

Chapter 2

Transformation Networks: A study of how technological complexity impacts economic performance

Christopher D. Hollander, Ivan Garibay, Thomas O’Neal

Abstract Under a resource-based view of the firm, economic agents transform resources from one form into another. These transformations can be viewed as the application of technology. The relationships between the technologies present in an economy can be modeled by a transformation network. The size and structure of these networks can describe the “economic complexity” of a society. In this paper, we use an agent-based computational economics model to investigate how the density of a transformation network affects the economic performance of its underlying artificial economy, as measured by the GDP. Our results show that the mean and median GDP of this economy increases as the density of its transformation network increases; furthermore, the cause of this increase is related to the number and type of cycles and sinks in the network. Our results suggest that economies with a high degree of economic complexity perform better than simpler economies with lower economic complexity.

2.1 Introduction

Ever since Robert Solow’s work on integrating technology into economic growth models, it has become generally accepted that knowledge, technology, and innovation are driving forces behind economic progress. Today, many existing economic models account for these forces and many research projects have arisen that attempt to understand how these forces impact economic performance [2–4, 6, 10]. However,

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many attempts to represent knowledge and innovation in the framework of mathematics have fallen short, causing their presence in real world economic models to be relegated to a mere constant factor in the name of tractability and analysis. One approach that address the difficulties in modeling these type intractable concepts, such as the role of knowledge, is known as “agent-based computational economics,” or ACE. In agent-based computational economics (ACE) [1, 5, 7, 9, 13, 18], economic agents are implemented *in silico* using techniques from computer science and artificial intelligence that make it possible to construct economic models that violate established assumptions of rationality and use concepts and ideas previously thought too hard to model from a purely mathematical standpoint. These advances are possible because ACE models *generate* economies from the ground up and once created, one can observe their growth in a controlled environment and modify economic parameters to gain a deep understanding for why observed phenomena may exist. Using agent-based computational economics, it is now possible to explore the relationship between knowledge, technology, innovation, and economic performance.

To address the role of knowledge in economic performance, we build on the existing resource-based [20] and knowledge-based [14] theories of the firm and view knowledge as the know-how that allows an economic agent to transform resources into goods or services. The knowledge of a particular agent can be represented as a set of transformation rules, with each rule representing a particular piece of technology that determines which economic inputs can be transformed into which economic outputs. Using this idea of knowledge as a set of technologies acting on a set of inputs and outputs, which we call *resources*, it is possible to construct a “transformation network” that can help define the *technological complexity* of an economy. A transformation network is an economic network [12, 16] that models how resources are connected to one another by technology. These networks are constructed from the knowledge contained in the individual agents of an economy, and as such, they coevolve with their underlying agent population. As the agents acquire new technology and as resources are discovered, created, and depleted, the structure of the transformation network changes. When viewed over time, the structure of a transformation network tells the story of technological change, adoption, and innovation within a society.

In this paper, we define transformation networks and use them to examine an artificial economy to study how technology and innovation can increase economic performance. In particular, we use an agent-based computational economics approach to simulate an artificial economy and explore how the density of its transformation network, along with the number of cycles and sinks in the network, can impact the economy’s performance as measured by the GDP. We hypothesize, based on previous research showing the positive correlation between R&D spending and number of patents on GDP [17] as well as the argument that diversity is beneficial to an economy [15, 19], that mean economic performance will increase with the density of the network. Additionally, we expect this increase because at the microlevel of agent interaction, additional edges result in more ways to produce, consume, and trade resources.

2.2 Resource-Based Agents and Transformation Networks

Modern economic and management science theories have seen the development of a “resource-based view” of firms [20], where economic entities are viewed as agents of resource use and transformation. Under the resource-based view of the firm, “resources” can be described as either resources or capabilities. A resource is an asset external to the firm, while a capability is a specific internal asset, such as knowledge. This resource-based view has been expanded with the knowledge-based theory of firms [14], that views knowledge as a special type of resource, with a much higher strategic value than all other resources.

Both the resource-based view and knowledge-based theory of the firm form the basis of a conceptual model of economic agents as engines of resource transformation. Under this conceptual model, every agent takes a set of resources as input, transforms them in some way that depends on that agent’s specific knowledge and capabilities, and then produces a different or modified set of resources as a result. Thus, *resources* and *resource transformation* form the core of an economic agent, and *technology* is the combined knowledge and capabilities of an economic agent. *Transformation networks* model the relationship between resources and available technology.

Every economy possesses an initial set of *resources* that can be combined to produce a set of *products*. These products, and the original set of resources, can then be traded between agents in order to satisfy needs and wants. The collection of initial resources and all future products obtainable from combining those resources or derived products form the *resource-product space*. This resource-product space coevolves with an economy. Formally, the resource-product space of an economy can be defined as follows. Let R_0 be the initial set of resources available to an economy at time $t = 0$, and let $P(X) = Y$ be a production function that transforms a set of resources, X , into a set of new products, Y . Then the resources available to an economy at time $t > 0$ are given by $R_t = R_{t-1} \cup P(R_{t-1})$ and the resource-product space, \mathcal{R} , is given by $\mathcal{R} = \lim_{t \rightarrow \infty} R_t$. If $P(X)$ is never equal to \emptyset , then there are infinitely many elements in the resource-product space. The specification of which products can be produced from which resources is codified in a set of *transformation rules*. The transformation rules of an economy form its available technology. Formally, a transformation rule, T , can be interpreted as a function that maps a set of resources into another, such that $T \in \mathcal{P}(\mathcal{R}) \times \mathcal{P}(\mathcal{R})$. A *transformation network* is a directed network that describes how sets of resources are connected via transformation rules¹. Each node, $v \in \mathcal{P}(\mathcal{R})$ represents a set of resources. Each directed edge represents a transformation rule from one set of resources to another. An edge is only present if the corresponding transformation rule is held by at least one agent in the population. The node at the tail of an edge is the input resource set for the rule, and the node at the head is the output resource set. The edge itself represents the technology required to transform the inputs into the outputs. Edges can be weighted, with a typical weight denoting

¹ Alternatively, a transformation network can be treated as a temporally-sensitive directed hypergraph [8], where each node, $v \in R_t$, represents a single resource and an edge connects all resources that act as the input of a rule to all resources that are produced by that rule.

the number of agents that hold the associated rule or the base cost to execute the transformation.

2.3 Experimental Setup

Recall that our hypothesis with regards to transformation networks states that, if all else is held equal, an increase in only the density of an economy’s transformation network will result in an increase in the mean GDP of the economy. That is to say, as an economy develops the ability to manipulate resources in new ways, it will experience an increase in economic performance.

We use an agent-based simulation to investigate the impact of a simple closed economy’s transformation network structure on the economic performance of that economy. Our simulation is constructed as follows. First, we define a set of resources, $R = \{00, 01, 10, 11\}$, that agents will be able to manipulate and trade. This set of resources is constant and does not change over time. We use resources from R to define transformation rules with a single resource as antecedent and a single resource as consequent, i.e., $\tau = (r_1, r_2)$. We construct 12 transformation rules, $T = R \times R - \{(00, 00), (01, 01), (10, 10), (11, 11)\}$. Each subset of T forms one possible transformation network of the economy without self-loops. Next, we construct a completely connected trade network consisting of 50 nodes. Each node is a computational economic agent, a , that possess an amount of wealth, $w_a \in \mathbb{R}, w_a \geq 0$, a single transformation, $\tau_a \in T$, and some quantity of one particular resource, $r_a \in R, r_a > 0$ that corresponds to the first element of τ_a . In the current simulation, agents do not die and do not learn.

All agents in the simulation are driven by a discrete clock. During each step of the clock, every agent acts once. The order that agents act in is randomly determined each step. Each time an agent acts, it assumes the role of a *buyer* and executes a sequential series of behaviors. First, it identifies the resource, r , that it needs in order to execute its transformation rule. This resource is identifiable as the first element in τ_{buyer} . If the quantity of resources currently possessed by the agent is greater than 1, then the agent does not need to buy. If, however, the quantity equals 0, then the agent searches for another agent, the *seller*, with the lowest cost, c_r , for that resource such that $c_r \leq w_{buyer}$. If the buyer is able to find a suitable seller, it buys the resource. This act of buying and selling produces a change of wealth in the buyer, $w_{buyer} = w_{buyer} - c_r$, and the seller, $w_{seller} = w_{seller} + c_r$. It also produces a corresponding change in the quantities of the associated resource. If an agent has the required resource after trading has been completed, it executes τ_{buyer} to transform the resource into something else. For the experiments in this paper, $c_r = 1$ for all resources. Costs are non-negotiable and fixed and no agent will never adjust the cost. If s is the total number of successful trades that occur during a time step, then the GDP is calculated by sc_r . The current experimental design ensures that the GDP will never be larger than 50, and may be 0 when there are no successful trades.

In order to investigate the impact that the number of edges in the transformation network has on the economic performance of our economy, we focus on the set of transformation rules that are available to the population, $T' \subset T$. Towards this end, we run a set of 4095 experiments, covering all possible edge configurations. Each experiment consists of 30 replications using one subgraph, T' , of the complete transformation network formed from T . Each subgraph represents an economy in which one or more transformation rules are present. Because we choose to only consider four resources, this enables us to examine every possible subgraph. If each rule in T is denoted by an integer, then all possible transformation networks can be generated from the combinations referenced by $\binom{12}{i}$ as i goes from 1 to 12. For example, the rule set $\{1, 4, 5\}$ corresponds to the transformation network in which rules 1, 4, and 5 are present in the economy.

To simplify our investigation, agents are assigned a transformation rule in accordance to a uniform distribution over T . Because pricing is fixed and there is no evolution or learning, each experiment is run for 1000 time steps in order to allow the economic behavior to stabilize. The data for the first 100 time steps is ignored because it represents the warm-up period of the simulation. The mean GDP of an experiment is taken as the mean of the GDP over the remaining 900 time steps.

Analysis of the simulation data is conducted on the set of isomorphic transformation networks. This approach is possible because all resources are equally valued, and thus the rule that maps resource 1 to resource 2 is effectively the same as the rule that maps resource 3 to resource 4. As a verification of this idea, a simple comparison of the mean GDP revealed that all graphs of isomorphic equivalence are statistically equal within a confidence interval of 95%.

2.4 Results and Discussion

The primary purpose of this paper is to introduce transformation networks as representations of technological interconnectedness and show how these networks can be used to provide new insight into why some economies may perform well while others perform poorly. Our current findings support the commonly held notion that technology is incredibly beneficial to an economy; however, our results also suggest that there are diminishing returns on how much technology an economy may need to employ in order to be successful.

2.4.1 Results

We present the data of our experiments as a series of box plots. In all cases, the thick bar in the middle of each box represents the median GDP and the diamonds represent the mean GDP. The top and bottom of the box represent the first and third quartile respectively, and the upper and lower whiskers extend to the most extreme

data point which is no more than the interquartile range from the box. The isolated circles represent outliers.

Figure 2.1 shows a box plot of the GDP versus the edge density of the transformation network. The y-axis represents the nominal GDP of the artificial economy and the x-axis represents the number of edges present in the transformation network used by that same economy. It can be observed that the mean and median GDP increases

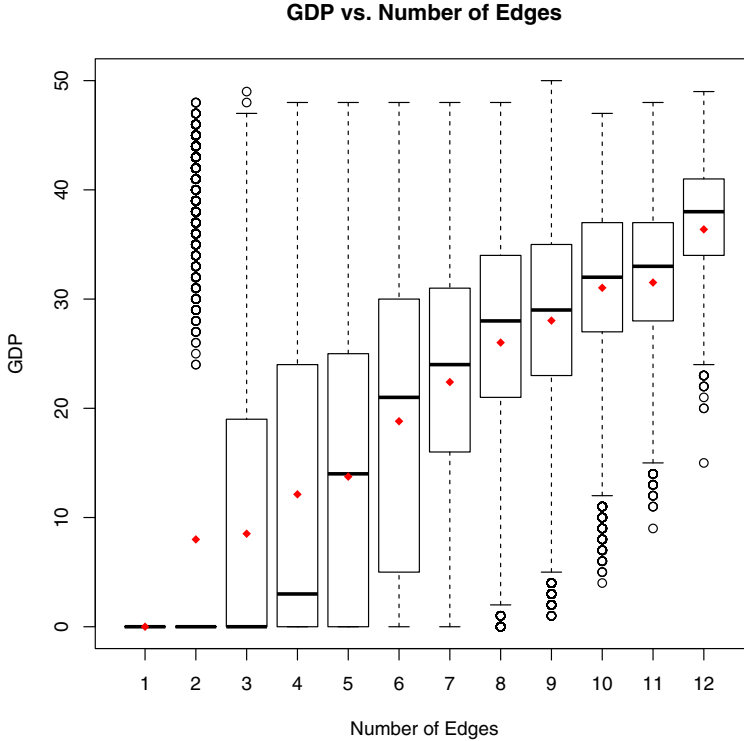


Fig. 2.1: The effect of the number of edges on the GDP of a simple artificial economy of 50 agents. The underlying transformation network has 4 nodes, yielding a maximum of 12 edges.

monotonically with the number of edges in the transformation network. It can also be observed that there appears to be a *critical point* where the number of edges exceeds 8. Once this critical point is crossed, the minimum GDP begins to increase as more edges are added to the network. The cause of this critical point can be understood in terms of other graph structures; in particular, the number of cycles and sinks that are possible for a given number of edges.

In static transformation networks on four resources, a cycle is guaranteed once there are at least 7 edges and all sinks are guaranteed to be removed once there are at least 10 edges. The presence of sinks in our transformation network prior to 10 edges may explain why it is still possible to generate very low GDP values just beyond the critical point. This relationship between the number of cycles, sinks, and edges is displayed in Figure 2.2. Figure 2.2a plots the number of cycles in a transformation

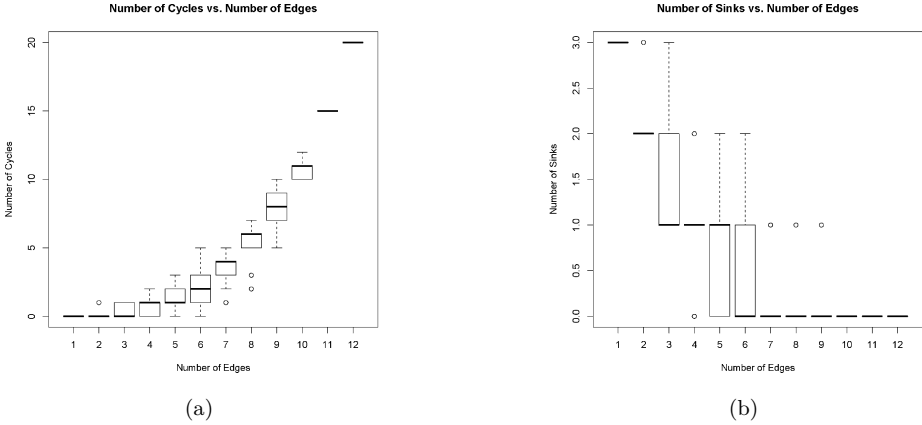


Fig. 2.2: How the number of sinks and cycles change with the number of edges in the graph

network against the number of edges. From this perspective, it can clearly be seen that once there are 7 edges in the transformation network, there will always be at least one cycle. As the number of edges in the transformation network exceeds 7, the number of cycles present quickly increases. Figure 2.2b plots the number of sinks in a transformation network against the number of edges. It can be observed that once the number of edges exceeds 10 the transformation network is guaranteed to no longer have any sinks.

The relationship between cycles and sinks on the GDP is displayed in Figures 2.3 and 2.1. Figure 2.3 shows box plots of the GDP versus the total number of cycles in the transformation network. The y-axis represents the nominal GDP of the artificial economy and the x-axis represents the total number of cycles present in the transformation network used by that same economy. It can be observed that the mean and median GDP initially increase with the number of cycles, but these increases appear to level off beyond 6 cycles. This behavior suggests that the ability for resources to be transformed full circle is important to a healthy economy, but only up to a point. Beyond this point, additional cyclic structures contribute only a marginal benefit. This point appears to correspond to the critical point observed in Figure 2.1. Once

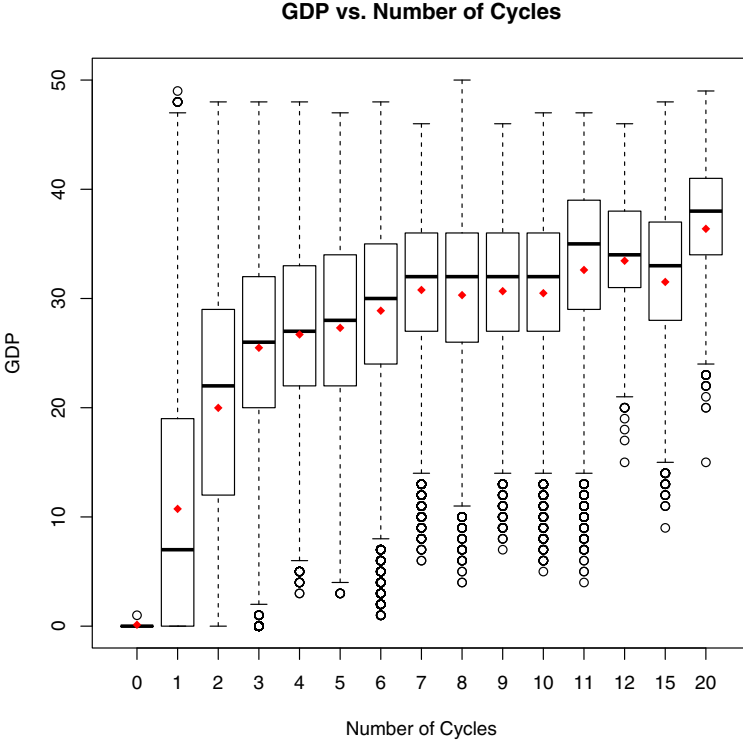


Fig. 2.3: The effect of the number of cycles on the GDP of a simple artificial economy of 50 agents. The underlying transformation network has 4 nodes, yielding a maximum of 12 edges.

the transformation network has 8 edges, it is possible to obtain 6 cycles (see [Figure 2.2a](#)).

[Figure 2.4](#) shows box plots of the GDP versus the total number of sinks in the transformation network. The y-axis represents the nominal GDP of the artificial economy and the x-axis represents the total number of sinks present in the transformation network used by that same economy. In [Figure 2.4](#), it is observed that the mean and median GDP decreases with the number of sinks in the transformation network. These observations also correlate with the behavior of the GDP in [Figure 2.1](#). As the number of edges increases, the number of sinks decrease, and the GDP increases. The presence of a large number of sinks when there are very few edges also helps explain why the GDP is so low for very sparse transformation networks (see [Figure 2.2b](#)).

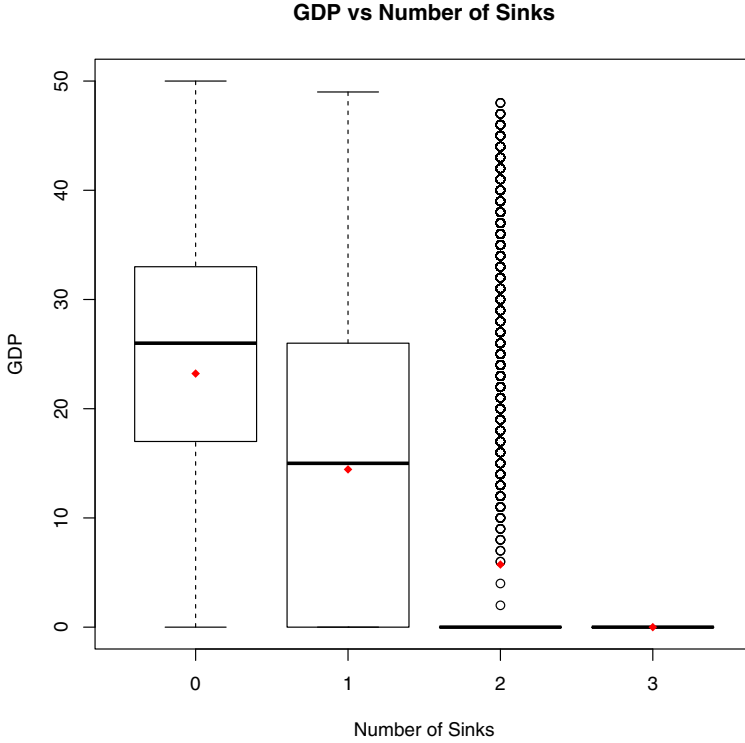


Fig. 2.4: The effect of the number of sinks on the GDP of a simple artificial economy of 50 agents. The underlying transformation network has 4 nodes, yielding a maximum of 12 edges.

2.4.2 Discussion

Our initial results appear to support our hypothesis that the mean economic performance of a system will increase with the density of its transformation network. In addition, we have observed that not only does the mean economic performance increase, but the minimum economic performance increases as well. This suggests that as societies make use of more technology, the influx of economic opportunities lifts everybody to a higher level of performance. Furthermore, the cause of this behavior appears to be linked to the formation of cycles and sinks in the transformation network, and the existence of a critical density at which there are sufficient edges to guarantee certain structural properties.

Based on our results, we suggest the structure of an economy's transformation network plays a significant role in the economic performance of a society. As the

density of a transformation network increases, it becomes possible for technologies to be connected through cycles, enabling the continuous circulation of resources. This amount of circulation grows quickly as the network approaches a state of complete connectivity. At the same time, an increase in density of cyclic structures results in a decrease in the number of sinks. Because sinks represent technologies that produce unwanted resources, their removal reduces waste in the system. This reduction in waste corresponds to an increase in overall demand, which produces higher levels of trade and thus higher levels of economic performance. However, it is not enough for a transformation network to simply be connected in such a way that it has at least one cycle. Networks should have at least enough edges to guarantee, with a high probability, that there are no sinks. This structural constraint is important because the number of sinks appear to be more important than the number of cycles. This claim is evidenced by results shown in [Figures 2.3](#) and [2.4](#) where the growth of performance based on the number of cycles quickly levels off, while the impact of the number of sinks appears to behave linearly.

The transformation network presented in this paper is a simple model. It is possible, given the appropriate data, to apply this same concept to real economies. For example, each country can be viewed as an economic agent with transformation rules that correspond to its imports and exports. Recent work on product spaces [11] suggest one source for this type of data. Given a complete set of countries and their rules, it is possible to create the associated transformation network by linking resources together in accordance to transformation rules that exist at the country level. The resulting network can then be augmented, such as giving each edge a weight that corresponds to the number of countries able to execute that transformation process. This same approach can also be used at lower levels to produce multiple networks that can then be compared to one another; e.g. a transformation network over the manufacturing sectors of the USA, China, and India.

Our current work only considers the role of density in a transformation network. Future work is needed to examine additional properties of an economy’s knowledge structure. For example, how redundancy, modularity, size, and average path length between resources impact economic performance. Related to this, the structure of real-world transformation networks also needs to be identified. Additionally, a transformation network becomes dynamic if knowledge is allowed to evolve. Does such evolution drive the underlying economy to optimal performance? Can policies be designed to help a simple economy evolve towards higher levels of complexity? Early experiments that we have conducted with dynamic transformation networks support our current findings, but indicate that driving agents to develop the optimal technologies is not an easy or straight forward process.

2.5 Conclusion

Transformation networks provide one way to describe the economic complexity of a society by modeling how that society’s resources are transformed. We showed that

the structure of an economy's transformation network has a significant impact on its performance. This result is not surprising given that real-world observations and previous research findings indicate a positive correlation between technological prowess and GDP. Our simple artificial economic model qualitatively reproduces these previously observed trends and offers a possible explanation for how the amount of technology, and the relationship between those technologies, affects economic performance.

If technological complexity is measured by the density of a economy's transformation network, then an increase in complexity exposes the underlying economic agents to a wider array of economically viable resources. This occurs because resources become more connected as the number of edges in the transformation network increases. With these extra connections, the demand for some resources increases, while the number of resources being transformed into unwanted goods or services decreases. Furthermore, as the technological complexity of an economy grows beyond a critical point, the minimum possible performance of that economy raises.

Transformation networks offer a knowledge-centric view of economic complexity that is not directly associated with the number of economic actors or actor interactions, but rather with the amount and interconnectedness of the knowledge present in an economic system. As a result, we propose that further research on these networks can contribute to the better understanding of knowledge-centric economic phenomena including knowledge-driven economic growth and innovation ecosystems. Additionally, further development of this model and the interplay of the agents can benefit economic development efforts at the practitioner level. A greater understanding of how local interventions can affect a local economy can positively influence the return of investment from local governments, economic development organizations, and philanthropic efforts aimed at effecting economic prosperity in a particular region.

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