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(Not) by chance? An application of Assembly Theory to infer non-randomness in Organizational Design

Abstract: Assembly Theory (AT) (Sharma et al, 2023) is a novel and ambitious perspective on the emergence of larger structures from smaller structures in the physical realm. It offers formal tools to infer the development trajectories of observed structures under some theory-driven assumptions. By mapping it onto the microstructural perspective of organizations, we show how AT can also help us model organizational development and estimate the extent to which an observed organizational structure is (un)likely to have arisen by chance. We apply these to illustrate how we can infer the extent of non-randomness in the development history of an organization based on its current structure. We note theoretical and empirical implications for the study of organization design.

Keywords: Assembly Theory, Micro-structural Analysis, Chance Explanations, Formal Modelling

Recently developed, Assembly Theory (AT) aims to bridge physics and biology, offering a new framework for understanding evolution and complexity in nature (Marshall et al. 2021; Sharma et al. 2023). It redefines objects based on their formation history through an Assembly Index, allowing for the quantification of complexity and the extent of "selection" (i.e. non-random influence) in the object's evolution. A podcast conversation between Lex Fridman and one of the authors of AT, Lee Cronin, carried Assembly Theory to its peak Google Search count two months after its publication and the article attracted almost 300,000 views in only four months. While AT has also been met with skepticism from some scientists (e.g. Uthamacumaran et al. 2022), others have begun exploring its applications to the evolution of cellular automata rules (Patarroyo, Sharma, Walker, and Cronin, 2023), the economics of innovation (Lee, Kempes, and West, 2023) and neural network development (Nicolle et al. 2024). The authors state that they "anticipate the theory to be sufficiently general to apply to a wide variety of other systems including polymers, cell morphology, graphs, images, computer programs, human languages, and memes, as well as many others" (p. 322).

Notwithstanding the eventual utility of AT in the natural sciences, we propose that the core approach to studying the emergence of complex structures in AT can be useful for studying organizations and their development. In essence, AT shows a systematic approach to modeling the assembly of complex systems from simpler systems in a process whose steps can be counted. The number of steps required to get to the final structure and the extent of recurrence of its subsystems can be used to assess the likelihood that it arose by chance rather than some sort of non-random process, such as adaptation or selection.

We adapt this approach for its utility to the micro-structural perspective on organizations, which proposes that "large, complex organizations can be understood as collections of smaller, simpler, and recurring patterns of micro-organizations" (Puranam, 2018). Put simply, the macro-structures of organizations can be understood as assemblies of micro-structures. AT offers a useful approach to formalizing the properties of the assembly process, and to measure the extent to which it shows signs of non-randomness arising from managerial fiat, emergence through informal organizing processes, competitive selection, or some combination of these. We will use the umbrella term "design process" to refer to all of these, bearing in mind that it does not presume the existence of an intelligent designer. Rather, design is used here as the opposite of randomness (Dennett, 1995; Dawkins, 1986; Puranam, 2018; Hodgson and Knudsen, 2004), another umbrella term for factors with no systematic connection to the organization's survival, such as co-incidence, uncoordinated local action, political agendas, taste, etc.

After showing how we can use AT to measure the extent of design in the developmental process through which complex organizational structures arise, we discuss how it can lead to new avenues for theoretical and empirical research.

Complexity, Assembly Theory, and Organizations

Explicitly or implicitly, many prevalent theories of organization design treat organizations as complex adaptive systems (Simon, 1962; Levinthal, 1997; Perrow, 2014; Puranam, 2018). Such a system, rather than being a unitary actor, comprises multiple interdependent parts that adapt to each other and the environment of the system (Holland, 1995). For instance, the information-processing view highlights the ability of the components of organizations to collect, process, create, and distribute knowledge (e.g. Boisot and Child, 1999; Moldoveanu and Bauer, 2004; Joseph and Gaba, 2020). Analyses of task interdependence patterns among the components address the predictability of tasks influenced by environmental turbulence, dependencies on other tasks, or the state of the business environment (e.g. Siggelkow and Rivkin, 2005; Eisenhardt and Piezunka, 2011; Puranam, Raveendran and Knudsen, 2012; Stieglitz, Knudsen, and Becker, 2016). Empirical studies have examined such interdependence patterns resulting from shared resources, knowledge, complementary actions, or technological dependencies (Fleming and Sorenson, 2001; Sosa, Eppinger, and Rowles, 2007; Zhou, 2013; Goh and Pentland, 2019; Burford, Shipilov, and Furr, 2022; Ganco, Kapoor, and Lee, 2020; Shipilov and Gawer, 2020).

A central idea in the literature on organization design is the concept of "fit" between the complexity of information-processing activities and the complexity of the task interdependence patterns that generate the need for information processing. Among organizations with the same objective, those that attain a better match between information processing capacity and needs perform better, survive selection and grow (Hannan and Freeman, 1977; Nelson and Winter, 1985; Ethiraj and Levinthal, 2004; Levinthal and Posen, 2007; Levinthal and Marino, 2015). Organizational performance and growth are thus understood to arise from an interaction between adaptation (which attempts to produce fit between information processing needs and capacities) and the pressures of competitive selection (Levinthal, 1997).

However, most of these approaches treat the organizational form itself as constant. In reality, organizations adapt and grow, and consequently their formal and informal structures change (Gulati and Puranam, 2009; Lee, 2022), sometimes quite dramatically. For instance, Github was a self-consciously flat organization when small, yet introduced hierarchical layers and roles as it grew (Burton et al. 2017). When large organizations need to innovate or adapt to changing external conditions, they are reorganized: responding to product and service integration pressures, both Cisco and Microsoft transitioned from a divisional structure to a functional form, the former in 2001 and the latter in 2013. Karim and Mitchell's (2004) detailed study of Johnson & Johnson between 1978-1997 provides rich data on the developmental path taken by the organization. The organizational origins of one of its business units, J&J Medical Inc. formed in 1993, extends back to 1975. Figure 1 illustrates a series of acquisitions (white square boxes) that were recombined into larger units (grey boxes) over 18 years, eventually forming J&J Medical Inc. in 1997 (each number identifies a business unit[1]). The arrows indicate the time period in which each acquired unit was combined into a joint division.

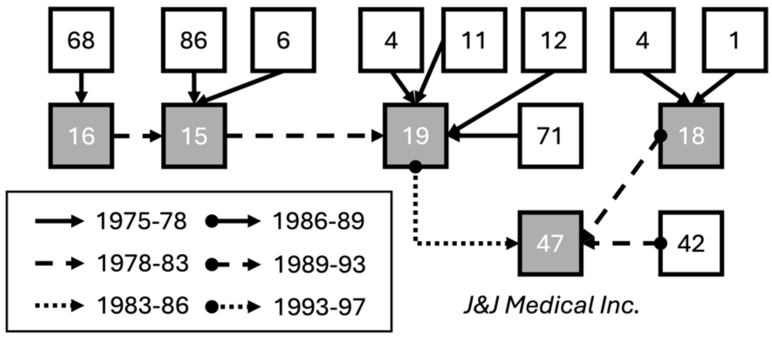


Figure 1: *J&J Medical Inc. as formed through recombination of acquired units. Recreated from Karim and Mitchell's (2004) documentation of acquisition and integration patterns.*

The changes in the system thus came from acquisition, internal development, and re-configurations that combined existing units. The authors document how J&J formed 88 business units, out of which 54 were acquired, 12 were internally developed, and 22 were reconfigured units. In this article, we show that AT can be used to theorize about processes such as the one through which the structure of J&J Medical Inc. evolved.

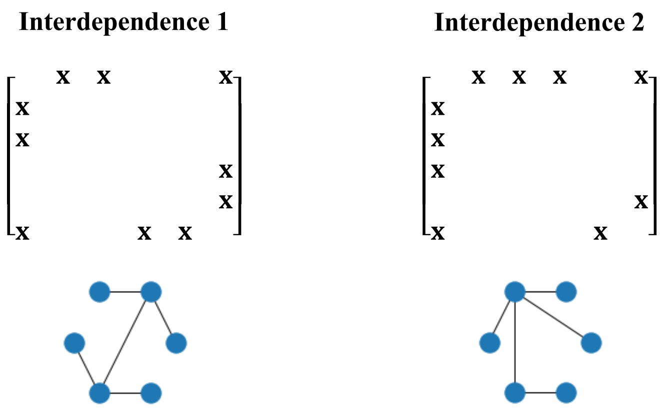
An important insight in organizational research is that observed organizational structures need not be only the result of design in the sense of adaptation or selection; some might simply owe their origins to randomness (in the sense of factors not systematically associated with performance; e.g. Levinthal, 1991). Since selection pressures may be weak, and the capacity for adaptation limited by bounded rationality, we must be open to the possibility that observed structures arise essentially through random processes (see Denrell, Fang, and Liu, 2015, for a useful compendium of random processes that may operate to shape organizational outcomes). AT provides an approach to estimate a bound for how much of such outcomes may be due to randomness.

For instance, in Figure 2, we show two hypothetical task interdependence patterns that could be empirically observed and analyzed. Many existing measures of complexity focus on the number of ties (complexity) and modularity of these structures (Ethiraj and Levinthal, 2004; Rivkin and Siggelkow, 2007). Given the same extent of modularity (each structure can be split into two modules by removing the entry in the top-right and bottom-left of the adjacency matrices) and complexity, the two patterns (I1, I2) seem equivalent. Yet, as we explain below, an AT perspective suggests that the development of these structures may have been quite different. Specifically, I2 is more likely than I1 to have been produced by a non-random process. The rest of this paper explains why we might reach such a conclusion.

In sum, in this paper, we aim to clarify how the tools offered by AT can complement existing complexity measures and help deepen our understanding of the role of non-random forces such as

[1] Refer to Karim and Mitchell (2004) for more details on each business unit and the reconfiguration events.

managerial authority, informal organizing and selection through competition, in the process through which complex structures may develop from simpler structures.



Complexity(I1) = Complexity(I2) = 5

Non-randomness in development
(Assembly Number (I1) ~ 7.4) < (Assembly Number (I2) ~ 8)

Figure 2: *Comparison of Complexity and Assembly Number of two interdependence structures.*

Illustration: An AT-based approach to the development of functional and divisional structures

Sharma et al. (2023) note that in applying AT "the challenge […] will be to construct an assembly space that has a clear physical meaning in terms of what operations can be caused to occur to make the object" (p. 322). Our first task is thus to clarify what we mean by objects, building blocks, physical laws, and assembly, when it comes to organizational design (summarized in Table 1). As a "proof of concept" on how AT inspired thinking may help us understand organization designs better, we analyze the development of organizational structure.

"Structure" in the most abstract sense refers to a stable pattern of interactions (Puranam, 2018). Albert (2024) usefully distinguishes between patterns of interaction resulting from a) division of labor and the resulting arrangement of activities needed to integrate effort b) the distribution of decision-making rights (such as the authority for managing exceptions or alter designs) and c) the demarcation of legal entities. These are not mutually exclusive, of course. In our model, we focus on the second aspect of structure, namely the distribution of authority, capturing the reporting relations among managers. We aim to apply AT to think about how complicated patterns of reporting structure can arise from simple building blocks.

For illustration purposes, we investigate the assembly of two archetypes of organizational structures, functional and divisional forms. We define a functional form as one where at the highest level of the reporting structure, functional managers directly report to a general manager. A divisional form is one where general managers report to other general managers at the highest reporting level. For example, Microsoft in 2002 was organized essentially as independent financial entities across different product and service segments, indicating that each had its own in-house financing, marketing, and other functional managers; the head of the divisions, senior vice presidents, would report to the CEO of the time, Steven Ballmer. Today Microsoft is a more functional organization after its reorganization in 2013; functional executives report directly to Satya Nadella, the current CEO.

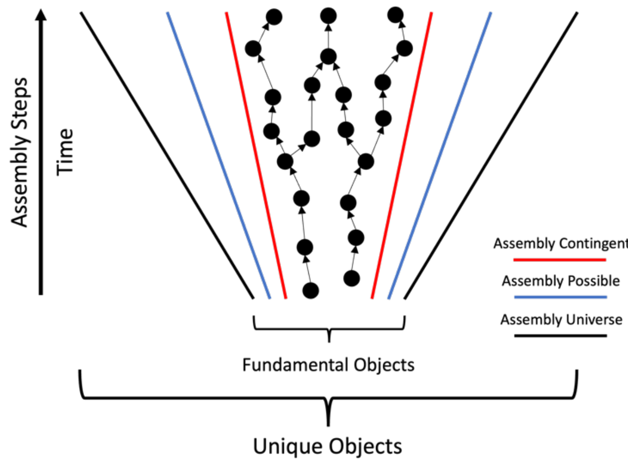


Figure 3: *Illustration of different Assembly Spaces, adapted from Sharma et al. (2023).*

Assembly Spaces. Sharma et al. (2023) organize the assembly processes into several different *Assembly Spaces* (see Fig. 3). Assembly Theory begins by looking at the *Assembly Observed*, the space of existing assembled objects and their substructures, and infers non-randomness in the developmental process through the analysis of the substructures and their frequency of occurrence. *Assembly Observed* is only the "empirical" end-product, a sub-space of the theoretical *Assembly Universe*. We discuss different *Assembly Spaces,* from *Assembly Universe* to *Assembly Observed,* through our example of functional and divisional structure assembly presented in Figure 4.

To keep our illustration simple, we chose as building blocks 1) two types of functional managers (production P and marketing M), 2) a general manager G, 3) and a (one-directional) "reports to" relationship (indicated by →) as the primary form of linkage. Accordingly, the *Assembly Universe* is then the collection of all directed networks with the 3 types of nodes we described. The number of combinations could be enormous after several assembly steps.

In AT, "laws of physics" constrain this large *Assembly Universe* into a sub-space called *Assembly Possible*. Once again, for illustration, we define three equivalents to the "laws of physics" in our model, which simply represent constraints on what is feasible. We assume these laws in our system to be 1) A general manager will not report to functional managers, 2) A general manager will only oversee at most one manager each of each different function, 3) A functional manager can only report to another manager of the same function or a general manager. Hence, a general manager who is already managing a marketing and production manager will not supervise any more marketing or production managers. Accordingly, already in assembly step 1 in Figure 4, we see that there are only 5 ways of connecting the managers through the reporting relation, instead of 9. In Figure 3, this narrows down the space delineated by black lines, *Assembly Universe*, to blue lines, *Assembly Possible*.

In assembly step 2, we focus on three objects—among many others—that are decisive for the rest of the assembly process. The formation of the functional form in the assembly step 4 is *contingent* on the assembly of the two objects in the top row $(M, M) \rightarrow M$ and $(P, P) \rightarrow P$, and the divisional form on the formation of $(P, M) \rightarrow G$. These assembly spaces are called *Assembly Contingent* (as their assembly would not be possible without the existence of some building blocks or assembled objects) and the space before the split at assembly step 2 is the *Co-Assembly Space*.

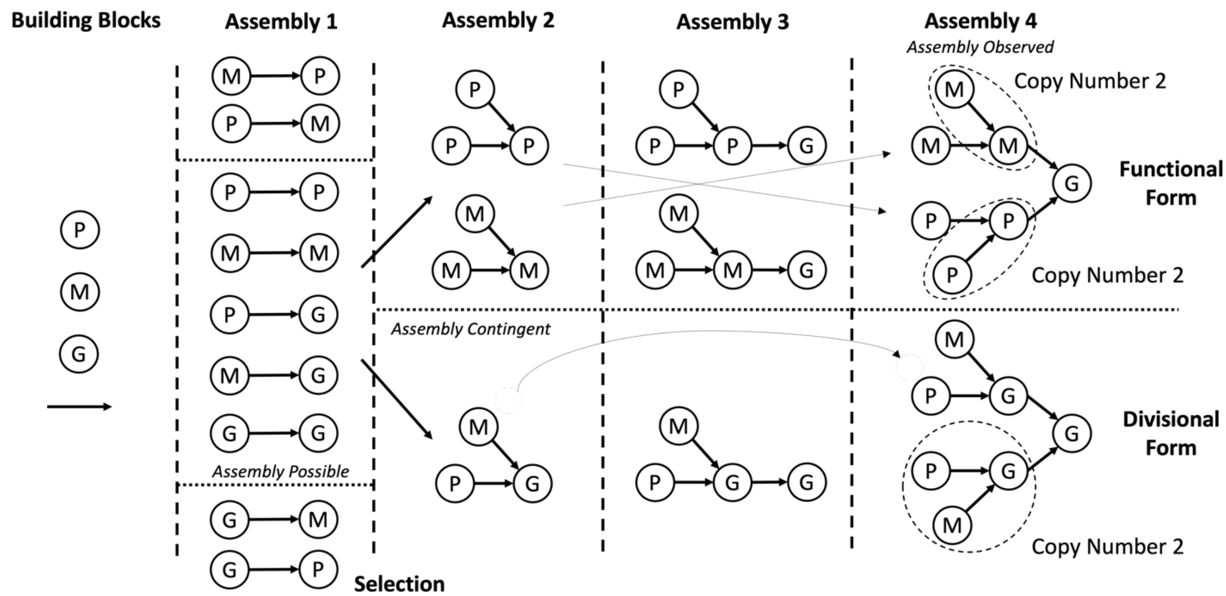


Figure 4: *A shared assembly path of functional and divisional organizational forms. P: Production Manager. M: Marketing Manager. G: General Manager.*

	Definition in AT (Sharma et al. 2023)	**Organizational equivalent**
Object	"Finite, distinguishable, persists over time, breakable such that set of constraints to construct it from elementary building blocks is quantifiable" (p. 322)	An organizational (macro-)structure
Assembly Universe	"all possible pathways for assembling any object composed of the same set elementary building blocks" (p. 324)	All possible pathways for using organizational micro-structures to build macro-structures
Assembly Possible	"the space of physically possible objects, which can be generated by means of the combinatorial expansion of all the known physical rules of object construction and allowing all rules to be available at every step to every object" (p. 325)	The micro-structures that are feasible given constraints on organizing, such as societal norms, human behavior, technological affordances

Assembly Contingent	"the space of possible configurations of objects […] where selection is possible, and the objects found in the space are controlled by a path-dependency contingent on each object that has already been built" (p. 325)	Path-dependent organizational development processes
Assembly Observed	the space of all observed objects	Empirically observed organizational macro-structures
Co-Assembly Space	A common space of objects from which observed objects are assembled	Similar developmental paths of organizations until deviation: Flat organizations leading to different organizational forms (Valve vs. Github), BellSouth and US West (Noda and Bower, 1996)
Assembly index	"the shortest number of steps required to generate the object from basic building blocks" (p. 322)	-
Copy number	Number of copies of a given object	-

Table 1: *Some fundamental concepts developed in AT and their organizational equivalents*

Assembly Contingent spaces appear from selection forces and are more confined than the *Assembly Possible*, visualized by red lines in Figure 1: A design process that assembles a functional form, for instance, will use the micro-structures $(M, M) \to M$ and $(P, P) \to P$. On the other hand, a design process that assembles a divisional form will have to use multiple divisions, i.e. $(P, M) \to G$. In Figure 4, these correspond to the points where the assembly lines are split into contingent sub-spaces. As illustrated, we then assemble objects produced in each assembly step to arrive at the final functional and divisional forms in assembly step 4, in the *Assembly Observed*.

Sharma et al. propose an Assembly number, A, which can be used to detect the extent to which an observed structure is the result of a design process, or which among two (or more) structures shows the greatest evidence of a design process at work. The Assembly number is defined by the following expression:

$$A = \sum_{i=1}^{N} e^{a_i} \left(\frac{n_i - 1}{N_T} \right), \quad (1)$$

where N denotes the number of unique microstructures, N_T number of all objects. Two crucial elements are e^{a_i} the exponentiated *Assembly Index* of an object i, and n_i the *Copy Number* of an object i. We discuss each in detail.

Assembly Index. Proxying the difficulty of developing an object, a_i the *Assembly Index* is the smallest number of steps to assemble an observed object from its substructures. In our example above, a multi-divisional form can be assembled in at least 4 steps, hence has the assembly index 4. In contrast, the very first multi-functional group appears in assembly step 2, bottom row: As per

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our definition, two managers of different functions report to one general manager $(P, M) \to G$; this form has an assembly index of 2. AT thus offers a new perspective on Chandler's (1962) observations about the appearance of U-form organizations before M-forms, as the former has a lower assembly index than the latter. It is important to note that the larger functional form of comparable size to the divisional one in our example still has an assembly index of 4, but the smallest functional form has an assembly index smaller than the smallest divisional structure.

Copy numbers n_i. AT asserts that we can put bounds on the extent of "selection"—what we call a design process —by looking at *copy numbers* in the *Assembly Observed*. Copy number, n_i, of any object (whether a building block or an assembled one) is the frequency with which this object occurs in the macro-structures. Table 2 summarizes the copy numbers of each unique object found in the functional and divisional forms of assembly step 4. For both forms, we begin by counting the copies of each building block, P, M, and G: For the divisional form, there are 2 production managers, 2 marketing managers, and 3 general managers. For the functional form, there are 3 production managers, 3 marketing managers, and 1 general manager. Sharma et al. argue that an object with copy number 1 may occur in any process by chance regardless of how complex its assembly may be. Hence, any object with $n_i = 1$ is neglected in Eq. 1, as their occurrence may be at random, and we omit the occurrence of 1 general manager in the functional form in Table 2.

In contrast, AT assumes that observing a high copy number of an object suggests that this object was assembled many times, indicating the presence of a design process that favors this object. Other objects with higher assembly indices and copy numbers greater than 1 are $P \to G$, $M \to G$, $G \to G$, $(P, M) \to G$, and $(P, M) \to G \to G$ for the divisional form, and $P \to P$ and $M \to M$ for the functional one. Accordingly, putting together the assembly indices and copy numbers of all unique objects and applying (1), we arrive at $A_{Div} - A_{Func} = (e^3 + e^2 + e)/13$.

Divisional Form	P	M	G	$P \to G$	$M \to G$	$G \to G$	$(P, M) \to G$	$(P, M) \to G \to G$
Assembly Index a_i	**0**	**0**	**0**	**1**	**1**	**1**	**2**	**3**
Copy Number $n_i - 1 > 0$	**2**	**2**	**3**	**2**	**2**	**2**	**2**	**2**

Functional Form	P	M	$P \to P$	$M \to M$
Assembly Index a_i	**0**	**0**	**1**	**1**
Copy Number $n_i - 1 > 0$	**3**	**3**	**2**	**2**

Table 2: *Summary of assembly indices and copy numbers of objects in functional and divisional forms*

This difference indicates that a divisional form shows greater evidence of non-randomness (or equivalently greater evidence of a design process) in its development than a functional form of the same size, although they both have the same assembly index (in other words require equal number of steps to form). Specifically, the divisional form has higher copy numbers for some of the objects with higher assembly index; higher copy numbers for objects with high assembly numbers indicate that the focal object is less likely to have arisen by chance. Why?

The expression for A offers an intuition: in the absence of any design process, the probability of observing an object twice or more times is less likely than observing objects of two different types. For higher assembly index objects, this difference in probabilities is even larger, as the combinatorial space grows exponentially. For instance, the double occurrence of $(P, M) \rightarrow G \rightarrow G$ with assembly index 3 in the divisional structure purely by chance is very unlikely; the contribution of this structure to the assembly number is e^3. The same applies to the divisions with high assembly index and copy number greater than 1, resulting in a contribution of e^2. Thus, we can say a divisional structure shows greater evidence of a non-random design process than a functional structure, and the difference can be captured by the difference in assembly numbers.

Applying AT to J&J's evolution. If we were to revisit the example of J&J from the AT perspective we would define two building blocks, namely acquired units (A) and internally developed ones (I) forming an *Assembly Universe* that is the set of all directed networks with acquired and internally developed units. The "laws of physics" for this universe, or the grammar of feasible recombinations, would determine the *Assembly Possible*. These may mean that business units operating in two different geographic locations or industries are not allowed to be combined or that going beyond a certain size of business unit may not be legally possible. Next, we would look at the assembled macro-structures and calculate the copy number of all objects and substructures in the *Assembly Observed*. As Karim and Mitchell pointed out, J&J intentionally implemented an innovation strategy to acquire resources through the acquisition of units that were at times integrated into the internally developed units. This is reflected in the high copy numbers of acquired units. In that regard, J&J has applied a design process to create an *Assembly Contingent* consisting of mostly acquired units. In addition, if we were to calculate the assembly indices of all other macro- and micro-structures assembled by J&J, then we can infer the extent to which the final resulting structures show evidence of a non-random design process, rather than randomness, even in J&J's integration processes.

Specifically, in the case of J&J Medical Inc., we have an assembly index of 6 (a_i) and 260 micro-structures with copy number (n_i) greater than 1, in total 2570 copies (N_T), which results from the recombination of 14 acquisitions over 20 years[2]. As hypothetical benchmarks, we form J&J Semi-Random Inc. and J&J Random Inc.: These are units of the same size, however we have randomly rewired 25% of the ties in the former and 100% in the latter (visually compared with J&J Medical Inc. shown in the Appendix A). The number of distinct micro-structures is 231 and 230 respectively, the assembly indices are 5, and the total number of copies is 1425 and 904.

In Figure 5, we see the effect of randomness on copy number distributions[3]: The more random is the development of a structure, the more skewed are the copy numbers to the left. The red

[2] Here, we assume that the assembly took place one unit at a time.
[3] The algorithm for their calculation is available upon request.

histogram of J&J Random Inc. is more concentrated around 1 in contrast to the green histogram of J&J Semi-Random Inc. and the blue histogram of real J&J Medical Inc. In Appendix A, we present the ten micro-structures both for the highest and lowest (greater than 1) copy numbers and the distribution of the copy numbers in J&J Medical Inc. The micro-structures with the highest six copy numbers have assembly indices 4, followed by three with assembly index 3, and one with assembly index 2. The top 10 highest copy number micro-structures of J&J Random Inc. in contrast, have low assembly indices. These randomized benchmarks illustrate how significantly high assembly index and significantly larger copy numbers, can be inferred from *Assembly Observed* in real data. If we had data on another corporations, say GSK over the same time frame, we could have calculated which of the two companies showed greater evidence of a non-random design process in their development.

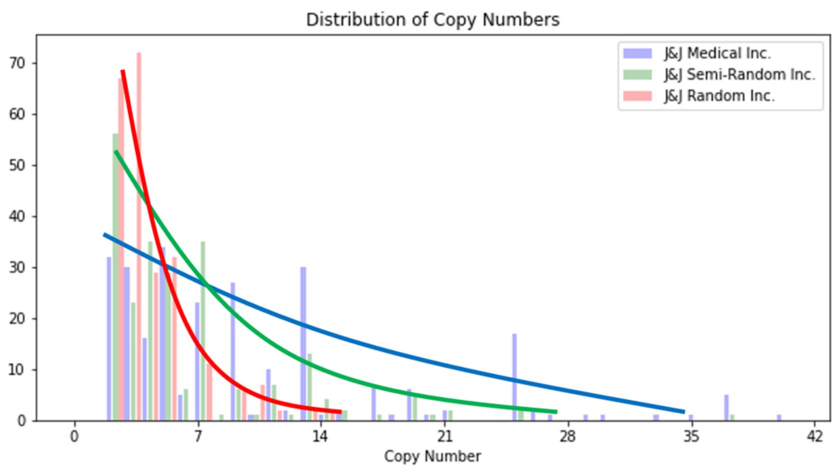

Figure 5: *Distribution of micro-structures' copy numbers in J&J Medical Inc. (blue), J&J Semi-Random Inc. (green), and J&J Random Inc. (red). The copy number distribution of J&J Medical Inc. is heavily skewed to the right in comparison to the randomized benchmarks.*

Discussion and Conclusion

In this work, we set out to take inspiration from Assembly Theory, an emerging perspective on the evolution and persistence of complexity in selective environments, to offer a new measure of use to researchers of organization design: the extent to which an observed structure shows signs of being the result of design process rather than randomness. The design process here could refer to either intentional design or competitive selection and is in contrast to random factors that are not systematically related to survival.

The micro-structural perspective on organizations emphasizes the process of building complex structures from simpler structures. "More complex structures can be created from these (simpler structures) through recursion (each node itself is a micro-structure) and scaling (adding nodes where there are dots)." (Puranam, 2018). AT offers formal tools and methods to quantify these recursion and scaling processes; it does so by incorporating both the difficulty of assembly and their copying, which together indicate a non-random process is more likely to be at work.

The interaction between organizational adaptation and environmental selection has been a staple feature in the organization sciences (e.g. Hannan and Freeman,1984; Levinthal 1997, 2021). Yet another stream of research offers randomness as an alternative to design, intention, and skill as an explanation for observed outcomes (e.g. Denrell and Liu, 2012; Denrell, Fang, and Liu, 2015). For instance, if we consider the interactions between people in a social system, some will be the result of non-random processes – including emergent design and selection, and some will be the product of random processes (e.g. Clement and Puranam, 2018). To assume that an observed structure is purely the result of adaptation and/or selection is inaccurate in a world of bounded rationality and weak selection. We believe that AT can help draw the line between random chance on the one hand and intention, emergence, and selection (i.e. design process) explanations on the other. Network theorists have been using techniques such as Exponential Random Graph Models (ERGM) methods to estimate the null probability of observing a network structure at random (e.g. Sosa, Gargiulo, and Rowles, 2015, see their Table 2 for a list of structures). AT complements such attempts that address cross-sectional data by offering a systematic theoretical approach to detect non-randomness in developmental processes, by computing the *improbability* of random processes producing an observed object.

This work also highlights that the extent of operation of a design process (vs randomness) that characterizes the development of a structure is not the same as the complexity of the resulting structure[4]. The number of interdependent tasks and how interdependencies are distributed within and between actors have implications for coordination complexity (Siggelkow and Rivkin, 2005) and a higher likelihood of conflict (Lee, Ilseven, and Puranam, 2023). Simon (1962) suggested that nearly-decomposable hierarchical systems are most likely to survive environments with disruptions arising from time to time and pointed toward the importance of redundancy in hierarchical components. With AT, we obtain a complementary understanding of how such patterns may have developed beyond the competitive selection arguments based on performance. In Appendix B, we show how the two equally complex interdependence structures in the introduction differ in their Assembly Numbers. AT suggests that developing organizations through modular recursive processes will reduce the assembly index of the final structure but increase the copy numbers.

Limitations. There are several theoretical and empirical limitations to our introduction of AT perspective on organizations that are to be developed in future works. As for any theoretical or empirical model, we made simplifying assumptions both for illustration and tractable analysis purposes. We defined the building blocks and their relations in the simplest manner possible and assumed that they are stable across the assembly process.

In chemistry, molecular compounds are assumed to consist of elements or smaller molecules that are stable in most of their properties. Similarly, in the organization design context, applying AT requires us to assume structural types, roles, or technologies that are stable over time and do not change. When these elements are fluid (e.g. Brown and Duguid, 1991), it is important to treat them akin to structural breaks that require specific treatment across different time windows (e.g. Pesaran et al., 2006) or incorporate the non-random fluidity of the role into the definitions. We have abstracted away from this complexity in our illustrations.

[4] The difference is similar to that between Shannon entropy and Kolmogorov complexity used in computer science. While the former captures the amount of disorder in a code, the latter is derived from the length of the shortest algorithm that can generate the code.

We also assumed that the objects are involved in only one assembly process. In reality, there are many co-evolutionary processes occurring in parallel in organizations which may have two consequences: First, objects might mix across such processes. For instance, this might happen when recruitment is conducted independently by departments, yet teams are formed across departments. This can be accounted for through a larger assembly space, thus a more accurate assembly space representation. Second, one assembly process may affect the selection forces in the other one, which is a less trivial consequence. J&J's case shows that business unit (re-) combination is interlinked with product (re-)combinations, Sosa et al.'s (2015) study of Pratt&Whitney engines shows that communication ties are interlinked with product interdependence, and even in a cultural context Godart and Galunic (2019) show that mobility patterns among fashion houses are interlinked with how cultural elements are assembled together. The analysis of such co-evolutionary paths is yet to be developed more rigorously in the AT framework in general, and perhaps organization scientists will take the lead in doing so.

Beyond theoretical concerns, we also recognize that it may be challenging to empirically identify objects and calculate their assembly indices and copy numbers, especially in large systems. To tackle this, the current AT approach in chemistry attempts to verify a relationship with the assembly index of simpler molecules and their empirically accessible attributes, such as the distribution of resonance frequencies in mass spectrometry (Marshall et al., 2021). Then, they reverse-engineer for larger molecules to predict their assembly indices. In the context of organizational scaling, we believe a path forward may lie in mapping attributes of organizations, such as span and number of hierarchical layers, based on relevant theoretical priors to objects. This is where the microstructural approach can play a useful role in helping to identify the building blocks, that can recursively generate larger and more complex structures. The decision-making models by Sah and Stiglitz (1986), Csaszar (2013), and Christensen and Knudsen (2010, 2013) explicitly take such an approach.

We encourage future research to take advantage of the developments in this field that can aid us in revealing the path that complex organizations take as they develop.

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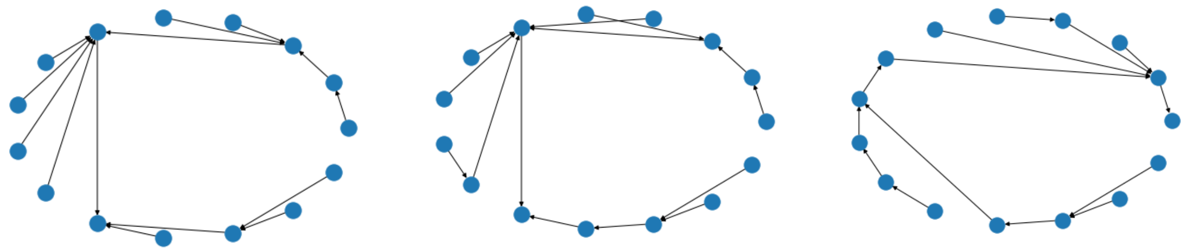
Appendix A) Assembly analysis of J&J Medical Inc. and its random counterpart.

J&J Medical Inc. | **J&J Semi-Random Inc.** | **J&J Random Inc.**



The graph representation of J&J Medical Inc.

(b) The graph representation of J&J Semi-Random Inc. which is generated by rewiring some connections of J&J Medical Inc.

(c) The graph representation of J&J Random Inc. which is a random graph generated by keeping node and edge number the same.

Figure A1

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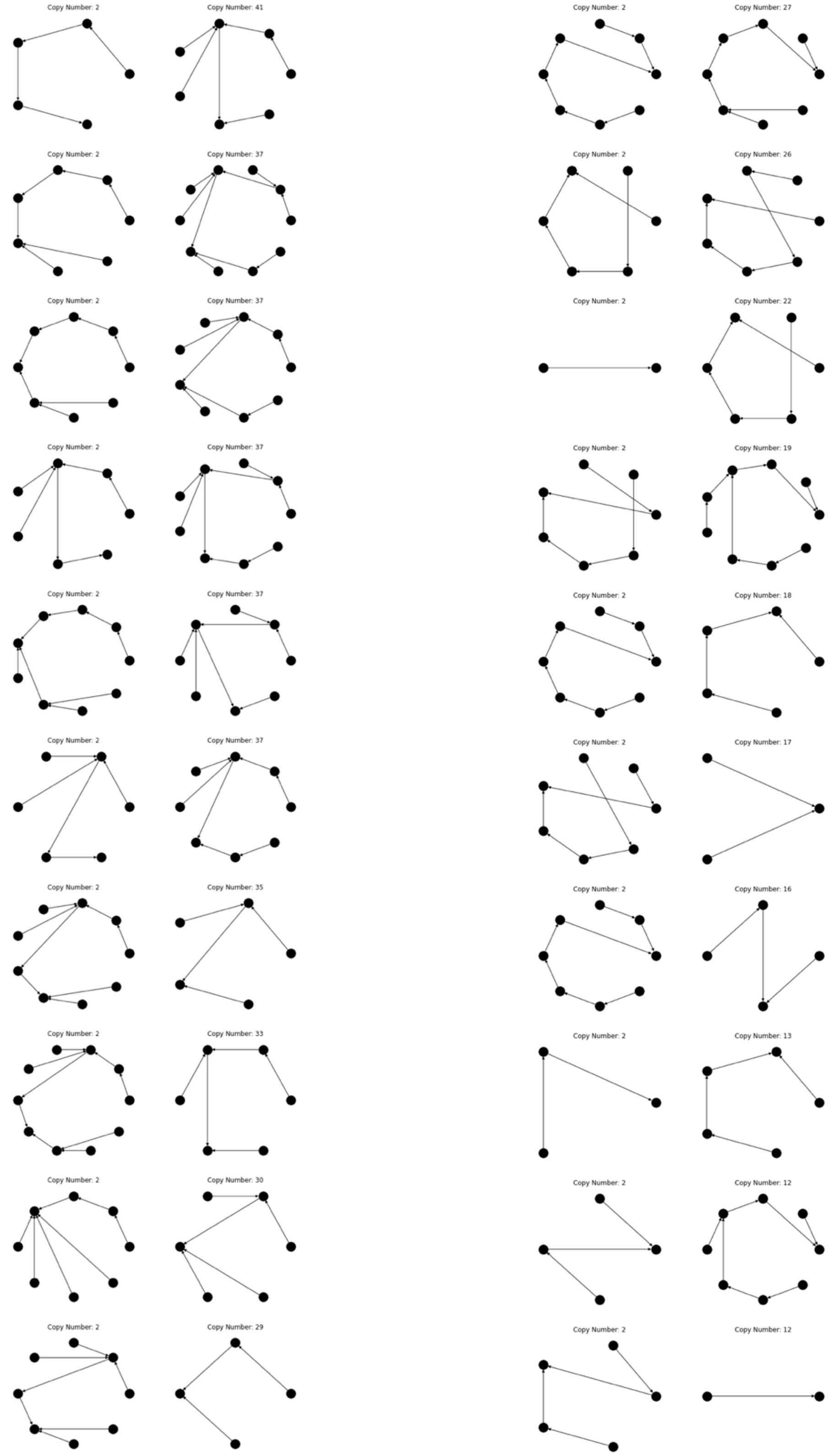
Journal of Organization Design, 1-12. https://doi.org/10.1007/s41469-024-00182-0



(a) J&J Medical Inc.: Least (left) and most (right) frequent microstructures

(b) J&J Random Inc.: Least (left) and most (right) frequent microstructures

Figure A2

Appendix B) Calculating Assembly Indices and Copy Number Tables for Interdependence Patterns I1, I2

Assuming one tie can be added at each assembly step, we show in Figure B1 how the two interdependence patterns are assembled and the copy numbers of their microstructures (those that are greater than 1) in Table B1. The resulting Assembly Numbers are derived from the Table B1 and Eq. 1.

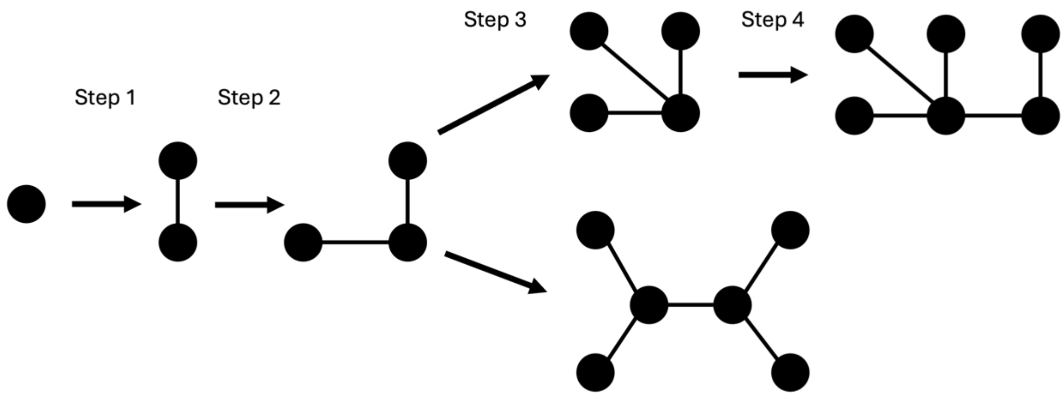
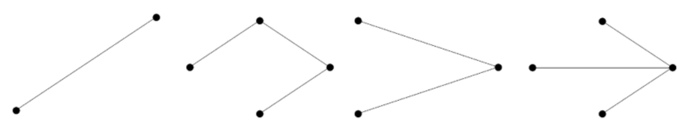


Figure B1



Structure	Assembly Index	1	2	2	3
I1	Copy Numbers	5	4	6	2
I2		5	3	7	4

Table B1