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THE MODELING STRATEGY OF COMPLEXITY ECONOMICS WITH IMPLICATIONS IN OPTIMAL POLICY–MAKING

Expanding on previous work done in the domain of modeling complexity economics we formulated a strategy to use as a modeling guide for modeling complexity economics. We identified two cases of complexity economics modeling and using common variables used in many studies demonstrated typical pitfalls and gaps in related to the confounding effects of various variables which can lead to misleading results. Since the framework of complexity economics is essentially boundless, we also introduced a limitation for modeling optimal policymaking within this framework which we believe will guide future research into taking steps to unveil the true potential of modeling with decreasing abstraction layers.

Key words: complexity economics, modeling complexity, macroeconomics, policymaking.

Introduction

Economic complexity has emerged as a vital framework in understanding and shaping policymaking, reflecting the intricate interplay between productive capacities and economic growth. It has the potential to inform policies for fostering sustainable development, reducing inequality, and enhancing innovation. It provides a robust framework for understanding and addressing the challenges of economic development. By linking productive knowledge to growth and social outcomes, it offers policymakers actionable insights into fostering innovation, reducing inequality, and achieving sustainable development. The integration of complexity metrics into policy frameworks represents a significant step toward data-driven economic planning and strategic resource allocation.

Literature review

Considerable progress has been made in understanding the complex dynamics of various parties interacting in a limited-resource environment. Economics, described by T. Sowell as the systematic study of cause and effect (Sowell, 2014, pp. 5-6) has been analyzed, at large, by aggregating various input-output metrics to gain a “summary” of the state of the economy and to guide the policy-making process. Complexity economics suggests a categorically different way of analyzing the economy by embracing non-aggregated, fine-grained details of the data and refusing to apply abstraction and aggregation in places where it is not necessary (Hidalgo, 2021, pp. 92-113). This line of thinking is not new, in fact, Simpson’s Paradox, well-known among statisticians since the 1970s, describes a situation where via data partitioning one can observe higher overall incidence, despite observing lower incidence in each partitioned category (Wagner, 1982, pp.46-48). Furthermore, the proliferation of data science tools and advanced models with big data enabled us to analyze economics with less abstraction and allow more complexity to seep into our analysis. As described by Hidalgo et al, the main driving force for unveiling the complexity of an economy has been the introduction of measures of relatedness and measures of complexity (Hidalgo, 2021, pp. 92-113). The latter, as defined by Hidalgo et al, revolves around the export structure of an economy in question and is understood as a derivative of a bipartite network where countries are connected to their exports (Hidalgo and Hausmann, 2009, pp. 10570-10575). A simpler, yet more effective measure of complexity was suggested by Inoua S., a core component of which was the log value of the number of products a country makes, e.g. out of 772 products surveyed the USA makes all of them, while less diversified economies such as Yemen and Libya make 213 and 189, respectively (Inoua, 2023, p. 104793). This and other techniques of modeling complexity within economies and among their interactions have proven effective in identifying future growth and development strategies. Nevertheless, it is crucial to underline that acknowledging the complex nature of the economy and its dynamics and coming up with some one-digit statistics to describe the complexity is just one way of modeling and de-abstraction. Krakauer et al suggested considering machine learning models in the schema of modeling complexity as a pre-processing technique, e.g. in terms of encoding data, and complexity science as a post-processing technique for decoding various non-trivial dependencies captured by ML and decoding them into a coarse-grained schema of understanding (Krakauer, 2023, p. 1235202). The basic nature of ML modeling gives us considerable leverage in understanding complex phenomena, i.e. as described by Goodfellow et. al learning from experience E with respect to some tasks T and a performance measurement P in a nutshell allows us to get a mapping of any relevant input-output pairs with varied degrees of interpretation (Goodfellow, 2016, p. 97). Nevertheless, as noticed by Molak, most ML models operate in the field of association rather than causation (Molak, 2023, p. 34), leaving us with a limited understanding of the variables that play a role in the modeling of a complex problem. This has the potential of working with confounding effects of various phenomena and leaves us wondering about the rank 2 and rank 3 levels of causality while most ML modeling efforts are essentially rank 1 associative models as defined by Pearl from casual perspective (Pearl, 2010, pp. 39-58).

Thus, a comprehensive strategy of approaching a modeling task in the framework of complexity economics should consider modeling a complexity economics phenomenon not only via machine learning but also from a causal perspective.

A broader perspective for understanding the modeling task of complexity economics can be derived from Hollings's definition of the dynamics of complex adaptive systems and the introduction of the concept of "panarchy" (Holling, 2001, pp. 390-405). The "panarchy" concept suggests that systems at various scales (ecological, economic, and social) operate through nested adaptive cycles. These cycles feature phases of growth, conservation, release, and reorganization. Adaptive cycles describe how systems accumulate resources, become rigid, and eventually undergo renewal and innovation. They integrate creativity with stability and highlight the importance of resilience and adaptive capacity. Sustainability involves creating and maintaining adaptive capacity, while development focuses on opportunities. Together, they balance change and persistence. Moreover, systems across different scales influence each other through "revolt" (small-scale disturbances affecting larger systems) and "remember" (larger systems stabilizing smaller ones) (Holling, 2001, pp. 390-405). Unique to human systems are foresight, communication, and technology, which enhance adaptability but can also lead to maladaptive traps if improperly managed. An earlier take on complexity by Herbert A. Simon suggests that hierarchical organization is fundamental to the structure, evolution, and functioning of complex systems. It provides efficiency, stability, and adaptability, making it a universal framework for studying systems across disciplines (Simon, 1977, pp. 245-261). Simon advocates a hybrid "Laplacian-Mendelian" approach: focusing on hierarchical laws between levels while acknowledging detailed underlying mechanisms that balance understanding emergent patterns with fundamental principles.

Another important consideration when it comes to modeling the complexity of economic systems is the accepted presumption of the character of economic growth. For our research scope, it is crucial to define endogenous growth theory, which challenges the neoclassical view by suggesting that long-term growth is driven by factors within the economic system, particularly the rate of technological progress. Endogenous growth theory implies that economic strategies should focus on fostering innovation and enhancing knowledge dissemination. It suggests that societal arrangements and policies must balance the incentives for innovation while ensuring inclusiveness and long-term adaptability (Aghion, Howitt, Brant-Collett, and García-Peñalosa, 1998, pp. 68-71). The overall approach towards complex economic systems from the endogenous growth perspective is very similar to economic complexity assumptions. Furthermore, S. Albeaik et al, demonstrated an improvement to the existing ECI score: ECI+ consistent with the endogenous perspective (Albeaik, Kaltenberg, Alsaleh, and Hidalgo, 2017). ECI+ effectively integrates export diversity and product sophistication, offering a better understanding of how economies can transition to higher growth trajectories leaving us with better predictions of economic growth and analysis of the knowledge embedded within an economy.

Regardless of the chosen methodology to capture economic complexity, the reward of conducting such an analysis is, of course, the policy implications that follow. César A. Hidalgo identified 4 main dimensions in his 4Ws framework, by asking the questions:

1. What – the specific sectors or activities that regions should diversify into, based on relatedness and complexity.
2. When – the timing for targeting related and unrelated activities, emphasizing the importance of balancing efforts across diversification strategies.
3. Where – the geographic diffusion of knowledge, highlighting the role of proximity and infrastructure in enabling knowledge spillovers.
4. Who – the role of agents such as migrants, foreign firms, and institutions in driving structural change (Hidalgo, 2023, p. 104863).

The appropriate modeling approaches and visualization techniques can help to derive answers to these questions from relevant data. Furthermore, a more nuanced perspective can be formulated for policymaking with the consideration of inclusive growth. By focusing on industries with higher economic complexity, policymakers can promote sectors that generate equitable opportunities, such as skilled labor and innovation-driven industries (Hartmann, Guevara, Jara-Figueroa, Aristarán, and Hidalgo, 2017, pp.75-93). Similarly, we can leverage the innate partition-favoring modeling paradigm of complexity economics modeling to enhance homogeneous growth strategies as opposed to heterogeneous regional growth strategies that can be observed in, e.g. Mexico (Chávez, Mosqueda, and Gómez-Zaldívar, 2017, pp. 201-219).

Given all the progress we have seen in the field of complexity economics, we still struggle to find research on a particular methodological approach to modeling, i.e. a modeling strategy, and from policy perspective, we have not seen a general evaluation of what is possible in the best-case scenario, which would also give us perspective on the perceived limitations of complexity economics.

Methodology, research design and strategy proposal

We conducted the augmentation of an existing model by complexity infusion in an earlier study (Vardanyan, 2023, pp. 48–58). Here we will cover the overall strategy and concentrate on the iterative steps to be taken. A substantial gap exists within the literature when it comes to emphasizing the level of understanding of the variables that we use to describe and model complexity economics. The problem usually involves confounding variables and spurious associations which lead to superfluous conclusions that do not reflect the data and data gathering biases. We will therefore complete the bigger picture here and concentrate on the initial steps of analysis as the actual modeling phase has already been proven to work in the earlier studies.

Thus, the objectives of this paper are to:

1. Formulate a data–driven strategy of modeling complexity.
2. Advance the decision–making capacity of such modeling strategy via the introduction of an optimal policy–making capacity roadmap.

The data

The data were taken from World Databank for 116 countries for 2019, 2020 and 2021 years. The variables used are among the most common variables taken for complexity analysis, i.e. relating to export structure and socio–demographic aspects of a country (Word Bank Oren Data , n.d.):

Population, male (% of total population), Final consumption expenditure (% of GDP), Gross domestic savings (% of GDP), Military expenditure (% of GDP), GDP per capita growth (annual %), Medium and high–tech exports (% manufactured exports), High–technology exports (current US$).

The modeling strategy proposal

The proposed strategy has the following structure:

Case 1: Starting with an initial set of beliefs to model certain phenomena – Model complexity augmentation.

- <u>Introduction of complexity</u> into the initial set of beliefs (chosen model).

Key result: **Complexity Augmented Model**

Case 2: Starting with a phenomenon and figuring out a model from the data – Model complexity discovery.

- The construction of models based on <u>revealed relationships</u>, i.e. “letting the data speak”.

Key result: **Complexity–driven choice for a model.**

In both cases, we talk about complexity as an ingredient that gets added to the modeling effort in different phases, where the 4Ws framework is used to complete the modeling strategy proposal (diagram 1).

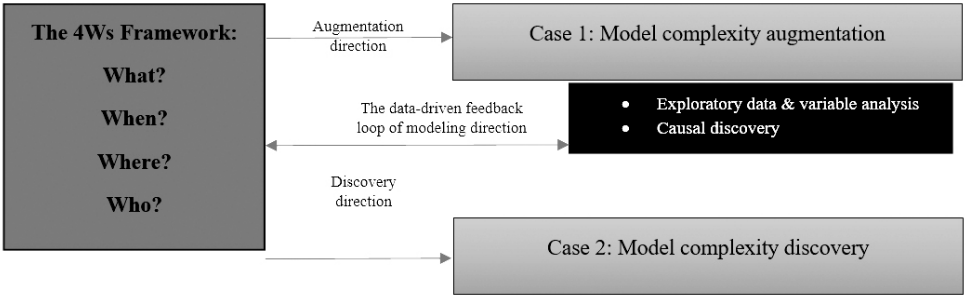

Diagram 1: Proposed modeling strategy of complexity economics

As is demonstrated the understanding of variables, their causal relationships, and the 4Ws framework's directions within that understanding is the key aspect of the proposed strategy, which, undoubtedly, starts at the exploratory data analysis stage.

To complete our introduction to the beforementioned strategy let's apply it to an example with the data described above.

Case 2: Example – strategy in action

To identify the <u>direction of discovery</u> we first need to conduct exploratory data analysis.

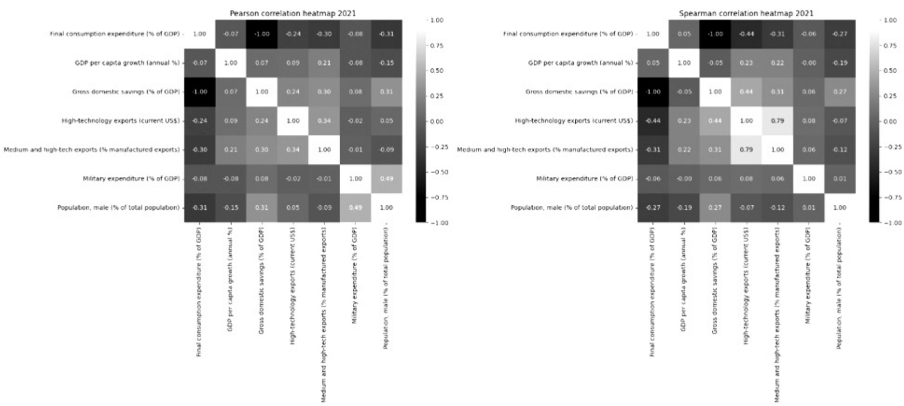

Figure 1: Correlation heatmaps of the chosen variables

We see interesting relationships between various variables, e.g. the negative Spearman correlation between final consumption expenditure and high-tech exports. Similarly, high-tech exports correlate with gross domestic savings while the male population ratio positively correlates with military expenditure. What we see here are the confounding effects of the variables under analysis. For example, the male population ratio can be treated as a proxy for the development degree of an economy as the female population usually has a higher life expectancy thus having a longer living population will result in a higher percentage of the female population. We can further explore the relationships present here via a biplot of PCA 2 components.

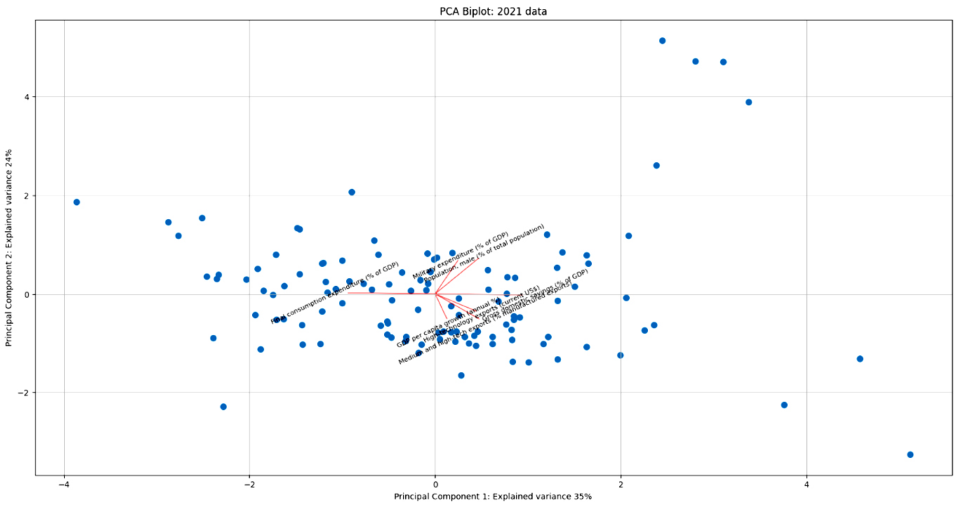

Figure 2: PCA 2 component biplot for 2021 data.

With approximately 60% variance explained by 2 components, we clearly see that the variables discussed here and usually included in complexity analysis demonstrate non-linear relationships that cannot be discounted. This leads us to causal discovery (figure 3).

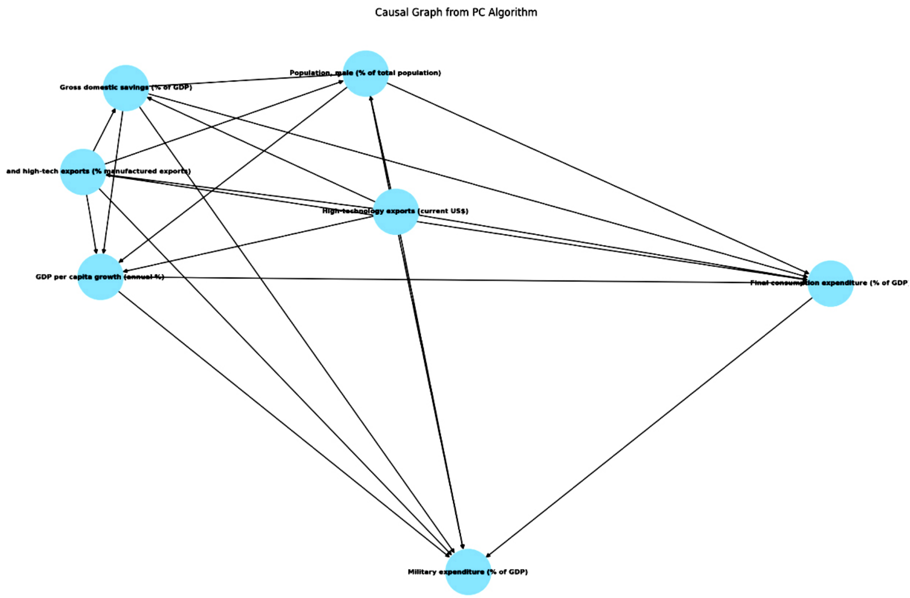

Figure 3: PC algorithm's resulting graph with a significance level of 0.5.

In terms of validating the results of PC algorithm (Molak, 2023, p. 34), we need to take into account domain knowledge and possible discrepancies with the data. Nevertheless, the algorithm shows us an interesting causal map among socioeconomic variables further underlining the fact that variables in any macroeconomic analysis should not be taken at face value. Moreover, when introducing complexity into the system we have to systematically conduct causal tests and discovery procedures to ensure that what we see is what the data is telling us, not the opposite.

Results, discussion and future research

Complexity economics grew in popularity partially due to the failure of classic economics to explain the tragic crises that kept returning unexpectedly, though the modeling capacity has been growing since the conception of economic thought. Kymlicka formulated the importance of two fundamental values and their importance: freedom and equality (Kymlicka, 2002, pp. 102–103). There is no arguing that both freedom and equality are valuable, but which one is more valuable? It turns out that this question alone is in fact at the root of economic policymaking, when we think of those who conduct liberal policy, i.e. with emphasis on the redistribution of wealth they do it to the detriment of the freedom of others to use resources they possess, similarly when individual freedom is prioritized it is prioritized over equality. Thus, can we optimize the distribution of limited resources via data-driven modeling with the help of complexity economics to **solve the equation for the right amount of freedom and equality?** We believe the answer to this question will be testing the limits of modeling complexity economics, and future research should pay close attention to this question.

Also, more robust causal discovery tools and techniques are needed to streamline and integrate causal discovery as a valuable tool for understanding the variables we use to model complexity.

Conclusion

In conclusion, as demonstrated above the strategy of modeling complexity via two cases provides a valid starting point to conduct robust economic analysis. The strategy of modeling complexity economics as it turns out needs many dependencies to work as intended, especially when it comes to understanding the variables we work with and their relationships. The fundamental nature of infusing more complexity into a system cannot be self-serving, thus the theoretical limitation of finding the optimal state policy between freedom & equality optimization is a good starting point for future research to concentrate on to test the limits of complexity modeling and its implications in policy. Certain limitations were taken in this case, most notably we neglected the time factor, due to the nature of the analysis conducted, which we hope to circle back with a point-based equilibrium approach.

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Միհեր Վարդանյան

Երևանի պետական համալսարանի Տնտեսագիտության մեջ
մաթեմատիկական
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ԲԱՐԴՈՒԹՅԱՆ ՏՆՏԵՍԱԳԻՏՈՒԹՅԱՆ ՄՈԴԵԼԱՎՈՐՄԱՆ ՌԱԶՄԱՎԱՐՈՒԹՅՈՒՆԸ ՕՊՏԻՄԱԼ ՔԱՂԱՔԱԿԱՆՈՒԹՅԱՆ ՎԱՐՄԱՆ ԱՌՆՉՈՒԹՅԱՄԲ

Ընդլայնելով բարդության տնտեագիտության մոդելավորման ոլորտում կատարված նախորդ աշխատանքը՝ մենք ձևակերպեցինք ռազմավարություն, որը կարող է օգտագործվել որպես մոդելավորման ուղեցույց բարդության տնտեսագիտության մոդելավորման համար: Մենք բացահայտեցինք բար–դության տնտեսագիտության մոդելավորման երկու դեպք և շատ ուսումնա–սիրություններում օգտագործված ընդհանուր փոփոխականների կիրառմամբ ցույց տվեցինք հաճախ հանդիպող խնդիրներ և հասկացողության բացեր տարբեր փոփոխականների շփոթեցնող ազդեցությունների առումով, որոնք կարող են հանգեցնել ապակողմնորոշիչ արդյունքների: Հաշվի առնելով այն հանգամանքը, որ բարդության տնտեսագիտության շրջանակը, ըստ էության, անսահման է, մենք նաև սահմանեցինք այս շրջանակում օպտիմալ քաղա–

քականության ձևավորման մոդելավորման սահմանափակում, որը, մեր համոզմամբ, կուղղորդի ապագա հետազոտություններին՝ նվազող աբստրակցիոն շերտերով մոդելավորման իրական ներուժը բացահայտելու քայլեր ձեռնարկելու ուղղությամբ:

Հիմնաբառեր. բարդության տնտեսագիտություն, բարդության մոդելավորում, մակրոտնտեսագիտություն, քաղաքականության վարում:

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СТРАТЕГИЯ МОДЕЛИРОВАНИЯ СЛОЖНОЙ ЭКОНОМИКИ С ПОСЛЕДСТВИЯМИ В РАЗРАБОТКЕ ОПТИМАЛЬНОЙ ПОЛИТИКИ

Расширяя предыдущую работу в области моделирования экономики сложности, мы сформулировали стратегию, которую можно использовать в качестве руководства по моделированию экономики сложности. Мы определили два случая моделирования экономики сложности и, используя общие переменные, используемые во многих исследованиях, продемонстрировали типичные подводные камни и пробелы в понимании с точки зрения смешивающих эффектов различных переменных, которые могут привести к вводящим в заблуждение результатам. Поскольку структура экономики сложности по сути безгранична, мы также ввели ограничение для моделирования оптимальной политики в рамках этой структуры, которое, как мы считаем, будет направлять будущие исследования к принятию мер по раскрытию истинного потенциала моделирования с уменьшением уровней абстракции.

Ключевые слова: экономика сложности, моделирование сложности, макроэкономика, разработка политики

Հոդվածը խմբագրություն է ներկայացվել՝ 2024թ. նոյեմբերի 22-ին:
Հոդվածը հանձնվել է գրախոսման՝ 2024թ. նոյեմբերի 25-ին:
Հոդվածն ընդունվել է տպագրության՝ 2024թ. դեկտեմբերի 26-ին: