can in fact be interpreted as special cases of the UEE system:

- Cobb-Douglas assumes smooth substitutability between inputs, a limiting case where UEEs are continuous and homogeneous.
- Leontief reflects perfect complementarity, analogous to a fixed network of UEEs with constant coefficients.
- Translog approximations correspond to higher-order expansions of composite UEE functions.

Thus, UEE generalises classical production theory by defining transformation at the task level rather than the firm level. The aggregate production function of a firm becomes a weighted sum—or more precisely, a convolution—of its constituent UEE functions. This provides a theoretical micro-foundation for any observed production law.

6.4. Intangible Outputs and Weighted Aggregation

While the previous example referred to tangible transformations, many economic activities produce intangible outputs such as information, digital services, or algorithmic results. Within the UEE formalism, these outputs are quantified through their measurable attributes—for instance, data volume processed, response time achieved, or computational cost incurred.

Aggregation of such heterogeneous outcomes relies on a weighting matrix W, which assigns relative importance or valuation coefficients to each partial output. In compact matrix form, the system output can be expressed as:

$$O = W \times F(I, C)$$

where $F(I, C)$ represents the vector of transformation functions across all entities. The weighting matrix can reflect economic value (e.g., market price, cost, or utility index) or technical significance (e.g., throughput share). This explicit notation links the UEE framework to input-output and productivity models and allows consistent integration of both tangible and intangible production processes.

7. Discussion and Broader Implications

UEEs enable transparency, comparability and control. Because all activities share a common grammar, analysts can compare heterogeneous processes—assembly, diagnostics, coding, customer service—on a commensurate basis.

In relation to existing approaches, the UEE framework differs conceptually from both activity-based costing (ABC) and process mining. Unlike ABC, which assigns costs to predefined activities, UEE formalises each transformation as a functional relationship among inputs, consumptions and outputs. Unlike process mining, which reconstructs operational flows from event logs, the UEE framework embeds explicit consumption variables and efficiency measures, thereby linking operational data directly to economic analysis. Together, these distinctions situate UEE as a bridge between accounting models and data-driven process analytics.

The introduction of UEE has implications beyond modelling.

1) Analytical Transparency. Every unit of output can be traced back to explicit inputs and consumptions, improving accountability and measurement accuracy.

2) Comparability Across Domains. Manufacturing, services, and digital processes share a common analytical language, facilitating cross-sectoral efficiency studies.

3) Integration with Digital Economy. In a data-rich environment, each UEE can be recorded automatically. This enables near-real-time productivity analysis and links economics to information-systems engineering.

4) Policy Applications. Public-sector services could evaluate efficiency in UEE terms—e.g. processing an application or performing a medical procedure—making cost-benefit assessments transparent.

5) Methodological Innovation. UEE merge mathematical economics with systems theory, bridging analytical precision and empirical measurability.

7.1. Relation to AI and Automation

As artificial-intelligence systems increasingly participate in production, their actions can also be represented as UEEs. Each algorithmic operation consumes computational resources and produces informational output. Modelling such digital transformations within the UEE framework allows integration of machine activity into economic analysis.

7.2. Epistemological Perspective

From a philosophical standpoint, UEE redefine the epistemic unit of economic knowledge. Instead of observing aggregates, economists can study *events of transformation* directly—where value is created or destroyed. This shift parallels developments in physics and biology, where systems are understood through their fundamental interactions.

7.3. Limitations and Scope of Applicability

While the concept of Unitary Economic Entities offers a coherent theoretical foundation, several limitations should be acknowledged.

First, the framework is primarily conceptual and has not yet been validated through large-scale empirical analysis. Its application depends on the availability of micro-level data—time stamps, resource logs, or cost allocations—which are not always systematically recorded.

Second, the definition of boundaries between entities may be context-dependent, varying across industries or organisational structures. Future methodological work must therefore focus on standardising how UEEs are identified and how consumption values are measured in practice.

Finally, although UEEs can theoretically represent any transformation, their computational complexity increases rapidly with system size. Implementing the model within digital platforms will require efficient data structures and simplified aggregation procedures.

Despite these constraints, the flexibility of the UEE framework ensures that it can evolve alongside advances in process monitoring and data analytics.

8. Conclusion and Future Research Directions

Unitary Economic Entities offer a coherent analytical grammar for representing economic processes at any scale.

By defining transformation in its atomic form, the framework reconciles micro-level measurement with macro-level interpretation.

8.1. Summary of Contributions

- Establishes a universal transformation function $O = f(I, C)$ applicable to all economic activities.
- Demonstrates hierarchical and compositional properties linking micro- and macro-structures.
- Extends production theory beyond firm-level aggregation.
- Provides foundations for digital, data-driven empirical measurement.

8.2. Future Research Directions

Further research should aim to:

1) Calibrate UEE functions empirically using process-level data from manufacturing and services.

2) Explore stochastic variants to model uncertainty and resilience.

3) Integrate UEE into computational general-equilibrium and agent-based simulations.

4) Apply the framework to sustainability metrics—energy efficiency, carbon accounting, circular-economy flows.

8.3. Systemic Implications

If systematically implemented, the UEE perspective could become as foundational as double-entry bookkeeping once was for classical economics.

By translating every action into measurable transformations, it could transform how economic performance, innovation, and policy outcomes are evaluated—replacing aggregates with transparent structures of causality.

8.4. Practical Outlook

In the long term, the UEE framework may have transformative implications for both research and policy.

For economic theory, it provides a unified formalism capable of bridging the micro-macro divide, allowing production functions, efficiency measures, and behavioural models to be expressed through a single analytical grammar.

For business practice, it can serve as a foundation for *process accounting*, where every task or transformation is transparently mapped to its inputs and consumptions, improving managerial control and cost attribution.

In public administration, the same principle could enhance the efficiency of services by measuring the real consumption of resources per administrative act.

Moreover, the digitalisation of economic processes makes this vision technically feasible: sensors, ERP systems, and AI analytics can already capture the data necessary for UEE-based modelling.

Ultimately, by redefining how economists observe value creation—not as an aggregate outcome but as a sequence of measurable transformations—the UEE framework has the potential to reshape both analytical economics and practical decision-making in the coming decades. Further methodological details on data collection and calibration are provided in **Appendix A**.

Acknowledgements

The author used ChatGPT for language polishing and structure refinement.

Authors' Contributions

The author is solely responsible for the conception, analysis, and writing of this manuscript.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Alpar, P. (1990). A Microeconomic Approach to the Measurement of Information Value. *Journal of Management Information Systems, 7,* 55-73. https://doi.org/10.1080/07421222.1990.11517889

Bartelsman, E., & Haltiwanger, J. (2019). Micro and Macro Dynamics of Productivity: From Devilish Details to Insights. *American Economic Journal: Macroeconomics, 11,* 1-37.

Cobb, C. W., & Douglas, P. H. (1928). A Theory of Production. *American Economic Review, 18,* 139-165.

Lagakos, D. (2023). Using Microdata for Understanding Structural Transformation. *Industry and Innovation, 30,* 923-945.

Leontief, W. (1936). Quantitative Input and Output Relations in the Economic Systems of the United States. *The Review of Economics and Statistics, 18,* 105-125.

https://doi.org/10.2307/1927837

Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature, 49,* 326-365. https://doi.org/10.1257/jel.49.2.326

Villas-Boas, S. B., & Judge, G. G. (2013). An Information-Theoretic Approach to Understanding the Micro Foundations of Macro Processes. *Theoretical Economics Letters, 3,* 156-163. https://doi.org/10.4236/tel.2013.31008

Appendix A

Methodological Notes for Empirical Calibration

This appendix sketches a protocol for turning raw operational data into UEE parameters. First, define candidate entities aligned with how activities are recorded (machine cycle, work order step, service ticket). Second, extract inputs (I) and consumptions (C): material quantities, labour minutes, energy draw, overhead allocation per minute. Third, specify outputs (O): counts, quality grades, or service completion probabilities. Fourth, estimate the functional form: begin with linear specifications and compare against non-linear alternatives using out-of-sample prediction error; when variability is high, include stochastic components and model heteroscedasticity. Fifth, compute elasticities ε_I and ε_C and efficiency η for each entity and aggregate by process, department and firm. Sixth, validate conservation/balance by reconciling $\sum I_i$ against $\sum \left(O_i + L_i\right)$; persistent gaps motivate instrumentation improvements. Finally, embed the calibrated UEEs in a system model to simulate interventions (e.g., reducing setup time, reallocating labour, changing batch sizes) and to forecast cost, throughput and resilience. This workflow enables evidence-based process design while preserving the theoretical coherence of the UEE grammar.