Chapter 5
Innovation in the Context of Networks, Hierarchies, and Cohesion

Douglas R. White

5.1 Introduction

This chapter attempts to bridge two different worlds, that of substantive social science theory and that of formal mathematical theory. It therefore has to be read and understood from both these perspectives simultaneously. Substantively speaking, this chapter explores how diverse, multi-level, sparsely (or densely) interconnected, complicated, and loosely (or tightly) integrated the structures and network processes involved in innovation may be. To study such intricate systems and processes, with very different forms and types and degrees of complexity, we need to reconsider and reconfigure the very basic concepts we use. That is where formal theories come in. The other goal of this chapter is to further the integration of formal theories of network dynamics with substantive theories of socio-historical dynamics and to outline how certain types of innovation play out within these dynamics.

Some readers will inevitably ask, "Why make things so difficult?" The reason is that by using substantive and formal theory in tandem, we can generate bodies of data that have substantive relevance but can be coded in formal and relational terms, enabling, on the one hand, potentially explanatory formal theories to be substantively tested, and, on the other, allowing the incorporation into substantive theory of proofs of outcomes that follow logically from definitions.[1] Such proofs, in turn, may help us to grasp complex relational phenomena in ways that are otherwise difficult to construct with any great precision within substantive theory.

The two worlds we are talking about are also distinguished by the fact that the social sciences have focused on static, structural descriptions of social organization that were primarily concerned with the *position* of individuals in the organization,

D.R. White (✉)
School of Social Sciences, University of California, Irvine, UK

[1] Michael Kearns et al. (2007) has shown in behavioral experiments that networks that are very hard to solve optimally, from a computer science/algorithmic perspective, were relatively easy for subjects paid according to each person's performance, while those networks that were algorithmically easy were appreciably harder for the subjects to do well. The significance is that concepts like structural cohesion relevant to substantive problems should not be avoided just because they are computationally "hard" or mathematically "hard to understand."

D. Lane et al. (eds.), *Complexity Perspectives in Innovation and Social Change*, Methodos Series 7, DOI 10.1007/978-1-4020-9663-1_6,

whereas the kind of formal approach we propose is, in essence, dynamical and focuses on *relationships* between individuals to understand the *organizations* that emerge and their evolution. In terms of Chapter 1 of this book, the social sciences traditionally *looked at the distribution of populations*, *power, riches, etc. in order to describe and categorize organizations* ('population thinking'), whereas the formal approach to which we refer here focuses on *looking at the underlying dynamics of organizations to understand relationships between individuals* ('organization thinking').

If we consider that events occur in a world in motion, inherently relational concepts benefit enormously from being well specified and measurable. This is particularly crucial for the study of the processes that affect innovation and for the study of change in general.

Our perspective aims to lay out conceptual and analytic foundations iteratively for a specific kind of relational social theory ("network theory"), while at the same time providing commensurate tools for the analysis of empirical phenomena. We do so by identifying entities and their various attributes and relations through the study of their appearance, transformation, and disappearance at different scales of resolution, rather than predefining entities and then studying how they relate. This allows us to identify the dynamics of interactions and to clarify how formal aspects of structures and movements operate in relation to one another. However, the intertwining of these two aims does not make the chapter easy to read. We have, therefore, decided to use this introduction to present you with a 'roadmap' of the paper.

The Section 5.2 of this chapter begins by clarifying specific formal definitions, used in network theory, that enable the study of forms of *hierarchy* and *cohesion*, and their various empirical manifestations to clarify and measure different aspects of the relational nature of agents and agency and their connections.[2]

In the Section 5.2.1, we present a general formal model of hierarchy that might be instantiated in very different substantive contexts. When we instantiate it, there immediately arises a multiplicity of substantive phenomena that could give that model very diverse contents. Conversely, multiple substantive phenomena could be mapped into the same formal model of hierarchical relations. The beauty of relational models is that they allow us to analyze such pluralities. They examine the richness of the many dimensions and structures involved in different contexts of interaction at multiple spatiotemporal scales. This enables us to improve our understanding of the dynamics involved and the consequences of these dynamics

[2] In mathematics and in physics, the concepts associated with the term "hierarchy" are well specified, conveying the precise relational structure of an ordered or pre-ordered set. They can also distinguish between types of cases and levels. Similarly, the concepts associated with the notion of "cohesion" specify and measure the specific strength and nature of bonds and linkages. But they also provide information on the consequences of the disconnection or removal of an element from other elements in the structure – and this is key for the study of networks and the measurement of the relationships within them.

for the outcomes of complex interactive processes – including the understanding of innovation and change at scales both large and small.[3]

The following sections illustrate different kinds of hierarchical structures from the (anthropological, archaeological, sociological, and business) literature in (formal) terms of varieties of *hierarchical structure*, *routes of traversal* (through which matter, energy and information flow throughout the network), and the *specific attributes of individual nodes and directions, qualities, and weightings of the linkages between them.*

Several of these examples link various manifestations of structural cohesion as a formal concept with substantive measures. They provide a variety of examples and arguments for why we should expect to find cohesive structures among the substantive underpinnings of hierarchy, and how structural cohesion is necessarily involved in the very construction of certain types of hierarchies. The aim along the way is to resolve some of the ambiguities of hierarchy by examining the distribution of attributes viewed as the outcome of network processes.

These sections flesh out some of the disparate evolutionary trajectories and discontinuities that are inherent in network phenomena. The empirical and historical examples for the existence of social hierarchy and its role in innovation that we present, vary from simple and small-scale to large-scale, complex urban systems. As the chapter proceeds, the reader will see that this approach also allows us to explore networks conceived as a multiple layering of social phenomena in overlapping but ambiguous hierarchies and the structurally cohesive groups that might support them. The possible ambiguity of what might be understood in any particular social context by an overlay of different hierarchies (along with other forms of relations), emphasizes the importance of understanding such systems in terms of their genesis and the outcomes of the complex interactions that are responsible for them.

Therefore, Section 5.2 ends with a discussion of validation criteria relevant to interpretation. It considers how the consequences of multiple processes – multiple outcome variables resulting from network interaction – can help us make more precise inferences about these processes.

Section 5.3 looks at the relationship between structure and dynamics. It begins by discussing Menger's Multi-Connectivity Theorem, in which the hierarchical and traversal aspects of cohesion unite to form a single concept ('*Structural cohesion*') with two independently measurable aspects: (a) degrees of invulnerability to node removal or outside attack on members that will disconnect the group (structurally) and (b) ease of (traversal) communication and transports within the group. It turns out that not only are (a) and (b) isomorphic, but that structural cohesion is scalable without increase in overhead, which enables the genesis of very large networks that are relatively invulnerable to disconnection until they encounter escalating

[3] At a detailed level of analysis, for example, aspects of a narrative approach can be intrinsically re-conceptualized and then recoded into selective modes that yield to network approaches that restrain the lens of theory, even if partially, to focus on general aspects of explanatory frameworks and to clarify how empirical specificities are defined and measured in ways that enable feedback from relevant and possible tests of theory.

opposition. Such opposition is based on the same very rapid scalability of structural cohesion among initially under-connected sets. Examples range from high-school groups and identities in the US, to social class formation, to the expansion and demise of Empires.

Next, structural cohesion is linked to innovation, and, in particular, to 'innovation waves' by pointing out that high levels of structural social cohesion and interaction among people with similar interests in innovation occur rarely, but, when they do occur, the diffusion of ideas within the group and the success of its members are significantly enhanced compared to isolated individuals or groups with lesser cohesion.

An example in the biotech industry is then used to illustrate the theorem that structurally cohesive groups in a hierarchy are always contained in the same (or a larger) set of nodes that are structurally cohesive at the next lower level, thus creating cohesive network hierarchies. Cities effectively consist of multiple (partly) overlapping structurally cohesive hierarchies. That characteristic allows them to scale up almost indefinitely, up to limits of collapse.

In the section "*Networks affecting hierarchy: the scale-up of city networks*," a novel perspective is presented on the relationship between the exponential world population growth prior to, and power-law growth dynamics of cities in the last two millennia. With the up-scaling of "multi-connectivity" through the spread of structural cohesion in large groups of the population, the flows of matter, energy, and information can now reach further and further, through trade, through the diffusion of technological innovation, and through attraction to cities, which allows higher "storage" of dense populations while the (higher) reproductive rates of rural areas replace and compensate for the out-migrants to cities.

It is then argued that the inherent instabilities in the network dynamics linking cities over long distances cause regional cycles of "power-law growth spurts" alternating with periods of relative stability, and that these cycles are linked to each other across continents. Hence, we need to apply a co-evolutionary perspective to cities and urban networks. When such a perspective is applied to size distributions of cities across Eurasia between 500 and 2000 CE, it appears that there are non-random oscillations between values that alternate significantly below or above the Zipf curve.

Section 5.4 tentatively searches for the causalities behind the dynamics thus outlined. It approaches this search first by focusing on the time lags involved between different, far away, parts of the system, but also between the evolution of larger and smaller cities. These indicate that technologically advanced areas are, in effect, diffusion sources for less advanced ones, and that the carriers of the correlations (and of innovative technologies) are the trade networks (and technology of war).

Borrowing from Turchin (2005a, 2005b), the Section 5.4.1 looks at density-dependent changes in population/resource pressure and socio-political instabilities in China and in Europe, to distinguish endogenous from exogenous dynamics in the context of a two-equation time series. The dynamics turn out to be dominated by a combination of endogenous cycles and – in work that goes beyond Turchin – exogenous shocks from major warfare events. A further prediction from the endogenous part of the model is that high rates of innovation occur in a relatively closed region, in the periods *following a downturn* after which total population is rising faster than resources. The actual innovations implemented in these periods often use inventions that trace back to periods in earlier cycles as well as trade networks expanded earlier.

This last section ends with a case study of innovation cycles in the contemporary U.S. that points out how, late in a cycle, the cross-links between innovations in different sectors are subject to hierarchical dynamics that keep these sectors separate, rather than fostering interactions that would lead to a new wave of innovation.

5.2 Understanding Network Structure

5.2.1 Hierarchy and Reverse Hierarchy

When a network consisting of a single kind or set of interpersonal linkages is portrayed as a graph, consisting of nodes and directed or bi-directed edges between them, the generic form of hierarchy is described as a *directed asymmetric graph*, or *dag*, where every edge is directed (asymmetric, nonreciprocal – or, as a refinement, at least between different levels) and there are no directed cycles (see Fig. 5.1A, omitting cycles within a level). The extent to which particular observed networks approximate the properties of a *dag* can be examined for different kinds of relations and contexts: inter-group, interpersonal, inter-positional, and inter-site relations, for example. A theorem for *dag* structures is that the nodes can be ordered in a minimal number of levels so that every directed edge orients in a consistent direction (Fig. 5.1B).

If a social network has the *dag* and a pyramidal structure with fewer nodes at the top and more toward the bottom (beware: not all *dag* structures have this property), then it defines a *social hierarchy*. The usual conception of a social hierarchy is that those (fewer) nodes at the "top" have greater power, prestige, income, information, expertise, etc. Such *dominance hierarchies* appear in many species as one of several basic and often co-occurring forms of social hierarchy. In network terms, individuals in such a hierarchy dominate others in acyclic directed chains, that is, *dags*, often with additional structural properties, such as density of links between different pairs of levels.

Another organizational form involving tendencies toward acyclic directed chains is the *reverse hierarchy*, identified by anthropologists, drawing on both field experiments and a huge array of ethnographic examples. Such hierarchies, based on the recognition of achievements or prestige, seem to be unique to humans and a crucial part of human culture (Henrich, 2001; Henrich et al., 2005). The reverse hierarchies reviewed by Boehm (1993, 2001) include altruistic relations such as sharing, aid, and redistribution. They might be thought of as hierarchies in which there are more obligations than privileges, such as a hierarchy of philanthropists in which those at the top are the ones who give most.

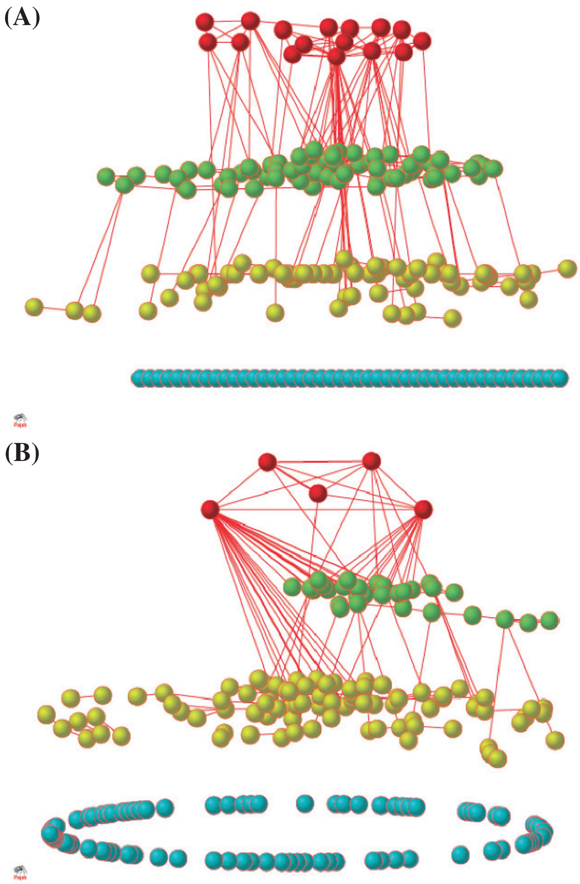


Fig. 5.1 Chinese women migrants' network discussing children, contraceptives. (**A**) Levels of advice are directed downward in the hierarchy; (**B**) levels of advice have laterally symmetricties

Flows of benefits and liabilities in terms of different overlapping network hierarchies form rather complex systems that are often difficult to unravel: are they hierarchies, reverse hierarchies, a mixture of both, or something else entirely? Do they have conditions for stability or instability that depend on tradeoff of benefits between different ranks or levels? Is inter-level mobility based on achievement and tradeoff of benefits or unfair competition, monopolies of power, and structural inequality?

To deal with these ambiguities, we can conceptualize networks and the dynamics in them simultaneously in terms of three fundamental characteristics: their *structure* (e.g., *dag*, pyramidal), their *routes of traversal* through which (directed or two-way) flows of information, materials, or energies are channeled, and the *specific attributes of individual nodes and of the linkages between them*. "Benefits," for example, may flow *both up and down* in multiple dimensions. For a network in which nodes *give* something to others, *giving* may be any of a whole array of possibilities, from taxes or tithes to punishments or gifts. In addition, if one relation forms a pyramidal *dag* hierarchy, it may be complemented by others, including *dag* hierarchies of the same or different types. The alignment of *dag* hierarchies and flows of various kinds then become research questions.

Ambiguities in the ways that hierarchies are constructed are a common source of instability in economic, social, and political systems. Even if we have data on multiple intersecting networks and processes that include sufficient indicators of hierarchy to understand the workings of these processes and their outcome ('population') distributions, the complexities of the interactions inflected by competing hierarchical structures, and the many direct and indirect traversal patterns that they allow, make prediction of trajectories difficult. These are complex nonlinear systems, and the best we can do probably is to model how their structural and flow properties provide an understanding of their dynamical instabilities.[4]

These instabilities at the core of complex systems may show up in market fluctuations between major periods of demand exceeding supply (scarcity, downturns) and those of supply exceeding demand (booms, bubbles), i.e., in business cycles or in the Kondratieff (1984) cycles of investment and degradation of infrastructure. They also occur in the Kuznets cycles of migration (in response to wages and benefits for labor) and, of course, in the cycles of leading sectors of innovation (Modelski & Thompson, 1996). As we will see, instabilities associated with inequalities in hierarchies and the ambiguous and often unpredictable quality of flows provide crucial points of entry into discussions of city and trading system dynamics.

One reason that markets require regulation by norms and laws is the need to maintain level playing fields in the face of such instabilities. Often, this is achieved by reverse hierarchies regulated by moral obligation and reciprocity.[5]

Figure 5.1 shows two examples of reverse social hierarchy, each with three levels of advice given by women migrants to others (directed either downward in the hierarchy or laterally symmetric, i.e., a semi-order) in a housing complex for urban workers (Du et al., 2007). Moral orders of this sort, in which leaders act on behalf of others, are common among the urban poor (Lomnitz, 1977) but are also very common in pre-state societies.

[4] Elements of my discussion of ambiguity and complex dynamics in multirelational interactions involving hierarchical elements are often referred to as "heterarchy," Definitions of heterarchy are somewhat elusive and may refer to distributed authority, hierarchy that is flattened by design, exploitation of overlap of different evaluative principles (Boltanski & Thévenot 1999), self-organization (Morel & Ramanujam 1999), organization of diversity, organizational self-similarity or fractality (Abbott 2001: 165), and the like.

[5] There are, of course, variants on the *dag* model, whether for hierarchy or reverse hierarchy. A *dag* structure may have transitivity or partial ordering as an additional property, and may be strict (irreflexive) or non-strict (reflexive). The latter terms may also describe a containment hierarchy or taxonomy. Variants of these sorts of hierarchies, such as semi-orders, may also have symmetric ties or directed cycles within levels, and partial orders between levels.

Network Example 1: A Hierarchical Network of Generalized Reciprocity
Not all human social hierarchies are based on power, domination, or authority. Survival on the margins of urban society might require, and surely mobilizes, networks of social support that are outside formal economic institutions (Lomnitz, 1977). Du, White, Li, Jin, and Feldman (n.d.) were surprised to find evidence of network hierarchy in their analysis of networks of assistance in everyday activities and of discussions concerning problems of social support (marriage and family, childbearing and planning, contraceptives, old age) among 200 women migrants in a Chinese industrial city. Some of the women's reports of their outgoing ties were mirrored symmetrically by others who reported outgoing ties back to them. When symmetric ties were excluded, however, the asymmetric ties in five of the seven relations reported for the network (all but emotional support and social activities) showed a nearly perfect hierarchical structure of the *dag* variety (above) in which the tendency is for help and advice to flow down from woman to woman through ordered levels, as in Fig. 5.1. Even when all five of these relations were combined into one, the resulting symmetries were only between pairs of women in adjacent or nearby levels of hierarchy. Women at the upper levels of these hierarchies of giving were those with higher status, higher income, and more family connections, including marriage. This is generalized exchange, and it exemplifies a social support system that is self-organizing. 'Generalized' reciprocity may take effect in the course of the life cycle but it is neither balanced in the short run nor necessarily even in the long term. The ranking in these hierarchies is one of responsiveness to a morality of obligation. Such hierarchies are not atypical of the moral orders of pre-state, pre-urban, and many village societies, in which leadership is more of a *primus-inter-pares* obligation to help others rather than one of domination. What is remarkable in this case is that when each woman's ranking in each of the five networks is normalized to a scalar measure between 0 and 1, the common variance among the five rankings in a principal components analysis is 78%, and the variance structure is single-factor. The morality of obligation transfers very strongly across these hierarchies of giving.

5.2.2 *Assessing Hierarchy in Reverse, Zipfian, and Intermediate Cases*

One way to assess inequality in social hierarchies, along with *dag* levels if they can be computed, is to measure the *outcomes* of resource access. For example, among the Cheyenne, leaders were expected to give certain gifts in response to requests. The distribution of horses among men was relatively flat in relation to the network or ranking of prestige differences, so leaders and officials were *primus inter pares* (Llewellyn & Hoebel, 1961). Inequality indices are useful in the assessment of how resources distribute on hierarchical networks. If, for a pyramidal *dag* hierarchy, the ranks r in the hierarchy differ in their occupancy probability for resource measure x, so that a resource distribution is unequal but evenly divided by equal intervals in the log of rank, we have the Zipfian rank-size "law" $p(x) \sim r^{-1}$ (or cumulative occupancy probability $P(x) \sim r^{-2}$). If rank 1 has x resources, rank 2 will have $x/2$, the third $x/3$, and so forth. For k occupants with the basic resource, $k/2$ occupants are expected with twice the resources, $k/3$ with three times the resources, and so forth. The occupancy distributions of numbers of women at different levels in Fig. 5.1 follow a power law $p(x) \sim r^{-1.5}$ in part A, with more pronounced inequality than the Zipfian, but follow a linear progression in part B that is non-Zipfian.

Structural properties of a network often provide the basis for hierarchy as if, for example, there is an advantage to having more ties. Figure 5.2 shows a pyramidal *dag* for buyer-seller links in a Tokyo industrial district (Nakano &

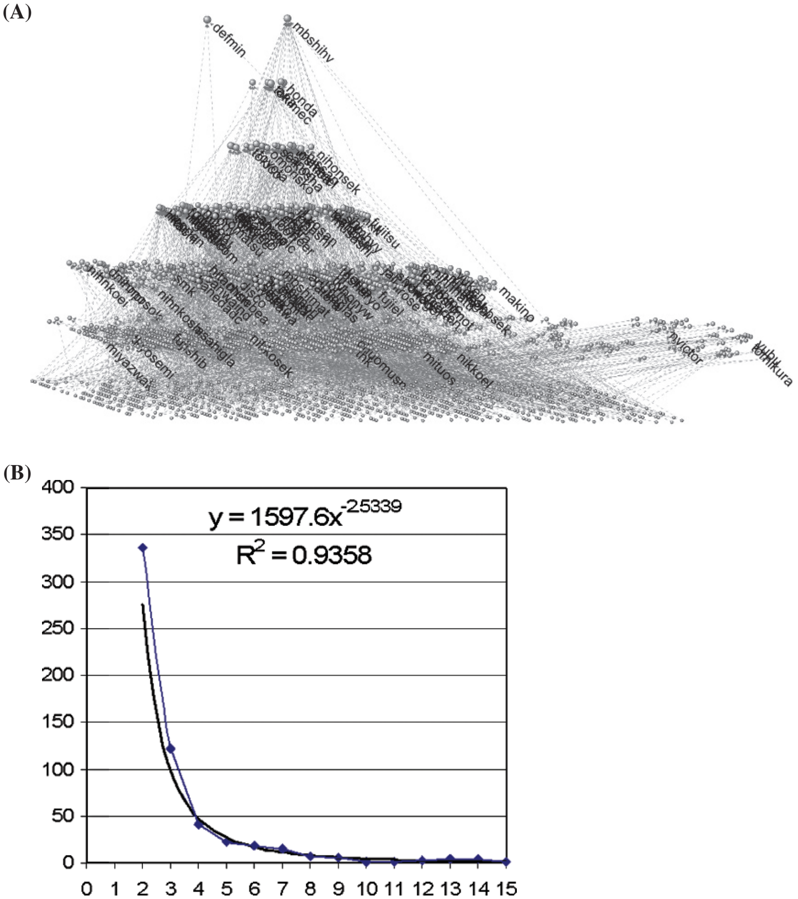


Fig. 5.2 Tokyo Industrial District network. (**A**) bi-component and (**B**) numbers of suppliers for the largest set of firms (1609) wherein every pair is connected by two or more independent paths. Over 300 firms (such as the Matsucom watch company) have two ties, 120 three ties, and so forth

White, 2006a, 2006b, 2007) in part A and a thinner-than-Zipfian power-law tail, $p(x) \sim x^{-2.5}$ ($P(x) \sim x^{-3.5}$) in part B. The upper firms have more ties than expected in the rank-size law, an amplified inequality that matches that of their capital and ability to organize suppliers in ways that can generate pricing advantages from them.

Figure 5.2B shows the type of distribution expected in a "preferential attachment" bias where a firm entering the hierarchy will connect to an existing node having in-degree k with probability $p(k) \approx 1/k$. Barabási and Albert (1999) call networks generated in this way "scale-free" because they have power-law degree distributions. In the industrial hierarchy, the contracting to suppliers is organized top–down, however, and network generation is not a "preferential attachment" of seller to buyer but an "organizing activity" bias of buyers recruiting suppliers. Still, if $p(k) \approx k^{-1}$ is an accurate generating probability for such a hierarchy (a finding that would require monitoring growth through time), the actual degree distribution will be a power-law, where the frequency of nodes with degree k will be $p(k) \approx k^{-\alpha}$ where $\alpha \rightarrow 3$ as the number of nodes grows large. The Tokyo distribution, for example, is within the range of the "scale-free" preferential or organizational attachment model.

A more general index of inequality is the Pareto II distribution, where x is the resource variable, y is the fraction with that resource level, and the probability of a cumulative distribution of having resources x or greater is $y = P_{\Theta,\sigma}(x) \approx (1+x/\sigma)^{-\Theta}$. As $\sigma \rightarrow 1$, the probability $P_{\Theta}(x) = (1+x/\sigma)^{-\Theta}$ converges to the Pareto power-law $P_{\Theta}(x) \approx x^{-\Theta}$. In this case $\Theta = 2$ is the Zipfian distribution in which every sum of resources is equal within equal log intervals. The P_{Θ} distribution becomes more exponential (converging to e^{-x}) as $\Theta \rightarrow \infty$, resembling a distribution of possessions that is random or independent of rank or resource level. The phenomenon of inequality generated by this random process is of interest because of the ambiguity of producing an apparent hierarchy in which "virtue" is attributed to winners of what might be a random lottery, as described for example by Farmer, Patelli, and Zovko (2005) for the rankings of hedge funds on the basis of their earnings.

5.2.3 Transitions from Reverse to Level Hierarchies

Another way to assess inequality in social hierarchies is to look at the structure of flows and transactions. Big-man systems (such as on New Guinea), chiefdoms, kingdoms, and early states provide useful examples for evaluating the initially ambiguous concepts of hierarchy and reverse hierarchy by the larger contexts in which many different kinds of entities, relations, and attribute distributions intersect. These examples move from kinship to nonreciprocal exchange structures.

Wright (2004) examines ethnographically well-described chiefdoms and archaeologically and historically known instances of the emergence of early states. The concept of reverse hierarchical ranking as developed here applies to his description of chiefdoms, marked by a single leader who does not delegate authority, in contrast to states with a delegated division of labor for authority. In his view, a stage-wise developmental process from chiefdom to early state is inappropriate. This is corroborated by the fact that pristine states emerged at Lake Titicaca (e.g., Griffin and

Stanish (2007, p. 24) after a long period of cycles in which multiple chiefdoms climb the population size gradient only to be fragmented by fission. In primary centers, the increase in productivity and population occur sporadically during that period, but without synchronization. Next, in one rapid burst, these unsynchronized features – including bipolarity of centers – emerge synchronously, passing a probability threshold for fission. As a result, a pair of networked city-states emerges, with extensive trade networks that include lesser centers.

A simulation, repeated hundreds of times, reconstructs the fission probability relative to settlement size as a humped or threshold distribution. It may be represented as the product of increasing resistance to political consolidation (which is roughly linear with size) and the ratio of resistance to chiefly strength (which decays exponentially with size).

It is important to note that this *synchrony*, as is often the case, is not an instance of homogeneous change (e.g., within the region), but a *network phenomenon* that occurs *between* the chiefdoms in the region, involving competitive innovation. As the new state polities consolidate, they assimilate the former chiefdoms by introducing the new, distinctive feature of hierarchical representatives of these old chiefdoms into the power structure.

Wright's (2006) *Atlas* clarifies the contrast between chiefdom and state in a way that is consistent with this dynamic of threshold transformation in level and scale. His sample of primary and secondary states all show *three or more* levels of mobilization of resources upwards through officials that are designated in a hierarchy of divided offices, but, furthermore, *state offices outlive and recruit their occupants*. Chiefs and paramount chiefs, in contrast, may govern subdivided territories with local leaders and ritual specialists but there are at most *two* levels of chiefly resource mobilization conducting directly to the chief and *all political decisions are integrated into the chiefly persona*. Cultural concepts govern how others connect to that person through relational ties and levels that embody differences of rank and reciprocal expectations. Succession is a matter of competition by personal exertion of power and negotiated rank rather than recruitment to office in a division of official political labor. While there is pronounced hierarchy, the notion of reverse hierarchy applies in several ways. The hierarchy is constructed interpersonally rather than through offices that concentrate the ability to command resources, and interpersonal orders of rank embody obligations to redistribute resources to counterbalance the processes whereby resources were concentrated through interpersonal network ties. The system of rank, resource mobilization, and redistribution operates as a segmentary system,[6] focusing on a single apex, in the person of the chief, as a unique element holding together the hierarchical flows and counter-flows of goods. Intermarriage and exchange within the chiefdom, however, integrate the chiefdom through cohesive hierarchies and cross-cutting ties and structural cohesion. Chiefdoms have a dynamical tendency for their cohesive integration

[6] In a segmentary lineage organization, minimal lineages (such as nuclear families) are encompassed as segments of minor lineages, minor lineages as segments of major lineages, and so on.

to fall apart as growth occurs and a tendency to fission at times of crisis, especially if these coincide with issues of political succession. There is no tendency in these dynamics for permanent offices to form within the political hierarchy or for any gradual evolution toward state organization. The mosaic of sub-chief territories mapped into the chiefly ranking are segments that recurrently fall apart and re-form in successive periods of political change (see Griffin and Stanish, 2007).

We might go so far as to think of paramount chiefs (two levels of offices), chiefdoms (one level of office), big-men systems (emergent leadership without office *per se*), and all combinations thereof and gradations within them as variants of personalized leadership systems that are distinct from the three-plus levels of less personalized offices of state systems. The emergent-leader systems that White and Johansen (2005) have studied in the Middle East constitute a more segmentary version, one with less recognition of leadership in the form of feasting and gift-giving (as in New Guinea) and a greater emphasis on giving advice for community decision-making. However, these are graded differences and not a solid basis for constructing a typology.

Wiessner & Tumu (1998, pp. 299–301) summarizes the results of a huge oral ethno-historical reconstruction project for the region of Highland Papua New Guinea, where the extensive Enga *Tee* ceremonial exchange systems developed following the introduction of the sweet potato. She details the network dynamics and constraints of systems in which exchanges, operating through kinship obligations and reciprocities and their extensions, not only expanded with new surpluses, but also supported innovations in the means of funding more distant exchanges by including in the network chains of clans linked through marriage along exchange routes.

The structure of these exchanges, following the trade routes along valleys in the first period of productivity and trade expansion (called the period of the Great Wars), was markedly segmentary. Big men competed for exchange advantages and accumulation of wealth to fund ceremonials, draw together support groups, wage wars at the cut-points in the segmentary structure, and, then, engage in regional ceremonials of reparations and peacemaking. But this did not lead to the emergence of hierarchical leadership. "The largest Great War . . . gave way to the *Tee* cycle in the late 1930s/early 1940s" (Wiessner & Tumu, 1998, p. 298), consisting of three phases of exchange ceremonies, moving from east to west and then back again, in which "thousands of pigs, goods, and valuables were distributed through a series of linked public festivals. . .. Prestige, influence, and the necessary resources for polygamous marriages accrued to those who were most successful in channeling wealth to themselves and their clans." Together with the shift from linear chains in the trade-route links of the Great Wars period to locally radial chains operating through polygyny in the *Tee* ceremonies, the overall social integration shifted from segmentary to cross-cutting, but without a change in political leadership structure. Sons of Big Men still had to compete for prestige, as did everyone else, and permanent political office never emerged.

Hence, both Big Man and Chiefdom systems, consistent with Wright's view, do not develop into pristine states with political offices. The development of states, arguably, is connected to the rise of divisions of specialized labor, production, and exchange within and between cities in the evolution of a very different kind of hierarchy. Ties of exchange in early states are somewhere *between* connecting and separating ties; they are competitive, but also cooperative.

White and Johansen's (2005) account of the ethnogenesis and sociopolitical dynamics of a pastoral nomadic clan shows a social system that is scalable through structural cohesion, and that expands through reproduction, kinship alliances, and fissions, and overcomes internal conflicts and those with neighbors along routes of migration through pastoral ecozones that promote high levels of human health and demographic reproduction. The resulting networks constitute a generative demographic engine for large sibling groups and extensive cooperation within and between these groups, which is constructed through reciprocal ties of marriage. The organization, in this case, blends scalable segmentary organization (through the fission/fusion dynamics of male groups) with the scalable structural-cohesion dynamics of marriage alliances. The hierarchical aspects of male rank are flexible, variable in terms of age-succession and migration options, highly egalitarian and achievement-oriented, with historical leadership in the local group not decided on an elective or ascriptive basis, but attained through emergence processes involving the leader's position in the structural cohesion hierarchy. In other words, it is not based on lineage but on a combination of segmentary and cross-cutting lineage and alliance dynamics.

This lineage and alliance study looks under the hood, so to speak, of one case of what is a widespread cohesive dynamic of certain segmentary systems with a complex, multi-hierarchical multinet. Some would call this a form of heterarchy, and it stands between hierarchy and reverse hierarchy in ways capable of rapid adaptations that easily assimilate and generate innovation. Of special interest is how these segmentary nomads adapt to the spread of the market economy and the shrinking of free space, while a form of egalitarian leadership endures, outside the state system, as a form of reverse hierarchy and acts in the broader interests of the larger community.

Economics might be seen here as an attempt to tame the opposition in terms of opposite tendencies between connecting and separating, competitive but also cooperative ties that might settle into equilibrium because of this opposition, which allows equilibrium states to be defined, whether stable or unstable. But the resolution of this opposition through pricing, with its alternations between over-supply and excess demand for investments, at many different spatiotemporal scales, leads, almost inevitably (although not uniquely as many other resolution mechanisms, like vengeance killing, are unstable) to recurrent near-equilibrium fluctuations. These become part of the story of innovation with the startup of city networks and states.

5.2.4 Segmentation and Cross-Cutting Integration

Once we consider complex multi-nets (multiple overlapping networks and attributes) such as the above, it may be better to use higher order terms for the *effects* of multi-net overlap rather than rely on the terms hierarchy and cohesion, which have well-defined formal properties but whose properties are poorly understood once they are overlaid in different ways. This is consistent with the argument I have made, so far, that "from their effects shall we know them," i.e., from their dynamics, including both in structure and process.

The contrasting terms for segmentary and cross-cutting organization have long been used in the social sciences and are widely understood. Comparative studies by Thoden van Velsen and van Wetering (1960) found correlations for contrast between segmentary and cross-cutting forms of organization in pre-state societies: while segmented male descent groups, each resident in their own localized communities, have high levels of feuding and internal warfare, while groups that are cross-cut by different organizational and residential affiliations have internal peace.

In a multi-net-multi-attribute perspective, *segmentation* highlights separability, efficiency, specialization, restricted access, and uniqueness of traversal, among other features. For example, Ojibwa society was historically segmented during six to eight months of the year because men would set off individually on long trapping expeditions. With so little male cooperation in the means for economic success, there were almost no overarching social, political, or religious institutions for larger groups of people, other than temporary and fluid aggregations when men came back in the summer. Two people in a canoe could harvest wild rice in the fall. Women cooperated in their activities in small groups.

In contrast, in the great Pueblo villages, the underlying productive technologies were highly collaborative, and there was every kind of social, political, or religious institution that cross-cut and integrated the many cohesive subgroups within the society that supported cooperation (White, 1969). *Cross-cutting integration* involves multi-nets that intersect and overlap in cohesive patterns opposite to those of segmentation. Intersecting social circles and overlaps in group affiliations were theorized and studied by Georg Simmel (and later Peter Blau) as the basis for urban social integration.

Finally, urban societies can be characterized in terms of segmentary versus cross-cutting transport patterns. The usual downtown city grid is cross-cutting relative to urban spaces, exposes diverse groups to one another, and typically is regarded in the history of cities as the peaceful zone of integration of diversity in interactions. Gated communities and branching street or road structures (Low, 2003), however, create community segregation at the cut-points where one branch separates from another. Segregation is augmented when there are structurally cohesive routes of traffic within a cut-point-segregated community. Further, while structurally cohesive residential streets connect to form traversal patterns that support social cohesion, secondary, primary, and freeway routes disconnect the zones on either side of them, and structural cohesion on these larger routes *does not* create traversal patterns for inter-community cohesion (Grannis, 1998). Grannis (1998) and others have quantified some of the relevant network measures for effects of the built environment on daily life and sociological outcomes. The correlates of these patterns turned out to be the same as those found by van Velsen and van Wetering (1960): more segmentation leads to more interethnic violence, more crime at both ends of the economic spectrum, and higher segregation on every major index of inequality (Grannis, 1998).

Two of the key developments still outstanding, however, are how to measure structural cohesion in a multi-net and how to identify more precise measures of segmentation versus cross-cutting integration in overlapping relational structures. The first extension of structural cohesion measurement to multiple relations is to study which relations are correlated across pairs of people. Clustered relations with similar kinds of content transmission can be identified as those that form interactive communities. Once those community-forming sets of relations are identified, they can be analyzed together by simple aggregation, and these aggregate networks can be analyzed for boundaries of structural cohesion. The communities may overlap, forming cross-cutting integration, or may segregate, forming segmentary structures. How societies and their transport and communication systems are constructed may have massive impacts on the types of conflicts and areas of cooperation that occur within contemporary social and information societies.

5.3 Relating Structure and Process

5.3.1 Hierarchies are Supported by Structural Cohesion

Biological organisms are supported by branching networks (blood vessels, bronchial and nervous system pathways) that often have a hierarchical *dag* single-root tree-structure, but they are also embedded inside cohesive structures of cells and organs and have return pathways that form various types of cycles, depending on whether we are considering pathways in the brain with lots of local cycles, circulatory vesicular pathways with separate branchings for vein and artery systems, or bronchial inhalation/exhalation two-way respiratory pathways. Social hierarchies are extra-somatic, but they also require such cohesive supports for multi-connected cooperation, independent of hierarchy.

Menger's multi-connectivity theorem[7] provides precise ways to define how cohesive network structures relevant to social organization and hierarchy are constructed. The multi-connectivity theorem is especially important because it connects the cohesive *structures* that occur in networks with the capacities for multiple independent *routes of traversal* within these very same structures. Recall that structure and traversal are the two fundamental kinds of properties that combine in networks. The multi-connectivity theorem makes it possible to understand scalability – i.e., the ability to scale-up the size of an organizational structure with roughly constant or diminishing cost per increment – of a radically different sort than "scale-free" networks. This is possible through *structural cohesion*, which I will

[7] In the mathematical discipline of graph theory and related areas, Menger's theorem is a basic result about connectivity in finite undirected graphs. It was proved for edge-connectivity and vertex-connectivity by Karl Menger in 1927.

explicate here. Scalability of cohesion seems like an impossible benefit of networks, but is achieved quite simply once the concepts that define structural cohesion are understood.

A *component* of a network is a largest possible connected structure; but as it may be minimally chain-link connected, it is potentially vulnerable to disconnection by removal of a single node. A *bi-component* is a largest possible connected structure that cannot be internally disconnected by single-node removal. Components, bi-components, tri-components, and k-components (vulnerable to disconnection only by removal of k or more nodes) are instances of the general concept of *structural cohesion* but differ in level of cohesion. Menger's theorem is that k-components (k measuring the extent of *structural cohesion*) are equivalent to largest sub-networks with at least k redundant pathways between every pair of nodes (i.e., all pairs have a minimum level k of cohesive *traversal* between them). The structural and traversal aspects of cohesion unite to form a single concept with two aspects: (a) structural cohesion as invulnerability to node removal of outside attack on members that will disconnect the group (structurally) and (b) ease of (traversal) communication and transport within.[8] If we identify k-components in social networks as subgraphs of nodes and the edges between them, i.e., structural cohesion *sets*, we can also call them by the term structural cohesion *groups.* Their cohesive properties of multi-connectivity involve hierarchically stacked subgroups. When the cycles that generate the cohesion are sufficiently overlapping and short the redundant paths of information passing between them (and the diffusion of shared attributes) can be assumed to entail knowledge about core members' identities.[9]

Structural cohesion groups can grow very large while minimizing the possibility that parts of the network will disconnect with the exit of a limited number of members. In this kind of structure, a sub-network can add nodes and links to strengthen traversability within and to reinforce immunity to disconnection from without. Scalability is achieved when most of the nodes in an expanding group stay close to a minimum threshold of k ties per node without diminishing the number of independent traversal pathways that this enables between every pair.

Unintended cohesive optimization occurs under these modest constraints even when the ties of new members are random. Scale-up may even diminish the increments of cost involved in connecting other nodes to every organizational node *inside the organization*, especially when the average network distance within a structurally cohesive group does not automatically entail longer spatial distances. Alternatively, the attenuation of spatial distance effects can be achieved by innovations in long-distance transport or communication.

---

[8] Every science has a concept of entities as cohesive units having sufficient internal bonding among all of their parts to provide resistance to external perturbation. It is important to note that *edges, per se*, are conceived of as entities as are nodes and possibly emergent structurally cohesive units.

[9] Such groups do not have to be named or formally organized, and mutual identification need not be assumed beyond core members. It is sufficient to assume that members of the less cohesive sectors of the cohesive hierarchy (not in a higher component but in a lower component that contains it) will have weaker identifications for members of the group cores.

5.3.2 Structural Cohesion as a Scalable Concept

Structural cohesion groups have obvious benefits for cooperation and collaboration, and, if they can scale up with little or no institutional cost or additional cost per participant, we should find that they are implicated in a wide variety of contexts, including social stability and the formation of social units on the one hand, and in innovation, social movements, competitive rivalry, and conflict on the other. How can k-components scale-up to have *more nodes* – conserving overall strengths of structure and traversal – *without* increasing the number of edges per node? How are organizational costs reduced when adding nodes and edges? The simple answer is that a constant *cost per node* can be distributed over benefits to *pairs*, i.e., by dividing the costs of k edges per node by the *square* of the number of nodes in the network. Because every node in a k-component has *k independent paths to each of the others*, a growing network that conserves this property, merely by the placement (random or not) of edges, can reduce costs accordingly. Successive growth can occur in which the edge/node ratio is constant while the n^2 node-node pairs with k independent pathways grow exponentially. Structurally cohesive groups have a network externality (Arthur, 1994), defined as marginal returns for items interconnected in the network, that increases with the number of nodes in the network. An example is a set of word processors that can exchange documents: the greater their fraction in a network, the more valuable it is to possess one of this set rather than one of an incompatible set.

Many networks contain cohesive sets with relatively low k-cohesive index numbers. There are several reasons why it is so poorly understood that scalability of a structurally cohesive organization permits it to grow indefinitely. First, intuitions about structural cohesion are often incorrect if they are based on the analogy of growth of clique sizes within a network that entails analogy of increases in network that density and in the number of average edges per node. The growth of groups of constant k-connectivity can occur while there is a reduction in overall network density, and edge/node ratios can remain constant within k-components. Second, the Menger theorem is one of the more intricate parts of graph and network theory, and the necessary ease of computation to deal with it has developed only recently (White & Harary, 2001; White & Newman, 2001; Moody & White, 2003). Third, because this is a new area of investigation, there are still relatively few studies that show how common are the properties of cohesive hierarchies that would allow them to be considered structurally cohesive groups rather than arbitrary sets of nodes and edges.

Structurally cohesive groups with informal organization can occur entirely outside of formal institutions. They can build on friendship networks, networks of trust, social movements, co-alignment based on opposition to other groups, structurally equivalent linkage to other groups, and the like. Hence, up-scaling of structural cohesion can occur without increasing institutional overhead. To see the potential power of structurally cohesive groups, we can look to Turchin's (2005a) documentation of how historical empires expand repeatedly, only to encounter boundaries where identities of groups exposed to conquest change sufficiently to provoke solidarity, so that further expansion is blocked by escalating opposition. Turchin found that interethnic frontiers tended to be the sites where emergent solidarity allowed groups that were relatively disorganized at the start to oppose and stop assimilation by the empire. The U.S. is currently experiencing such a situation in Iraq, and we may see the same resurgence against occupation by the U.N. in Afghanistan. Often, such resistance movements come to overthrow empires that were initially much more powerful. Alternatively, by repeatedly attacking settled populations at their boundaries, groups with low population density like the historical Mongols develop the cohesion to overrun powerful state systems.

A *small-world* is a large connected network in which the edges around certain sets of nodes tend to form denser clusters (something that is possible but not required in structurally cohesive groups) and average distance between nodes is at or below that of a network formed by random rewiring of edges (Watts & Strogatz, 1998). A large clustered network requires only modest random rewiring to retain the small-world property. Similarly, only a modest amount of random rewiring is needed to create a cohesive k-component among almost all the nodes in sub-networks with k or more edges per node. This explains the mechanism that underlies Turchin's findings – that when ethnically distinctive groups are attacked by intrusive empires, initial disorganization may quickly transform into a scale-up in size and resistance of structurally cohesive groups, whose size is virtually unlimited as more contestants are brought in against a common outside enemy. This can be achieved almost effortlessly even when new bonding occurs randomly, as in the chaos of war, and may produce high levels and wide dispersal of structural cohesion. It gives rise to solidarity and *asabiya*, or emergent cooperation, as defined by historian and Muslim scholar Ibn Khaldun (1332–1406).

White (1996) was the first to theorize, and Brudner and White (1997) to demonstrate that cohesive social class boundaries could be formed by structural cohesion.[10] Following them, Fitzgerald (2004) showed cohesive breaks corresponding to (and partially defining) social class boundaries in one of the historical religious communities in London. These studies challenge views about pluralist political systems within contemporary states. It is shown that structurally cohesive marriages often link the political class into a coherent social unit, or power elite, through structural *endogamy* (White, 1996). Moody & White (2003) found as a general result for American high school students, that attachment to school may be predicted, other things being equal, as a function of the degree of structurally cohesive membership in school friendship circles. This result was replicated precisely in each of a sample of twelve randomly chosen high schools, among those surveyed in the AdHealth

[10] In these studies, structural *endogamy* was used as a special case of structural cohesion that describes the cohesion added to forests of genealogical trees by the facts of common ancestries in earlier generations and intermarriage or offspring of two genealogical lines below. A specialized literature has developed in ethnology around this concept that will not be reviewed here. The line of research leading from structural endogamy to the more general concept of structural cohesion was supported by NSF Award BCS-9978282, "Longitudinal Network Studies and Predictive Social Cohesion Theory," to D.R. White, 1999–2003.

study of 100 representatively selected American high schools, and was validated through a multiple regression using all grades and all available network and attribute measures as competing and control variables.

5.3.3 Structural Cohesion and Innovation

As for innovation, the Roman historian Velleius (ca. 19 BC–AD 31) noted "I frequently search for the reasons why men of similar talents occur exclusively in certain epochs and not only flock to one pursuit but also attain like success." (Velleius, 1924, p. 5). Could this be because high levels of structural social cohesion and interaction among people with similar interests in innovation occurs rarely but, when it does occur, the diffusion of ideas within the group and the success of its members are significantly enhanced compared to isolated individuals or groups with lesser cohesion? Kroeber's (1944) *magnum opus* on creativity and cultural growth found Velleius's observation to hold for the vast majority of innovations in philosophy, science, philology, sculpture, painting, drama, literature, music, and national growth over the course of history covered in his review. The one regularity he found was that innovations and creativity – individual "genius" – occur in temporal spurts in certain places involving social interactions in specific groups. In addition, diffusion occurs in and around those groups in spatial and temporal clusters. Florida (2005) has recently introduced this phenomenon in the economic literature by explaining inventiveness in certain cities as due to the aggregation of creative individuals into a 'creative class' linked by 'spillovers' between different creative activities.

Allowing for network interaction that is not necessarily spatially proximal, Kroeber's finding is no less true today. It is not unusual to see cohesive hierarchies of collaborations in new industries that grow out of innovations, which are enhanced by the multiplier effects of multi-connectivity, another name for structural cohesion. The biotechnology network below, studied through its collaborative inter-industry contracts during the early florescence of the industry (1988–1999), illustrates structural cohesion in early stages of a developing industry operating in recruitment for technological innovation and knowledge discovery.

Network Example 2: Organizational Cohesion in the Biotech Industry
Here, networks of innovation emerged out of the potentials provided by changes in the laws governing patents and commercialization that had developed out of innovations in Silicon Valley and the IT industry. These provided the scaffolding for organizations and institutions to build networks of scientific collaborations that expand the knowledge base and technology for development of new products. Rather than competing with large pharmaceutical companies for improved mass-market products for illness, healing or health-enhancing treatments, specialized niches were sought through collabo-

rative ties. Rather than protecting new privately held knowledge following the pattern of the pharmaceuticals, the industry built through successes as parent firms spawned specialized offspring. Emergent organizational couplings between complementary firms resulted in rapid emergence of a single broad structurally cohesive core of organizations linked through collaborative ties in a division of labor, including capital and marketing. In so doing, core organizations in the field benefited from broader diffusion of knowledge but, by bringing new recruits into a mixing process for new knowledge potentials and skills, also managed to prevent stultification that could result from sharing and homogenization. This involved a dynamic of periods of heavy recruitment of newcomers alternating with periods that focused on integration of knowledge as between new recruits and established practitioners (Powell et al., 2005; White, 2004). Balancing broad cohesion with innovation, the success of the industry led to scaling-up of overall size and dispersion of the industry sufficient to enable internal niche diversity to withstand competition by the pharmaceuticals, instabilities of the marketplace, and volatility of R & D funding sources. In the biotech industry study, variables measuring structural cohesion were pitted against several hundred variables other entered into a time-series database used to test hypotheses about predictors of new contracts between biotech firms and partners. McFadden's (1973, 1981) discrete choice model for each of 11 time-lagged periods showed two major sets of predictors that beat all other competitors in these predictions: levels of structurally cohesive multi–connectivity and measures of diversity. Powell et al. (2005) statistically demonstrated that new link formation and repeat links in the biotech industry showed proportionality effects for multi-connectivity: the more multi–connectivity, the more the attraction for potential collaborators, leaving only very slight effects for Barabási and Albert's (1999) model of preferential attachment to hubs.

5.3.4 Cohesive Network Hierarchy

Another theorem of structural cohesion is that every k-component is contained in the same (or larger) set of nodes that are structurally cohesive at the next lower level: a tri-component within a larger bi-component, for example, with the bi-component within a component, and the component within the total network, which, if not connected, is a zeroth-order component of itself. Structurally cohesive groups form hierarchies in this sense of ordered containment or *dag* structures of inclusion relations, not excluding the possibility that two k-components of higher order are contained in one of lower order.

The short take on the network of contracts in the biotech industry is that they form a cohesive hierarchy with a single cohesive group at the apex, which, in the period of study, oscillated between a 6-component and an 8-component. The regression results are summarized by two findings: a firm's formation of new contracts favors those higher in the cohesive hierarchy, but those firms higher in the cohesive hierarchy *also* favor contracts with new entrants that bring innovation to the industry. These two tendencies counterbalance greater diversity within a firm's network with greater integration, while avoiding greater homogeneity. As for traversal of information, connection into the higher k-components also provides firms with a broader window on diversity within the industry (for advantages of diversity see Page, 2007).

5.3.5 Urban Cohesive Hierarchy

In a division of labor, it should be obvious that for large-scale organizations to get things done, they are dependent on those at lower scales, and that this is one basis for such scaling laws that exist. Another is that as organizations scale up in size, they require exchanges at greater distances, including those with the larger organizations at a distance. They do so as mediators of exchange or flows in the multi-relational network that sustains their existence, as producers of goods they consume, and as consumers of goods that they produce. City systems necessarily entail diverse levels and boundaries of structural cohesion and, thus, constitute cohesive network hierarchies. Unlike the single focus of cohesive hierarchies in the world biotech industry, linked by high-speed travel and communication, the geographic sites of urban cohesive hierarchies worldwide will be multiple and overlapping, with multiple apical cohesive groups.

The inequality indices discussed earlier (cf. Network Example 1 and Section 5.2.1) are relevant as outcome distributions for processes in urban cohesive hierarchies. Cumulative city populations at different city size levels tend to be Zipfian (Pareto slope 2) for larger cities but Pareto II overall. A Zipfian distribution implies that as you successively multiply a given level x of resources by a constant (additive log interval), the quantity of resources added at that new level is constant. The network itself, and its boundaries and levels of cohesion, provides a basis for hierarchy.

5.3.6 Network Dynamics Affecting Hierarchy: The Scale-Up of City Networks

City systems and their growth provide a useful example by which to examine network dynamics in a familiar context. World population growth rates from the Paleolithic through the Neolithic agricultural revolution are difficult to estimate and compare to growth rates after the rise of cities. Although mitochondrial DNA (mtDNA) "nuclear sequence data do not support a simple model of recent population growth, we nonetheless know that a drastic population expansion occurred at least 12 kya with the advent and spread of agriculture. Furthermore, archaeological evidence suggests that human population sizes have expanded over the last 40–50 kya or more" (Walla & Przeworski, 2000). If the trend of that early expansion were characterized as a small positive constant rate of world population growth (such as 1.0001 or .01% per annum), the growth curve would be exponential.[11] Once interdependent cities arose through networks of trade, however, world population growth displayed distinctive bursts, in which the rate of growth varied with size of the population. These are bursts of power-law growth,[12] and they are followed by periods of leveling or no-growth (Fig. 5.2). Although the existence of such bursts has not been ruled out prior to the advent of cities, the ability of cities to attract an influx of population and to sustain high population densities provides an explanation for these bursts whenever rural areas have the ability to replenish their population. The advantages and attractions of cities are multiplicative rather than simply additive with size (Algaze, 2005). The earliest urban settlements also show Pareto size distributions, hierarchies of size, that tend to follow power laws even in the earliest periods of urbanization (Adams, 1981).[13]

With the rise of cities, total world population shows concave functions mirroring growth rates with increase proportional to size, unlike constant rate or simple exponential growth. This is expressed as $N_t = C(t_0 - t)^{-\alpha}$, where t is historical time. The t_0 is a time in the future, a "singularity" that acts as an absolute historical limit to the power-law growth trend. Such growth is unsustainable and requires readjustment as population explosion precipitates a crisis of energetic and material resources.

The first to identify power law population growth[14] were Foerster, Mora, and Amiot (1960), who gave a "structural" explanation in terms of increase in network connectivity in the last millennium. When the interconnected component of a population grows to a considerable fraction, they argued, it is possible to conceive of a growth law such as $dN/dt = N^2/K$ where it is some proportion of connected *pairs* in the population of N elements that have an effect on growth. Only when connectivity or traversability through large portions of a total population is possible can there be diffusion effects that result from that connectivity. Adaptations learned

[11] The population curve through time for a fixed rate of growth is an exponential, i.e., population $N = N_0 e^{kt}$ at time t starting from an initial population N_0, where k is close to zero. Percentage growth on a savings account is an example of fixed rate growth.

[12] Power-law growth, $N_t = C(t_0 - t)^{-\alpha}$, given a constant C and coefficient α, cannot continue past t_0 because N would become infinite, so that power-law growth benefits are self-limiting.

[13] Here, the frequency $f(s)$ of cities of size s varies inversely to size, $f(s) \sim s^{-\alpha}$. In power-law growth, the savings account analogy would entail a rise in interest rise proportional to size of the account (the rich get richer faster).

[14] It is easy to confuse this exponential growth – occurring at a steady growth rate – which will outstrip linear growth, say, for resources, as argued by Malthus. Power-law growth – with a growth rate proportional to some power of the current population – is super-exponential even if the power is 1.

in one part of a population can then diffuse to others, provided that communication is possible. This cannot occur if the smaller groups do not connect to allow diffusion from local regions to larger portions of the total population. (Exponential growth, $dN/dt = aN$, in contrast, can operate without this interactive component.) I would add that the ramp-up effect of multi-connectivity on population growth does not scale with *n* by *n* interactions in a population of *n* elements, but at the much lower cost and density of scalable cohesion, involving the spread of structural cohesion rather than more links per node. The effect is transmitted through trade, through the diffusion of technological innovation, and through attraction to cities that allows higher "storage" of dense populations while the higher reproductive rates of rural areas replace the out-migrants to cities.

Figure 5.3 shows, from Kremer's (1993) world population figures, population growth data as presented in von Foerster et al.'s (1960) log-log format and a semi log plot of the same data. Because the log-log plot in part A includes logged "time to singularity" in an infinite succession of divisions by 10, it entails a population growth to infinity as the time scale expands to the left beyond what is shown here. It is also somewhat deceptive in suggesting greater linearity in power-law slope after 1500 because the data-points are increasingly compressed later in time. The semilog plot in part B shows the same data in equal-interval historical time from the Neolithic to the present. Here it can be seen that roughly exponential growth gives way to what might be power law growth – i.e., increasing growth *rates* – after the rise of cities in the fourth millennium BCE. Each of the intermittent precipitous growth trends after the rise of cities hit a limit and then flattened to start a new but similar growth trend. Although there is certainly room for improvement on Kremer's data as a basis of these generalizations, the empirical and theoretical basis for power-law urban growth has now been given by Bettencourt et al. (2007), and I think that its prevalence will be verified further with improvements to the population data available.

Accelerating population growth *rates* associated with urbanism occur first at circa 500 BCE during the crisis of archaic civilizations, several thousand years before the singularity that would have occurred if the world population growth trend of that time had continued without change. Food production is a predominant factor limiting the acceleration of population growth. The findings of West et al. (this book) and Bettencourt et al. (2007) show that cities have to run to stay in place and to import managers and skilled workers in production to maintain their position *vis-à-vis* other competing cities in a regional and/or world-system economy. Extrapolating these findings back in time might explain the peculiar population growth phenomena observed even in the earliest phases of urban civilizations (Algaze, 2005). Page (2007, pp. 329–335, 340) argues for the super-additivity of diverse tools for problem solving that cohabit in cities as the driver of city growth. Structural cohesion provides a scalable model of low-cost network mixture in cities that facilitates such super-additivity and, hence, innovation through problem solving. While Tainter (2000) explains how the demise of large empires might be due to the increasing cost of problem solving, this lack of scalability may be due to the

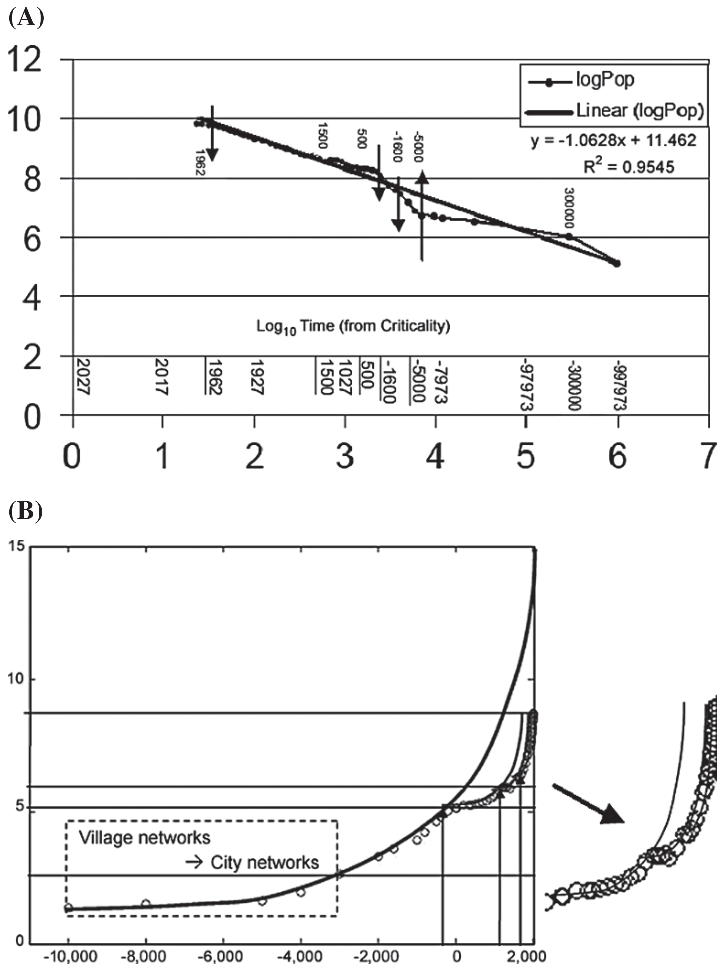


Fig. 5.3 World Population Power-Law Growth Spurts and Flattening as shown in: (**A**) von Foerster et al.'s (1960, redrawn) log-log plot with updated population estimates back to 1 million years BCE, with downward arrows marking the start of reduced growth rates, and (**B**) a semilog plot of the same data with successive power-law fits

structure of bureaucracies, replacing decentralized structural cohesion with competitive segmentary groups as the vehicle for network organization and collaborative problem solving.

After 500 BCE, there are three phases shown in Fig. 5.3 where world population growth flattens but then begins a precipitous rise toward singularity. Flattening occurs at about 1250 CE, then again at about 1650; and again at about 1860 (data from Kremer 1993). Each time, after the flattening, a new growth resumes similar to power-law growth, each curve pointing roughly, to the same singularity at t_0. These growth spurts and halts are due partly to the growth of cities *per se* but may also be due to the new technologies and communications thresholds developed out of leading urban economies and world powers that provide significant innovations and productive breakthroughs (van Duijn, 1983, pp. 176–179).[15]

5.3.7 Co-Evolution of Cities and Urban Networks

The concept of power-law tails of urban population distributions of leading cities has long predominated in urban studies and gives a false impression (noted by Batty, 2006) of cities as self-organizing systems (Bak, 1996) with universal rank-size scaling. City sizes are not scale-free and city-size distributions do not conform to invariant or even fully scale-free power laws. There is no commonly accepted explanation for this discrepancy in the urban studies literature, from Zipf to Sassen, nor for the Zipf "law" itself (Krugman, 1996). For a test of whether city size distributions are stable over time or have characteristic oscillations, data can be found in Chandler's (1987) inventory of sizes for the world's largest cities. Figure 5.4 tells the story by showing, for European, Chinese, and Mid-Asian city systems, two parameters for

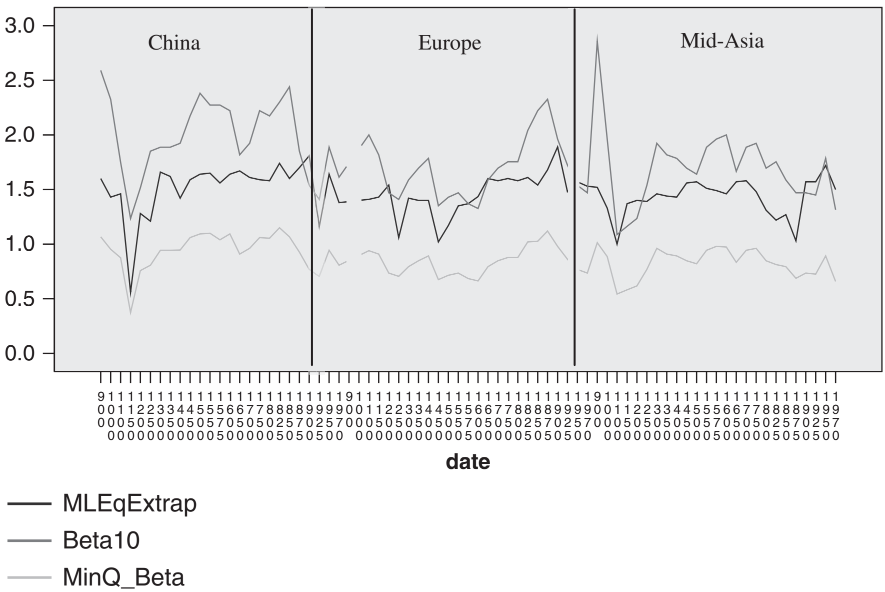


Fig. 5.4 Fitted parameters for city size distributions in Eurasian Regions (β in Pareto I tail, q in Pareto II body, and their normalized minimum)

15 It would be useful to explore the extent to which these include innovations in agricultural production that can support more population and organizational forms that can help cities overcome centrifugal tendencies. There may be exceptional agricultural innovations in rural England in the 18th century and the US in the 19th century but these are taking place within urban industrializing economies with market supports of agricultural innovation.

different curve fits to the city size distributions for each of 25 historical periods (White and Tambayong & Kejžar, 2007). The upper lines show the linear log-log slope β coefficients for the linear Pareto I log-log plots for the top 10 cities in each region and for each time period. The middle lines show variations in q, a shape coefficient for a Pareto II distribution[16] that has a power-law tail but a crossover toward an exponential distribution for smaller city sizes. The equation fitted for the Pareto distribution is $\Pr(X > x) \approx 1/x^{\beta}$. The Pareto II equation that is fitted is $\Pr(X > x) \approx 1/(1-(q-1)x/\kappa)^{1/(q-1)}$ (Shalizi, 2007), where κ affects the crossover, and the slope of the distribution asymptotes in the tail to $1/(q-1)$. This asymptotic slope would equal $-\beta$ if the tail and the body of the distribution were consistent, which they are not. This tells us that larger cities and smaller cities are affected historically in differing ways, possibly, because large cities suffer declines with a foreign invasion, while their size distribution elongates with imperial expansions and broader world trade. Size distributions for smaller cities may be affected by regional trade volumes.[17]

The q coefficient varies around 1.5, for which the Pareto II curve has a Zipfian tail. The Pareto coefficient varies around 2, also conforming to the Zipfian distribution. The lower line is the Zipf-normalized average of the two, dividing β by 2 and q by 1.5. Each of these measures shows statistically significant runs of values that remain significantly above or below their mean for long historical periods. Their oscillations are nonrandom, and they define historical periods of ups and down in the tails and bodies of city distributions. Variations in β reflect historical fluctuations of larger cities, and q those of smaller cities.

Thus, as shown in Fig. 5.4, between 900 and 2000 CE there are alternating periods of high and low β and q values for each of our three regions. Between different major historical periods, they change between high-q periods (with thicker power-law tails and greater heterogeneity) and low-q periods (more exponential in the shape of the distribution and egalitarian in terms of more thin-tailed city size differences). Low q, low β periods represent collapses in city systems; low β being collapse of large cities, low q the collapse of smaller cities.

To gauge the effects of major wars on the irregular oscillations shown in Fig. 5.5, we defined a dichotomous variable W that measured sufficient SPI magnitude, duration, and extent of conflicts that may be considered as external shocks affecting

Fig. 5.5 Socio-Political Instability (SPI) recoded as dichotomy (W) for warfare shock to cities

---

[16] Defined in the first section as $y = P_{\Theta,\sigma}(x) = (1 + x/\sigma)^{-\Theta}$ the only difference being a linear transformation of these parameters (σ, Θ) into κ and q (see Shalizi, 2007).

[17] We have also found that our MLE estimates can give unbiased estimates with reasonable confidence limits for total population in China in different historical periods, and for Europe and other regions as well.

urban population movements, based on a 0/1 coding of Lee's data for China, and comparable data from multiple sources on European wars, as diagrammed for the historical intervals in Fig. 5.5.

Using W as a measure of exogenous shock, we then modeled the dynamics of alternation between periods of city system collapse and city-rise or growth as shown in Fig. 5.4, for both Europe and China, by two time-lagged equations that summarize the puzzling relation between β and q and the effects of major disruptive wars (the C parameters are regression constants).[18]

$$\beta_{t+1} \approx -q_t + q_t\beta_t + C_\beta \text{ (overall R}^2 \sim .79,\ \text{China} \sim 0.75,\ \text{Europe} \sim 0.69) \tag{5.1}$$

$$q_{t+1} \approx -\beta_t + q_t\beta_t + C_q - W_t \text{ (overall R}^2 \sim .57,\ \text{China} \sim 0.54,\ \text{Europe} \sim 0.66) \tag{5.2}$$

These equations express a pair of time-lagged multiple regressions that predict, with a lag of a single generation (25 years), that

1. β and q affect one another inversely, i.e., the health or decline of one end of the size distribution ramifies to the other,
2. Their product, with a magnitude of disruption in consistent growth, affects each, and
3. Major wars affect q adversely, i.e., they are most directly disruptive to the smaller cities.

These effects occur with a time lag. Disregarding the effect of war, these interactions are positive feedbacks, and without war, they imply a dynamic that would lead to a city size distribution equilibrium close to the Zipfian.[19] Major wars disequilibrate city size distributions, according to these findings (White et al., 2007).

Figure 5.6 shows some of the distributions of cumulative population by city size for China (part A) and world cities (part B). The curves in the log-log plots for the bodies of these distributions bend toward the horizontal as they approach the y-axis, consistent with the q-exponential. These fitted curves show dramatically how the city population curves differ from power-laws (which are straight lines in log-log; but this departure is more evident when the number of cities is cumulated), and how much the distributions differ from one period to another. On the y-axis, in logged units of 1,000, are the cumulative city populations of the logged city-size bins in the x-axis. Large differences are evident in the shapes of the curves between 1800, 1875, 1914 and 1950 for China, for example, and in the case of the cities of the world, one is struck by how 1700 differs by degree from 1850 and 1900. In their

[18] W for China and SPI for Western Europe were coded by Tambayong. Equations (5.1) and (5.2) were also his work.

[19] A two-equation reciprocal time-lag model such as Equations (5.1) and (5.2) produces fluctuations if the signs of the right hand elements are opposite, but convergence or divergence if they are the same. This can be verified in difference equations using initial values that generate a full time series.

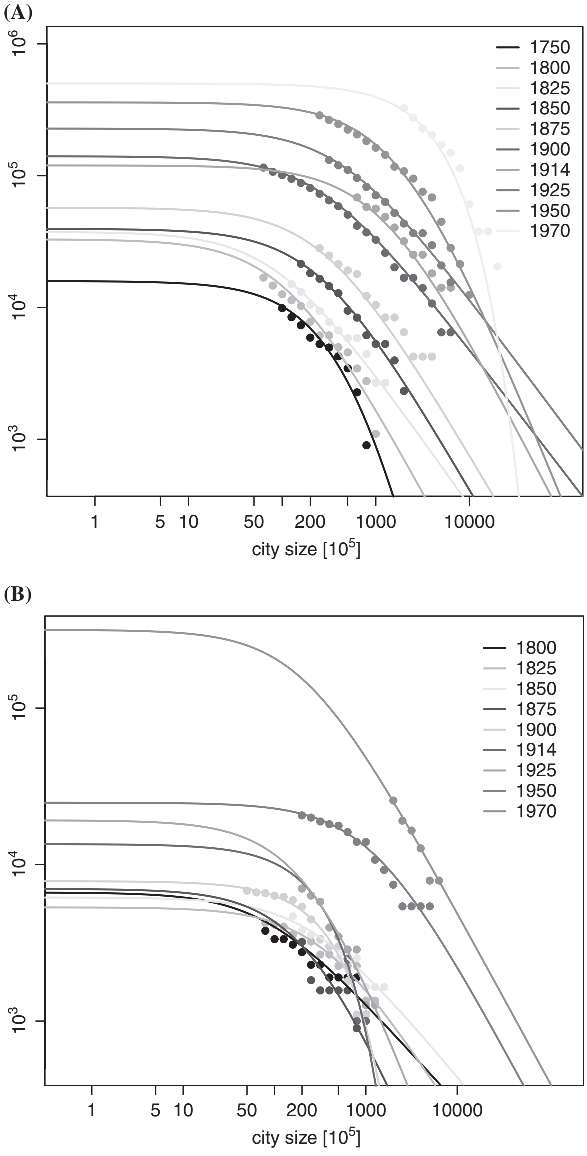


Fig. 5.6 Fitted q-exponential curves for World and Chinese city distributions. (**A**) World Cities 1750–1970 and (**B**) Chinese Cities 1800–1970 Largest sizes are limited by a diagonal for cities at the lower right of these graphs. Projection lines beyond that limit are meaningless

cumulative distributions all these curves asymptote at the tail, to a power law with slope β measured by $1/(q-1)$ if $q > 1$, and approach the total urban population as they asymptote toward the y-axis when city sizes on the x-axis approach 4,000 people.

Many of the actual data points in the tails, however, differ from the slope expected from fitted q (here fittings were weighted by the cumulative number of cities in each bin, and, since these weights increase from right to left, they give weighting priority to the body of the distribution). A key feature of these distributions is that of systematic exaggeration of the sizes of the very largest city as compared to what is expected from the rest of the distribution. This occurs up to 1950 for China, and to 1850 for the largest world cities. These exceptional sizes of historical cities tend to disappear with globalization. Thus, the exceptional primacies of capital cities in the historical periods may reflect their integration into cross-regional trading networks – trading connections to the hubs of other regions –an integration that is not shared by smaller cities until the economy becomes fully globalized.

5.4 Causality and Dynamics at the Macro Level

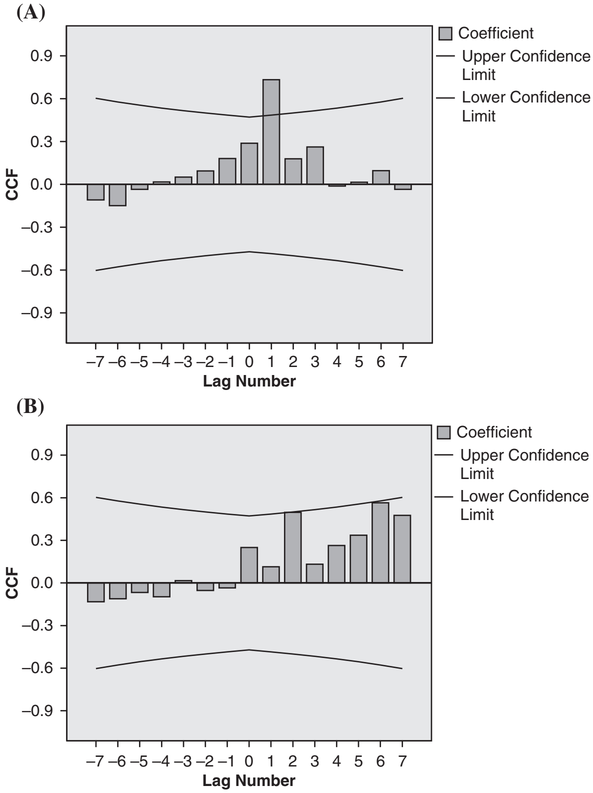
Networks and node attributes have all the elements for causal analysis, as implemented by Pearl (2000, 2007), H. L. White (2007), and White and Chalak (2007), and in simpler forms for historical dynamics by Turchin (2005b). Our use of MLE estimation (unbiased even for small samples) of q and β supports the validity of one of the most striking pieces of evidence of causal effects in our cities dataset: a time-lagged regression model, which replicates well in all three of our regions, shows that q values reflecting rise and fall in the smaller cities sector of the distribution at time t affects commensurate changes in the power-law tail at time $t + 1$ ($R^2 = 0.50$ for all three regions). This is relevant for innovation if we interpret the health of the small cities' economy, trade network, and city size distribution as indicative of innovative and competitive industries and exports, with the larger city distribution benefiting with a generational time lag.

The results illustrated above are only the beginning of our city system oscillations studies. Further early results show strong long-distance correlations between the parameters of city size distributions whose time lags indicate diffusion effects: changes in q in one region that have a temporally lagged correlation with changes in q in another. Temporal cross-correlations are shown in Fig. 5.7A for changes in the Islamic region (Mid Asia) that precede those in China 50 years later, and in Fig. 5.7B for changes in China that precede those in Europe 100 years later. The Mid-Asian dynamics only weakly link to changes in Europe 150 years later, which suggests that these effects are mediated by the Chinese cross-continent trade through the silk routes (Fig. 5.8).

It is clear in these time lags that when regions that are more technologically advanced as a diffusion source, in a given historical period (early on, Mid-Asia over China over Europe, later on, China over Europe), show a rise in q, a less advanced region rises in q with a time lag, but only when there are major trade flows between them. The same is true for the lag when q declines in the source.[20] This result supports the hypothesis that the carriers of positive long-distance correlations

[20] These graphs reflect improvements in accuracy in our scaling estimates using maximal likelihood estimation (MLE) methods for Pareto I and II developed in collaboration with Shalizi (2007). Pareto II scaling gives equivalent results as q exponential scaling.

Fig. 5.7 Cross-correlations for temporal effects of one region on another. (**A**) changes in the Islamic region (Mid Asia) and (**B**) changes in China that precede those precede those in China 50 years later in Europe 100 years later



in city sizes are the intercity networks, operating primarily through trade relationships (cf. Turchin & Hall, 2003) and, with secondary effects in the smaller cities, as primary producers and mediators of trade networks. For example, these correlated oscillations, when lagged by 100 years, begin in Eurasia after the Song invention of national markets and credit mechanisms in the 900s and first diffuse to Europe through the silk routes.

Mobile states or groups, such as the Mongols, play significant roles both in establishing and furthering long-distance trade and in its disruption (Chase-Dunn et al., 2006). World-system wars that lead to disruptions of trade networks have a negative effect on city population distributions. Trade, warfare, and diffusion of information and innovations (or materials that can be used for innovations) play significant roles in city-rises and city-quakes at the population distribution level.

5.4.1 *Innovation, Socio-Political Upheavals, Secular Cyclicity and Trade Networks in Complex Urban Societies*

The processes examined here are among those that require a coarser, aggregated level of analysis to measure statistical and causal relationships. For a statistical

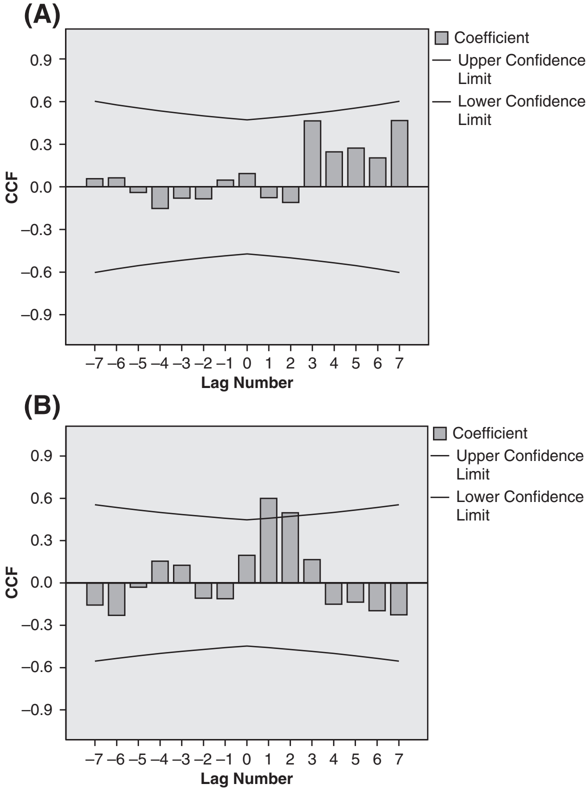


Fig. 5.8 Time-lagged cross-correlation effect. (**A**) Effect of Mid-Asia q on Europe and (**B**) effect of the silk road trade on European β (ten top cities)

model, a *sufficient statistic* is one that captures the information relevant to statistical inference within the context of the model, including the size and composition of the units of study. A *sufficient unit* is one for which a random sample of aggregate statistics are sufficient in the statistical sense that validity of inference is demonstrable in comparison with analysis using units and variables at smaller levels of aggregation.

We will here apply statistical models that relate the dynamics of changing population size relative to resources in units of a size and composition sufficient to capture interactive effects with other variables. If the population variable were broken up, in these examples, into its components – births, morbidity, deaths, and migration – we can easily lose sight of primary effects such as Malthusian pressures and get lost in a mass of detail that entails particular areas of demographic study but fails to see the forest for the trees.

In particular, we will begin by focusing on large, “sufficient” regions that are relatively unaffected, for long periods, by exogenous shocks such as external wars, and we will apply models of how resources bear on reproduction, how population pressure on resources bears on social conflict or cooperation, on differential well-being, on growth or decline of social inequality, on social hierarchy, and on social mobility. Then, we continue, at the level of comparably large regional units, to consider the rate of innovations relative to historical periods of growth, decline, or conflict. Lastly, we turn to how innovations and growth in transport systems within regions in such periods affect the augmentation of structural cohesion in regional trade networks and increase the capacity and likelihood of growing intraregional trade volumes, which connect dynamically to long-distance trade, and in some instances to innovations at the regional level such as monetization.

Using the sufficient statistics approach, scientists like Turchin have been able to take what can be transferred from the study of animal ecologies to specify and amplify problems in historical dynamics that do permit use of available data to examine hypotheses about the dynamics of change and periods of innovation. The key move is to look at the demographic variables per area (such as sheer number of people) as they bear on available resources. Large bounded areas may serve as a control for migration if there is little migration in and out of the region as a whole. Total numbers of people per area – and how these numbers change relative to resources – allow empirical study by means of models of direct and delayed *density-dependent* mechanisms of change (Turchin, 2003, p. 138). In this context, *endogenous* refers to *density-dependent* feedback mechanisms (e.g., population/resources; predator/prey) and *exogenous* refers to such factors as affect population (e.g., climate, carrying capacity) but are not affected by population growth rates in the short to medium run.

The British historical records, comprehensively analyzed by the Cambridge Group for the History of Population and Social Structure, now provide "sufficient statistics" that are aggregated over successive intervals for total populations, total bushels of wheat, etc., to provide Turchin and others with a plenitude of data for successive periods in English history. Historical research on the Roman Empire and various dynasties in China provides a similar breadth of data that enables us to compare regional statistics over successive historical periods.

Access to these kinds of sources provided relatively reliable regional data on *density-dependent* changes in population/resource pressure and sociopolitical instabilities (the so-called socio-political violence index, SPI) for Turchin (2005b, 2006) to identify *endogenous dynamics* in a number of Eurasian populations. His findings on interactive dynamics between population pressure and sociopolitical instability and conflict have been replicated by Kohler, Cole and Ciupe (2009) for one of the best-studied regions of the Southwestern Pueblos. Turchin (2005b, p. 10) notes for his two-equation time-lagged regression that "the statistical approach . . . can yield valuable insights into the feedback structure characterizing the interactions between different aspects of the studied dynamical system – when data are reasonably plentiful (for example, at least two or three complete oscillations), cover different aspects of the system, and the measurement errors are not too large."

Such a two-equation time series regression is useful when there is a known length of time lag, like generational reproduction, for one variable to affect the other positively (e.g., population pressure → transfer of competition levels into overt sociopolitical conflict), while fit to the second equation examines the reverse (negative) lag (e.g., sociopolitical conflict → lowered reproduction reducing population pressure in the next generation) to check for an endogenous time-lagged feedback loop. The competing hypothesis is that each variable has an endogenous cycle length and so is predictable from an inertial rather than interactive feedback process (Turchin, 2005b, p. 16).

Turchin's tests of the alternative hypotheses show that interactive rather than inertial dynamics account for the historical data for England and the Han and Tang dynasties in China. Panels (a) and (b) in Fig. 5.8, reprinted from Turchin (2005a), show how fluctuations in population pressure (i.e., population divided by bushels of grain) lead those of SPI by about a generation. Each period repeats a similar endogenous dynamic, defined by the negative time-lagged feedback between P, population density per resource, and SPI (data from Lee, 1931), fitting, with appropriate constants, a 2-equation model:

$$SPI_t \approx +P_{t-1} \text{ (Population change drives change in SPI)} \tag{5.3}$$

$$P_t \approx -SPI_{t-1} \text{ (SPI has a reverse effect on Population)} \tag{5.4}$$

Part C of Fig. 5.9 shows that Turchin's model is compatible with the Song dynasty data (960–1279) on population (Zhao & Xie, 1988), and with Lee's (1931) SPI index of internecine wars. The time-lagged correlation is consistent with Turchin's cycles, and we see in the period 960–1250 CE that the sociopolitical violence index (SPI) lags population growth by a generation.[21]

We saw earlier in Equations (5.1) and (5.2) that the "shocks" of major wars, through sociopolitical instability W, tend to have an immediate effect on the relation between the size scaling of smaller and larger cities for Europe and China, a shock that affects q but not β. Without the effect of SPI, these two equations would predict positive feedback between β and q that would result in either a convergent or a divergent time series. It is only the "shock" index, W_i given the locations of SPI events in the Turchin dynamics (which we also estimated for Europe from historical data) that acts as an external shock and makes the predicted time series oscillatory, often clocking with Turchin's endogenous dynamic. With the warfare "shock" included, however, Fig. 5.10 shows how the Equations (5.1) and (5.2), applied recursively as a difference equation with only initial q and β values, form an oscillatory pattern between q and β that would eventually converge to equilibrium if there were no further wars. Optimized difference equations lead to an oscillating trajectory that converges to $q = 1.43$ and $\beta = 1.75$ for both China and Europe toward the middle *third* millennium, i.e., still a long time into the future, and with an assumption of no further dis-equilibrating wars.

The prediction from the Turchin model is that high rates of innovation occur in a relatively closed region, in the periods following a downturn in which total

[21] The research groups doing these population estimates (Zhao and Xie, 1988) and extrapolations (Korotayev et al., 2006), may have used peasant rebellions and wars, including invasions from without, to infer population decline, and the reconstructions of other authors will differ from these estimates, but the general pattern in Turchin's data for Han, Tang, England, Rome and elsewhere is that after dividing population by resources (e.g., bushels of grain), population shifts lead SPI shifts by about a generation.

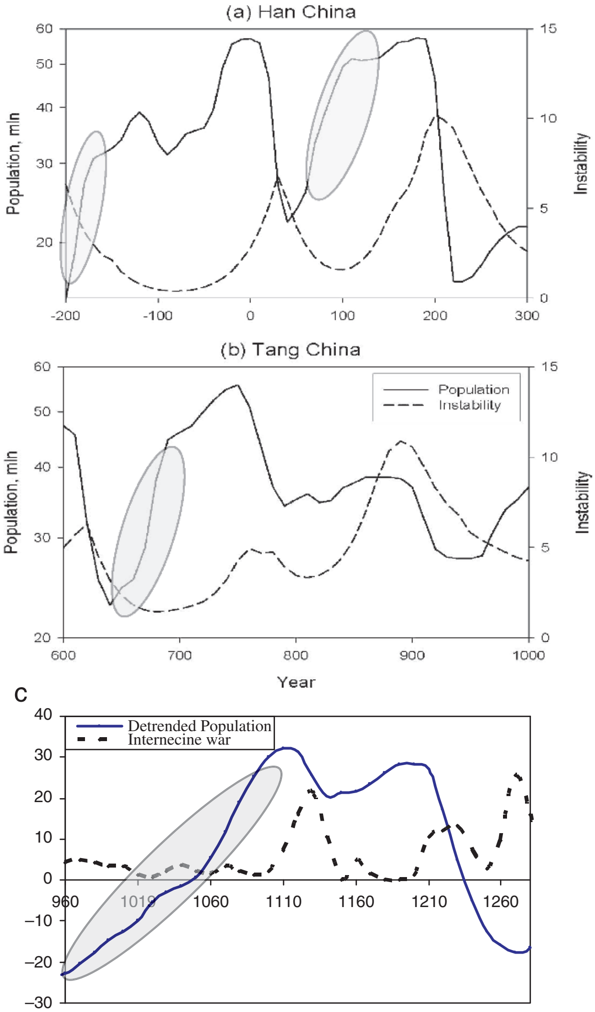


Fig. 5.9 China's interactive dynamics of sociopolitical instability (broken curve for internecine wars, after Lee (1931) and population (*solid curve*: Zhao & Xie, 1988): (**A**) Han (200 BCE to 300 CE), (**B**) Tang (600 to 1000 CE), from Turchin (2005a), with population detrended by bushels of grain; and (**C**) Song period population (960 to 1279 CE), divided by successive trend values

population is rising faster than resources. This is reported in research by Nefedov (2003), Turchin and Nefedov (2008), and Korotayev, Malkov, & Khaltourina (2006). These authors find that the major periods of innovation in these historical fluctuations are the periods of *growth following prior collapse*, as shown by the shaded areas in Fig. 5.9. The prediction is also borne out for the dates of major innovations during the Song period (Temple, 1986; see Modelski & Thompson, 1996, pp. 131–133, 142–145, 160–176), as shown in part C of Fig. 5.9. Periods of innovation tend to be growth periods with ample resources and stability for a rebuilding and expansion of infrastructure and productivity, following depopulating and disruptive regional and city-system conflicts. The actual innovations implemented in these periods often utilize inventions that trace back to the periods of earlier cycles, many of which diffuse to other regions before they are adopted, often in different ways

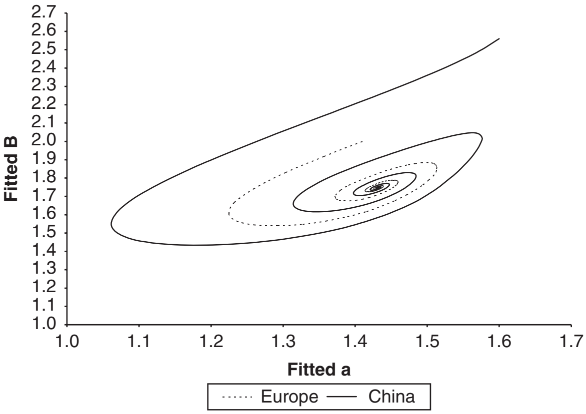


Fig. 5.10 Phase diagram for difference equations (5.1) and (5.2), with exogenous shocks to 1970 and convergent tendencies modeled to 2500 CE, barring disequilibration by warfare

than originally intended. This is well documented, for example, in the history of Chinese technological inventions that take hundreds of years to become European innovations (Temple, 1986), but the same occurs between other pairs of regions.

In a closer examination of the relation between innovation, Turchin or 'secular' (centuries-long) cycles, and trade networks, our historical project carried out a detailed European region study for 1100–1500 CE using the data of Spufford (2002), and found, like Spufford, that in medieval Europe, innovations were most pronounced not only in the periods of population rise relative to resources, following previous crises, and before the period of stagnation following the rise, but relate to *monetization* as one of the primary dynamics of innovation and economic reconfiguration (White & Spufford 2005).

Monetization had come earlier to Sung China, with its period of demographic rise, and later to Medieval Europe, with the spread from China, especially along the silk routes, involving credit and paper instruments and currencies. Demographic/conflict cycles may have been going on every time that new forms of money (M2, M3, M4, M5, etc.) developed. The relation to secular demographic/conflict cycles is that elites gain advantage as the population/resource ratio becomes Malthusian, labor becomes cheap, landlords and owners of productive property benefit, so that the rich grow richer and the poor poorer, if only for a period.

In Medieval Europe, elites exporting goods for cash in periods of scarcity used their monetary income to move to cities, hire wage retainers, kick peasants off their estates, fuel conspicuous urban demand for long-distance luxury trade, etc. The benefits of increased trade and profit margins for merchants were enormous, and, as the volume of trade expanded, merchant organizations, rural estates, and all kinds of other organizational structures expanded. In doing so, they recurrently surpassed thresholds at which innovative reorganizations of transport, production, accounting and all the other related areas occurred in nonlinear explosions.

In this study of Medieval European transformation (White & Spufford, 2005), we also identified how differences in network properties – such as betweenness and flow centrality for individual cities, or structural cohesion for regions – affected the trading benefits and growth of population or the wealth of different cities. The growth of merchant capital and attendant innovations, for example, were affected in the short run by the relative betweenness centralities (Freeman, 1977) of cities in which the finance capital was affected in the longer run by flow centrality. As a general consequence, the building of roads and their contribution to improvement of structural cohesion in regional trade routes had massive effects on trade, innovation, and development (see Spufford, 2002).

Finally, to illustrate how the historical cycles approach applies to the contemporary problems of political and business leadership, one last case study of innovation cycles in the U.S. may be useful. Policymakers, rather than address global warming, the scarcity of nonrenewable fuels, overpopulation, and multiple insurgencies, have, until very recently, maintained a defensive, nationalistic, competitive, partisan, and expansionist approach characteristic of strictly segmentary organization, fostering the collapse of cohesive or cross-cutting integration at the national level and level of international alliances. Segmentary competition among elites and exploitation of the strategic advantage of the elite position in periods of scarcity is historically characteristic of large-scale polities that are in the resource shortage and crisis phase of Turchin's secular cycles (drafted in 2006, this sentence is consistent with Turchin's model of collapse for the U.S.A. in the present period and the actual financial meltdown of fall 2008).

There is a vast amount of innovation in the American economy, but it is directed at high-end medical technologies that will benefit elites over common citizens, at pharmaceuticals, at military technology, surveillance technology, and genetic and information technology battlegrounds over private ownership and patents and open source technology. We have a huge number of inventions that could be mobilized toward solutions of major world and national problems that go beyond issues of security and competitive rivalry over ownership. These inventions are not being mobilized to create the innovations that would solve these problems. Until recently, our business leaders, from Bill Gates to IBM, are concerned with stamping out the open source and collaborative open access technologies where innovations might occur outside the competitive frameworks of corporations, partisan political blocks, and the vested interests of elite factions.

5.5 Conclusions

This chapter has looked at structure and dynamics in human groups – and problems such as social organization and behavioral patterns – within a network formulation that is illustrative of aspects of social and historical theory that bear on concepts of innovation. Re-conceptualizing cohesion and hierarchy within a dynamical network framework so as to extend the foundations of social theory has been the central task of the chapter.

In spite of the ambiguity of social hierarchy, large-scale urban systems provide empirical and historical examples that validate the existence of social hierarchy but also explore major fluctuations and instabilities in the indicators of hierarchy. I argue that multinet and node/edge attribute analysis can be employed at multiple spatiotemporal scales to improve our understanding of dynamics of hierarchy and cohesion, of how innovation is fostered, and how conflict – our variables SPI and SPI "shocks" (variable W) in city size dynamics – can work for or against one's own group and, at times, for the benefit of those one chooses to make war against. I argue that such studies of the dynamics of hierarchy and cohesion are important to understanding innovation because they create the contexts for variable rates of occurrence of inventions and later innovations involving prior inventions.

Which conclusions about innovation can we draw from this chapter? We can see abundant evidence that there is a great deal of variability in pre-state and pre-urban innovation and transformation in the structures and dynamics of social organization and exchange, a diversity that tended to be constrained within the moral regulatory universes associated with kinship, obligation, reciprocity and reverse hierarchy. Although there is enormous human inventiveness and spread of innovations in forms of exchange, growth of "surplus" does not produce automatically the kinds of hierarchy seen in development of pristine states and their elites.

Instead, what is seen is the startup of networks of cities as ensembles with internal division of productive labor oriented toward a division of labor in the exchanges between cities, along with specialized roles that facilitate external predation and trade, on the one hand, and organizational channeling of production into export trade, on the other. Superadditivity in interaction of diverse problem solving approaches might be the key to urban competitiveness, but surfeits of inequality and competitiveness may also destabilize entire city systems, as shown in the historical investigations of Section 5.5. Temporally shifting imbalances between supply and demand, even in the absence of market pricing systems, are already implicit in these intercity trading/warfare systems. By any means, the attraction of population into cities to fuel labor demands as well as to staff specialized oversight, military, and other specialized roles, leads to a related set of instabilities, those between growing population and the eventuality of limited resources. This, in turn, leads to alternating periods of scarcity and plentitude caused by population pressure, on the one hand, and the alternation of blowback effects of inequalities and internal sociopolitical instabilities reacting to these imbalances (population pressure producing scarcities, lowering of effective wages for workers while advantaging elites) on the other. Sociopolitical instability reacts to the eventual reduction in population pressure. This is the secular cycles model of agrarian state polities. In this chapter, I have sought to extend some of the findings and insights gained from such models to broader classes of problems where multi-relation and multi-attribute dynamics can be examined within a network approach to social theory.

Some of the work summarized here, on the historical and network dynamics in regional and interregional city systems, shows that urban system fluctuations and crises are at least negatively coupled through the sociopolitical instabilities (SPI) and shocks that follow from the structural-conflict cycles of agrarian states. On the network side, these studies also show strong interregional diffusion effects for inventions (e.g., China to Europe, as just one example) and eventually for innovations made possible by the diffusion of inventions, which are often put to very different uses in later times and different regions. Further, the growth periods of these great swings in dynamics, in urban and regional economies, and in the consequences of politico-military interventions abroad, provide conditions and incentives for innovation.

If these results (and subsequent ones in this line of work) do show that the kinds of innovations that help solve problems in the crisis periods of civilizations and city systems do not come into play in those actual crisis periods where they are needed, but usually only after the fall following the crisis, then my contention would be that we need to rethink our understanding of the dynamics that affect innovation and the policy implications that we derive from them.

Further, conflicts that serve as shocks to city systems seem, according to quantitative historical dynamic studies, to drive city systems away from settling into a more stable equilibrium between the smaller cities that often have been the most dramatic sites of creativity, and the largest cities that often seem to draw out the economic vitality of larger regions. One is left to consider and to hypothesize the potentially beneficial effects of reducing sources of conflict while increasing diversity, especially in contexts where peaceful diversity can lead to cooperation and greater problem solving rather than innovation mainly for the sake of competitive advantage. If the approaches reviewed in this chapter have been productive beyond expectations, perhaps they will prove efficacious in investigations that could shape avenues toward a more benign set of futures than the ones we face now.

Acknowledgments Special thanks to David Lane, for his suggestions on organizing this chapter, and to Sander van der Leeuw, for rewriting the introduction and doing a superlative job in editing.

References

Abbott, A. (2001). Chaos of disciplines. Chicago: University of Chicago Press.

Adams, A. E. (1981). *Heartland of cities*. Chicago, IL: University of Chicago Press.

Algaze, G. A. (2005). The Sumerian takeoff. *Structure and Dynamics, 1*(1), 5–48.

Arthur, W. B. (1994). *Increasing returns and path dependence in the economy*. Ann Arbor, MI: University of Michigan Press.

Bak, P. (1996). *How nature works: The science of self-organized criticality.* New York, NY: Springer-Verlag.

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*(5439), 509–512.

Batty, M. (2006). Rank clocks. *Nature (Letters), 444*, 592–596.

Bettencourt, L. M. A., Lobo, J., Helbing, D., Kühnert, C., & West, G. B. (2007). Growth, innovation, scaling, and the pace of life in cities. *Proceedings of the National Academy of Sciences, 104*(17), 7301–7306.

Boehm, C. (1993). Egalitarian behavior and reverse dominance hierarchy. *Current Anthropology*, *34*(3), 227–254.

Boehm, C. (2001). *Hierarchy in the forest: The evolution of egalitarian behavior*. Cambridge, MA: Harvard University press.

Boltanski, L., & Thévenot, L. (1999). The sociology of critical capacity. *European Journal of Social Theory*, *2*(3), 359–377.

Brudner, L. A., & White, D. R. (1997). Class, property and structural endogamy: Visualizing networked histories. *Theory and Society*, *26*, 161–208.

Chandler, T. (1987). *Four thousand years of urban growth: An historical census*. Lewiston, NY: Edwin Mellon Press.

Chase-Dunn, C., Niemeyer, R., Alvarez, A., Inoue, H., Lawrence, K., & Carlson, A. (2006). *When north-south relations were east-west: urban and empire synchrony (500 BCE–1500 CE)*. Paper presented at the International Studies Association meeting, San Diego, CA.

Du, H., White, D. R., Li, S., Jin, X., & Feldman, M. W. (n.d.) "Network Models for Chinese Women's Rural-Urban Migration Experience" Ms.

Farmer, J. D., Patelli, P., & Zovko, I. (2005). The predictive power of zero intelligence in financial markets. *Proceedings of the National Academy of Sciences, 102*(6), 2254–2259.

Fitzgerald, W. (2004). *Structural and non-structural approaches to social class: An empirical investigation*. PhD Dissertation, Program in Social Networks. University of California Irvine.

Florida, R. L. (2005). *The flight of the creative class: The new global competition for talent*. New York: HarperCollins.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry, 40*, 35–41.

Grannis, R. (1998). The importance of trivial streets: residential streets and residential segregation. *American Journal of Sociology, 103*(6), 1530–1564.

Griffin, A. F., & Stanish, C. (2007). An agent-based model of prehistoric settlement patterns and political consolidation in the Lake Titicaca Basin of Peru and Bolivia. *Structure and Dynamics, 2*(2), Article 2.

Henrich, J. (2001). Cultural transmission and the diffusion of innovations: adoption dynamics indicate that biased cultural transmission is the predominate force in behavioral change and much of sociocultural evolution. *American Anthropologist, 103*, 992–1013.

Henrich, J., Boyd, R., Bowles, S., Gintis, H., Fehr, E., Camerer, C., et al. (2005). 'Economic man' in cross-cultural perspective: ethnography and experiments from 15 small-scale societies. *Behavioral and Brain Sciences, 28*, 795–855.

Kearns, M., Suri, S., & Montfort, N. (2006). An experimental study of the coloring problem on human subject networks. *Science, 313*(5788), 824-827.

Kohler, T. A., Cole, S., & Ciupe, S. (2009). Population and warfare: a test of the Turchin Model in Puebloan societies. In S. Shennan (Ed.), *Pattern and process in cultural evolution*. Berkeley, CA: University of California Press. Also as a Sante Fe Institute Working Paper, 06-06-018, Preprint: http://www.santafe.edu/research/publications/wpabstract/200606018

Kondratieff, N. D. (1984). *The long wave cycle* (G. Daniels, Trans.). New York: Richardson and Snyder.

Korotayev, A. V., Malkov, A., & Khaltourina, D. A. (2006). *Introduction to social macrodynamics: Secular cycles and millennial trends*. Moscow, Russia: URSS Press.

Kremer, M. (1993). Population growth and technological change: One million B.C. to 1990. *The Quarterly Journal of Economics, 108*(3), 681–716.

Krugman, P. (1996). Confronting the mystery of urban hierarchy, *Journal of Political Economies, 10*(4), 399–418.

Lee, J. S. (1931). The periodic recurrence of internecine wars in China. *The China Journal* (March–April): 111–163.

Llewellyn, K. N., & Hoebel, E. A. (1961). *The Cheyenne way: Conflict and case law in primitive jurisprudence*. Norman, OK: University of Oklahoma.

Lomnitz, L. (1977). *Networks of marginality: Life in a Mexican Shantytown*. New York: Academic Press.

Low, S. M. (2003). *Behind the gates: Life, security and the pursuit of happiness in fortress America*. New York: Routledge.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105–142). New York: Academic Press.

McFadden, D. (1981). Econometric models of probabilistic choice. In C. Manski & D. McFadden (Eds.), *Structural analysis of discrete data: With econometric applications* (pp. 198–272). Cambridge, MA: MIT Press.
Modelski, G., & Thompson, W.R. (1996). *Leading sectors and world powers: The co-evolution of global economics and politics*. Columbia, SC: University of South Carolina Press.
Moody, J., & White, D. R. (2003). Social cohesion and embeddedness: A hierarchical conception of social groups. *American Sociological Review, 68*(1), 1–25.
Morel, B., & Ramanujam, R. (1999). Through the looking glass of complexity: the dynamics of organizations as adaptive and evolving systems. *Organization Science, 10*(3), 278–293.
Nakano, T., & White, D.R. (2006a). The large-scale network of a Tokyo industrial district: small-world, scale-free, or depth hierarchy? *COI Working Paper June 2006*. New York: Center on Organizational Innovation, Institute for Social and Economic Research and Policy, Columbia University.
Nakano, T., & White, D. R. (2006b). *The "visible hand" in a production chain market: A market equilibrium from network analytical perspective*. Santa Fe, NM: The Santa Fe Institute. (Santa Fe Institute Working Paper 06-05-015).
Nakano, T., & White, D. R. (2007). Network-biased pricing mechanisms of complex production-chain markets: Positions and roles affecting the equilibrium. *Structure and Dynamics, 2*(4), 130–154.
Nefedov, S. A. (2003). Theory of demographic cycles and social evolution of the ancient and medieval societies of the East. *Vostok Oriens, 3*, 5–22 (the English translation is available at http://repositories.cdlib.org/imbs/socdyn/wp/wp4/).
Page, S. E. (2007). *The difference: How the power of diversity creates better groups, firms, schools, and societies*. Princeton, NJ: Princeton University Press.
Pearl, J. (2000). *Causality*. Cambridge, UK: Cambridge University Press.
Pearl, J. (2007). Comments on *A unified framework for defining and identifying causal effects*. H. White & K. Chalak, University of California Complexity Videoconference. http://eclectic.ss.uci.edu/~drwhite/center/ppt_pdf/Pearl(2007-Feb09)_Cause.pdf
Powell, W. W., White, D. R., Koput, K., & Owen-Smith, J. (2005). Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences. *American Journal of Sociology, 110*:1132–1205.
Shalizi, C. (2007). *Maximal likelihood estimation for q-exponential distributions*. http://arxiv.org/PS_cache/math/pdf/0701/0701854v2.pdf
Spufford, P. (2002). *Power and profit: The merchant in Medieval Europe*. Cambridge, UK: Cambridge University Press.
Tainter, J. A. (2000). Problem solving: complexity, history, sustainability. *Population and Environment, 22*, 3–41.
Temple, R. (1986). *The genius of China: 3,000 years of science, discovery, and invention*. New York: Simon and Schuster.
Thoden van Velsen, H. U. E., & van Wetering, W. (1960). Residence, power groups and intra-societal aggression. *International Archives of Ethnography, 49*, 169–200.
Turchin, P. (2003). *Historical dynamics: Why states rise and fall*. Cambridge, UK: Cambridge University Press.
Turchin, P. (2005a). Dynamical feedbacks between population growth and sociopolitical instability in agrarian states. *Structure and Dynamics, 1*(1), 49–69.
Turchin, P. (2005b). A primer on statistical analysis of dynamical systems in historical social sciences (with a particular emphasis on secular cycles). *Structure and Dynamics, 1*(1), 70–81.
Turchin, P. (2006). *War and peace and war: The life cycles of imperial nations*. New York: Pi Press.
Turchin, P., & Hall, T. D. (2003). Spatial synchrony among and within world-systems: insights from theoretical ecology. *Journal of World-Systems Research, 9*, 37–66.
Turchin, P., & Nefedov, S. (2008). *Secular Cycles*. In contract for publication. Princeton, NJ: Princeton University Press
van Duijn, J. J. (1983). *The long wave in economic life*. London, UK: Allen and Unwin.

von Foerster, H., Mora, P. M., & Amiot, L. W. (1960). Doomsday: Friday, 13 November, A.D, 2026. *Science*, *132*, 1291–1295.

Velleius, C. (1924). *Velleius Paterculus: The Roman History*. (F. W. Shipley, Trans.), Cambridge, MA: Loeb Classical Library.

Walla, J. D., & Przeworski, M. (2000). When did the human population size start increasing? *Genetics, 155*, 1865–1874.

Watts, D., & Strogatz, S. (1998). Collective dynamics of 'small-world' networks. *Nature, 393*, 440–442.

Weissner, P., & Tumu, A. (1998). The capacity and constraints of kinship in the development of the Enga Tee Ceremonial exchange network (Papua New Guinea Highlands). In T. Schweizer & D. R. White (Eds.). *Kinship, networks, and exchange*. (pp. 277–302). Structural Analysis in the Social Sciences Series. New York and Cambridge: Cambridge University Press.

White, D. R. (1969). *Cooperation and decision making among North American Indians*. Ann Arbor, MI: Dissertation Reprints.

White, D. R. (1996). Enfoque de redes al estudio de comunidades urbanas. *Estudios Demográficas y Urbanas, 26*, 303–326.

White, D. R. (2004). Ring cohesion theory in marriage and social networks. *Mathématiques et Sciences Humaines, 168*, 5–28.

White, D. R., & Harary, F. (2001). The cohesiveness of blocks in social networks: node connectivity and conditional density. *Sociological Methodology, 31*, 305–359.

White, D. R., & Johansen, U. C. (2005). *Network analysis and ethnographic problems: Process models of a Turkish nomad clan*. Lanham, MD: Lexington Books.

White, D. R., & Newman, M. E. J. (2001). Fast approximation algorithms for finding node-independent paths in networks. *Santa Fe Institute Working Papers 7035*, http://www.santafe.edu/sfi/publications/wpabstract/200107035

White, D. R., & Johansen, P. (2005). *Civilizations as dynamic networks: Medieval to modern*. UCI Irvine Social Dynamics and Complexity Working Paper.

White, D. R., Tambayong, L., & Kejžar, N. (2007). Oscillatory dynamics of city-size distributions in world historical systems. In G. Modelski, T. Devezas & W. Thompson (Eds.), *Globalization as evolutionary process: Modeling, simulating, and forecasting global change*. pp. 190–225. London: Routledge.

White, H. L. (2007). A comparison of Pearl's causal models and settable systems. *UCSD Department of Economics Working Paper* W32.

White, H. L., & Chalak, K. (2007). A unified framework for defining and identifying causal effects. Submitted to Journal of Machine Learning Research.

Wright, H. (2004). *Raising civilization: Three Stanislaw Ulam memorial lectures on DVD*. Santa Fe, NM: Santa Fe Institute.

Wright, H. (2006). Atlas of chiefdoms and early states. *Structure and Dynamics, 1*(4), 738–758.

Zhao, W., & Xie, S.-Z. (1988). *History of Chinese population*. Peking, China: People's Publisher (in Chinese).