New careers, more complex careers?

Empirical and methodological results concerning the "complexity hypothesis" in career research.

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Submitted to the
European Group for Organizational Studies (EGOS),
20th Colloquium, Subtheme 9: Careers
“Relating the Individual to the Context”
Ljubljana, Slovenia, July 1-3, 2004

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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.

1 Introduction

For quite some time, career research was almost exclusively limited to careers within organizations (Becker & Strauss, 1956; Dyer, 1976; Glaser, 1968; Gunz, 1989; Hall, 1976; Hughes, 1951; Schein, 1978; Super, 1957). However, a different type of careers is gradually gaining more and more theoretical as well as practical relevance. It 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. In addition, it is almost solely up to the individual actor to take care of his or her career, with little or no external support. The resulting less stable, less predictable career path is 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). Regardless of one's enthusiasm for the idea of a radically changing career environment, common wisdom has it that careers nowadays are 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). Such approaches have great merit, 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. However, in order to add "quantitative" insight into the "*new careers*", we propose another way of investigating the complexity hypothesis in career research, applying quantitative methods from research domains that can be subsumed under the label of "*chaos research*" (cf. e.g. Haken, 1990; Prigogine, 1987). Although these methods have their origin in the sciences of nature, they have already been applied successfully to the social sciences (for an overview e.g. Mainzer, 1999; Tschacher, Schiepek, & Brunner, 1992). Chaos theory has already had its first appearances in career research, too (Baruch, 2002; Bird, Gunz, & Arthur, 2002; Chakrabarti & Chakrabarti, 2002; Drodge, 2002; Gunz, Bird, & Arthur, 2002a; Gunz, Lichtenstein,

& Long, 2002b; Lichtenstein, Ogilvie, & Mendenhall, 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 (Sokal & Bricmont, 1998). Nonetheless, using these methods from chaos theory in career research should prove fruitful, especially when it comes to a description of career as a *dynamic process*.

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

1. **Complexity Hypothesis.** 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 definition of complexity.
2. **Determinism vs. Haphazardness.** 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. **The Appeal of Chaos Theory for Career Research.** Two methods stemming from "chaos research" will be introduced and examined as to their suitability for the description and analysis of career paths. The main issue here is the transferability of these methods that have their origin in the sciences of nature to career research.

2 Complexity Hypothesis

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).

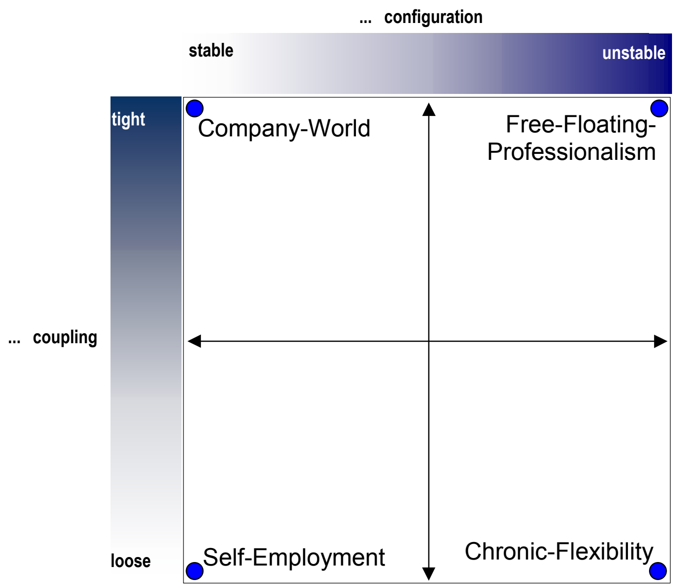

Figure 1: The Fields of Career

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. 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. Reetz & Reitmann, 1990; IBW, 1997) (see Figure 2).

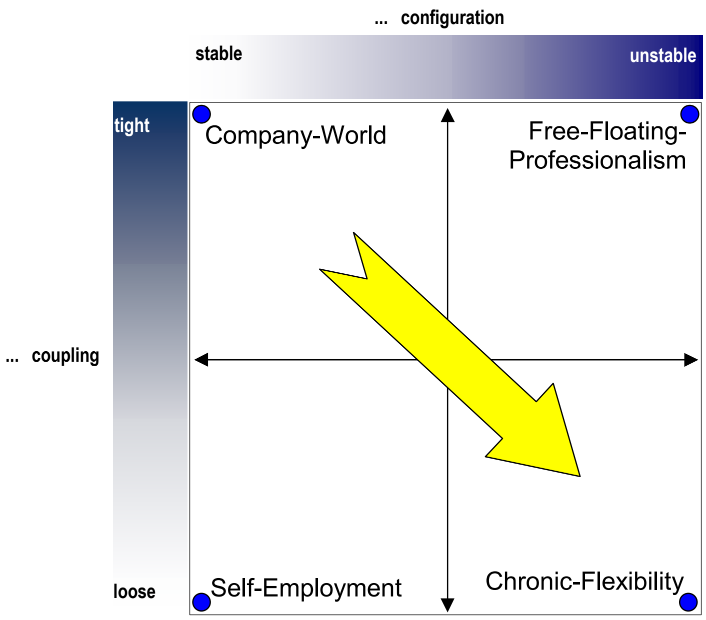

Figure 2: Assumed Development of Careers

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).

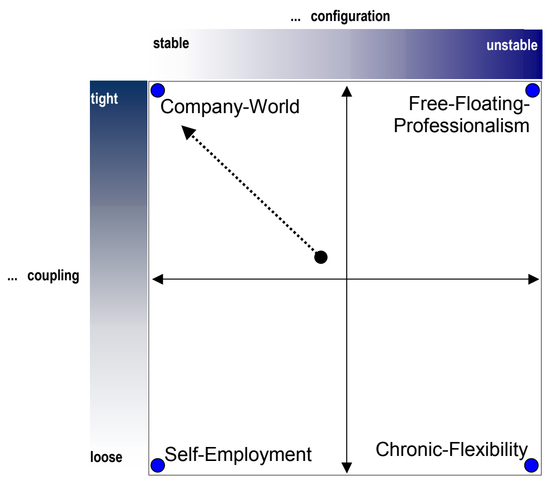

Figure 3: Linear, Straight Career Path

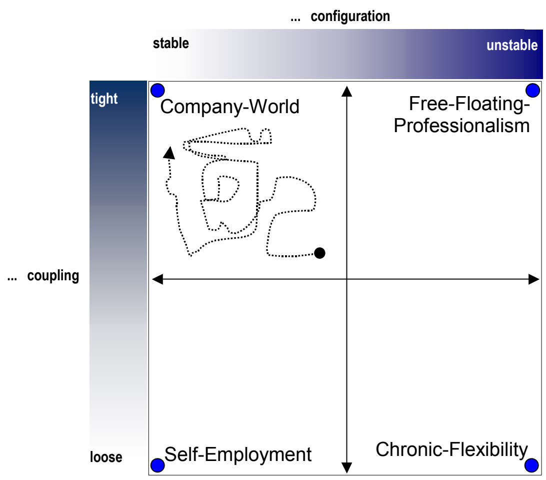

Figure 4: Erratic, Complex Career Path

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?), we 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 research, which includes a broad spectrum of theories, such as the theory of non-linear dynamic systems (e.g. Schuster, 1989a), synergetics (e.g. Haken, 1990) 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.

3 Definitions of a Dynamic's Complexity

Theories on dynamical systems offer a broad spectrum of statistical and mathematical tools in order to obtain precise quantitative measurements of complexity, order, determinism, and chaoticity. Most of these algorithms have been developed in the last 20 years, frequently based on older precursors. In the following section, we will give a brief overview over two different methods. The first one is relatively easy to implement and can be applied for nominal data. The second represents a class of complexity measurements based on the concept of fractal geometry. In order to keep it short, details of algorithms are not presented here but can be found in the appendix of the paper.

3.1 Complexity and Order in Sequences of Events

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.

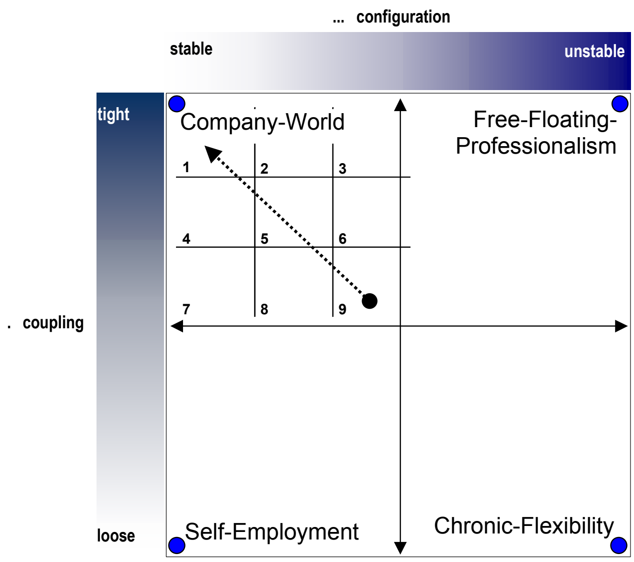

Figure 5: Career Path of a Person as Movement Over a Grid

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 of 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 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: $$\sqrt{a} = x_{n+1} = \frac{1}{2}\left(x_n + \frac{a}{x_n} \right), n = 0, 1, 2, 3, \ldots \infty$$

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). One of the easiest ways to calculate measurements on algorithmic entropy is to use a data compression algorithm (similar to file compression used on computers) on to the data. While it is not possible to compress random data very much, it is possible to distinguish random time series from ordered ones. We used a compression algorithm called *Grammar Complexity* (Ebeling & Jiménez-Montano, 1980; Jiménez-Montano, 1984; Rapp, Jiménez-Montano, Langs, Thomson, & Mees, 1991). As a data set arranged by size leads to the best compression, and a randomly shuffled data set results in less compression, the algorithmic entropy of a person's career path is supposed to be in the middle. According to our hypothesis a person's career path is more complex then a totally ordered path but far from being 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.

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.

3.2 Ordered Complexity from Fractal Dimension

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.

An important feature of chaotic motion is their fractal structure (Ruelle & Takens, 1971) visualized in a *phase space portrait*. 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 examples of simple phase space representations. The changes in coupling and configuration are not depicted as time series but plotted along the two axes. Following the trajectory represents the development over time. Figure 6 shows the three-dimensional phase space of the chaotic weather system, first described by Lorenz (1963). The structure of the chaotic motion shows a highly ordered but complex geometrical form, known as a fractal.

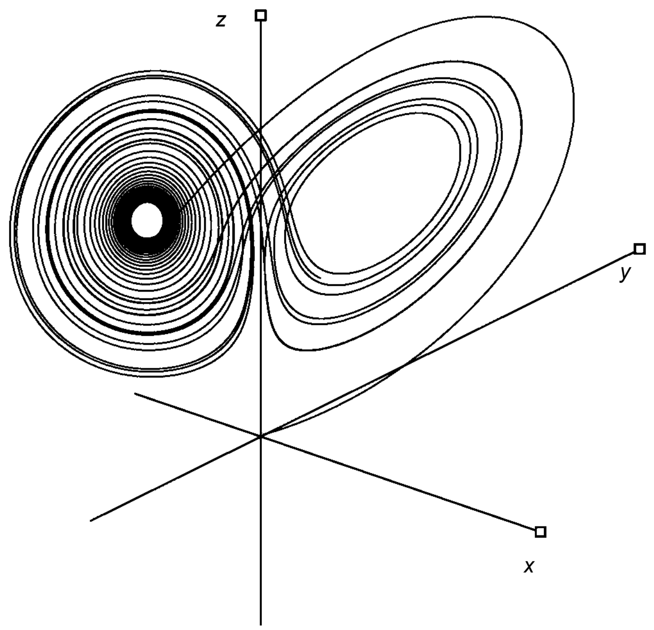

Figure 1: Phase Space Portrait of the Chaotic Lorenz-System (Weather-Model)

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 determine 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.

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. Several methods have been proposed to determine the fractal dimension of a time series. The most common one that is also used here is the *Correlation Dimen-*

sion D2 (Grassberger & Procaccia, 1983a, b). What all these methods have in common is that they theoretically require an infinitely long time series for a reliable calculation. 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 see Tsonis, 1992), this is still a hard requirement for behavioral science.

Since the work of Grassberger and Procaccia (1983a; 1983b) a lot of publications has shown the fractal structure of a broad variety of processes. But not all of them are actually chaotic. The calculation of fractal dimension still leaves some methodological problems, since it is an appropriate method of calculating the complexity of a time series, but not for the detection of chaos (e.g., due to the limited length of the time series). Nevertheless, a successful determination of the fractal dimension of a dynamic process allows to draw the following conclusions:

1. **Measuring Complexity.** The higher the fractal dimension of a dynamic process, the higher its complexity
2. **Determinism vs. Haphazardness.** If the fractal dimension of a dynamic process derived from empirical data can be determined, the process in question is not a random process.
3. **Calculation of the System's Degrees of Freedom.** 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

Several authors in career research have recently advanced conjectures according to which careers can be viewed as chaotic processes (cf. Bird et al., 2002; Chakrabarti et al., 2002; Drodge, 2002; Gunz et al., 2002a; Gunz et al., 2002b; Lichtenstein 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 & Strunk, 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.

4 Methods

Since 2000, the Vienna Career Panel Project (ViCaPP) has collected data on the careers of Austrian business school graduates. The analyses are based on the first 13 career years of 95 graduates who completed their studies around 1970 and 120 graduates who did so around 1990. 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 with a sampling frequency of one year. Figure 9 gives a graphic representation of the research design. For the 90s cohort (sample B), data 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.

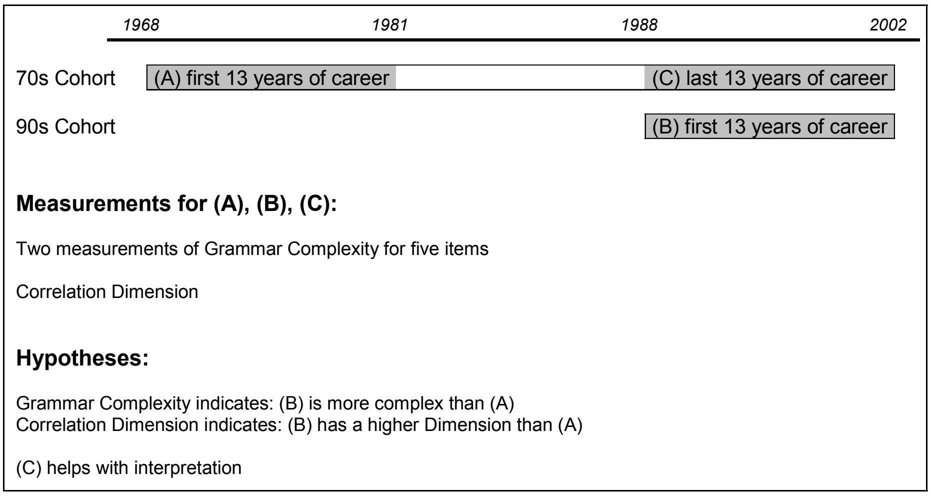

Figure 9: Design of the Study

The following analyses are based on five time-series per person, representing her/his career patterns in time. Based on Mayrhofer et al. (2000), three of the five variables are related to the coupling dimension (how tightly linked and mutually dependent actors are in their career-related actions and decisions) of career field theory. 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).

The other two time series refer to instability and variation in actors' professional relationships and job content. This concept is also based on Mayrhofer et al. (2000) and is called the configuration dimension. 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)

A factor analysis results in a two-factor solution (as proposed by the underlying theory), which explains about 60% of the total variance.

4.1 Sample Description

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 are quite similar for both 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 a proportion of 14% and 42%, respectively. This is because fewer women commenced and finished their studies at the Vienna University of Economics and Business Administration 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.

4.2 Calculations

Both definitions of ordered complexity of dynamical processes are used here for investigating the questions already mentioned above: First, we will focus on the "complexity hypothesis" in career research; second, we will test the underlying deterministic structure of career paths.

In order to determine algorithmic entropy, the Grammar Complexity procedure (measurement of the length of a compressed time series; see the appendix for details) was used. For the first 13 career years of both cohorts (samples A and B) and for the last 13 years for the 70s cohort (sample C), 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. **Measuring Complexity.** The Quotient of the Grammar Complexity of the original time series divided by the Grammar Complexity of the sorted time series is a measurement for complexity. The larger the quotient, the higher the complexity.
2. **Determinism vs. Randomness.** The Z-Transformation of the Grammar Complexity values of the original time series via the means and standard deviations of 200 randomly shuffled surrogates (see the appendix for details) is a measurement of determinism. 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.

In order to test the differences between the three samples, the sample means for both measurements were compared via T-tests.

In contrast to Grammar Complexity, Correlation Dimension makes use of the additional information provided by interval scaled data (see the appendix for details), 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 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 quasi-time series with 1.235 sampling points for the 70s cohort (95 members), and 1.560 sampling points for the 90s cohort (120 members). In order to simplify the calculation, not the five original time series but the two underlying dimensions (coupling and configuration) are used as sources for the quasi-time series, by taking the means of the two and three items assigned to configuration and coupling, respectively.

Putting the data of all persons together is only a methodically sound procedure if the dynamics of the individual career paths are not too distinct from each other. 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, if 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. Therefore, Correlation Dimension allows differentiating between deterministic and random processes, too. If the calculation of a finite Correlation Dimension is possible, the underlying processes are ordered temporal patterns. On the other hand, if the Correlation Dimension value becomes infinite, the processes in question are just random.

The algorithms for calculating Grammar Complexity and Correlation Dimension were both implemented by the first author in C++ and tested extensively on various known time series.

5 Results

5.1 Algorithmic Entropy

The results of the calculations of algorithmic entropy suggest that career paths are indeed more complex for the 90s cohort than for the 70s cohort. However, these results should 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, and the nominal data.

The first indicator for complexity (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) for the two cohorts is presented in Figure 10 and Table 1.

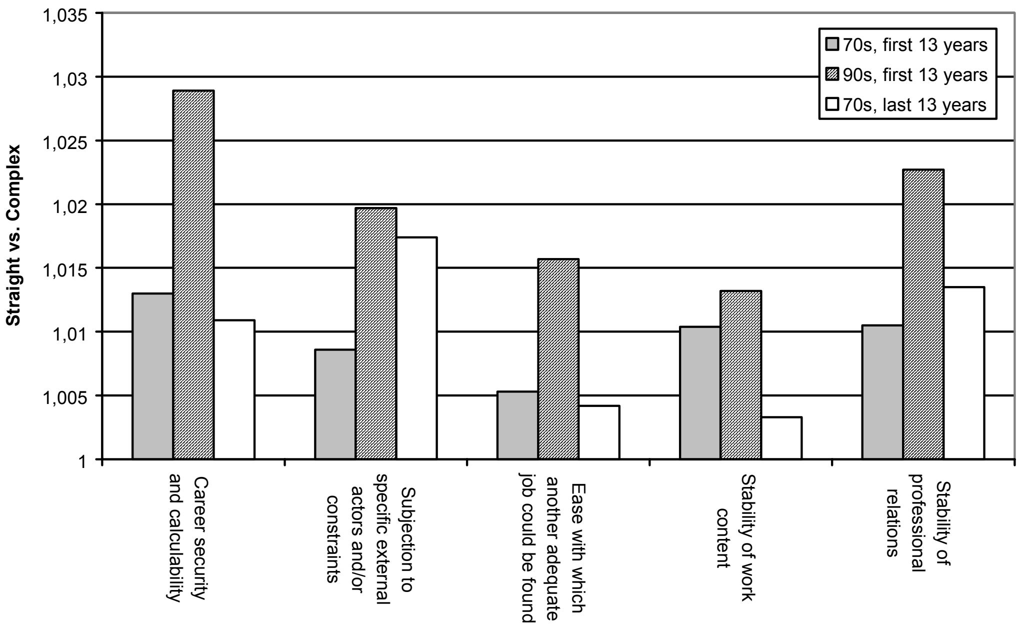

Figure 10: Grammar Complexity Quotient for the Two Cohorts and Observed Periods

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). 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 11 and Table 2 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.

Straight vs. Complex		**70s Cohort**			**90s Cohort**			
Dimension	**Sample**	**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

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

Table 1: Comparison of the Grammar Complexity Quotients

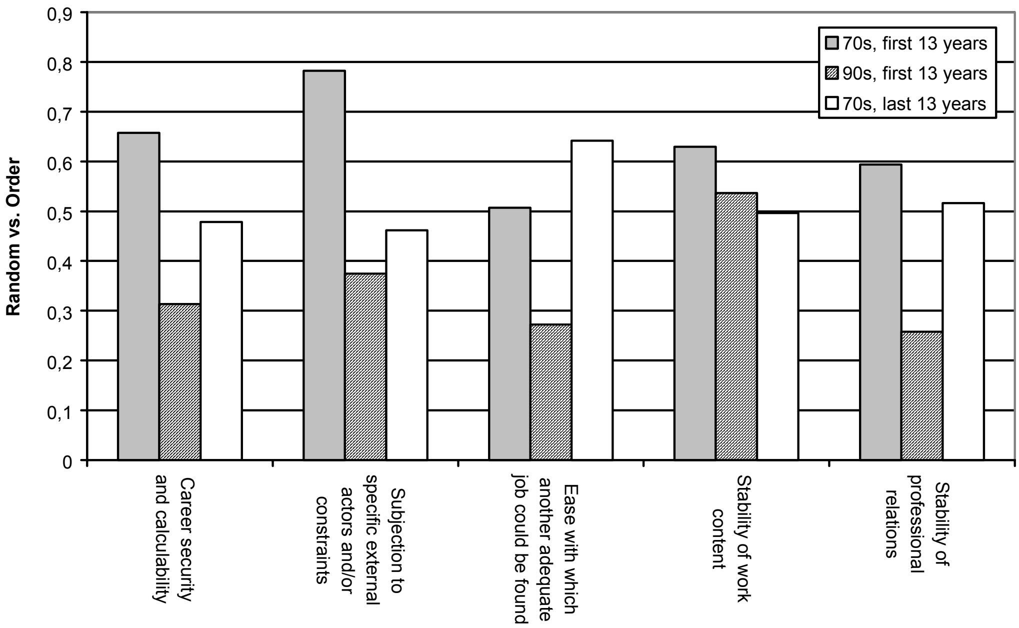

Figure 11: Mean Grammar Complexity Values after Z-Transformation for Both Cohorts

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 clearly distinct 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.

Random vs. Order		70s Cohort			90s Cohort			
Dimension	**Sample**	**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*			*

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

Table 2: Comparison of the Mean Grammar Complexity Values after Z-Transformation for the Cohorts

5.2 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. One crucial feature of this method is the distinction between a chaotic and a random process – the latter can be clearly identified by an infinite fractal dimension. Accordingly, a finite fractal dimension 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 11 shows the two-dimensional phase space portraits for randomly chosen variants of quasi-time series for the three samples. As was already found for empirical data in social sciences, but also in medicine (e.g. Schiepek et al., 1997), no clearly structured figures could be observed, as opposed to mathematically generated time series (see Figure 8 as an example).

While a simple order structure cannot be identified with the naked eye, 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.

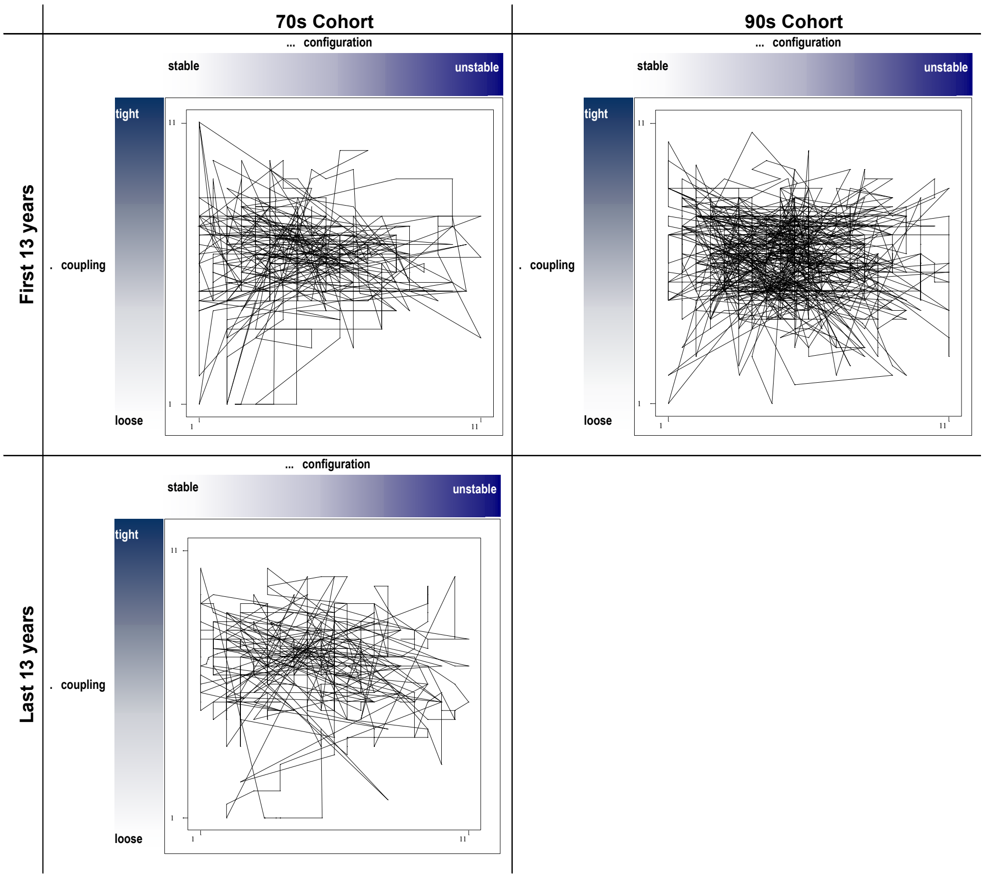

Figure 11: Two-Dimensional Phase Space Portrait of Career Paths

The calculations of the respective Correlation Dimensions confirm this impression. As Table 3 shows, a finite 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 on a finite value. For the 90s cohort, the respective number was twelve. For the last 13 years of the 70s cohort, all 100 variants reached a finite D2 value.

	70s Cohort			90s Cohort			
Sample	**Mean D2**	**Standard Deviation**	**Valide N** (total N = 100)	**Mean**	**Standard Deviation**	**Valide N** (total N = 100)	**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*			**

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

Table 3: Correlation Dimension (D2) for the Three Samples

The small number of variants of the quasi-time series that did not attain a finite 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.

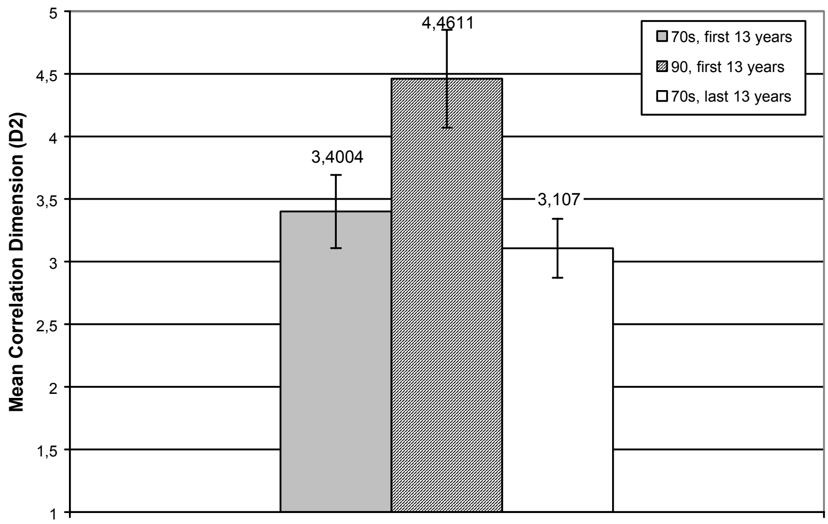

Figure 12: Mean Correlation Dimension (D2) for the Three Samples

The D2 value for the 90s cohort is higher by about one dimension than that of the 70s cohort (see Figure 12 and Table 3). 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.

6 Discussion

As outlined in the introduction, the present article dealt with three questions. First, it should examine whether careers have indeed become more complex during 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 view 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.

6.1 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.

6.2 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 finite D2 value was attained for almost all variants of all 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.

6.3 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, Swift, Swinney, & Vastano, 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 short-comings, 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.

7 Appendix

In the following sections, we will introduce the statistical algorithms used in this paper a bit more extensively. For more details, please refer to the cited literature.

7.1 Grammar Complexity

The Grammar Complexity algorithm (Ebeling et al., 1980; Jiménez-Montano, 1984; Rapp et al., 1991) 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 footnote 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:

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

[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.

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 many surrogate sequences that consisted of the same elements as the original sequence (randomly shuffled in many different ways) and calculating the Grammar Complexity for these surrogate sequences. The obtained 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.

Unlike Shannon's algorithm presented above (see Equation 1), 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 produced 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).

7.2 Correlation Dimension

An important feature of chaotic motions in phase space is their fractal structure. The concept of fractals was introduced by Benoît B. Mandelbrot (e.g. 1987) 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. 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.

Several methods have been proposed to determine the fractal dimension of a time series. The most common one, also used in this text, is the *Correlation Dimension* D2 (Grassberger et al., 1983a, b). Besides requiring a time series with as many sampling points as possible (about 1.000 sampling points are generally regarded as a small yet sufficient number for attractors of a low fractal dimension), another feature of the Correlation Dimension is that it aims 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 on a finite value 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 et al., 1985).

For the dynamic system entered into the analyses, two mutually independent time series for both coupling and configuration 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 (resulting in 2.470 sampling points for the 70s cohort and 3.120 sampling points for the 90s cohort), 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., 1983a, b):

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 13). 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).

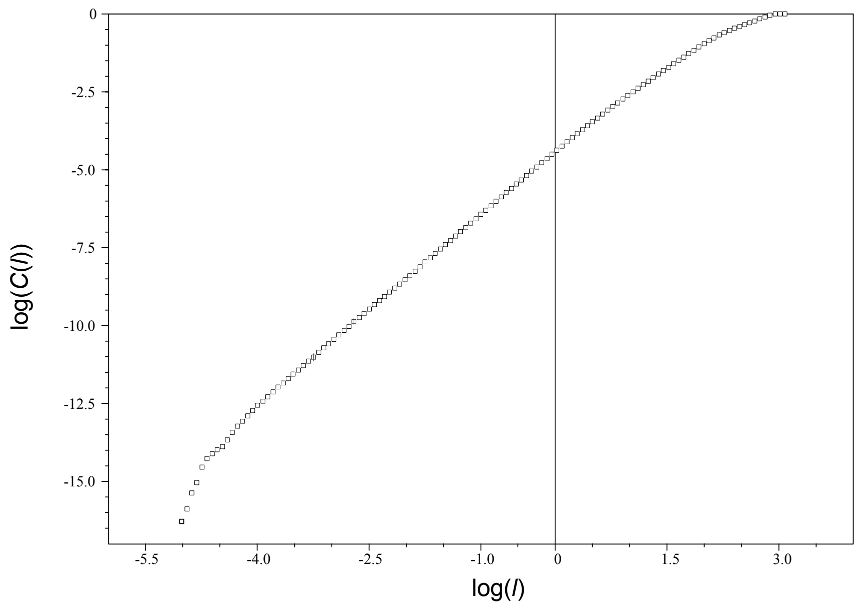

Figure 13: The Correlation Integral in Dependency on log(l)

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.

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