Careers, Chaos, and Complexity

Guido Strunk, Michael Schiffinger, Wolfgang Mayrhofer

Interdisciplinary Department of Management and Organizational Behavior
Vienna University of Economics and Business Administration (WU-Wien)
Althanstrasse 51, A-1090 Vienna, Austria
http://www.wu-wien.ac.at/inst/ivm/

Tel. +43-1-31336-4553
Fax +43-1-313 36-724

mailto:Guido.Strunk@wu-wien.ac.at
Michael.Schiffinger@wu-wien.ac.at
Wolfgang.Mayrhofer@wu-wien.ac.at

This paper was supported by the Austrian Science Fund (FWF). Project Number P14307-SOZ

Careers, Chaos, and Complexity

Guido Strunk, Michael Schiffinger & Wolfgang Mayrhofer

Abstract:
The article deals with the question whether careers have indeed become more complex during the last years and/or decades by applying methods stemming from chaos research. The movements of 215 business school graduates from two different cohorts (graduation around 1970 and 1990 respectively) along two career-related dimensions (coupling, i.e. career-related security, dependency, and number of job alternatives, and configuration, i.e. stability of work content and professional relations) are examined with regard to their complexity. The results show that the complexity of careers for the 1990s cohort is generally higher than for the 1970s cohort. Furthermore, the results obtained suggest that the career paths of both cohorts along the two dimensions mentioned above are not random but form a complex yet deterministic system.

CAREERS AND COMPLEXITY

While the field of activity of career research was until quite recently almost exclusively limited to careers within organizations (Becker & Strauss, 1956; Glaser, 1968; Hughes, 1951; Super, 1957; Becker & Strauss, 1956; Dyer, 1976; Gunz, 1989; Hall, 1976; Schein, 1978), a different type of careers is now apparently gaining more and more theoretical as well as practical relevance – a type of careers that is marked by numerous transitions between jobs, organizations, or fields of professional activity, as well as a lack of institutionalized and "ordered" career paths and/or career rules, and the fact that it is almost solely up to the individual actor to take care of his or her career, with little or no external support, resulting in a less stable, less predictable career path labeled for instance as "boundaryless career" (Arthur, Inkson, & Pringle, 1999; Arthur & Rousseau, 1996), "protean career" (Hall, 1996), "post-corporate career" (Peiperl & Baruch, 1997), or "chronic flexibility" (Mayrhofer et al., 2000). Whether one enthusiastically accepts the idea of a radically changing career environment or not, it is probably hard to deny that careers are nowadays more erratic and diverse than they were several decades ago. In the following, we will term this claim of increased career complexity as "complexity hypothesis in career research".
Although most of these "new career" concepts appear valid and sound, empirical support for the complexity hypothesis is still rather scarce. Most empirical research so far is based on case studies, interviews and anecdotes (e.g. Arthur et al., 1999; Arthur et al., 1996), and despite the undisputed value of these results, especially when it comes to grasping the diverse and interwoven facets of these changes of the global career context that affect many different aspects of life, we want to propose another way of investigating the complexity hypothesis in career research, by applying quantitative methods that stem from research domains that can be subsumed under the label of "chaos research" (cf. e.g. Haken, 1990a; Kolmogorov, 1965; Prigogine, 1955, 1987; Schuster, 1989a; Seifritz, 1987). Although these methods have their origin in the sciences of nature, they have already been applied successfully to the social sciences (e.g. Ambühl, Dünki, & Ciompi, 1992; Babloyantz, 1990; Elbert et al., 1994; Haken, 1990b, 1992; Haken, Kelso, & Bunz, 1985; Kowalik, Schiepek, Kumpf, Roberts, & Elbert, 1997; Kriz, 1990, 1992; Schiepek, 1993, 1996; Schiepek et al., 1997; Schiepek & Schoppek, 1991; Schiepek, Schütz, Köhler, Richter, & Strunk, 1995; Tschacher, Scheier, & Grawe, 1998; Tschacher, Schiepek, & Brunner, 1992; Weidlich & Haag, 1983), and chaos theory has also had its first appearances in career research (Bird, Gunz, & Arthur, 2002; Baruch, 2002; Gunz, Bird, & Arthur, 2002a; Lichtenstein, Ogilvie, & Mendenhall, 2002; Drodge, 2002; Gunz, Lichtenstein, & Long, 2002b; Chakrabarti & Chakrabarti, 2002; Parker & Arthur, 2002). But in spite of several bold attempts to bring chaos theory and career research together, one has to concede that a serious and methodically sound application of methods from chaos research to the social sciences is far from trivial. The examined data have to fulfill several

high standards that are not frequently met in social sciences. Nonetheless, using these methods from chaos theory in career research should prove fruitful, especially when it comes to a description of career *dynamics*.

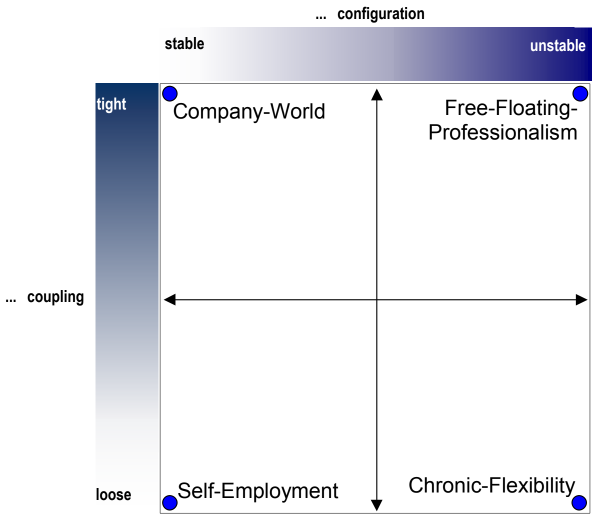
In the present paper, methods from chaos research are applied to a set of empirical data on actual career paths, in an attempt to investigate whether careers have indeed become more complex over the last few decades, as the complexity hypothesis in career research postulates. More specific, the article deals with three questions:

1. Have careers indeed become more complex during the last years and/or decades? Aside from the evidence provided by the sources mentioned above (among others), we will examine this question within a mathematically formalized complexity concept.
2. Should careers be perceived as a complex yet deterministic system or a random process? Although both chaotic systems and random processes are complex, chaotic systems are deterministic and not random in their behavior. The difference is an important one, considering the limited value of theories and research attempts that would try to discover and explain the dynamics of a *random* process.
3. Are the methods used here (algorithmic entropy and correlation dimension) appropriate for the analysis of career paths?

THE VIENNA CAREER PANEL PROJECT, AND HOW IT RELATES TO CAREER COMPLEXITY

Based on Bourdieu's capital, habitus and field concept (e.g. Bourdieu, 1986), Mayrhofer et al. (2000) suggested four different fields of careers resulting from an interplay of two dimensions: coupling and configuration between actors (Figure 1).

FIGURE 1
The fields of career



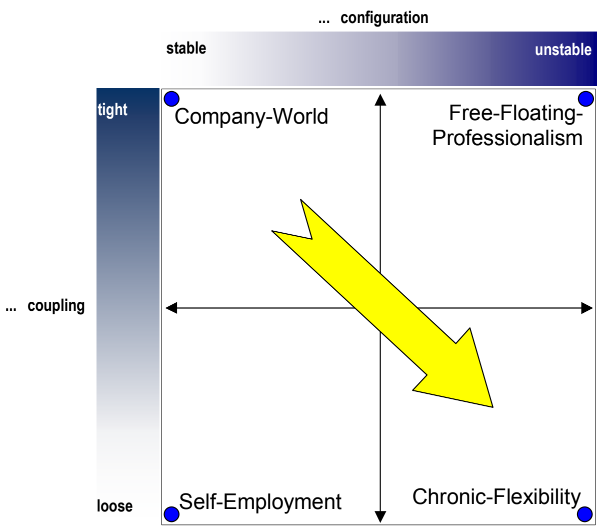
The *coupling dimension* focuses on the closeness of relationships and the degree of mutual influence between the focal actor and the other actor(s) in the field (e.g. Orton & Weick, 1990; Staehle, 1991; Weick, 1976). Tight coupling means that the actors are closely intertwined in their decisions. On the other hand, loose coupling stands for a type of relationship where the decisions of one actor have very little consequences for the decisions of the other. Thus, in a tightly coupled relationship the decisions of one partner reduce the other's degrees of freedom much more than in a loosely coupled relationship.

The *configuration dimension* focuses on changes over time in the configuration of relationships between the focal actor and other relevant actors. A stable configuration implies that neither the social environment nor the tasks of the focal actor change rapidly and frequently. Conversely, an unstable configuration means that there is a frequent change in the configuration of actors and/or work-related tasks. This dimension refers rather to the rate of change in the configuration than to the number of actors relevant for the focal actor. Combining these two dimensions into a matrix results in a simple typology with four ideal types of careers that can be labeled as follows (see Mayrhofer et al. 2000):

- *Company World (CW)* stands for the field of the traditional organizational career. It refers to the structure of jobs in an organization where there are few points of entry other than at the bottom. It is defined in terms of the two dimensions by tight coupling and a stable configuration between an individual actor and other actors (in most cases represented by an employing company).
- *Free-Floating Professionalism (FFP)* can be defined as the field of specialists. Individuals work closely with one customer, but only for a limited time, which results in tight coupling but an unstable configuration.
- *Self Employment (SE)* is the field of career with individuals working outside organizations. Typically, these are either self-employed professionals or entrepreneurs, who work in a rather stable and limited field of expertise. This sort of occupation typically results in comparatively loose coupling between actors, but a stable configuration.
- *Chronic Flexibility (CF)* may appear quite similar to Free-Floating Professionalism, since those careers are also characterized by frequent job changes. The fundamental difference lies in the disappearance of the boundaries of a domain of expertise. This means that changing from one job to another may imply not only a change from one organization to another, but also from one industry to another, from being employed to self-employment, and so on. These loosely coupled and unstable relations are the key definition of that field of career.

Apart from these ideal types that shall rather serve as an illustration here, a tendency towards careers that are marked by more loosely coupled and unstable relationships between actors could be observed in recent years (see Figure 2). The increasing number of part-time jobs, fixed-time contracts, company layoffs as well as concepts such as life-long learning and employability are just a few examples of these developments (e.g. European Communities, 1999a,b; Reetz & Reitmann, 1990; IBW, 1997).

FIGURE 2
Assumed development of careers



This tendency towards loose coupling and an unstable configuration already represents one concept of increased career complexity. Accordingly, the career of a person in an occupational situation marked by loose coupling and an unstable configuration (Chronic

Flexibility) is more complex than the career of a person in a situation marked by tight coupling and a stable configuration (Company World). The perspective taken here, however, is a different one: we shall focus on complexity as a criterion regarding the movement of a person along the two dimensions of coupling and configuration. Therefore, complexity can also be attributed to a career that is limited to e.g. the Company World career field (see Figure 3 for a straight and non-complex career path, and Figure 4 for a highly complex one).

FIGURE 3
"Linear", "straight" career path

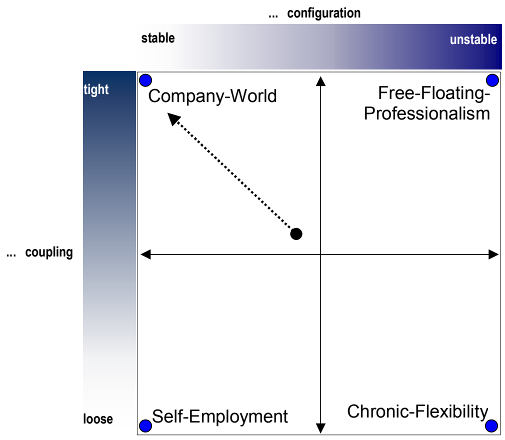
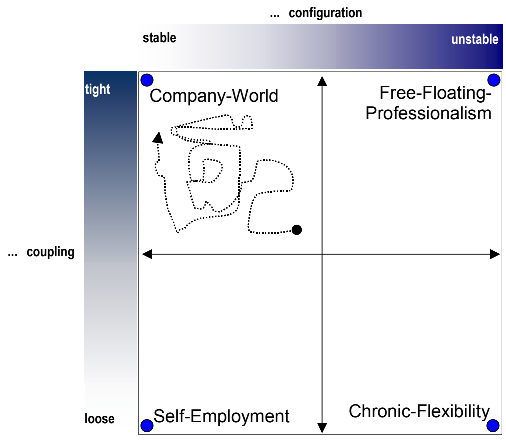


FIGURE 4
Erratic career path



So, instead of adopting a "static" perspective in order to examine whether careers have indeed become more complex during the last years and/or decades (e.g.: How has the relative distribution of a sample of persons changed with regard to the four fields? Do people report a less stable configuration and looser coupling now than 30 years ago?), the article will deal with this question from a dynamic standpoint: If one perceives career paths as movements along these two dimensions, do the career paths of persons who graduated from a business school and entered professional life more than 30 years ago differ from those of persons who did so about 12 years ago?
The theoretical and methodological fundament for the following analyses will be drawn from the domain of chaos theories, which includes a broad spectrum of theories, such as the theory of non-linear dynamic systems (e.g. Schuster, 1989a), synergetics (e.g. Haken, 1990a) and the theory of dissipative structures (e.g. Prigogine, 1955, 1987). More precisely, we will employ two measurements of dynamic complexity stemming from this field of research that will be outlined in the following chapter: the concept of algorithmic entropy and the determination of fractal structures of so-called strange and/or chaotic attractors.

COMPLEXITY AND ORDER – THE ALGORITHMIC ENTROPY

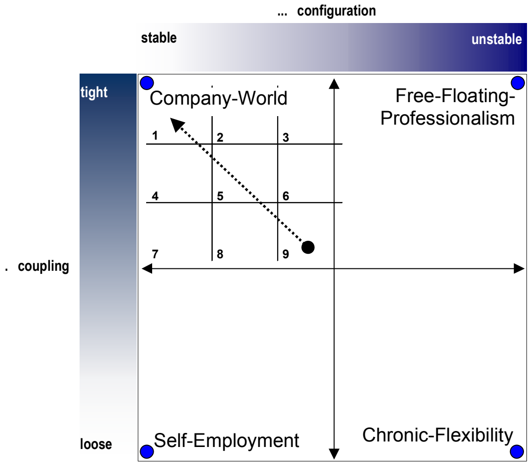
One standard method to determine the complexity of a sequence of events or symbols is Shannon's definition of the information content (Shannon, 1948). According to this definition, the information content of a sequence of values is equal to the sum (over all values) of the probability of the appearance of one value, multiplied with the logarithm of this probability:

Equation 1: $$I_s = -\sum_{i=1}^{N} P(s_i)\log_2 P(s_i).$$

The information content of a person's career movements (within the theoretical framework outlined above) could therefore be determined by putting a grid over the career path in question and recording the boxes the person is located in during his or her career. Figure 5 shows the linear career path already presented in Figure 3 with such a grid.

FIGURE 5

Career path of a person as movement over a grid



Assuming a uniform movement towards the "upper left corner" and the recording of 16 sampling points, the resulting sequence of "visited boxes" would look somewhat like the following (a "box" may appear more than once as the person stays in that "box" during several years):

$$9 \rightarrow 9 \rightarrow 9 \rightarrow 9 \rightarrow 8 \rightarrow 8 \rightarrow 5 \rightarrow 5 \rightarrow 5 \rightarrow 5 \rightarrow 5 \rightarrow 5 \rightarrow 4 \rightarrow 4 \rightarrow 1 \rightarrow 1$$

The information content of this sequence of events can now quite easily be calculated according to Equation 1 and amounts to 2.35 bit for the presented example.

Although Shannon's definition of the information content is one of the most widely used calculations for a sequence of values, it has some serious shortcomings, one of the most important lying in the fact that any sequence containing the same symbols as the example presented above yields the same result of 2.35 bit, such as the following one which would however imply a more complex career pattern:

$$9 \rightarrow 1 \rightarrow 9 \rightarrow 5 \rightarrow 9 \rightarrow 5 \rightarrow 8 \rightarrow 5 \rightarrow 8 \rightarrow 5 \rightarrow 9 \rightarrow 4 \rightarrow 5 \rightarrow 5 \rightarrow 4 \rightarrow 1$$

We therefore face the question how the idea of information content can be extended to taking the dynamic order of a career path into account. One solution proposed for this problem is the so-called algorithmic entropy

The Algorithmic Entropy

The fundamentals of algorithmic entropy are based on work in the field of algorithmic information theory (Chaitin, 1974; Kolmogorov, 1965; Zvonkin & Levin, 1970), which determines the information content of a sequence of values by the information content necessary to completely describe the sequence.

The square root of two, for example, is a number with infinitely many decimals that produce an extremely complex sequence of digits. Nonetheless the square root of two can be calculated using a quite simple algorithm:

Equation 2:

$$\sqrt{a} = x_{n+1} = \frac{1}{2}\left(x_n + \frac{a}{x_n}\right),\ n = 0,1,2,\ldots\infty.$$

In order to calculate the square root of *a*, an arbitrary *x* is assumed as the correct result in a first step. Entering both *a* and *x* into the equation yields a new *x* that is again entered into the equation, and so on. For a large *n*, the value of *x* converges towards the square root of *a*.

Algorithmic information theory is based on these ideas, assuming that a rather simple algorithm is able to describe and/or produce complex (but still ordered!) structures. Put in a somewhat simplifying way, the algorithmic entropy of a sequence is defined by the minimum

length of an algorithm that can (re)produce the original sequence. Sequences that show patterns of ordered complexity can normally be put down to simpler algorithms, but in the case of a random sequence, the necessary algorithm is just as complex as the sequence itself, and maximum algorithmic entropy is attained (Hubermann & Hogg, 1986).
Software that is used to compress files works on a similar basis – the compressed file is an algorithm that is able to reproduce the original file. The Grammar Complexity algorithm is an example for such a compression algorithm (Ebling & Jiménez-Montano, 1980; Jiménez-Montano, 1984; Rapp, Jiménez-Montano, Langs, Thomson, & Mees, 1991). Unlike the algorithm presented above that determines the square root of any given number a, the Grammar Complexity algorithm does not attempt to "grasp" the content of the whole sequence with a short formula. It can therefore on the one hand be applied for any sequence of numbers, even if the "best" algorithm that describes the whole original sequence with a minimum of information content is unknown. On the other hand, the values of algorithmic entropy obtained by applying the Grammar Complexity algorithm are "upper bound" values – with another algorithm (which cannot always be found, however), the algorithmic entropy of the sequence might be lower.

Grammar Complexity

The Grammar Complexity algorithm can probably be most easily explained via an example, which is why we turn once more to the career path of our virtual person shown in Figure 5. Writing down the indices of the boxes the person enters and/or crosses during his or her career path results in the sequence of numbers already seen above, which shall be called x:

$$x = 9\ 9\ 9\ 9\ 8\ 8\ 5\ 5\ 5\ 5\ 5\ 5\ 4\ 4\ 1\ 1$$

The algorithm now looks for pairs of symbols that repeat themselves in the sequence more than twice[1] and replaces these by another symbol, the meaning of which is entered into a "symbol registry". When there are no pairs left that appear more than twice, the algorithm looks for triples, then for quadruples, and so on. When no more replacement is possible, the algorithm stops.
For the given sequence, the string (9 9) appears twice, which doesn't make it eligible for compression (see endnote 1). The string (5 5), however, appears three times and is therefore replaced by another symbol a, which is entered into the symbol registry:

$$x = 9\ 9\ 9\ 9\ 8\ 8\ a\ a\ a\ 4\ 4\ 1\ 1$$
$$a = 5\ 5$$

As there are no more pairs that appear more than twice in the sequence, the algorithm now looks for triples. For the given sequence, there is no triple that appears more than once, neither is there a tuple of a higher order, so the algorithm stops here.
To further simplify the notation of the sequence, recurring symbols can be written down in "power notation", e.g. (a a a) can be written as a^3:

$$x = 9^4\ 8^2\ a^3\ 4^2\ 1^2$$
$$a = 5^2$$

The Grammar Complexity can now be computed by summing up the number of all remaining symbols (including those in the symbol registry) and the absolute values of the logarithms to the base two of all used powers.
For our sample sequence, the calculation looks as follows:

$$\text{Grammar Complexity} = \underbrace{5 + |\log_2 4| + |\log_2 2| + |\log_2 3| + |\log_2 2| + |\log_2 2|}_{\text{"}x\text{" term}} + \underbrace{1 + |\log_2 2|}_{\text{"}a\text{" term}} = 13.59$$

In order to better interpret the results, two procedures can be employed. One consists in rearranging the sequence from smallest to largest value and calculating the Grammar Complexity for the sorted sequence. In our case, this ordered sequence looks as follows:

$$x' = 1\ 1\ 4\ 4\ 5\ 5\ 5\ 5\ 5\ 5\ 8\ 8\ 9\ 9\ 9\ 9$$

Calculating the Grammar Complexity for this sequence yields the same result of 13.59, suggesting that the original sequence x is a highly ordered one – a result that is in accordance with the depiction of the career path in Figure 5.

Another way of interpreting results was proposed by Tschacher and Scheier (1995). They examined data via a surrogate data procedure, generating 50 surrogate sequences that consisted of the same elements as the original sequence (randomly shuffled in 50 different ways) and calculating the Grammar Complexity for these surrogate sequences. The obtained 50 values are normally distributed, allowing to examine whether the Grammar Complexity of the original sequence differs significantly from that of the randomly shuffled surrogate sequences (Tschacher & Scheier, 1995).

Unlike Shannon's algorithm presented above, the Grammar Complexity algorithm does differentiate between ordered and less ordered structures. Taking the randomly arranged sequence already shown above in connection with Shannon's information content formula:

$$9 \rightarrow 1 \rightarrow 9 \rightarrow 5 \rightarrow 9 \rightarrow 5 \rightarrow 8 \rightarrow 5 \rightarrow 8 \rightarrow 5 \rightarrow 9 \rightarrow 4 \rightarrow 5 \rightarrow 5 \rightarrow 4 \rightarrow 1$$

calculation of the Grammar Complexity for this sequence yields a result of 16, suggesting that this sequence has a higher degree of complexity.

The Grammar Complexity procedure has already been employed successfully in social sciences to determine the complexity of a nominal sequence of values (Friedlmayer, Reznicek, & Strunk, 1996; Rapp et al., 1991; Thiele, 1997; Tschacher et al., 1995). Its shortcomings are that both the length of the examined sequence and its distribution of values influence the results yielded by this algorithm.

Along with Grammar Complexity, other algorithms have been proposed that are also based on methods of data compression (for a comparative overview, see e.g. Schürmann & Grassberger, 1996).

Application

If we consider careers within the theoretical framework outlined above, as more or less complex movements along the two dimensions of coupling and configuration, one question that arises is how the complexity of these movements can be quantified. Algorithmic entropy offers different methods that attempt to find recurring patterns in a given sequence of symbols, resulting in a value that specifies the complexity of the sequence.

Referring to these concepts and methods, one may ask whether the sequence of "career positions" within the area framed by coupling and configuration (with each position represented by a symbol, similar to the example presented in Figure 5) for an actual person ...

a) on the one hand shows a lower degree of algorithmic complexity than a random sequence of positions,
b) but on the other hand is more complex than a completely ordered sequence.

The concept of algorithmic entropy, and in particular Grammar Complexity, allows us to represent the possible range of sequences on a continuum between complete order and random (see Figure 6).

FIGURE 6

Complexity continuum of the grammar complexity

Completely ordered	Complex but not random	Random
Lower Bound Grammar Complexity of the ordered Symbols	Significantly more ordered than random but not completely ordered	Normal distribution of many random surrogates
Example 1 1 1 2 2 2 3 3 3 4 4 4	1 2 3 4 4 3 2 1 1 2 3 4	3 4 1 3 2 1 4 3 2 1 2 4

Grammar Complexity (ordered) < Grammar Complexity (complex) < Grammar Complexity (random)

If the assumption that careers have become more complex over the last decades holds true, the algorithmic entropy of careers that have begun more than 30 years ago should be lower (i.e., those careers should be more ordered) than the algorithmic entropy of careers that have begun about 20 years later.

STRANGE ATTRACTORS

Procedures for calculating algorithmic entropy are not very sensitive with regard to the sample data. A nominal sequence of symbols or values is sufficient. However, this may entail a loss of information for sample data that feature a higher level of measurement. Within the framework of theories of non-linear dynamic systems, several methods have been proposed that allow to examine the complexity of an interval scaled sequence.

Dynamic Structures in Chaos Theory

The best-known term within the theories of non-linear dynamic systems, which has also become quite common in popular science, is probably the concept of chaos. Chaos (in the sense of non-linear dynamics) denotes extremely complex dynamic processes that can only be forecast for a very limited period of time ("butterfly effect"; e.g. Lorenz, 1963), but that are not random either. As such hardly predictable processes can be found within deterministic systems, chaos – unlike random – always has a certain degree of order.

It came to one of the first confrontations with chaos on a "scientific level" already in 1889, when Henri Poincaré discovered – upon attempts to solve the problem of three interacting bodies by means of the Newtonian law of gravitation – that even tiny errors and/or deviations in initial conditions produced vastly different outcomes. What is generally regarded today as an enormous merit of Poincaré bothered him considerably when he made his discovery:

> "...it may happen that small differences in the initial conditions produce very great ones in the final phenomena. A small error in the former will produce an enormous in the latter. Prediction becomes impossible, and we have the fortuitous phenomenon" (Poincaré, 1908; cited from Peterson, 1999).

It was not before the sixties in the 20th century that this discovery by Poincaré was thoroughly understood (e.g.. Prigogine, 1987; Prigogine & Stengers, 1986, 1993; Haken, 1985, 1990a; Haken & Wunderlin, 1991) and in some cases re-discovered (Peitgen, Jürgens, & Saupe, 1992; Peitgen, Jürgens, Saupe, & Zahlten, 1990; Lorenz, 1963; Lorenz, 1991).

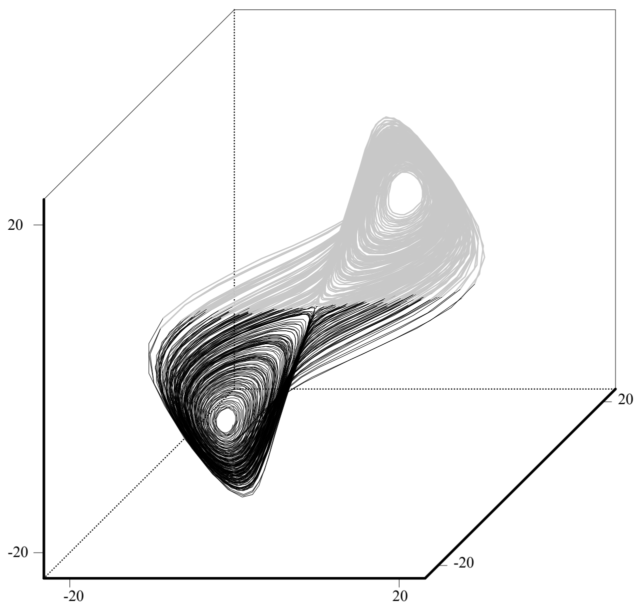
Some of the basic tools that are still widely employed today in order to describe the dynamics of complex systems had already been developed by Poincaré, among others the so-called phase space representation of a dynamic system.

The term "phase space" stands for a coordinate system where the variables that affect the system form the coordinate axes. The career paths shown in Figures 3 and 4 are an example of simple phase space representations. The changes in coupling and configuration are not

depicted as time series but plotted along the two axes. The development over time can only be represented by following the trajectory.
Phase space representations are particularly useful when there are many variables that generate a system's dynamics (which would normally require several time series for representation), as they allow condensing all changes into one "image" of the system's behavior. There are four basic categories of behavior that a complex system may adopt (cf. Schiepek & Strunk, 1994):

a) fixpoint: the system always settles down to a constant value;
b) limit cycle: the system oscillates periodically;
c) torus: in a three-dimensional phase space, a system can show complex and intertwined oscillations that are either periodical or approximately periodical;
d) chaos: in a three-dimensional phase space, a system can show very complex patterns of dynamics. Despite their complexity these patterns do not appear fortuitous and/or without order. (see Figure 7).

FIGURE 7
A strange/chaotic attractor (Lorenz attractor)



Each of the four patterns of dynamics outlined above is a so-called attractor (attracting behavior). If a system is diverted from its "natural" trajectory (the representation of its behavior in a phase space representation) by an external influence, it will return to it after some time. The chaotic attractor (also called strange attractor because of its weird appearance) is one of these attracting behaviors. Although the dynamics of such a behavior cannot be predicted in detail (butterfly effect), it still follows a defined pattern. In that, chaotic system behavior differs from random system behavior. If the dynamics of the system were random, it would stretch over the whole phase space, as every system state may occur.
An important feature of chaotic attractors is their fractal structure. The concept of fractals was introduced by Benoît B. Mandelbrot to designate geometrical forms that differ from classic Euclidian forms (such as circles, squares, triangles, cubes etc.) insofar as they show an irregularity that cannot be described by common mathematical methods. Mandelbrot (Mandelbrot, 1987) categorically denies the possibility to ascertain the length of a fractal line or the area of a fractal surface. Nonetheless there are possibilities to describe fractals mathematically, by examining their structural complexity. The basics of such a method were already formulated early in the 20th century by mathematicians like Hausdorff and

Besicovitch (Besicovitch & Ursell, 1937; Hausdorff, 1919). The description of a fractal's complexity is based on concepts of a body's dimensions.
The following example shall illustrate the concept of measuring the dimensionality of "Euclidian" and fractal bodies: in order to measure the length of a straight line with an item (e.g. a ruler) that is only half as long as the line, the item will have to be applied twice (three times respectively if the ruler is only a third as long as the line, etc.). In order to determine the area of a square with a side length of k by using a square with a side length of $k/2$, one would need four such squares to cover the whole area of the former square. Applying the same principle in order to determine the volume of a cube with a side length of k by smaller cubes with a side length of $k/2$, one would need eight such cubes to "fill" the original cube. If the side length of the "measuring" items were $k/3$, one would need nine squares and twenty-seven cubes respectively.
So if the length (or side length) of the original form is x times the length (or side length) of the "measuring" item, one needs x^1 items to measure length, x^2 items to measure area, and x^3 items to measure volume. The exponent thus always corresponds to the dimensionality of the object in question. However, this is *not* the case for a fractal, as Mandelbrot has shown by using the example of a coastline.
If one measures the length of a coastline with a "long ruler" (e.g. one that spans the beeline between two points A and B on the coastline that are far apart), then breaks the ruler into x smaller pieces and measures the length of the coastline (not the beeline distance between the two points) again, starting from A, one will "run out of ruler" way before point B is reached, due to the complex structure of the coastline that "unfolds" as the ruler pieces used to measure the length of the coastline become shorter. The number of pieces necessary to measure the length of the coastline is therefore larger than x, but remains smaller than x^2. The dimensionality of the coastline is therefore higher than that of a straight line but lower than that of an area (and therefore obviously not an integer number). The more complex and jagged the coastline, the higher its dimensionality. Put in a very simplified way, whenever a form has a higher dimensionality than would be expected and its dimensionality is not an integer number, it is a fractal.
Chaotic attractors in phase space are also fractal structures. If it can be shown that a phase space structure based on empirical data is a fractal, this would suggest that the underlying system is a chaotic one. This conclusion is not a compelling one, as Pincus (1991) aptly remarked. Nevertheless, a successful determination of the fractal dimension of a dynamic process allows to draw the following conclusions:

a) the higher the fractal dimension of a dynamic process, the higher its complexity
b) if the fractal dimension of a dynamic process derived from empirical data can be determined, the process in question is not a random process.
c) the fractal dimension rounded up to the next integer number specifies the minimum number of independent but interacting factors the system needs to generate its dynamics

Conclusions

Several authors in career research have recently advanced conjectures according to which careers can be viewed as chaotic processes (cf. Bird et al., 2002; Gunz et al., 2002a; Lichtenstein et al., 2002; Drodge, 2002; Gunz et al., 2002b; Chakrabarti et al., 2002; Parker et al., 2002). Assuming that the dynamics of careers are influenced by more than three influencing variables and that the relationship between these variables is not a linear one (either a premise for chaotic systems; cf. Schiepek et al., 1994), career paths could indeed be chaotic processes. In that case, however, the factors that influence careers would indeed have to form a system, and careers ought not to be determined by random influencing factors.
If phase space representations of career paths similar to those shown in Figures 3 and 4 turn out to have a fractal structure, this would at least imply that these career paths are not completely determined by random factors. Furthermore, the fractal structure of careers that have begun more than 30 years ago should be less complex than that of careers that have begun 20 years later.

Both methods just outlined (Grammar Complexity and determination of fractal structure) shall be applied in this paper in order to examine whether careers can be identified as complex yet deterministic systems or rather appear as random processes, and whether careers have indeed become more complex from a dynamic perspective over the last few decades.

METHODS

Started in 2000 and supported by the Austrian Science Fund (FWF), the Vienna Career Panel Project (ViCaPP) attempts to explore the professional careers of business graduates in Austria. In addition to a sample of 650 graduates who successfully completed their studies at the Vienna University of Economics and Business Administration (Wirtschaftsuniversität Wien – WU Wien) in the past two years, data were also collected from persons having graduated several years ago.

Data Collection

In summer 2002, two cohorts of former graduates of the WU Wien were asked to participate in a survey that consisted of a mail questionnaire as well as a highly standardized questionnaire about their professional development that was filled out during a face-to-face interview. The cohorts consisted of graduates that finished their studies around 1970 and around 1990 respectively, in most cases starting their professional careers soon thereafter. Up to now, 215 former WU graduates have participated in this study, of which 95 belong to the 70s cohort and 120 to the 90s cohort.

Based on a curriculum-vitae-like list of professional activities for each person, their professional development was charted for each year since their graduation along several variables, such as income, career satisfaction, attributed career success, and five variables in sum that referred to coupling and configuration (see below). Among many other variables that were collected, the survey resulted in a total of twelve time series per person, with a sampling frequency of one year.

Operationalizing Coupling and Configuration

One central element of the theoretical framework introduced by Mayrhofer et al. (2000) to describe careers are the two dimensions of coupling and configuration already mentioned above. Although the survey collected information on a much broader set of variables (among these, seven other time series), the following analyses will focus on these two dimensions. Three likert scales referring to coupling and two scales referring to configuration were included in the interview questionnaire.

Coupling was operationalized by the following three items:

- Security and calculability of career-related prospects (very secure vs. very precarious)
- Subjection of career-related prospects to specific external actors and/or constraints (very dependent vs. completely independent)
- How easily another adequate job could be found should the need arise (very easily vs. not at all)

Configuration was represented by the following two items:

- Stability of work content (very stable vs. ever-changing)
- Stability of professional relations (very stable vs. ever-changing)

In order to "anchor" the scales, the interviewees were asked to rank the four career types described above (Company World, Free-Floating Professionalism, Self-Employment, Chronic Flexibility) on the five scales before ranking themselves for each year of their career.

A factor analysis showed that a principal components analysis extracting factors with eigenvalues larger than 1 indeed results in a two-factor solution (as proposed by the underlying theory), which explain about 60% of the total variance. Coupling and configuration were then operationalized by taking the means of the two and three items assigned to configuration and coupling respectively.

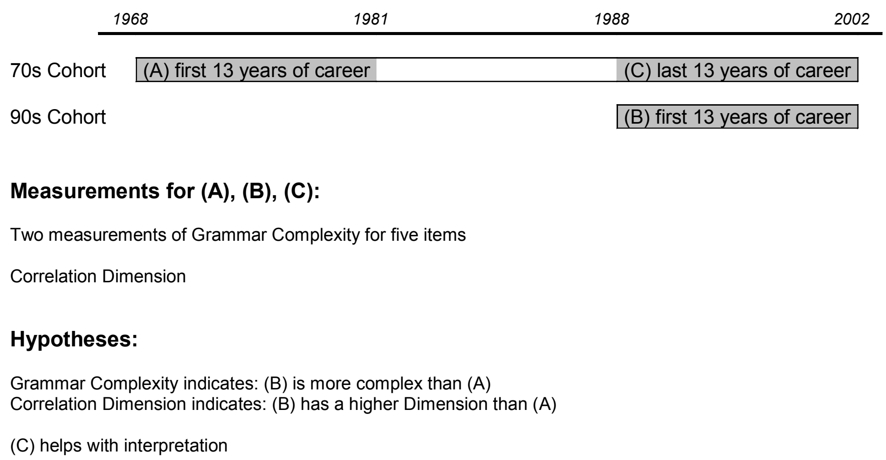
Sample Description

The structural differences between the two cohorts are not very pronounced. If one examines the first 13 career years, the proportions of self-employed persons vs. salaried employees resemble each other for the two cohorts. About 67% of the 90s cohort have never been self-employed during their first 13 years of professional experience, while the respective proportion for the 70s cohort is about 78%. Although the difference of 11% seems considerable at first sight, it is not statistically significant (Fisher test: p (two-tailed) = 0.1033). Those persons that claimed to have been self-employed during the first 13 years of their career have mostly done so only for a limited time. In both cohorts, about 17 % of the interviewed persons were self-employed for more than four years.
The differences regarding gender were more conspicuous. Women are quite underrepresented in the 70s cohort compared to the 90s cohort, with 14% and 42% respectively. This is due to the fact that there were fewer women who commenced and finished their studies at the WU Wien in the 70s. In the years 1972/73, the proportion of female graduates was 16%, compared to 39% in 1989/90.
Mean age was 37.1 years (± 2.0 years) for the women and 37.9 years (± 3.8 years) for the men in the 90s cohort, and 55.6 years (± 2.1 years) for the women and 57.4 years (± 3.2 years) for the men in the 70s cohort.

Research Design

Figure 8 gives a graphic representation of the research design. For the 90s cohort (sample "B"), data on coupling and configuration are available for a period of 13 years. In order to make results comparable, the first 13 working years are also chosen for the 70s cohort (sample "A"). Sample "C" contains the last 13 career years for the 70s cohort, allowing us to compare the career paths of the two cohorts in identical calendar years.

FIGURE 8
Design of the study



Analysis of Algorithmic Entropy

In order to determine algorithmic entropy, the Grammar Complexity procedure already outlined above was used. For the first 13 career years of both cohorts, the five items referring to coupling and configuration were used as time series, and the following calculations were executed for each person and each item:

1. Determination of Grammar Complexity for the original time series,
2. Grammar Complexity mean and standard deviation for 200 randomized surrogate time series,
3. Grammar Complexity of the sorted original time series (maximum order and therefore minimum Grammar Complexity value)

These three values then allow to execute the calculations and draw the conclusions outlined below:

1. Quotient between the Grammar Complexity of the original time series and the Grammar Complexity of the sorted time series. Values larger than 1 indicate that the original time series is more complex.
2. Z-Transformation of the Grammar Complexity of the original time series via the means and standard deviations of the surrogates. Z-values that are larger than 1.96 imply that the original time series is significantly more ordered than the random sequences of the surrogates.

The three values described above are calculated for all five items and each person separately. In order to compare the two cohorts, means are calculated for each cohort. The algorithms for calculating Grammar Complexity and fractal dimension (see below) were both implemented by the first author in C++ and tested extensively on various known time series.

Analysis of Fractal Dimension

Several methods have been proposed to determine the fractal dimension of a time series (e.g. Grassberger & Procaccia, 1983b, 1983a). What all these methods have in common is that they theoretically require an infinitely long time series to reliably determine the fractal dimension of an attractor. Even though about 1.000 sampling points are generally regarded as a small yet sufficient number for attractors of a low fractal dimension (for a controversial discussion about this topic cf. Jedynak, Bach, & Timmer, 1993; Lorenz, 1991; Nerenberg & Essex, 1990; Seitz, Tschacher, Ackermann, & Revensdorf, 1992; Tsonis, 1992) , this is still far beyond the 13 sampling points provided by the 13 career years of the 90s cohort. Therefore, the determination of the fractal dimension of the data shall be executed via a somewhat unorthodox procedure: the time series of all persons in each cohort are put together. This results in two quasi-time series with 1.235 sampling points for the 70s cohort with 95 members, and 1.560 sampling points for the 90s cohort with 120 members.
In order for such a procedure to be methodically sound, the dynamics of career paths must not differ too much between the individual cases. However, this cannot be examined at the outset, therefore 100 different variants of the time series for each of the two cohorts were generated and calculated separately. Additionally, in case the individual time series that are used to form one of sufficient length really do differ very much from each other, the generated "overall" time series should be identified as a random process and fill the whole phase space, therefore showing no fractal structure.
Besides requiring a time series with as many sampling points as possible, another feature shared by all methods mentioned above that determine the fractal dimension is that they aim at generating a representation of an attractor in phase space. Two problems arise: first, it is rarely known at the outset how many factors influence the system's dynamics, i.e. how many dimensions are needed for proper representation; second, the whole phase space has to be reconstructed based on single time series (in most cases just one time series).
As to the first problem, a rule-of-thumb says that the number of the phase space's dimensions should at least be equal to the fractal dimension of the attractor rounded up to the next integer number. Although the fractal dimension of the attractor is unknown at the outset, it can be determined by a recursive algorithm due to the fact that the fractal dimension remains constant if the attractor is embedded in a phase space with too many dimensions. Put differently (and simplifying a bit), calculating the fractal dimension for a two-dimensional

phase space, then for a three-dimensional phase space, and so on, will result in increasing values for the fractal dimension of the attractor until the dimensionality of the phase space is higher than that of the attractor. However, this saturation will only occur if the attractor is indeed a fractal. If one applies the same method to a random process, saturation is never reached.

A solution for the second problem is provided, for instance, by Packard and Takens (cf. Packard, Crutchfield, Farmer, & Shaw, 1980; Takens, 1981), who proposed a theorem according to which the whole phase space of a dynamic system can be reconstructed via a single time series. Simply spoken, their method is based on choosing a constant time lag (this method is therefore known as time lag reconstruction) that determines to which dimension each sampling point is assigned. The value of the first sampling point of the time series is assigned to the first dimension of the phase space. The value of the sampling point after one times the time lag is assigned to the second dimension, the value of the sampling point after two times the time lag is assigned to the third dimension, and so on. If the time lag is well chosen, the reconstructed attractor in phase space is topologically equivalent to the attractor of the underlying system. Several methods have been proposed that serve to find an appropriate time lag for the reconstruction of the attractor (cf. Buzug & Pfister, 1992; Frazer & Swinney, 1986; Liebert & Schuster, 1989; Schuster, 1989b; Tsonis, 1992; Tsonis & Elsner, 1988; Wolf, Swift, Swinney, & Vastano, 1985).

For the dynamic system entered into the analyses, two mutually independent time series for coupling and configuration respectively have been recorded. Adding up the measurement readings for both dimensions alternately (t_0-coupling, t_0-configuration, t_1-coupling, t_1-configuration, ...) results in a quasi-time series which is twice as long as the original time series (2.470 sampling points for the 70s cohort and 3.120 sampling points for the 90s cohort respectively), and has a known time lag of 1.

One crucial element for determining the fractal dimension within the computational framework chosen here is the so-called correlation integral (cf. Grassberger et al., 1983b, 1983a):

Equation 3:
$$C(l) = \lim_{n\to\infty}\left[\frac{1}{n^2}\sum_{i,j=1,i\neq j}^{n}\Theta\left(l-\left|\vec{X}_i-\vec{X}_j\right|\right)\right]$$

n points of the attractor are examined in terms of their Euclidian distance. As the Euclidian distance between two points $P_i(X_{i,k=1}, X_{i,k=2}, \ldots, X_{i,k=n})$ and $P_j(X_{j,k=1}, X_{j,k=2}, \ldots, X_{j,k=n})$ within an m-dimensional space is given by:

Equation 4:
$$d_{ij} = \sqrt{\sum_{k=1}^{m}(X_{ik}-X_{jk})^2}$$

the correlation integral can be written like the following:

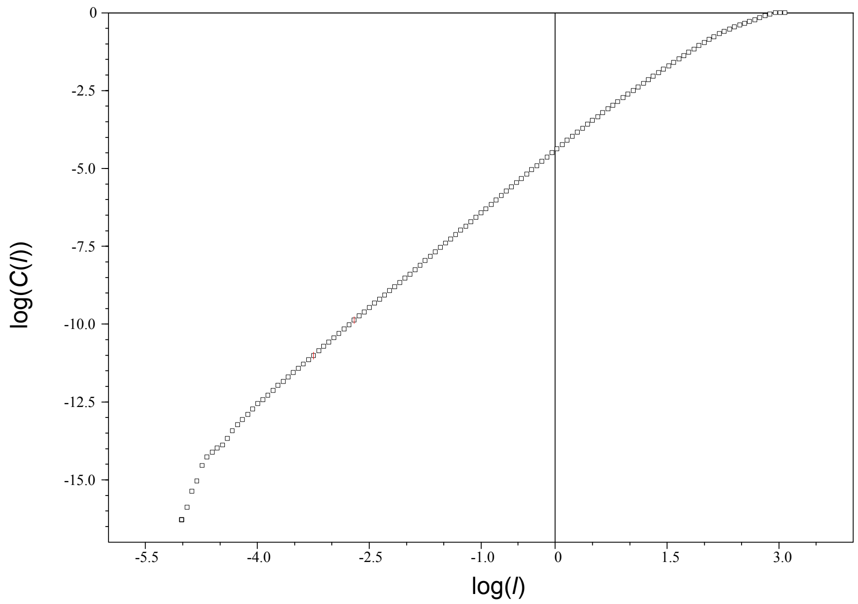
Equation 5:
$$C(l) = \lim_{n\to\infty}\left[\frac{1}{n^2}\sum_{i,j=1,i\neq j}^{n}\Theta\left(l-d_{ij}\right)\right]$$

with Θ being a Heaviside-function assuming the value 1 if d_{ij} is smaller than l and assuming the value 0 if this is not the case. Therefore, for a given embedding of a time series with time lag coordinates and a certain time lag in m-dimensional space, the correlation integral counts all distances between all possible pairs of points within the given space that are smaller than the value l and divides this number by the overall number of possible distances.

This equation can be quite easily implemented into a software algorithm that calculates the distances between all points for each point and sorts them in ascending order. The position of a chosen $l = d_{ij}$ in that list then immediately indicates how many distances between points d_{ij} are smaller than l. If this number is then divided by n^2, $C(l)$ is easily calculated for all l.

The correlation dimension D2 can now be represented by the ascending slope of a straight line when plotting log($C(l)$) against log(l). However, this straight line can only be identified for a limited range of the plot (the so-called scaling range), which is a quite serious drawback of this method (see Figure 9). The scaling range is frequently assessed by visual judgment, but this would have been too laborious here given the number of data sets analyzed. Instead, an automated algorithm was used to determine the scaling range (best least square approximation to a straight line, cf. Babloyantz & Destexhe, 1987).

FIGURE 9
The correlation integral in dependency on log(l)



If the scale range can be determined, the slope of the straight line can be regarded as a good estimate for the correlation dimension. In some cases the scaling range and/or the slope cannot be determined due to noisy data or a badly chosen time lag for phase space reconstruction. If the slope can be determined, its interpretation as an estimate for D2 requires that the value for the appropriate embedding dimension be known. As this is usually not the case for empirical data, the determination of D2 must be executed for different embedding dimensions *m* with *m* = 1, 2, 3, 4, ..., *M* (see above).
Ideally, plotting D2 against the embedding dimension *m* yields a logarithmic curve, i.e. in the beginning D2 increases alongside with *m*, until saturation is reached and D2 does not increase anymore, even if *m* is further increased. The shape and goodness-of-fit of the curve can be examined via logarithmic correlation coefficients. In this paper, saturation is determined by means of linear regression over the D2 values for the highest embedding dimensions. If the slope of the regression line exceeds a limit of 0.07 D2 per embedding dimension, saturation cannot be assumed.

RESULTS

A "Static" Overview

Before turning to the core issue of this article, namely the differences in dynamic complexity of career paths, a short overview of the results for "static" data that also relate to complexity, albeit from a different perspective, shall be presented in the following.
While the 70s cohort reports 3.7 professional transitions (promotions, changing departments, leaving an organization, transition from salaried to self-employment etc.) on an average, the respective number for the 90s cohort is 5.3. This (statistically highly significant) difference already suggests that the complexity of careers has increased over the last years. Counting the number of transitions of individuals between organizations results in a very similar picture: while the members of the 70s cohort change their employing organization 1.2 times during their first 13 career years, the respective number for the 90s cohort is 1.6. The proportion of part-time jobs is also higher in the 90s cohort, whereas the two cohorts do not differ much as far as fixed-term contracts are concerned.

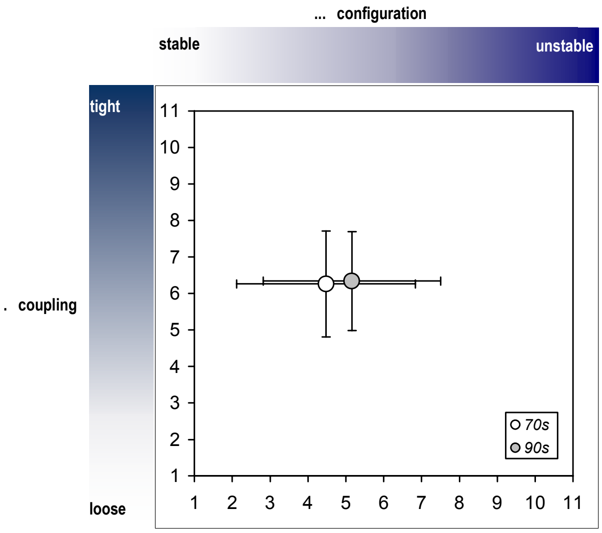
All in all these structural features already suggest a higher complexity of careers for the 90s cohort than for the 70s cohort. These findings are also reflected in the average values for coupling and configuration. If the five raw items of the questionnaire are summed up to measure coupling and configuration (as outlined in the methods section), the 90s cohort shows a significantly less stable configuration than the 70s cohort (see Table 1 and Figure 10), with this trend being reflected in both of the raw items (see Table 2). These results are in accordance with the developments postulated above in the first section, however, they should be accepted with due caution as the scales have no universally valid "anchor" and the ratings of the interviewees are merely based on their subjective judgement. The high values for N are due to the fact that not each person, but each year was entered as a separate case, resulting in over 2.000 cases altogether.

TABLE 1
Mean and standard deviation for coupling and configuration (both cohorts)

	70s cohort			90s cohort			
Dimension	**mean**	**standard deviation**	**N+**	**mean**	**standard deviation**	**N+**	**T-Test (1-tailed)**
Coupling (higher values = tighter coupling)	6.26	1.45	1204	6.34	1.35	1422	ns
Configuration (higher values = less stable configuration)	4.48	2.36	1196	5.16	2.35	1402	**

N^{+}: the number of values is determined by the number of persons times the number of sampling points (13 years for each person unless there is a missing value)
* $p < 0.05$
** $p < 0.01$

FIGURE 10
Mean and standard deviation for both cohorts on the two dimensions of coupling and configuration



Compared to the configuration factor, there were no marked differences between the two cohorts for coupling. Contrary to our assumptions, the 90s cohort shows a slightly higher degree of coupling (which does not become statistically significant). If one takes a closer look and examines the three raw items, it is apparent that the ratings of the 90s cohort reflect a comparatively adverse job market situation – the career perspectives of these persons are seemingly less secure, they feel more dependent on external factors, and assess their chances of finding another adequate job less optimistically. The same limitations as for the configuration factor do also apply here, in addition, the differences found are all but pronounced and become significant mostly due to the number of cases.

TABLE 2

Mean and standard deviation for the five items concerning coupling and configuration (both cohorts)

Dimension	70s cohort mean	70s cohort standard deviation	70s cohort N^+	90s cohort mean	90s cohort standard deviation	90s cohort N^+	T-Test (1-tailed)
Coupling			1204			1422	
Career security and calculability (higher values: more secure)	8.80	2.38		7.91	2.53		**
Subjection to specific external actors and/or constraints (higher values: more dependent)	6.90	2.92		7.24	2.71		**
Ease with which another adequate job could be found (higher values: less easily)	3.31	2.28		3.88	2.56		**
Configuration			1196			1402	
Stability of work content (higher values: less stable)	4.94	3.11		6.01	3.06		**
Stability of professional relations (higher values: less stable)	3.99	2.67		4.30	2.55		**

N^+: the number of values is determined by the number of persons times the number of sampling points (13 years for each person unless there is a missing value)

* $p < 0.05$

** $p < 0.01$

Altogether the results presented here suggest that the complexity of careers has increased over the last decades, but reveal nothing about an increase or decrease in dynamic complexity, i.e. whether the processes (career paths) have also gained complexity. The following sections will deal with that question.

Algorithmic Entropy

The results of the calculations of algorithmic entropy suggest that the career paths (conceived as movements along the two dimensions of coupling and configuration over time) are indeed more complex for the 90s cohort than for the 70s cohort. However, these results should also be accepted with caution, as the test power of the method employed here is rather poor due to the extremely short sequences consisting of merely 13 values.

Two indicators were calculated for each person in order to analyze the algorithmic entropy (via Grammar Complexity). The first one is the quotient of the Grammar Complexity value of the original time series divided by the Grammar Complexity value of the same time series sorted in ascending order (see above). The higher the quotient, the more complex the observed sequence. The mean quotient values for the two cohorts are presented in Figure 11 and Table 3. It is apparent that the values scarcely exceed the theoretical minimum of 1, which is largely due to the limited sensitivity of this method in the case of short symbol sequences (cf. Rapp et al., 1991).

FIGURE 11
Grammar Complexity quotient for the two cohorts and observed periods

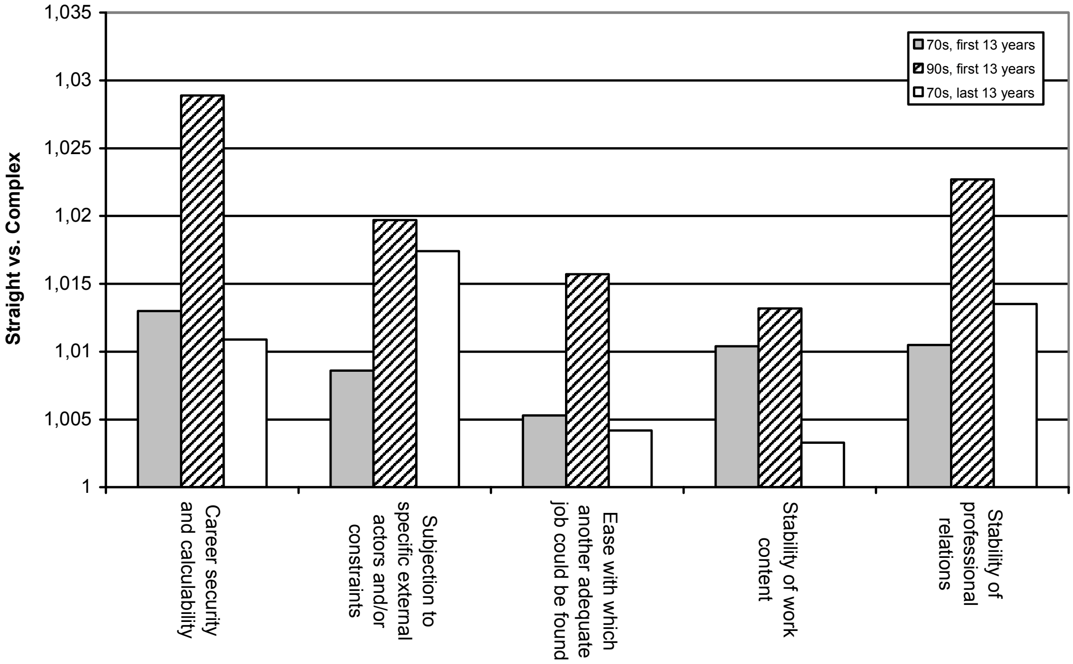


TABLE 3

Comparison of the Grammar Complexity quotients

Straight vs. Complex		**70s cohort**			**90s cohort**			
Dimension	**Period**	**mean**	**standard deviation**	**N**	**mean**	**standard deviation**	**N**	**T-Test (1-tailed)**
Coupling				95			120	
Career security and calculability	*First 13 years*	1.0130	0.0391		1.0289	0.0721		*
	Last 13 years	1.0109	0.0397		*last 13 years 70s vs. first 13 years 90s*			*
Subjection to specific external actors and/or constraints	*First 13 years*	1.0086	0.0344		1.0197	0.0552		*
	Last 13 years	1.0174	0.0517		*last 13 years 70s vs. first 13 years 90s*			ns
Ease with which another adequate job could be found	*First 13 years*	1.0053	0.0270		1.0157	0.0518		*
	Last 13 years	1.0042	0.0197		*last 13 years 70s vs. first 13 years 90s*			*
Configuration				95			120	
Stability of work content	*First 13 years*	1.0104	0.0418		1.0132	0.0485		ns
	Last 13 years	1.0033	0.0211		*last 13 years 70s vs. first 13 years 90s*			*
Stability of professional relations	*First 13 years*	1.0105	0.0413		1.0227	0.0595		*
	Last 13 years	1.0135	0.0425		*last 13 years 70s vs. first 13 years 90s*			ns

* $p < 0.05$
** $p < 0.01$

Despite all these limitations, the 90s cohort has higher complexity values on all five scales, both when compared to the first and last 13 working years of the 70s cohort. For the comparison of the first 13 career years of both cohorts, all observed differences but one (stability of work content) are statistically significant.

Both aspects just mentioned – the limited sensitivity of the method employed for short time series as well as the nevertheless higher complexity values for the 90s cohort – are also reflected in the results for the second indicator, based on the test of surrogate sequences already outlined above, where the Grammar Complexity value for the original sequence is compared to a distribution of Grammar Complexity values for 200 randomized surrogate sequences (consisting of the same elements). The results presented in Figure 12 and Table 4 show the mean of the z-transformed Grammar Complexity values for both cohorts. The higher the value, the more ordered the underlying sequence, compared to a random sequence. Additionally, z-values larger than 1.96 indicate that the observed sequence is significantly more ordered than a random sequence. It is apparent that the results for both cohorts fall short of this value.

FIGURE 12
Mean Grammar Complexity values after z-transformation for both cohorts

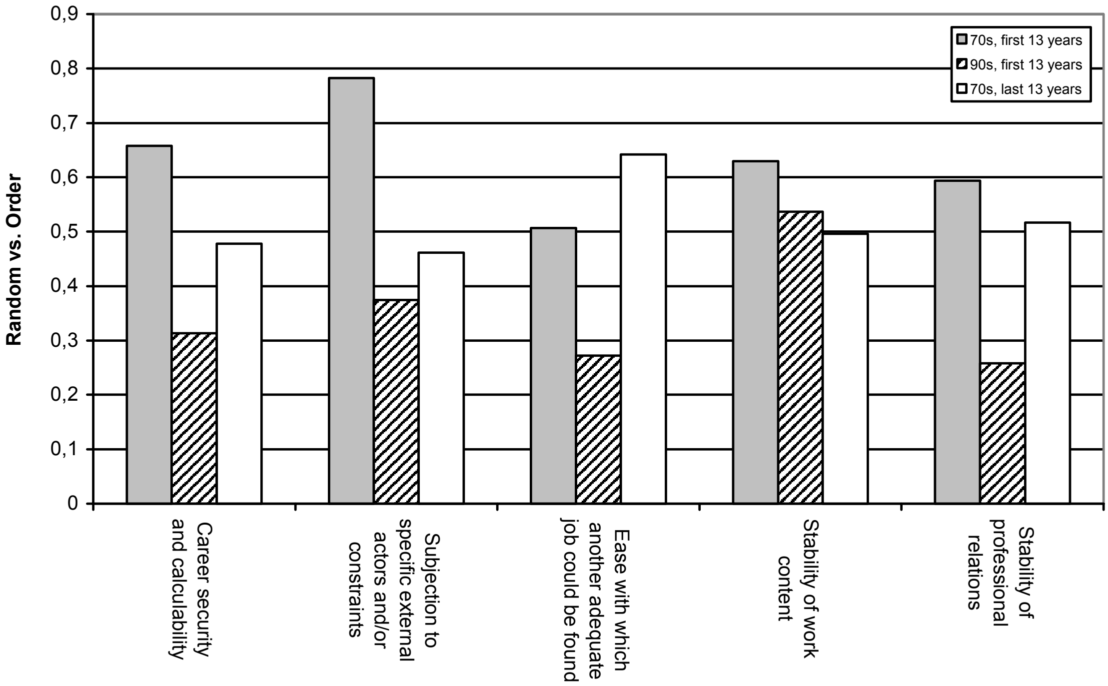


TABLE 4
Comparison of the mean Grammar Complexity values after z-transformation for both cohorts

Random vs. Order		70s cohort			90s cohort			
Dimension	**period**	**mean**	**standard deviation**	**N**	**mean**	**standard deviation**	**N**	**T-Test (1-tailed)**
Coupling				95			120	
Career security and calculability	*First 13 years*	0.6575	0.9895		0.3136	1.0791		**
	Last 13 years	0.4784	0.8535		*last 13 years 70s vs. first 13 years 90s*			ns
Subjection to specific external actors and/or constraints	*First 13 years*	0.7826	1.0212		0.3745	0.9646		**
	Last 13 years	0.4618	0.8445		*last 13 years 70s vs. first 13 years 90s*			ns
Ease with which another adequate job could be found	*First 13 years*	0.5068	0.7862		0.2722	0.9853		*
	Last 13 years	0.6417	0.9409		*last 13 years 70s vs. first 13 years 90s*			**
Configuration				95			120	
Stability of work content	*First 13 years*	0.6295	0.9946		0.5366	1.1797		ns
	Last 13 years	0.4964	0.9305		*last 13 years 70s vs. first 13 years 90s*			ns
Stability of professional relations	*First 13 years*	0.5936	0.9301		0.2581	1.0540		**
	Last 13 years	0.5165	0.9087		*last 13 years 70s vs. first 13 years 90s*			*

* $p < 0.05$
** $p < 0.01$

Overall, the first indicator suggests that the observed career paths are at least a bit more complex than their "most ordered" variant, while the second indicator implies that the complexity found in these career paths does not clearly distinguish them from a random process. Although both indicators are basically in accordance with the "complexity hypothesis in career research", they both yield rather dissatisfactory results. On the one hand, the observed sequences only show a very limited complexity, on the other hand this limited complexity is not very different from a random process. Both these aspects reflect the very limited testing power of this method, with an extremely high β-error for short time series. With only 13 sampling points, it is almost impossible to clearly differentiate the original sequence from random and/or complete order (cf. Rapp et al., 1991) – even when comparing the ordered sequences to the random surrogates, clear differences scarcely appear for the given data. It can therefore not be clearly decided on the basis of the results for algorithmic entropy whether the observed career paths do indeed follow a pattern of ordered complexity, determined rather by a complex yet deterministic system than by random biographic events. On the other hand, the observed differences between the two cohorts regarding the complexity of their career paths do indeed support our predictions.

Comparing the complexity values for the five raw items that refer to coupling and configuration, it is apparent that the item "Security and calculability of career-related prospects" showed the highest degree of complexity, especially for the 90s cohort. These persons therefore not only reported having less career-related security than the 70s cohort on an average, but there are also more and quicker changes between occupational situations marked by pronounced insecurity and situations that provide a certain degree of career-related security and predictability. These developments cannot be found within the 70s cohort, whose career path looks more stable as far as career security is concerned (and who also report a higher degree of career security overall).

The pattern for the item "Subjection of career-related prospects to specific external actors" resembles the aforementioned one in several ways: the values for the 90s cohort again reflect a rather erratic process, whereas the 70s cohort enjoy a higher (and more stable) degree of independence. Contrary to the first item, the complexity for this item declines for the 70s cohort, and the differences between the cohorts become less distinct, suggesting an increasing number of perceived changes between phases of high and low independence for both cohorts over their last few career years.

The item "ease with which another adequate job could be found" yields the lowest complexity values for the 70s cohort, whereas the respective value for the 90s cohort is much higher. The results found for this item are similar to the "career security" item, suggesting that frequently postulated developments on the labor market that entail an increasingly adverse situation for employees are reflected in the results here.

The two items concerning stability differ from the three items presented above in the way that they already include a dynamic aspect at the outset. The complexity calculations executed, however, do not deal with stability itself, but with the changes in stability over time. The item "stability of work content" shows little differences between the 90s and the 70s cohort (although the former have slightly higher complexity values on an average), and changes in the stability of the work content become rarer and less important for the 70s cohort in their last 13 working years.

Compared to the "stability of work contents"-item, the results for the item "stability of professional relations" show a bigger difference between the two cohorts, with the 90s cohort generally reporting a more erratic development as far as the stability of their professional relations is concerned, despite a slight increase in the complexity value for this item for the 70s cohort as well in their last 13 career years.

Overall, the calculations for Grammar Complexity support the assumption that the complexity of career paths has generally increased for the dimensions of coupling and configuration (as measured by the underlying raw items). At this stage, however, it cannot be determined whether these career paths are due to random or show ordered complexity. The following section will examine this question by means of the correlation dimension (D2).

Correlation Dimension

Contrary to Grammar Complexity, correlation dimension makes use of the additional information provided by interval scaled data, compared to nominal symbol sequences. However, it has stricter standards concerning the required length of the examined time series, which also depends on its complexity. While several hundred sampling points are sufficient for moderately complex time series, highly complex systems require several thousand sampling points for this method to be applied.

Therefore, the individual time series were added up here to form a quasi-time series of sufficient length. In order to examine whether the specific complexity found for this resulting time series is actually due to the dynamics of the process and not to the order in which the original time series were added up, 100 (differently assembled) quasi-time series were examined for each cohort.

One crucial feature of this method is the distinction between a random process, which can be clearly identified by the absence of a saturation of the D2 value for growing embedding dimensions, and a deterministic process that shows such a saturation. A saturation of the D2 value for the quasi-time series (in different orders) would imply that the time series are deterministic and that the process dynamics for the single persons are quite similar.

Figure 13 shows the two-dimensional embedding for a randomly chosen variant of each of the three time series. As was already found for empirical data in social sciences, but also in medicine (e.g. Schiepek et al., 1997), no clearly structured attractors could be identified, as opposed to mathematically generated time series.

A simple order structure cannot be identified with the naked eye, nevertheless the phase space embedding for the 90s cohort appears more complex than that for the 70s. This may (partly) be due to the fact that more points were available from the quasi-time series for the 90s cohort than from the first and last 13 working years of the 70s cohort (1.560 vs. 1.235 points). Examining the results for the 70s cohort only, it is also apparent that the representation for the last 13 years looks less complex than for the first 13 years, with the number of points being equal for these two quasi-time series.

The calculations of the respective D2 correlation dimensions confirm this impression. As Table 5 shows, a saturation of the D2 value could be attained for almost all variants of the three quasi-time series. For the first 13 years of the 70s cohort, only six variants out of 100 failed to saturate given a 20-dimensional embedding. For the 90s cohort, the respective number was twelve. For the last 13 years of the 70s cohort, all 100 variants reached saturation of the D2 value.

FIGURE 13
Two-dimensional embeddings for samples of the three quasi-time series

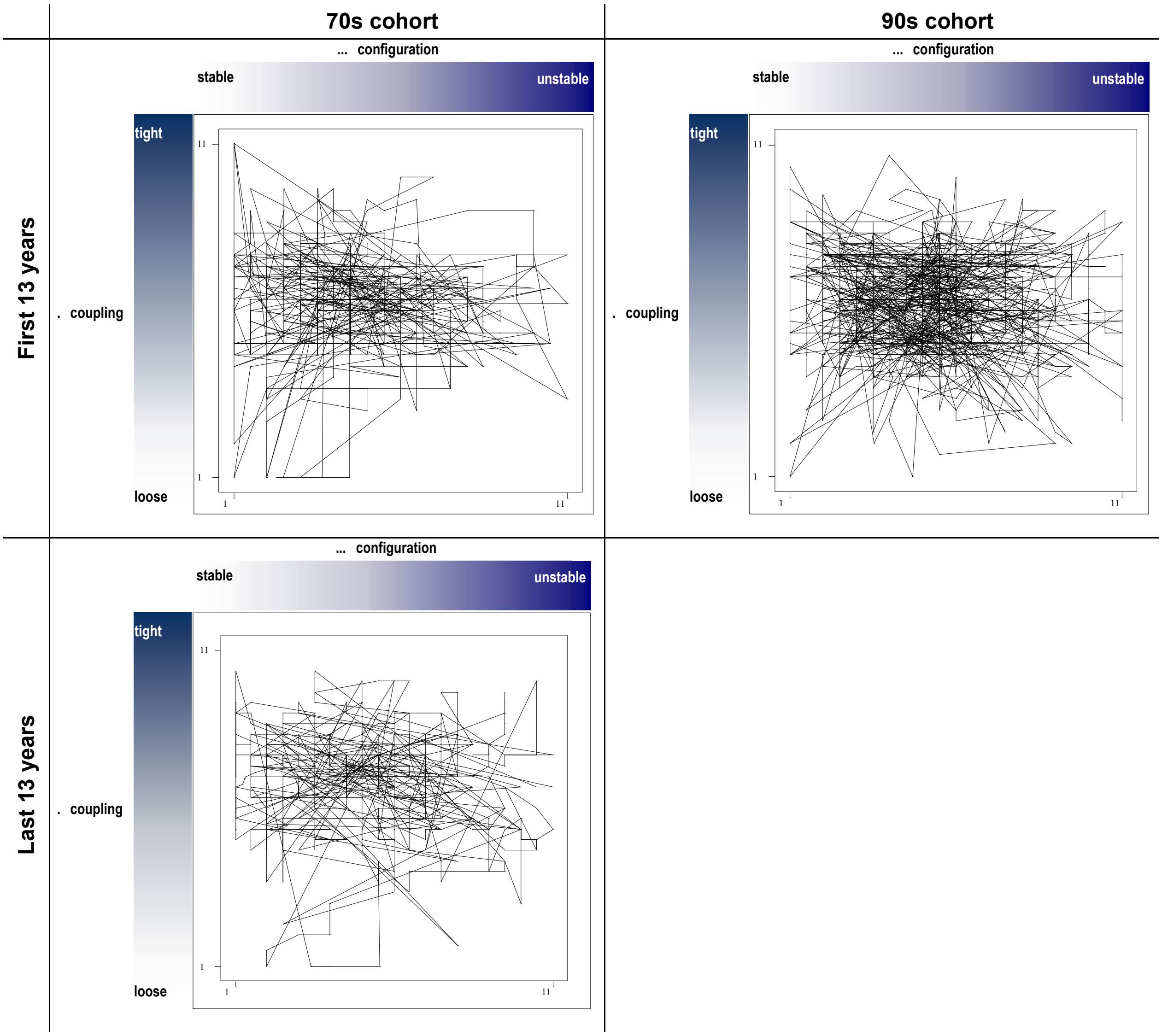


FIGURE 14
Correlation dimension (D2) of the three quasi-time series

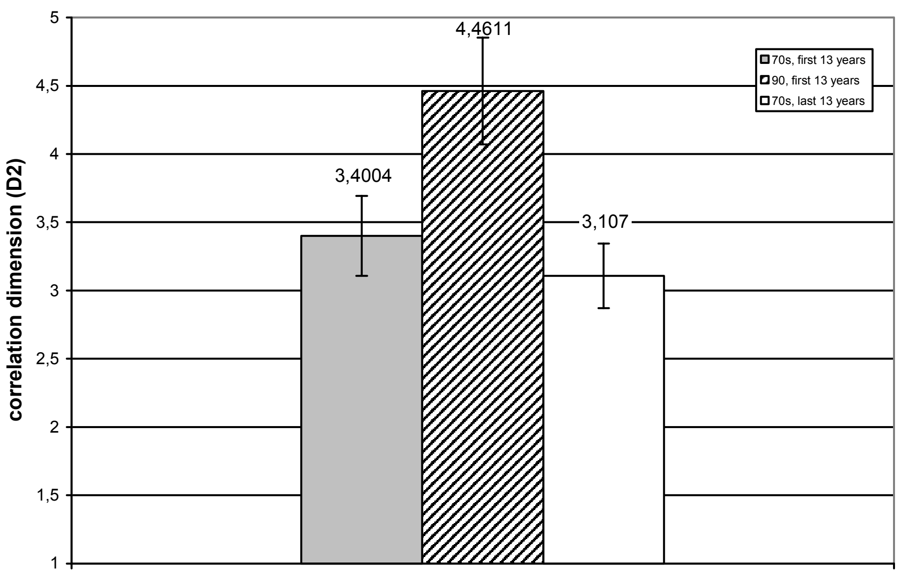


TABLE 5
Correlation dimension (D2) of the three quasi-time series

	70s cohort			90s cohort			
period	**Mean D2**	**standard deviation**	**N**	**mean**	**standard deviation**	**N**	**T-Test (1-tailed)**
First 13 years	3.4004	0.2923	94	4.4611	0.3906	88	**
Last 13 years	3.1070	0.2360	100	*last 13 years 70s vs. first 13 years 90s*			**

* $p < 0.05$
** $p < 0.01$

The small number of variants of the quasi-time series that did not attain saturation of the D2 value is quite astonishing. Much more clearly than expected, these results suggest that the career paths represented by the quasi-time series are not random processes. Rather, the results imply that career paths are complex, dynamic structures that can be put down to deterministic processes. Furthermore, there are only marginal differences between the results for the 100 different calculations which rarely exceed the error margin (scatter of the D2 estimates around the common mean value within the saturation range).
The D2 dimension for the 90s cohort is higher by about one dimension than that of the 70s cohort (see Figure 14 and Table 5). Consequently, while at least four interacting variables of a deterministic system are necessary to describe the career paths of the 70s cohort, the respective number for the 90s cohort is five. In addition, it is apparent that the system formed by the last 13 working years of the 70s cohort is less complex than the system formed by their first 13 years. This difference is much smaller however than that between the cohorts.

DISCUSSION

As outlined in the introduction, the present article dealt with three questions. First, it should examine whether careers have indeed become more complex over the last years ("complexity hypothesis in career research") via a mathematically formalized concept of complexity stemming from chaos theory. The second question was whether the results obtained would support the concept of careers as a complex yet deterministic system or rather the concept of careers as a random process. The third question aimed at investigating whether the methods applied here are appropriate for career research. The results obtained shall now be discussed in a bit more detail.

Complexity Hypothesis

In view of the fact that the available data hardly met the standards normally required for the application of chaos research methods, the results are surprisingly clear and significant. Both methods employed suggest that the career paths of persons who started their professional career in the 90s are more complex than for persons who graduated around 1970, and the results were even more conspicuous for the more complex and demanding method of correlation dimension than for Grammar Complexity, although the latter seemed more appropriate for the given data at the outset. Nevertheless, there are several limitations to our study that should be taken into account:
The data used here came from questionnaire-based interviews where the interviewees were asked to assess their whole careers retrospectively. It seems plausible that this task is more difficult for a person with more than 30 years of professional experience than for someone who started his or her professional career around 12 years ago. Therefore, the difference in observed complexity may partly be a consequence of the "mellowing" effect of time on career recollections. On the other hand, the last 13 career years of the 70s cohort (which are just as "recent" as the working years experienced hitherto by the 90s cohort), show an even lower degree of complexity than the first 13 years (which in turn could be due to a reduction of career complexity in later career stages). In order to better understand and explore these

issues, the Vienna Career Panel Project attempts to establish a panel of business graduates that will be asked to participate in a survey of their professional development in fixed intervals.

Complex or Random?

The methods for identifying a deterministic system and distinguishing it from a random process are still slightly embryonic. Only rather simple processes with limited complexity can already be identified as deterministic systems. The attempt to reveal these career paths as complex yet deterministic systems via Grammar Complexity did not yield a successful result, which is probably due to the very limited testing power of this method for short time series. The fact that a saturation of the D2 value was attained for almost all variants of all three quasi-time series suggests that the observed career paths are based on a rather simple system, despite all complexity. In any case, the results obtained say nothing about the complexity of the individual career paths.

Appropriateness of these Methods for Career Research

The approaches introduced here are just a small fraction of the methods, tools and algorithms currently used and discussed in chaos research. We believe that a more widespread use of methods stemming from chaos research faces two main obstacles. First, the data collected within career research will in many cases not meet the standards that are required to successfully apply methods of chaos research. For example, we did not attempt to demonstrate here that the observed career paths are chaotic processes in a mathematical sense, as this would have to be done via the calculation of Lyapunov exponents (Lyapunov exponents are a proof for the butterfly effect; cf. Rosenstein, Collins, & De Luca, 1993; Wolf et al., 1985), which cannot be done with the available data. Second, the methods employed here are far less widely-used than "standard" statistical procedures, which is also reflected in a lack of computer software that can perform this sort of calculations. Despite all these shortcomings, we think that this article represents a successful application of methods from chaos research to career-related questions. Furthermore, we believe that the merit of this paper and the concepts and methods contained therein lies less in the results as such, but rather in the fact of having introduced a theory that is able to describe and quantify career dynamics in a precise and methodically sound way.

ENDNOTES

[1] If a pair of symbols appears only twice, no compression is possible since each of the two pairs would be represented by another symbol (two symbols overall so far), and the replacing symbol would be represented by the two values, which adds another two symbols to the algorithm, resulting in the same number of symbols (four) as at the beginning. This restriction does not apply to triples, quadruples etc. which are already replaced on their second appearance.

REFERENCES

Ambühl, B., Dünki, R., & Ciompi, L. 1992. Dynamical Systems and the Development of Schizophrenic Symptoms - an Approach to a Formalization. In W. Tschacher & G. Schiepek & E. J. Brunner (Eds.), *Self-Organisation and Clinical Psychology*: 195-203. Berlin: Springer.

Arthur, M. B. & Rousseau, D. B. (Eds.). 1996. *The Bounderyless Career. A New Employment for a New Organizational Era*. New York, Oxford.

Arthur, M. B., Inkson, K., & Pringle, J. K. 1999. *The New Careers*. London: Sage.

Babloyantz, A. & Destexhe, A. 1987. Strange Attraktors in Human Cortex. In L. Rensing & U. a. d. Heiden & M. C. Mackey (Eds.), *Temporal Disorders in Human Oscillatory Systems*: 48-57. Berlin: Springer.

Babloyantz, A. 1990. Chaotic dynamics in brain activity. In E. Basar (Ed.), *Chaos in brain function*: 42-49. Berlin: Springer.

Baruch, Y. 2002. Developing Career Theory Based on "New Science": A Futile Exercise? The Devill's Advocate Comentary. *M@n@gement*, 5(1): 15-21.

Becker, H. S. & Strauss, A. L. 1956. Careers, Personality, and Adult Socialization. *American Journal of Sociology*, 62(Nov.): 254-263.

Besicovitch, A. S. & Ursell, H. D. 1937. Sets of fractional Dimensions (V): On dimensional Numbers of some continous Curves. *Journal of the London Mathematical Society, 12*: 18-25.

Bird, A., Gunz, H., & Arthur, M. B. 2002. Careers in a Complex World: The Search for New Perspectives from "New Science". *M@n@gement*, 5(1): 1-14.

Bourdieu, P. 1986. The Forms of Capital. In J. G. Richardson (Ed.), *Handbook of Theory and Research for the Sociology of Education*: 241-258. New York.

Buzug, T. & Pfister, G. 1992. Optimal Delay Time and Embedding Dimension for Delay-Time Coordinates by Analysis of the Global Static and Local Dynamical Behavior of Strange Attractors. *Physical Review, 45 A*: 7073-7084.

Chaitin, G. J. 1974. Information theoretic computational complexity. *IEEE Trans. Inf. Theory*, IT20: 10-15.

Chakrabarti, I. & Chakrabarti, S. R. 2002. Have We Been Too Successful in Making Corporations Organism-Like? *M@n@gement*, 5(1): 89-104.

Drodge, E. N. 2002. Career Counseling at the Confluence of Complexity Science and New Career. *M@n@gement*, 5(1): 49-62.

Dyer, L. (Ed.). 1976. *Careers in organizations*. Ithaca, NY.

Ebling, W. & Jiménez-Montano, M. A. 1980. On grammars, complexity and information measurs of biological macromolecules. *Mathematical Biosciences*, 52: 53-71.

Elbert, T., Ray, W. J., Kowalik, Z. J., Skinner, J. E., Graf, K. E., & Bierbaumer, N. 1994. Chaos and Physiology - Deterministic Chaos in excitable Cell Assemblies. *Physiological Reviews, 74*: 1-47.

Frazer, A. M. & Swinney, H. 1986. Independent Coordinates from Strange Attractors from Mutual Information. *Physical Review, A 33*: 1134-1140.

Friedlmayer, S., Reznicek, E., & Strunk, G. 1996. *Sozialisationschancen und Betreuungsstrukturen*. Wien: Amt für Jugend und Familie der Stadt Wien.

Glaser, B. G. 1968. Career Concerns and Footholds in the Organization. In B. Glaser (Ed.), *Organizational Careers - A Sourcebook for Theory*: 181-183. Chicago: Aldine.

Grassberger, P. & Procaccia, I. 1983a. On the Characterization of strange Attraktors. *Physical Review Letters*, 50: 346.

Grassberger, P. & Procaccia, I. 1983b. Measuring the Strangeness of strange Attraktors. *Physica 9 D*: 189-208.

Gunz, H. 1989. *Careers and Corporate Cultures. Managerial mobility in large corporations.* Oxford, New York.

Gunz, H., Bird, A., & Arthur, M. B. 2002a. Response to Baruch: We Weren't Seeking Canonization, Just a Hearing. *M@n@gement*, 5(1): 23-29.

Gunz, H., Lichtenstein, B. M. B., & Long, R. G. 2002b. Self-Organization in Career Systems: A View from Complexity Science. *M@n@gement*, 5(1): 63-68.

Haken, H. 1985. *Synergetik. Eine Einführung*. Berlin: Springer.

Haken, H., Kelso, J. A. S., & Bunz, H. 1985. A Theoretical Model of Phase Transitions in Human Hand Movements. *Biological Cybernetics*, 51: 347-356.

Haken, H. 1990a. *Synergetics. An introduction*. Berlin: Springer.

Haken, H. 1990b. Synergetics as a Tool for the Conceptualization and Mathematization of Cognition and Behavior - How Far Can we Go? In H. Haken & M. Stadler (Eds.), *Synergetics of Cognition*: 2-31. Berlin: Springer.

Haken, H. & Wunderlin, A. 1991. *Die Selbststrukturierung der Materie*. Braunschweig: Vieweg.

Haken, H. 1992. Synergetics in Psychology. In W. Tschacher & G. Schiepek & E. J. Brunner (Eds.), *Self-Organization and Clinical Psychology*: 32-54. Berlin: Springer.

Hall, D. T. 1976. *Careers in Organizations*. Santa Monica.

Hall, D. T. (Ed.). 1996. *The Career is dead - long live the career. A relational approach to careers.* San Francisco.

Hausdorff, F. 1919. Dimension und äußeres Maß. *Mathematische Analen, 79*: 157-179.

Hubermann, B. A. & Hogg, T. 1986. Complexity and adaptation. *Physica 22 D*: 376-384.

Hughes, E. C. 1951. Career and Office. In R. Dubin (Ed.), *Human Relations in Administration*: 96-99. New York: Prentice-Hall.

IBW (Ed.). 1997. *Lebensbegleitendes Lernen*. (Vol. 104). Wien: ibw (Institut für Bildungsforschung der Wirtschaft).

Jedynak, A., Bach, M., & Timmer, J. 1993. Failiure of Dimension Analysis in a Simple 5-Dimensional System. *Physical Review, E*.

Jiménez-Montano, M. A. 1984. On the syntactic structure of protein sequences and the concept of grammar complexity. *Bull. Math. Biol.*, 46: 641-659.

Kolmogorov, A. M. 1965. Three approaches to the definition of the concept quantity of information. *IEEE Trans. Inf. Theory*, IT14: 662-669.

Kowalik, Z. J., Schiepek, G., Kumpf, K., Roberts, L. E., & Elbert, T. 1997. Psychotherapy as a chaotic Process. Part II: The Application of Nonlinear Analysis Methods on Quasi Time Series of the Client-Therapist Interaktion: A Nonstationary Approach. *Psychotherapy Research (International Journal of the Society for Psyychotherapie Research, SPR)*, 7(2): 197-218.

Kriz, J. 1990. Synergetics in Clinical Psychology. In H. Haken & M. Stadler (Eds.), *Synergetics of Cognition*: 393-404. Berlin: Springer.

Kriz, J. 1992. *Chaos und Struktur*. München: Quintessenz.

Lichtenstein, B. M. B., Ogilvie, J. R., & Mendenhall, M. 2002. Non-Linear Dynamics in Entrepreneurial and Management Careers. *M@n@gement*, 5(1): 31-47.

Liebert, W. & Schuster, H. G. 1989. Proper Coise of Time Delay for the Analysis of Chaotic Time Series. *Physical Letters, A 142*: 107-111.

Lorenz, E. 1963. Deterministic non-periodic flow. *Journal of Atmosphere Science*, 20: 130-141.

Lorenz, E. N. 1991. Dimension of Weather and Climate Attractors. *Nature, 353*: 241-242.

Mandelbrot, B. B. 1987. *Die fraktale Geometrie der Natur*. Basel: Birkhäuser.

Mayrhofer, W., Steyrer, J., Meyer, M., Erten, C., Hermann, A., Iellatchitch, A., Mattl, C., & Strunk, G. 2000. *Towards a habitus based concept of managerial careers*, Toronto, Canada.

Nerenberg, M. A. H. & Essex, C. 1990. Correlation Dimension and Systematic Geometrie Effects. *Physical Review, A 42*: 7065-7074.

Office for Official Publications of the European Communities (1999) Gemeinsamer Beschäftigungsbericht der Europäischen Union Teil 1.

Office for Official Publications of the European Communities (1999) Gemeinsamer Beschäftigungsbericht der Europäischen Union Teil 2.

Orton, J. D. & Weick, K. E. 1990. Loosely Coupled Systems: A Reconceptualization. *Academy of Management Review*, 15(2): 203-223.

Packard, N. H., Crutchfield, J. P., Farmer, J. D., & Shaw, R. S. 1980. Geometry from a Time Series. *Physical Review Letters, 45*: 712-716.

Parker, P. & Arthur, M. B. 2002. Bringing "New Science" into Careers Research. *M@n@gement*, 5(1): 105-125.

Peiperl, M. & Baruch, Y. 1997. Back to Square Zero: The Post-Corporate Career. *Organizational Dynamics*(Spring): 7-22.

Peitgen, H.-O., Jürgens, H., Saupe, D., & Zahlten, C. 1990. Fraktale in Filmen und Gesprächen. Heidelberg: Spektrum der Wissenschaften Videothek.

Peitgen, H.-O., Jürgens, H., & Saupe, D. 1992. *Bausteine des Chaos. Fraktale*. Berlin: Springer; Klett-Cotta.
Peterson, I.; Prophet of Chaos; http://www.sciencenews.org/sn_arc99/11_13_99 /mathland.htm; 19.05., 2002.
Pincus, S. M. 1991. Approximate entropy as a measur of system complexity. *Proceedings of the National Academy of Sciences (USA)*, 88(Mathematics): 2297-2301.
Poincaré, H. 1908. *Science et méthode*. Paris.
Prigogine, I. 1955. *Thermodynamics of Irreversible Processes*. New York: Wiley.
Prigogine, I. & Stengers, I. 1986. *Dialog mit der Natur. 5. Auflg.* München: Piper.
Prigogine, I. 1987. *Die Erforschung des Komplexen. Auf dem Weg zu einem neuen Verständnis der Naturwissenschaften*. München: Piper.
Prigogine, I. & Stengers, I. 1993. *Das Paradoxon der Zeit. Zeit, Chaos und Quanten*. München: Piper.
Rapp, P. E., Jiménez-Montano, M. A., Langs, R. J., Thomson, L., & Mees, A. I. 1991. Toward a Quantitative Characterization of Patient-Therapist Communication. *Math Biosci, 105*: 207-227.
Reetz, L. & Reitmann, T. (Eds.). 1990. *Schlüsselqualifikationen*. Hamburg: Feldhaus.
Rosenstein, M. T., Collins, J. J., & De Luca, C. J. 1993. A practical Method for Calculating Largest Lyapunov Exponents from Small Data Sets. *Physica D 65*, 65: 117.
Schein, E. 1978. *Career Dynamics*. Reading, Mass.
Schiepek, G. & Schoppek, W. 1991. Synergetik in der Psychiatrie: Simulation schizophrener Verläufe auf der Grundlage nicht-linearer Differenzengleichungen. In U. Niedersen & L. Pohlmann (Eds.), *Selbstorganisation. Jahrbuch für Komplexität in den Natur-, Sozial- und Geisteswissenschaften, Bd. 2*: 69-102. Berlin: Duncker & Hombolt.
Schiepek, G. 1993. Die Beziehungsgestaltung in der Psychotherapie - ein chaotischer Prozeß? *Systeme. Interdisziplinäre Zeitschrift für systemtheoretisch orientierte Forschung und Praxis in den Humanwissenschaften*, 7(2): 49-59.
Schiepek, G. & Strunk, G. 1994. *Dynamische Systeme. Grundlagen und Analysemethoden für Psychologen und Psychiater*. Heidelberg: Asanger.
Schiepek, G., Schütz, A., Köhler, M., Richter, K., & Strunk, G. 1995. Die Mikroanalyse der Therapeut-Klient-Interaktion mittels Sequentieller Plananalyse. Teil I: Grundlagen, Methodenentwicklung und erste Ergebnisse. *Psychotherapie Forum*(1): 1-17.
Schiepek, G. 1996. *Der Appeal der Chaosforschung für die Psychologie*. Stuttgart: Philipp Reclam jun.
Schiepek, G., Kowalik, Z. J., Schütz, A., Köhler, M., Richter, K., Strunk, G., Mühlnwinkel, W., & Elbert, T. 1997. Psychotherapy as a chaotic Process. Part I: Coding the Client-Therapist Interaction by Means of Sequential Plan Analysis and the Search for Chaos: A Stationary Approach. *Psychotherapy Research (International Journal of the Society for Psyychotherapie Research, SPR)*, 7(2): 173-194.
Schürmann, T. & Grassberger, P. 1996. Entropy estimation of symbol sequences. *Chaos*, 6(3): 414-427.
Schuster, H. G. 1989a. *Deterministic Chaos*. Weinheim: VCH (2. Ed.).
Schuster, H. G. 1989b. Information Content of Chaotic Signals. *Physica Scripta. Vol. 40*: 367-372.
Seifritz, W. 1987. *Wachstum, Rückkopplung und Chaos*. München: Hanser.
Seitz, A., Tschacher, W., Ackermann, K., & Revensdorf, D. 1992. Applicability of Dimension Analysis to Data in Psychology. In W. Tschacher & G. Schiepek & E. J. Brunner (Eds.), *Self-Organization and Clinical Psychologie*: 367-384. Berlin: Springer.
Shannon, C. E. 1948. A Mathematical Theory of Communication. *Bell System Technical Journal*, 27: 379-423 and 623-656.
Staehle, W. H. 1991. Redundanz, Slack und lose Kopplung in Organisationen: Eine Verschwendung von Ressourcen? In W. H. Staehle & J. Sydow (Eds.), *Managementforschung 1*: 313-345. Berlin, New York: De Gruyter.
Super, D. E. 1957. *The Psychology of Careers*. New York: Harper & Row.

Takens, F. 1981. Detecting strange Attraktors in Turbulence. In D. A. Rand & L. S. Young (Eds.), *Lecture Notes in Mathematics*: 368-381. Berlin: Springer.
Thiele, C. 1997. Selbstorganisation und Komplexität in der Psychotherapie. *systeme*, 11(2): 21-32.
Tschacher, W., Schiepek, G., & Brunner, E. J. (Eds.). 1992. *Self-Organisation and Clinical Psychology. Empirical Approaches to Synergetics in Psychology*. Berlin: Springer.
Tschacher, W. & Scheier, C. 1995. Analyse komplexer psychologischer Systeme. II. Verlaufsmodelle und Komplexität einer Paartherapie. *System Familie, 8*: 160-171.
Tschacher, W., Scheier, C., & Grawe, K. 1998. Order and Pattern Formation in Psychotherapy. *Nonlinear Dynamicis, Psychology, and Life Sciences*, 2(3): 195-215.
Tsonis, A. A. & Elsner, J. B. 1988. The Weather Attraktor Over Very Short Time Scales. *Nature, 33*: 545-547.
Tsonis, A. A. 1992. *Chaos: from Theory to Applications*. New York: Plenum Press.
Weick, K. E. 1976. Educational organizations as loosely coupled systems. *Administrative Science Quarterly*, 21: 1-19.
Weidlich, W. & Haag, G. 1983. *Concepts and Models of a Quantitative Sociology*. Berlin: Springer.
Wolf, A., Swift, J. B., Swinney, H. L., & Vastano, J. A. 1985. Determining Lyapunov Exponents from a Time Series. *Physica, 16 D*: 285-317.
Zvonkin, A. K. & Levin, L. A. 1970. The complexity of finite objects and the development of the concepts of information and randomness by means of the theory of algorithms. *Russ. Math. Survey*, 15: 83-124.