Available online at www.sciencedirect.com
ScienceDirect
Poetics 37 (2009) 267–294
POETICS
www.elsevier.com/locate/poetic

Creativity from interaction: Artistic movements and the creativity careers of modern painters

Fabien Accominotti [a,b]

[a] Department of Sociology, Columbia University, New York, USA
[b] Ecole des Hautes Etudes en Sciences Sociales, Paris, France

Abstract

This article revisits David W. Galenson's work on the relationship between artistic creativity and the life cycle of artists. Galenson introduces a simple classification of creativity careers (early *vs.* late-bloomers), relates it to a bipartite typology of creativity (conceptual *vs.* experimental innovators) and builds on this typology to explain the decreasing trend of age at which artists were most creative over several generations in the 19th and 20th centuries. Drawing on Galenson's measures, the present paper uses a different approach to overcome possible criticisms to his design. Applying sequence analysis to creativity careers of 41 major modern painters, it also yields a fairly different story from the one Galenson proposes. In particular, I show that a typology of creativity should distinguish between creativity occurring within artistic movements and other forms of creativity. This distinction is important, for the decrease in age at peak creativity over time seems actually driven by the evolution of movement-related creativity alone. Investigating the specific issue of creativity over the life cycle of artists, and showing that movements and interactions play an important part in the picture, the paper thus suggests there is something more than the mere individual involved in artistic creativity.

1. Introduction

This paper deals with a specific issue in the study of artistic production: that of the relationship between the life cycle of artists on the one hand and artistic innovation on the other. Doing so, it more generally aims at showing that quantitative approaches can provide valuable sociological insight on a topic apparently so intimately related to the individual that it should be of little relevance to quantitative social scientists – namely, artistic creativity. The developments below are thus distinct from – though not incompatible with – studies examining the social dimension of

E-mail address: fa2175@columbia.edu.

0304-422X/$ – see front matter
doi:10.1016/j.poetic.2009.03.005

artistic creativity through in-depth case studies of individual artists (*e.g.* DeNora, 1995; Elias, 1991; Montias, 1989). Offering a complementary approach, I show that collective mechanisms involved in artistic creativity can also be powerfully uncovered through quantitative accounts. Yet, as should be clear from the specific focus of this paper, not any quantitative account will do. The bulk of what follows is actually devoted to challenging one such account, and suggesting an alternative one.

The relationship between artistic creativity, conceived of as the production of innovative pieces of art, and the professional life cycle of artists has been investigated in recent work by economist David W. Galenson. This work, primarily focusing on visual artists, will be presented in the first section of the paper. Suffice it to say here that Galenson introduces systematic measures of creativity at various ages, for the most renowned French and American painters of the 19th and 20th centuries. He then compares the patterns of creativity over the life cycle of these various artists, and accounts for the observed differences by relating typical patterns to various individual approaches to innovation: artists producing their most creative work at early stages in their career are seen as conceptual innovators, while late-bloomers are regarded as experimental innovators. Not surprisingly, Galenson's overall endeavor, as well as the typology of creativity he introduces, have been criticized as oversimplifying, if not irrelevant, by academic art historians (see Kousser, 2004).

Putting such criticism aside, and building on the very data used by Galenson, I here tackle the issue again, yet with a slightly different focus and very different methods. The paper thus concentrates on the evolution of creativity over the life cycle of the 41 French (or mainly active in France) painters, born between 1830 and 1900, that art historians acknowledge as the most significant of their time. More importantly, my chief purpose here is to answer questions raised by Galenson's methodological choices, and ensuing theoretical conclusions.

In order to compare patterns of creativity over the lifetime for various artists, Galenson first reduces each of the creativity careers to *one point*—namely age at highest creativity. Would his conclusions, specifically his typology of artistic creativity, hold true if *entire sequences* of creativity were instead compared for various artists? Sequence analysis methods are implemented below in order to answer that question.

Furthermore, Galenson's endeavor eventually rests on a strong, though implicit assumption: that creativity sequences and the approaches to innovation they mirror are essentially individual features. In particular, experimental and conceptual approaches to innovation are considered deeply inscribed in each artist's personality, and barely subject to change once the artist has completed his or her early training. Put shortly, creativity in Galenson's view only stems from the individual's inside out. And his typology quite accordingly has no room for considering interactions, such as collaboration or competition between artists, as possible sources for the enhancement of artistic innovation. Therefore, Galenson's work in a sense reasserts the view of the creator as a loner. The present paper in contrast challenges this view, by pointing to artistic movements as the driving force shaping both interindividual differences in creativity patterns and the succession of typical patterns over time.

The paper unfolds as follows: the first section is a brief overview of Galenson's main studies devoted to artistic creativity and the life cycle of artists. Criticisms specific to the present contribution, and their implications in terms of how Galenson's conclusions should be further brought to test, are introduced in Section 2. The data and methods I build upon to implement these complementary tests are discussed in Section 3. The final section presents findings which both support the criticisms previously addressed, and make a clear case for the collective dimension of artistic creativity in modern art history.

2. Artistic creativity and the life cycle of artists: David Galenson's view

2.1. Measuring creativity

Most original to Galenson's project is definitely his attempt to provide a systematic grip on a notion apparently as untraceable as artistic creativity.

At a very general level, it is first worth mentioning that Galenson's diverse indices of creativity actually measure the *significance*, in modern art history, of works executed by various artists. Seeing these measures as indices of *creativity* requires admitting one further assumption, namely that the creative or innovative nature of a work of art is what makes it significant in modern art. Drawing on a wealth of work by art critics and academic art historians, Galenson provides support for this assumption.[1] Considering his demonstration sufficient, I hereafter endorse it as well.

Galenson then introduces several indices for creativity and its evolution over artists' professional lives. Prices at contemporary auctions of works executed by each artist at various ages (controlling for size, medium and year of auction sale) are used most often (Galenson, 2001; Galenson and Weinberg, 2001). Two additional indices, designed to reflect the scholarly appraisal of creativity and assess the robustness of the auctions index, are displayed in Galenson (2001): the number of illustrations devoted to each 5-year period of an artist's career in reference art history textbooks, and the number of works presenting each 5-year period in retrospective solo exhibitions. The great consistency of these diverse indices, demonstrating the agreement between the opinions of scholars and the art market on what constitutes modern artists' most creative work, is considered robust evidence of the objective variations of creativity over the professional life of artists.

Galenson should certainly be praised for thus having diversified and confronted indices. Yet one may also wonder whether these measures actually confirm each other, or are on the contrary so interdependent as to undermine the methodological value of this confirmation. Purchasers on the market and art history experts (art historians, exhibitions curators) are indeed likely to influence each other as far as the appraisal of works of art is concerned, thus constructing some parts of the production of an artist as more significant than others (Moulin, 1986). Galenson himself actually mentions this possible interdependence, and suggests a number of mechanisms that could account for it.[2] I shall deal more thoroughly with this issue in the data section.

2.2. Galenson's two main conclusions

Drawing on the measures above, Galenson first finds that more or less creative periods are not distributed similarly over the lifetime of the various artists. More precisely, observed creativity careers can be seen as lying in-between two ideal-types. In the first one, the period of highest creativity occurs at the dawn, and in the second one at the twilight, of the artist's professional life. Picasso and Cézanne are considered instantiations of respectively the former and the latter typical careers, with respectively a very early and a very late creativity peak.

Elaborating on this first finding, Galenson then makes a case for the association of each type of creativity career with an equally ideal-typical way of innovating in art (Galenson, 2001, 2002a,

[1] Galenson (2001:32–48). This hypothesis is consistent with the work of a number of scholars interested in artistic creativity: Martindale (1990), following Bloom (1975), thus suggests that creativity and significance can be equated in the arts since the very nature of artistic activity is its orientation towards novelty.

[2] Galenson (2001:29–31).

2004). Artists with an early creativity peak are seen as usually innovating through ‘‘conceptual execution’’. In making their most significant contributions, so-called ‘‘conceptual innovators’’ tend to implement an idea that precedes actual execution of the work of art. ‘‘Their goals for a particular work can usually be stated precisely, before its production, either as a desired image or as a desired process for the work's execution’’. In contrast, artists with a late creativity peak are better characterized as ‘‘experimental innovators’’. Their approach to innovation typically is ‘‘aesthetically motivated experimentation’’, and their major contributions result from repeated experimentations performed on the work itself. ‘‘These artists repeat themselves, usually painting the same subject many times, gradually changing its treatment in an experimental process of trial and error. [. . .] Experimental artists build their skills gradually over the course of their careers, improving their works slowly over long periods’’.[3] Galenson (2001, 2004) finally insists that this bipartite typology of innovators should be considered an ‘‘approximation to an underlying continuum of approaches’’. We shall see in the following section what criticisms can be addressed to Galenson's classification of creativity careers, and as a consequence to his typology of ways of innovating in art.

Now, although one might not subscribe to this classification or this typology, another significant conclusion can be drawn from this line of work. Galenson indeed finds that age of major modern artists at peak creativity declines on average as one moves from earlier to later generations. To support this claim, Galenson and Weinberg (2001) build four cohorts from a sample of 33 painters born between 1820 and 1900, mainly active in France, and selected for their significance in modern art history. For each artist, they estimate age at peak creativity from prices at contemporary auctions. Mean age at peak creativity is then shown to significantly decrease in more recent cohorts.[4]

To account for this empirical finding, Galenson essentially suggests a mechanism involving a selection process over time among the two types of innovators previously introduced. One scope condition, for this mechanism to work as an explanation, is that the shape of a painter's creativity career – in particular the position of his creativity peak – is mainly a consequence of his individual approach to innovation. The argument then goes as follows. Conceptual innovators' approach to innovation generally makes them more responsive than their experimental counterparts to demands of artistic novelty. Accordingly, confronted with a growing demand for innovation in the art world over the late 19th and early 20th centuries, conceptual innovators gradually proved more adapted, and eventually were the only ones to innovate quickly enough to be able to leave a mark on their period. This process may have involved pressures toward innovation either from the restricted circle of fellow artists, from the larger world of critics and collectors, or of course from both. In a nutshell, and to quote Galenson, ‘‘an increased demand of innovation, experienced by artists in the form of intellectual and financial pressures in a central location of the artworld, can strongly encourage conceptual innovation, because of the greater speed with which conceptual breakthroughs can be made’’.[5] Other parts of Galenson's work refine the argument by adopting a more sociological point of view. In particular, institutions and institutional change in the world of painting are taken into account in order to explain the observed succession of typical careers across generations (Galenson, 2002b; Galenson and Jensen, 2002). Yet the underlying explanatory mechanism remains similar.

[3] Galenson (2004:124–125).

[4] Though Galenson and Weinberg nowhere explicitly discard this possible explanation, it is worth mentioning that the latter result does not stem from an unequal distribution of short careers across generations (if later generations of artists were shorter-lived, their peak would necessarily tend to occur earlier in their career).

[5] Galenson (2001:165).

That most famous artists' most creative work came at progressively earlier ages in France over the generations born between 1820 and 1900 seems undebatable, provided one admits Galenson's measurements of creativity and creativity peaks. As observed above, however, Galenson's account for this phenomenon ultimately rests on one additional assumption, namely that individual approaches to innovation are the main cause shaping artists' creativity careers. The following section should help clarify and question this assumption.

3. Two criticisms

3.1. Creativity sequences reduced to one point and the danger of a self-generated typology

I here turn to the main criticisms this work intends to address to Galenson's approach. The first of these criticisms focuses on the way observed creativity careers are handled and classified in this approach, but in the end it spreads to the typology of ways of innovating presented above. Similarly, the second criticism, though methodological in the first place, eventually also leads up to challenging Galenson's view of artistic creativity.

The main criterion Galenson uses to compare shapes of creativity careers is age at highest creativity, approached as one single year or as a 5-year period. In other words, as soon as one compares it to others, each creativity career is summed up into *one point*. This cannot be objected as long as one solely examines the evolution of mean age at peak creativity across generations, as Galenson and Weinberg (2001) do. Yet an issue arises when age at peak creativity is used to ground a classification of observed creativity careers. Therefore, the current criticism specifically directs towards Galenson's first conclusion. An example will here help identify the problem: among artists considered in Galenson (2001), some present several creativity peaks along their career path, though these peaks are not necessarily equally high. Others on the contrary have unimodal creativity sequences. One may thus imagine – and one cannot reject in the first place – that what best distinguishes between these various artists' creativity sequences is not mainly age at peak creativity, but instead the number of creativity peaks the various sequences exhibit. By first reducing each sequence to its highest point, one inevitably overlooks this possible structuring dimension of the set of creativity careers, and one necessarily comes across a classification based on the greater or smaller precociousness of the highest creativity peak. Put shortly, by focusing on age at peak creativity and consequently reducing sequences to points, Galenson quite trivially generates a one-dimensional, two-type classification of creativity careers (young prodigies *vs*. late-bloomers), and the corresponding typology of approaches to innovation. What is more, Ginsburgh and Weyers (2006) have shown that the testimonies Galenson brings up to sustain the latter typology cannot be considered supportive of it by themselves. Cubism for instance, which Galenson regards as a typical conceptual innovation, could as well be seen, from various accounts of Picasso's and Braque's activity, as the result of repeated, though confined to a short time span, experiments on the canvas (Baxandall, 1985; Ekelund, 2002). Therefore, Galenson's typology of approaches to innovation mainly rests on his classification of patterns of creativity over the life cycle. One may thus wonder: would this typology hold true if patterns of creativity were handled differently? Specifically, this paper builds on the idea that paying attention to entire observed sequences rather than just ages at peak creativity may indicate a more suitable classification of such patterns. The following section will present the methods available to take such a step. Yet a second, related criticism ought to be articulated before going any further.

3.2. Interdependent observations and the overlooking of artistic movements

While the previous observations mostly questioned Galenson's first conclusion, the ones following rather deal with his second claim, namely that age of artists at peak creativity decreased over the generations of modern French painters. Galenson and Weinberg's demonstration that age at highest creativity significantly falls over time implicitly rests on the assumption that creativity is an *individual* phenomenon. To put it brief, they consider observed creativity careers independent of one another, in such a fashion that each individual observation – each artist's observed age at peak creativity – equally contributes to reinforcing their conclusion. Now, assume that the kind of artistic creativity peak which propels you into the 40 most acknowledged painters of your time is entirely provided, say, by interactions, or group dynamics, between artists, and that such interactions usually take place for a short period of time between artists about the same age. Also suppose that two such dynamic processes successively occured over time, the earlier process enrolling 20 old artists while the later one involved 20 young ones. There is little doubt we will come across a statistically significant drop of the most famous artists' age at peak creativity over the generations. Yet, the conclusions one can draw from such a result rest on shaky ground, as a consequence of having overlooked the interdependence of ages at peak creativity within the artistic groups.

As might already be clear, there is no real fantasy in the fictional case above. Group dynamics between artists of roughly the same age happen all the time in the history of modern art: they are called artistic movements. Galenson and Weinberg seem to overlook the importance of such movements in both defining the most acknowledged painters in modern art history and shaping their creativity careers. At best, collective artistic traditions are invoked to account for ''anomalies'' in the creative lifecourse of some painters (Galenson, 2004): Monet for instance made his major contributions at a very early age, although he can be regarded as an experimental innovator. In Galenson's view, ''the resolution of this apparent contradiction follows from the recognition that the development of innovations need not be made entirely by individual artists. Monet's early breakthrough appears to have resulted from his ability to take advantage of a research project that several older artists had begun'' (namely impressionism, the way for which was paved by forerunners such as Jongkind and Boudin). Artistic innovations are thus seen as sometimes relying on a body of more or less innovative previous work, the swift or slow assimilation of which can only marginally speed up or delay the blossoming of other artists' subsequent innovations. In contrast, I argue, one may expect intragenerational artistic movements – rather than intergenerational traditions – to play a tremendous role in shaping artists' careers. Top-ranking modern artists are typically associated with such movements, and what is regarded as their most creative work was also often produced in the context of such movements. Table 1 gives a feeling of the latter relationship by simply reporting creativity peaks (approached as most illustrated 5-year periods) over time for the 41 painters in the scope of the present study. Artists whose creativity peak can be regarded as due to their actual involvement in an artistic movement – as opposed to their mere *ex post* sorting by art historians in an loose aesthetic vein – have been grouped together under the name of the movement at stake. As one can see, movement-related peaks cluster on very short periods of time, typically the time when the movement was active.

We can now take one more step. Considering artistic movements does not only challenge the methodological robustness of Galenson and Weinberg's conclusion. At a more theoretical level, it eventually questions the content of Galenson's typology of creativity. Indeed, this typology implicitly regards approaches to innovation as idiosyncratic features, deeply rooted in each

Table 1
Overall creativity careers and 5-year periods of peak creativity over historical time (1845-1984) for the 41 French artists in Galenson (2001)[a].

Movement (if possibly accounting for creativity peak)	Name	1845-1849	1850-1854	1855-1859	1860-1864	1865-1869	1870-1874	1875-1879	1880-1884	1885-1889	1890-1894	1895-1899	1900-1904	1905-1909	1910-1914	1915-1919	1920-1924	1925-1929	1930-1934	1935-1939	1940-1944	1945-1949	1950-1954	1955-1959	1960-1964	1965-1969	1970-1974	1975-1979	1980-1984
-	Bissière																							P					
-	Bonnard																		P										
-	Cassatt										P																		
-	Cézanne													P															
-	Chagall														P														
-	Gauguin										P																		
-	Herbin																			P	P	P							
-	Manet								P																				
-	Modigliani															P													
-	Redon												P																
-	Rouault																			P									
-	Rousseau H.											P			P														
-	Seurat									P																			
-	Soutine																P	P											
-	Toulouse-Lautrec										P																		
-	Van Gogh										P																		
Impressionism	Caillebotte							P																					
Impressionism	Degas							P																					
Impressionism	Guillaumin					P																							
Impressionism	Monet					P	P																						
Impressionism	Morisot						P																						
Impressionism	Pissarro						P																						
Impressionism	Renoir							P																					
Impressionism	Sisley						P	P																					
Impressionism	Whistler							P																					
Nabi Movement	Vuillard											P																	
Fauvism	Derain													P															
Fauvism	Dufy R.												P					P											
Fauvism	Matisse													P															
Fauvism	Vlaminck													P															
Cubism	Braque													P															
Cubism	Delaunay R.														P														
Cubism	Gris														P														
Cubism	Léger															P													
Cubism	Picasso													P															
Dada	Arp															P													
Dada	Duchamp M.														P														
Dada	Picabia															P													
Surrealism	Masson																	P											
Surrealism	Miró																	P											
Surrealism	Tanguy																	P											

[a]Source: see text and Appendix A. For each artist (in rows), shaded cells represent his or her career as a succession of 5-year periods. As a convention, careers start at age 15. Letters P in one cell indicate the 5-year period where an artist was most creative, according to Galenson's computations of illustrations in art history textbooks. Artists with several Ps have several peak periods, equally illustrated. Artists whose peak seems to occur due to their involvement in an artistic movement have been grouped at the bottom of the table. The movement at stake is then reported in the left column.

artist's personality. Discussing the failed attempt by Pissarro to change his approach from experimental to conceptual by adopting a neo-impressionist technique in the 1890s, Galenson thus notes: ''Pissarro's account shows a clear awareness that an artist's ability to use a conceptual approach was not simply a matter of choice, but instead stemmed from basic traits of personality he did not possess'' (Galenson, 2004:129). To be sure, an artist's approach can be influenced by his or her early training (Galenson, 2001:164). Yet on the whole Galenson's stance toward creativity is thoroughly individualistic. This does not rule out the existence of interdependences between artists—an obvious example being the selection process outlined earlier. But there is one thing this stance also definitely has no room for, namely considering interactions between artists as a possible source for the enhancement of individual creativity, through collective mechanisms such as collaboration or competition (*e.g.* Uzzi and Spiro, 2005; Bourdieu, 1996). Galenson's typology is therefore blind to one additional dimension of creativity: does it originate in a collective mechanism or in the isolated individual?[6]

Making collective mechanisms enter the picture thus ultimately introduces a model of creativity thoroughly alternative to Galenson's one. While the latter implicitly perpetuates the myth of the creator as an isolated individual, the former challenges this view. Though not discarding the possibility of merely individual-driven innovations, it regards interactions as another plausible driving force for creativity. Can we adjudicate between these competing models, using creativity sequence data? I suggest we do so by testing whether the alternative model does better than its counterpart in accounting for Galenson's most significant observations. This requires addressing two main questions. First, do interactions between artists explain observed differences in patterns of creativity over the lifecourse better than the mere conceptual *vs.* experimental distinction? Second, does the consideration of collective mechanisms help further understand the succession of typical careers over time? The remainder of this paper is mostly designed to answer these questions, by building on the data and methods briefly presented in the following section.

4. Data and methods

Optimal matching methods have been introduced in the social sciences to measure resemblance in sequence data, *i.e.* resemblance between sets of elements of which the order of appearance matters (*e.g.* Abbott and Hrycak, 1990; Stovel *et al.*, 1996; Abbott and Tsay, 2000; Stovel, 2001; Lesnard, 2006). Such methods are used here to compare various artists' creativity careers, and ultimately generate an empirical classification of the 41 careers under examination. Implementing these methods, which are further presented in Appendix C, required noticeably

[6] Ginsburgh and Weyers (2006), though discussing the very content of Galenson's typology, fail to question its individualistic core. As a consequence, they can only test this typology with another population of artists. Finding no difference in age at peak creativity between colorists (experimentalists) and disegno artists (conceptualists), they question the relevance of Galenson's theory, but they do not really suggest an alternative account for his observations. Recent psychological work, on the other hand, has stressed the collective dimension of creativity (*e.g.* Gardner, 1993; Csikszentmihalyi, 1996). This is done mostly through the concept of field, which describes the gatekeepers – individuals and institutions – who assess an innovation and contribute to its acceptation or rejection, ultimately sometimes reshaping it through recursive loops between themselves and the creative individual. This approach has a sociological counterpart of special relevance here in the work of White and White (1965), whose emphasis on institutional changes in the 19th century French art world, and their role in the success of impressionism, is well-known. Psychological approaches have also paid attention to creative interactions between artists, of the kind that take place within artistic movements (see for example the pages Gardner, 1993:160–169 devotes to ''the partnership [between Picasso and Braque] that made cubism''; Csikszentmihalyi, 1996; for a social psychological view, see Farrell, 2001).

transforming the raw data published by Galenson, so as to neutralize interindividual variance in absolute levels of creativity, and eventually build classes of resembling careers based on similarities in the mere shape of sequences.

In the analyses below, I use the data Galenson gathered from art history textbooks only. If such data and those drawn from auctions are independent and strongly confirm each other, little information is lost this way. If on the contrary the two indices are interdependent, as might reasonably be feared, no robustness of the measures is lost when relying on one of them only. Furthermore, to the end of assessing creativity, the number of illustrations in modern art history textbooks seems more trustworthy than prices at auctions, for a reason Galenson does not bring up. Among factors possibly accounting for the variations of an artist's works' prices besides age at execution, one expects differences in scarcity of works executed at various ages to play a role. The relative dearness of paintings of a given period could hence partly result from their lesser availability.[7] Therefore, despite controls introduced by Galenson and Weinberg, the measures of creativity against age they derive from prices at auctions seem biased. On the contrary, differential availability of works of art produced at various moments of an artist's life should have little consequence on the illustration of these periods in textbooks. This is the reason why I build on the latter index below.[8]

The data I draw on have been previously published in Galenson (2001). Forty-one painters, born between 1830 and 1900 and mainly active in France over their lifetime, were first selected according to their outstanding significance in modern art history.[9] For each of these painters, the author computed the overall number of illustrations devoted to each of the 5-year periods making up her professional career, approached as the period between ages 15 and 89, in 33 English or American art history textbooks dealing with the modern era.[10] Finally, for each of the 5-year periods, the annual average number of illustrations was calculated. In this initial form, the data are here reported in Appendix A.

Consistently with our approach, the shape of individual creativity careers alone should be taken into account when assessing distances between them. This is why, for each artist, I first turn absolute levels of creativity of various periods into indices, the reference index 100 being

[7] Czujack (1997) thus finds that scarcity has a significant positive impact on prices of Picasso's works sold at contemporary auctions, for instance making the paintings from the Blue and Rose periods more expensive than the cubist ones, although the latter can hardly be considered less innovative.

[8] There is indeed one additional, implicit assumption here – as well as in Galenson's use of reference art history textbooks – namely that today's art historians are able to tell the past innovativeness of a work of art. That the creative or innovative nature of a piece is what makes it significant in modern art is not enough here. One also wants to be confident that what is perceived to have been pioneering in retrospect was likewise deemed innovative by contemporaries—rather than later constructed as innovative by critics and historians (*e.g.* Van Rees, 1983, 1987). Galenson does not explicitely sustain this hypothesis. To fill in this gap, I analyzed art historical accounts written by French critics in the 1920s, and covering the time period and locale under scrutiny here. I found them in remarkable accordance with Galenson's data when it comes to singling out the most innovative artists and their most innovative work. The identification of innovativeness, as it happens, does not seem to have evolved much over time. The equation between innovativeness and significance, however, was far less obvious back in the 1920s. According to many an author in those days, the most pathbreaking work was not necessarily bound to endure most as part of the artistic canon.

[9] Painters under consideration are those of whom at least one work is reproduced in three or more among six canonical modern art history textbooks (Galenson, 2001:194, note 17).

[10] The list of textbooks consulted can be found in Galenson (2001:222, note 1). Relevance and quality of such a measure of creativity are presented at length on pp. 24–31 of the same source. Four painters in the sample – Chagall, Masson, Miró and Picasso – lived beyond 89, but no work executed after this age is reproduced in any of the 33 textbooks. Bruegel and Galenson (2002) find that French art history textbooks provide similar measures of creativity for the various artists.

attributed to the 5-year period in which the artist receives his highest average annual number of illustrations. In a second step the values of indices are rounded off and made discrete.[11] The resulting sequences, presented in Appendix B, are the ones analyzed below.

5. Findings

Pairwise optimal matching distances between sequences were calculated with the cost specification presented in Appendix C. Applying an agglomerative clustering algorithm based on Ward's minimum variance method to these distances indicates either a two- or a four-cluster partition as most appropriate to summarize the set of careers. In Table 2 the 41 sequences are sorted according to the four-cluster partition thus obtained.[12] I shall now describe the clusters, bearing in mind the issues raised in the second section above. Does the application of an inductive categorization to entire sequences – a method *a priori* more satisfying because it is more faithful to the data – generate a classification of patterns of creativity over the life cycle different from the one Galenson proposed in the first place? If so, what precisely is different? And does this support the alternative model of creativity outlined earlier?

5.1. Short vs. long careers

The most obvious contrast between cluster 1 and all other clusters can also be seen as a fortunate one. It has to do with the mere length of sequences. As already appears by eye, painters in cluster 1 typically have short lives—hence short creativity careers. Actually, none of them goes through more than nine 5-year periods, whereas all sequences in other clusters last for at least ten such periods. Cluster 1 thus contains the sequences of artists who died young, or very young, such as Modigliani, Seurat, or Van Gogh. *T*-tests show a strong and significant difference in means of age at death between painters of cluster 1 (mean = 45.8 years old) and painters of each other cluster ($p < 0.01$). On the other hand, the differences between clusters 2 to 4 taken pairwise are neither of such magnitude, nor as significant. To be sure, painters in cluster 4 (mean = 83.8) appear to die older than those in both clusters 2 (mean = 75.4) and 3 (mean = 75.6).[13] Yet the difference does not exceed 9 years.

The optimal matching procedure thus seems to have distinguished sharply between long careers and short or very short ones. This – which in fact we had been seeking when setting the costs for optimal matching – turns out to be fortunate. Indeed, it is uneasy to analyze differences in patterns of creativity for artists whose career lengths are very unequal (see Appendix C). In the remainder of this analysis, cluster 1 is actually ignored, so as to compare patterns of creativity for artists with roughly similar lifetimes.[14]

[11] Analyses conducted with continuous values of indices yielded similar results.

[12] The two-cluster partition distinguishes between cluster 1 of Table 2 on the one hand, and all other clusters on the other. As shall be seen shortly, this distinction, if welcome, is not very interesting for the issue at stake, since it merely sets apart short- and long-lived artists – hence the decision to focus on the four-cluster partition. In the latter, differences between the mean of within-cluster distances and the mean of between-cluster distances are significant for any pair of clusters ($p < 0.001$).

[13] Both differences are significant at the $p < 0.05$ level.

[14] Artists from cluster 1 can be seen as randomly distributed across generations: there is no significant difference in means of date of birth between members of cluster 1 and members of any other cluster. Unequal distribution of very short careers over time, once again, is not the trivial reason for the decline of age at peak creativity over the generations.

Table 2
Four-cluster partition of the set of sequences, obtained with Ward's minimum variance clustering method.

Cluster	No.	Name	15–19	20–24	25–29	30–34	35–39	40–44	45–49	50–54	55–59	60–64	65–69	70–74	75–79	80–84	85–89
1	5	Caillebotte	0	0	9	3	0	0	0								
	10	Delaunay R.	0	1	9	0	0	0	0	0	0						
	14	Gauguin	0	0	0	0	0	9	4	1	0						
	15	Gris	0	1	9	1	1	0									
	19	Manet	0	0	1	9	5	3	1	9							
	23	Modigliani	0	0	1	9	0										
	25	Morisot	0	0	1	9	5	1	4	0							
	33	Seurat	0	0	9	4											
	35	Soutine	0	0	9	9	2	0	0	0							
	36	Tanguy	0	0	9	0	6	6	0	4	0						
	37	Toulouse-Lautrec	0	1	9	3	0										
	38	Van Gogh	0	0	0	2	9										
2	2	Bissière	0	0	0	0	0	0	0	0	0	0	9	0	0		
	3	Bonnard	0	1	4	6	0	1	6	0	1	3	9	3	1	0	
	7	Cézanne	0	0	0	2	1	1	3	2	3	2	9				
	17	Herbin	0	0	0	0	0	0	0	0	9	9	9	0	0		
	28	Pissarro	0	0	0	0	5	9	5	1	7	0	5	2			
	29	Redon	0	0	0	0	2	5	8	0	2	9	5	5	2		
	31	Rouault	0	1	0	4	9	1	2	1	2	2	9	1	0	0	0
	32	Rousseau H.	0	0	0	0	0	1	4	9	0	4	9				
3	6	Cassatt	0	0	0	2	5	1	9	0	0	0	0	0	0	0	
	9	Degas	0	0	1	2	4	9	3	4	1	1	0	0	0	0	
	18	Léger	0	0	1	6	9	8	1	1	6	1	0	0			
	21	Matisse	0	0	0	1	9	6	3	2	1	1	0	0	1	2	2
	26	Picabia	0	0	0	3	9	5	2	0	0	0	0	0			
	30	Renoir	0	0	6	4	9	8	4	2	1	0	1	1	1		
	34	Sisley	0	0	0	9	9	0	0	3	0	0					
	41	Whistler	0	0	4	2	6	9	1	0	0	0	0				
4	1	Arp	0	0	1	9	3	1	1	1	0	0	1	0	0	0	
	4	Braque	0	0	9	3	2	1	1	0	1	0	1	0	0	0	
	8	Chagall	0	9	9	6	2	0	0	1	2	1	0	0	0	0	1
	11	Derain	0	0	9	0	0	0	0	0	1	0	0	0			
	12	Duchamp M.	0	1	9	4	4	0	0	0	0	0	0	0	0	0	
	13	Dufy R.	0	0	9	0	0	0	0	9	0	0	0	3	0		
	16	Guillaumin	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0
	20	Masson	0	0	2	9	0	2	7	0	0	0	0	0	0	0	0
	22	Miró	0	1	2	9	2	7	4	0	0	0	1	0	0	0	0
	24	Monet	0	0	9	9	5	1	1	9	1	1	1	0	1	4	1
	27	Picasso	0	4	9	8	1	5	2	2	3	0	0	0	0	0	0
	39	Vlaminck	0	1	3	9	0	0	0	0	1	0	1	0	0	0	
	40	Vuillard	0	4	9	7	1	3	0	0	0	0	0	0			

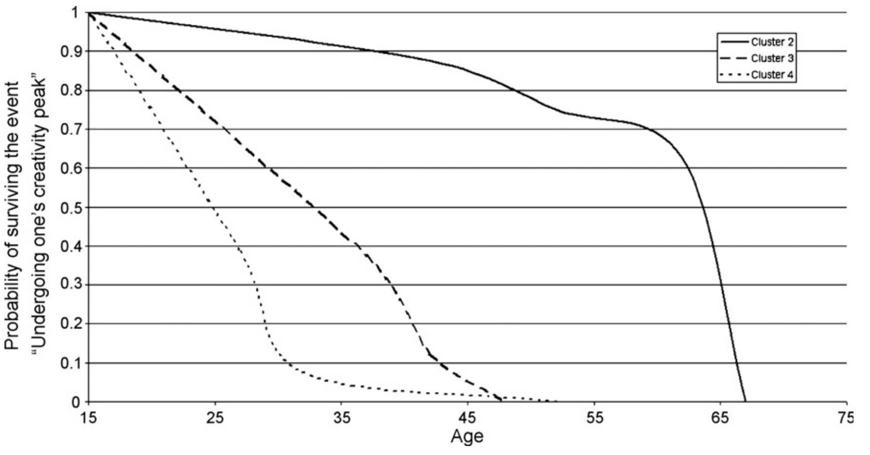

Fig. 1. Survival functions to the event ''Undergoing one's creativity peak'' for artists of clusters 2 to 4. (Reading: artists in cluster 4 have a 0.05 probability of not having had their creativity peak at age 35.)

5.2. Age at peak creativity

Let us now focus on what Galenson considers to be the main variable of interest, namely age at peak creativity. The inductive approach to categorization implemented with optimal matching actually stresses this variable as relevant. Yet Galenson's distinction of early *vs*. late peaks, as also his conception of a continuum between them, need to be further worked out.

On average, artists in clusters 2 to 4 respectively exhibit peaks at ages 61, 40 and 30.[15] Fig. 1 plots survival functions to the event ''Undergoing one's creativity peak'' for artists in the three clusters. It calls for a number of comments.

First, age at peak creativity obviously plays a role in carving out the various clusters. Specifically, the sequence analysis approach clearly disentangled a group of late peakers (in cluster 2) from a group of early ones (in clusters 3 and 4). Yet, the large gap in Fig. 1 between the solid line on the one hand and the dashed lines on the other also surprisingly suggests a sharply bimodal distribution of creativity peaks. A more careful look at Table 2 actually confirms this feeling. Creativity peaks in clusters 2 to 4 concentrate on two main ranges of ages, far remote from one another—before 44 on the one side, and after 65 on the other. Peaks on the contrary occur relatively seldom between ages 45 and 65. Fig. 2, showing the distribution of the number of creativity peaks by age for artists in clusters 2 to 4, further supports this idea of a bimodal distribution of the population between late and early innovators, as does also a clustering of long sequences based merely on age at peak creativity. This, in contrast to Galenson's view, makes a case for a not so ideal-typical interpretation of the division between early and late innovators. Our endogeneous categorization thus challenges the very nature of Galenson's distinction: instead of seeing early and late-bloomers as extreme cases at the ends of a continuum, one should rather wonder what mechanism generates such a clear-cut bimodal distribution of creativity peaks.

[15] Age at peak creativity is here calculated as age at the middle of the most illustrated 5-year period. When there were several such periods, I picked the age closest to the market measure reported in Galenson (2001). Age at peak creativity can be considered non-normally distributed in all three clusters. Non-parametric tests indicate significant pairwise differences in means between all clusters taken pairwise ($p < 0.01$).

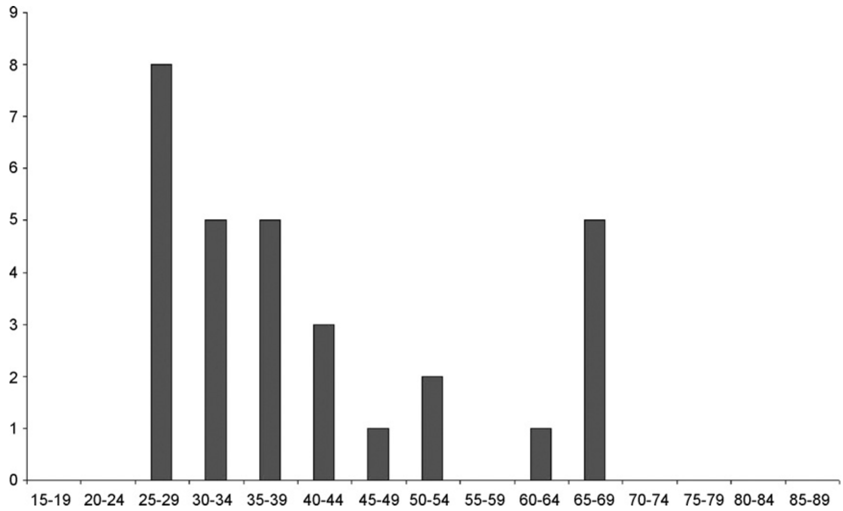

Fig. 2. Distribution of the number of creativity peaks by age of occurrence for artists with long careers. (Artists in clusters 2 to 4 only are considered. For artists with several most illustrated 5-year periods, I picked the period closest to the market measure of peak creativity reported in Galenson (2001).)

To be sure, one could also here just drop this idea of continuum, and stick to a strictly bipartite version of Galenson's model of creativity. Remarkably, though, Galenson's ultimate identification of conceptual and experimental innovators seems to do a fairly poor job at explaining the observed bimodal distribution of creativity peaks. Although the author nowhere provides a comprehensive sorting of individual artists in conceptual and experimental innovators, it is possible, drawing on Galenson (2001, 2004, 2008), to quite unambiguously ascribe a creativity type to 23 of the 29 artists in clusters 2 to 4. The result is presented in Table 3.

All three artists belonging to cluster 2 in Table 2 (*i.e.* to the ''late peaks'' part of the bimodal distribution of peaks) whose type can be identified are indeed sorted by Galenson as experimental innovators. However, 10 out of the 20 artists belonging to the ''early peaks'' part and whose creativity type is about clear are also considered experimentalists in Table 3. Hence, unless we resort to additional *ad hoc* explanations, Galenson's distinction of experimental *vs.* conceptual artists seems of little use to account for the main pattern of interest in the data on peaks, namely their bimodal distribution and the relative gap of peaks between ages 45 and 64. Note that this does not mean that the artists Galenson refers to as experimentalists do not have significantly later peaks. They really do. Yet, again, the lack of fit of Galenson's theory with the pattern in the data suggests that there might be more powerful explanations for the observed distribution of creativity peaks.

Fig. 1 furthermore makes it clear that the split introduced by the optimal matching approach between clusters 3 and 4 likewise has to do with age at peak creativity. More precisely, the latter clusters comprise careers respectively exhibiting early and very early peaks. When trying to account for the typical shapes of observed creativity careers, one should therefore provide an explanation that makes sense of this observed distinction. As we shall see, such an explanation can be found by turning to simple covariates associated with membership in the various clusters. The split between clusters 3 and 4 thus cannot be considered a mere refinement. It reveals a pattern of substantial interest in the data.

That the various splits between clusters 2, 3 and 4 somehow pertain to age at peak creativity could finally suggest that the classification produced with optimal matching methods in fact boils down to a clustering merely based on age at peak creativity. When we take a closer look, however, this conclusion proves misleading for at least two reasons.[16] First, a classification solely resting on age at peak suggests a two- rather than a three-cluster partition as most relevant for the purpose of describing the 29 long careers. Not too surprisingly, in this two-cluster partition each of the clusters centers on one of the modes in the bimodal distribution of peaks charted in Fig. 2. If, notwithstanding, we break down the classification so as to distinguish three clusters, the latter do not exactly overlap with the clusters obtained from optimal matching methods. In particular, Dufy, Pissarro and Henri Rousseau are not sorted similarly in the two partitions. As we will see shortly, these differences pertain to the fact that the steadiness of careers, and not only age at peak creativity, shapes the partition obtained from optimal matching distances.[17]

5.3. Creativity careers' steadiness

Differences in age at peak creativity actually do not account alone for the observed splits between late, early and very early innovators. There is more to these splits, and this can be regarded as a true contribution of the sequence analysis approach, since they also partly rest on differences in the shape of entire creativity sequences. More specifically, typical sequences cannot be regarded as equally steady.

For each sequence, a steadiness index can be computed as the mean of creativity indices outside the peak. The higher that index, the more equally an artist's creativity spreads between his peak and other moments of his career. There are no significant differences, as far as this index is concerned, between sequences in cluster 3 on the one hand and clusters 2 or 4 on the other.[18] In contrast, sequences in cluster 2 (mean steadiness = 1.63) and cluster 4 (mean = 0.98) differ significantly with respect to their steadiness ($p < 0.05$). Late-bloomers thus enjoy noticeably steadier creativity careers than some (but some only) of their young prodigies counterparts. This observed difference is definitely a payoff of our focusing on whole sequences instead of isolated creativity peaks. At first glance, it also seems to support Galenson's typology of innovators. Indeed, due to their incremental approach, experimental innovators are expected to produce significant paintings over longer periods. If their main contributions take the form of repeated and gradually improved experimental canvases, then arguably their important work will not only spread over more paintings, but also over longer spans of time (Galenson, 2002a: 14–15). This apparently happens in cluster 2—provided we regard the late-peakers gathered in this cluster as

[16] The following observations rest on the analysis of a clustering of the 29 long careers based on age at peak creativity, measured as age at the middle of the most illustrated 5-year period.

[17] Although it does not appear as the most relevant partition based on optimal matching distances, one might finally also want to compare a two-cluster partition of long sequences obtained from such distances with the two-cluster partition pointed out by a clustering based merely on age at peak creativity. These two partitions are actually at odds: the latter, as has just been seen, groups careers with early and very early peaks on the one hand, and careers with late peaks on the other. On the contrary, the two-cluster partition obtained from optimal matching distances groups early and late peaks (clusters 2 and 3 in Table 2) on the one hand, *vs.* very early peaks (cluster 4) on the other. One of its clusters is therefore fairly heterogenous in terms of age at peak creativity. Actually, the split between the two clusters is better described in terms of steadiness, with one cluster made up of steady careers while the other comprises more irregular ones. Again here, it can be shown that Galenson's identification of experimental *vs.* conceptual innovators is of little help to explain this split.

[18] Within each cluster, values of the index are fairly normally distributed. *T*-tests for the difference in means between cluster 3 on the one hand and clusters 2 or 4 on the other were never significant at the $p < 0.05$ level. I found no other obvious difference in shape between the sequences of clusters 2 to 4.

Table 3
Experimental and conceptual innovators in clusters 2 to 4, according to Galenson (2001, 2004, 2008).

Name	Approach to innovation
Arp	Experimental
Bissière	–
Bonnard	Experimental
Braque	Conceptual
Cassatt	Experimental
Cézanne	Experimental
Chagall	–
Degas	Experimental
Derain	Conceptual
Duchamp M.	Conceptual
Dufy R.	Conceptual
Guillaumin	Experimental
Herbin	–
Léger	Conceptual
Masson	Experimental
Matisse	Conceptual
Miró	Experimental
Monet	Experimental
Picabia	Conceptual
Picasso	Conceptual
Pissarro	Experimental
Redon	–
Renoir	Experimental
Rouault	–
Rousseau H.	–
Sisley	Experimental
Vlaminck	Conceptual
Vuillard	Conceptual
Whistler	Experimental

experimentalists. Conversely, conceptual innovators' breakthroughs should typically concentrate on very short periods, and as a consequence their creativity careers should be more uneven, which is the case in cluster 4. In a sense, observed variations in steadiness therefore support Galenson's interpretation of the distinction between early and late innovators. Yet in a sense only, since early innovators in cluster 3 paradoxically *do not* exhibit significantly less even creativity careers than late innovators in cluster 2. This apparent anomaly could be accounted for in a way still respectful of Galenson's interpretation. Artists gathered in cluster 4 could be seen as extreme, and those in cluster 3 as moderate, conceptual innovators. The features of the latter, if still typical of conceptual innovators, would also make them slightly closer to experimental ones, with respect to career steadiness in particular. This explanation certainly cannot be discarded. But one should not lose sight of the fact that it reintroduces the notion of a continuum between late and early bloomers, or experimental and conceptual innovators. In contrast, I shall hereafter provide another explanation of pairwise differences in steadiness in clusters 2 to 4, consistent with the mechanism that also accounts for the bimodal distribution of artists into early and very early innovators on the one side, and late ones on the other. Differences in steadiness thus ought to be borne in mind as a piece of the puzzle as we now turn to further, external covariates correlated with membership in the various clusters.

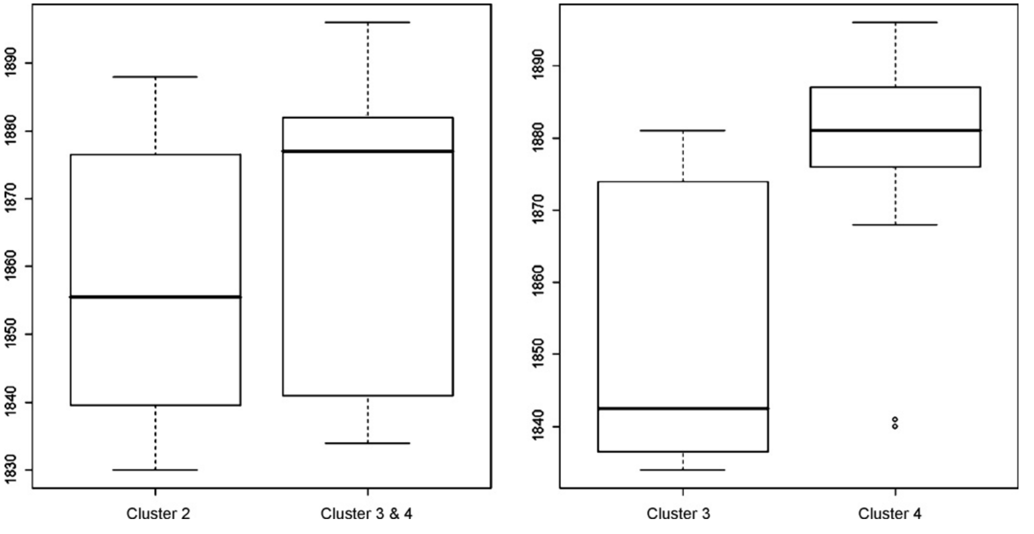

Fig. 3. Date of birth of artists in clusters 2 to 4.

5.4. Generations

The first of these covariates brings us back to Galenson's second conclusion. Recall that, according to Galenson, age at peak creativity drops over time as a consequence of a selection process of conceptual innovators—whom he associates with early creativity peaks – over experimental ones. As a consequence, one may here expect late-peaker artists in cluster 2 to be born earlier than artists in clusters 3 and 4. This, yet, is not the case, as graphically shown in the left chart of Fig. 3.[19] In contrast, an unexpected and significant generational difference appears between painters in cluster 3 (mean date of birth = 1853) and those in cluster 4 (mean = 1873) ($p < 0.05$; see right chart in Fig. 3).

In sum, artists with late creativity peaks do not significantly more often belong to earlier generations. As a consequence, Galenson's claim that the drop of age at peak creativity over time is due to the ousting of late, experimental innovators by early, conceptual ones does not fit our findings.

Instead, this drop seems driven by a process that makes age at peak creativity decrease over time, among so-called conceptual innovators, from early to very early peaks. Focusing on one more covariate to membership in clusters 2 to 4 will help uncover that process.

5.5. Artistic movements

Going back to the second criticism articulated in Section 2, I now address the issue of the role of artistic movements as possibly shaping patterns of creativity of artists over their life cycle. In order to do so, I first create a dummy variable recording involvement of artists in such

[19] Date of birth can be considered non-normally distributed in clusters 3 and 4 taken together or separately. Non-parametric tests show no significant differences in means of year of birth between cluster 2 on the one hand, clusters 3 and 4 taken together or separately on the other. Mean date of birth is 1858 in cluster 2, 1853 in cluster 3, and 1873 in cluster 4.

movements. It takes the value 1 if an artist is documented to have been an actual member of a self-aware, organized artistic movement at least once over his lifetime, and the value 0 otherwise. Actual involvement in a movement for instance implies that an artist signed this movement's manifesto, or voluntarily took part to exhibitions explicitely held under the label of this movement. I seek to discard affiliations of artists to movements performed *ex post* by art dealers or modern art historians. Among the 29 painters in clusters 2 to 4, four only seem to never have been actually involved in any artistic movement (Bissière, Chagall, Redon and Henri Rousseau). In a second step, I test for the independence of involvement in movements and membership in cluster 2 on the one hand, 3 and 4 taken together on the other.[20] Artists in clusters 3 and 4 seem to take part in movements more often than their counterparts in cluster 2 (Bissière, Redon and Rousseau all belong to cluster 2, Chagall alone belongs to cluster 4). However, statistical significance here is questionable. It might thus be that involvement in artistic movements shapes creativity careers towards earlier creativity peaks, yet being too conclusive on that topic appears somewhat rash.

The problem can actually be reframed, in a fashion both more precise and more consistent with the developments above—especially with the intuition summarized in Table 1. Indeed, the divide between clusters 3 and 4 on the one side and cluster 2 on the other is not so much between artists who once enrolled in movements and artists who never did. Rather, it opposes painters whose peak is associated with their involvement in a movement to painters whose peak is not. Put differently, painters in clusters 3 and 4 more often "owe" their peak to their participation in an artistic movement. To show this, I build an extra variable reporting whether an artist's peak is chronologically associated with his involvement in a movement. This variable takes the value 1 if an artist's peak is related to his actual belonging to a self-aware, organized movement by the time the peak occurs, and 0 otherwise. Seven painters do not seem to owe their peak to such an involvement (Bissière, Bonnard, Cézanne, Chagall, Redon, Rouault and Rousseau). An additional test shows that artists in clusters 3 and 4 significantly more often have their peak associated with their participation in a movement than those in cluster 2 ($p < 0.01$). Six of the seven painters previously mentioned actually belong to cluster 2, and only two painters in that cluster have their peak associated with their involvement in a movement. Conversely, Chagall is the only painter, out of 21 in clusters 3 or 4, whose peak cannot be related to his participation in a movement. Hence, for the use of describing the set of creativity careers, a powerful demarcation lies between artists whose peak is the outcome of their involvement in a movement, and others. Note that this demarcation also matches the clear-cut divide between early (in clusters 3 and 4) and late-bloomers (cluster 2).[21] In accounting for the bimodal distribution of creativity peaks over age, then, it is clear that Galenson's distinction between conceptual and experimental innovators should better be recast as a distinction between movement-related innovators and others. This challenges the underlying assumption in Galenson's view, namely that artistic creativity ought to be considered as originating in the mere individual. On the contrary, artistic movements, doubtless an instance of interactions between artists, matter when it comes to understanding observed differences in patterns of creativity over the life cycle.

To summarize, individuals involved in movements generally owe their peak to this involvement—the odds here are 22 to 3. Provided this is the case, their peak occurs early, both

[20] The test used was Fisher's exact test, best suited to the study of small *n* populations.

[21] More precisely, movement-related peaks occur on average at 36, while their non-movement-related counterparts occur at 58.

because artists enroll in movements early (further analysis shows that, on average, they do so at 32) and because participation in a movement has immediate rewarding effects in terms of creativity—movements generally revolve around an innovation, or a family of innovations, from the very outset. If, as may still happen, artists involved in a movement *do not* owe their peak to this involvement,[22] then their creativity sequence resembles that of artists who do not partake in any movement over their lifetime. Their careers are steadier, and their peak occurs way later.[23]

5.6. Individual careers and the dynamics of movements

It is finally possible to go one step further, by relating this finding on movements to the ''generation puzzle'' observed earlier—the fact that the generation gap cannot be found where it was expected (between cluster 2 and cluster 3 or 4), but on the contrary occurs where it should not (between clusters 3 and 4). Here, recall that painters in cluster 3 do not only exhibit later peaks, but were also born earlier than painters in cluster 4. Additionnally, we now know that painters in both clusters 3 and 4 tend to owe their creativity peak to their involvement in artistic movements. It follows that artists whose peak is associated with their involvement in a movement have earlier and earlier peaks over the generations. This, though, could in turn have been generated by two very different processes. Artists of various ages could have enrolled in a unique movement (or in roughly co-occurring movements); or successive movements could have recruited younger and younger artists.[24] Actually, the second solution suits the data better. In particular, two-thirds of the painters in cluster 3 are affiliated with impressionism, a movement clearly prior to all other movements under consideration here. Moreover, cluster 3 contains no painter involved in surrealism, the latest movement in the period. On the contrary, three out of four painters in cluster 4 are affiliated to fauvism or a later movement, and all surrealist painters in the sample belong to the latter cluster. We are therefore in a position to conclude: in the population under study, later movements seem to have provided earlier creativity peaks—to artists owing their peak to movements.[25] In other words, the pattern of artistic movements on the time axis, together with the age structure of artists they recruit, can be regarded as driving the decline of age at peak creativity over the generations. Not only can we thus discard Galenson's account of this decline – the idea that conceptual innovators ousted experimental ones. It is also possible to point to the dynamics of movements as the relevant level of analysis for suggesting an alternative one.

[22] For example because they were marginal to the movement, or because the movement was not very successful in producing pathbreaking innovations.

[23] This is the reason for the imperfect association observed earlier between age at peak and involvement in a movement: late peakers (in cluster 2) are fairly heterogenous with respect to their initial participation or non-participation in movements.

[24] There is as a matter of fact little chronological overlap between movements, which can be considered fairly delimited in time. The chronological order of movements is therefore clear-cut enough, as Table 1 was already showing: impressionism, the nabi movement, fauvism, cubism, dada and surrealism.

[25] This is further confirmed by a glance at mean age at peak creativity of artists owing their peak to the diverse movements (as approached in Table 1). Impressionists on average exhibit a peak at 36, significantly older than artists of all succeeding movements: these on average have a peak at 30. By the time of their highest creativity, fauve artists were approximately 30, cubists under 28, dadaists and surrealists respectively just above and just under 31. Focusing on age at involvement in a movement yields almost identical figures. That the two later movements – dadaism and surrealism – seem to break the pattern of a decline of age at peak (or involvement) over time may be due to the delaying effect of World War I.

Better insight in such dynamics may finally come from briefly focusing on one more piece of the puzzle. As noted earlier, artists in cluster 2 on average have more even careers than the ones in cluster 4. On the contrary, careers in respectively clusters 2 and 3 cannot be considered different as far as their steadiness is concerned. Now suppose that involvement in a movement does not only generate innovative artistic achievements by the time of an artist's peak, but also shapes her work for a longer period. Though it should be further investigated, the latter assumption does not sound too blatantly at odds with the careers of most artists in clusters 3 and 4. Under such an assumption, pairwise differences in steadiness in clusters 2 to 4 can receive the following, simple interpretation. Over the generations, movement-driven innovation did not only occur at earlier and earlier ages; it also provided ever shorter-lasting flows of important work. As a consequence, earlier generations of movement-driven innovators do not differ significantly from late innovators with respect to career evenness. Later generations of movement-driven innovators, in contrast, exhibit noticeably less steady careers than late innovators.

These various conclusions may be considered a first glimpse in the underlying dynamics of movements yielding the successive observed patterns of individual creativity. Numerous reasons could of course explain both the decreasing steadiness of movement-driven creativity and the fact that later movements provided earlier peaks, and adjudicating between these reasons may fall beyond the scope of this work. Nonetheless, considering these patterns together suggests a simple, plausible story. In the late 1860s and the 1870s, impressionism emerged as an artistic movement independent from the French academy, yielding original pieces of art by a number of closely connected individuals (*e.g.* White and White, 1965). Some 30 years later, it had become obvious, from the appraisal of both critics and the art market, that the movement had actually generated the most creative art in its time. This might have spurred new-coming (and therefore young) artists of the early 20th century into reacting to the first movement by themselves organizing into movements – since this now appeared as a powerful way to leave a mark in art history – to produce challenging, innovative works. Put briefly, new movements might have responded to the old one by adopting the same organizational shell, yet with an innovative content. Such a response, if repeated by several successive generations of newcomers, could not only have taken down age at peak creativity in later movements, or at least kept it low. It could also have caused the observed decreasing steadiness of movement-driven creativity. Indeed, newcomers commited to the aesthetics of a movement can only be considered innovative as long as the next generation of newcomers, devoted to another, reacting aesthetics, has not yet entered the picture. Therefore, and though simple enough, this model of movements dynamics could explain the observed changes in movement-driven creativity careers over the generations.

6. Conclusion

Examining the creativity careers of 41 most acclaimed modern painters through optimal matching methods thus yields a picture fairly different from the one proposed by Galenson. The early *vs*. late-bloomers partition, to be sure, remains roughly relevant to classify entire careers. Yet I first find that artistic movements, rather than individual approaches to innovation, play a key role in explaining this partition, with early-bloomers generally owing their creativity peak to their involvement in one such movement while late-bloomers do not. Galenson's typology of conceptual *vs*. experimental innovators, furthermore, fails to explain the striking gap between the age of respectively early and late-bloomers at peak creativity.

Is there a way to reconcile this first finding with Galenson's explanation of patterns of creativity? One could of course argue that conceptual innovators are typically those whose creativity comes forth within artistic movements. This, however, would entail a very different outlook on conceptual innovation. Instead of being the implementation of ideas shaped in the mind of lonesome creators, it would have to be seen as the outcome of a collective process made of interactions – collaboration, mutual support, emulation – between artists within movements. Conversely, experimental innovations could no longer be regarded as merely generated through repeated experiments. They would instead need to be redefined as breakthroughs due to artists working on their own. As can be seen, most of the content of Galenson's concepts would be lost in the operation.

I also find no clear-cut evidence of an ousting of so-called experimental innovators by conceptual ones over time. Artists with late creativity peaks do not significantly more often belong to earlier cohorts. Instead, movements seem to account for the drop of age at peak creativity over the generations of modern French painters. This, I suggest, can be regarded as the outcome of a mechanism involving interactions again—in this instance, competition and the borrowing of an organizational form. Over time, organizing into movements increasingly became a strategy for artists eager to supplant older, more established ones. This strategy spread after the success of the impressionnists, once it had become clear that at least some contemporaries regarded movements as the place where significant contemporary art was being produced. As an organizational form, movements thus became appealing to young, ambitious artists. Such a mechanism, as I have shown, also has the advantage of accounting for the decreasing steadiness of creativity over the lifecourse in later generations of painters owing their peak to movements.

Back to the main issue at stake, we can finally adjudicate between the competing models of creativity outlined earlier. Galenson's model involves individuals endowed with a particular approach to creativity, seen as a permanent, personal feature. It also introduces interdependences between artists – in the form of a selection process in an evolving context – to explain the drop of age at peak creativity over the generations. In the alternative account I suggested, individual creativity is not considered fixed, but rather depends on interactions between artists. More precisely, common membership in an artistic movement (a proxy for interactions such as collaboration or emulation), as well as competition and borrowings between movements, can drive the unfolding of creativity over individual careers and historical time.

Empirically, taking movements seriously does help better understand differences of shape between creativity careers. It also sheds better light on the succession of typical careers over time. Therefore, interactions seem to matter when it comes to explaining observed patterns of individual innovation, and this eventually pleads for our second model of creativity. More generally, it also makes a case for bridging the study of individual artists with sociological accounts of the collective settings in which artistic activity unfolds.

Acknowledgements

I am grateful to the Institute for Social and Economic Research and Policy at Columbia University for its hospitality while writing part of this article. For suggestions and criticisms, I thank the editor of this journal and three anonymous referees. I am also indebted to Hrag Balian, Peter Bearman, Claire Lemercier, and Harrison White for helpful comments on earlier drafts. Responsibility for errors and misinterpretations remains mine.

Appendix A

Mean number of illustrations a year for each 5-year period of each artist[a].

No.	Name	Sex	Country of Birth	Date of Birth	Date of Death	15–19	20–24	25–29	30–34	35–39	40–44	45–49	50–54	55–59	60–64	65–69	70–74	75–79	80–84	85–89
1	Arp	M	France	1886	1966	0	0	0.2	3	1	0.4	0.2	0.2	0	0	0.2	0	0	0	
2	Bissière	M	France	1888	1964	0	0	0	0	0	0	0	0	0	0	0.6	0	0		
3	Bonnard	M	France	1867	1947	0	0.2	0.6	1	0	0.2	1	0	0.2	0.4	1.6	0.4	0.2	0	
4	Braque	M	France	1882	1963	0	0.4	12.6	3.4	2	1	1.6	0	1.2	0	0.8	0.2	0	0	
5	Caillebotte	M	France	1848	1894	0	0	0.8	0.2	0	0	0								
6	Cassatt	F	USA	1845	1926	0	0	0	0.4	1	0.2	2.2	0	0	0	0	0	0	0	
7	Cézanne	M	France	1839	1906	0	0.2	0.4	3	1.2	1.8	4.2	2.6	4	2.2	12.7				
8	Chagall	M	Russia	1887	1985	0	2	2.2	1.4	0.4	0	0	0.2	0.4	0.2	0	0	0	0	0.2
9	Degas	M	France	1834	1917	0	0.2	0.8	1.2	2.2	6	1.8	2.6	0.8	0.4	0.2	0	0	0	
10	Delaunay R.	M	France	1885	1941	0	0.4	5.4	0	0	0	0	0	0						
11	Derain	M	France	1880	1954	0	0	4.6	0.2	0	0.2	0	0	0.4	0	0	0			
12	Duchamp M.	M	France	1887	1968	0	0.8	7.2	3.2	3.2	0	0	0	0	0	0	0	0	0	
13	Dufy R.	M	France	1877	1953	0	0	0.6	0	0	0	0	0.6	0	0	0	0.2	0		
14	Gauguin	M	France	1848	1903	0	0	0	0	0.4	13.2	5	0.8	0						
15	Gris	M	Spain	1887	1927	0	0.2	2.8	0.4	0.4	0									
16	Guillaumin	M	France	1841	1927	0	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0
17	Herbin	M	France	1882	1960	0	0	0	0	0	0	0	0	0.2	0.2	0.2	0	0		
18	Léger	M	France	1881	1955	0	0	0.4	1.8	3	2.4	0.2	0.2	1.8	0.4	0	0			
19	Manet	M	France	1832	1883	0	0	1.4	10.4	5.6	3	1.2	10.5							
20	Masson	M	France	1896	1987	0	0	0.2	1.2	0	0.2	0.8	0	0	0	0	0	0	0	0
21	Matisse	M	France	1869	1954	0	0	0.6	1	13	7.4	3.4	2.4	1.2	0.8	0.6	0.4	0.8	2.2	2.2
22	Miró	M	Spain	1893	1983	0	0.4	1	4.4	1	3.2	1.6	0	0.2	0.2	0.6	0.2	0	0	0
23	Modigliani	M	Italy	1884	1920	0	0	0.2	1.8	0										
24	Monet	M	France	1840	1926	0	0	5.6	5.6	2.8	0.6	0.6	5	0.2	0.6	0.6	0	0.8	2	0.6
25	Morisot	F	France	1841	1895	0	0	0.2	1.6	0.8	0.2	0.6	0							
26	Picabia	M	France	1879	1953	0	0	0	0.6	2	1	0.4	0	0	0	0	0			
27	Picasso	M	Spain	1881	1973	0.4	7.4	18.4	14.8	2	9.6	3.2	3	6.4	0.6	0.4	0.4	0.2	0	0
28	Pissarro	M	Denmark	1830	1903	0	0	0	0	1	2.2	1	0.2	1.6	0	1.2	0.4			
29	Redon	M	France	1840	1916	0	0	0	0	0.2	0.6	1	0	0.2	1.2	0.6	0.6	0.2		
30	Renoir	M	France	1841	1919	0	0	2.4	1.6	4	3.2	1.6	0.6	0.4	0	0.2	0.4	0.4		
31	Rouault	M	France	1871	1958	0	0.2	0	0.8	1.6	0.2	0.4	0.2	0.4	0.4	1.8	0.2	0	0	0
32	Rousseau H.	M	France	1844	1910	0	0	0	0	0	0.2	0.8	2	0	0.8	2				
33	Seurat	M	France	1859	1891	0.2	0.4	9.4	3.3											
34	Sisley	M	France	1839	1899	0	0	0	0.6	0.6	0	0	0.2	0	0					
35	Soutine	M	Lithuania	1893	1943	0	0	1.2	1.2	0.2	0	0	0							
36	Tanguy	M	France	1900	1955	0	0	1	0	0.6	0.6	0	0.4	0						
37	Toulouse-Lautrec	M	France	1864	1901	0	0.8	5.4	1.8	0										
38	Van Gogh	M	Netherlands	1853	1890	0	0	0.4	5.6	28.7										
39	Vlaminck	M	France	1876	1958	0	0.2	0.6	1.8	0	0	0	0	0.2	0	0.2	0	0	0	
40	Vuillard	M	France	1868	1940	0	0.6	1.4	1	0.2	0.4	0	0	0	0	0	0			
41	Whistler	M	USA	1834	1903	0	0	1	0.4	1.6	2.6	0.2	0	0	0	0				

[a] Source: Galenson (2001). Reading: each year of Braque's activity period between ages 25 and 29 is on average illustrated by 12.6 reproductions in the whole set of art history textbooks.

Appendix B

Mean number of illustrations a year for each 5-year period of each artist, indices in 10 classes[a].

No.	Name	15–19	20–24	25–29	30–34	35–39	40–44	45–49	50–54	55–59	60–64	65–69	70–74	75–79	80–84	85–89
1	Arp	0	0	1	9	3	1	1	1	0	0	1	0	0	0	
2	Bissière	0	0	0	0	0	0	0	0	0	0	9	0	0		
3	Bonnard	0	1	4	6	0	1	6	0	1	3	9	3	1	0	
4	Braque	0	0	9	3	2	1	1	0	1	0	1	0	0	0	
5	Caillebotte	0	0	9	3	0	0	0								
6	Cassatt	0	0	0	2	5	1	9	0	0	0	0	0	0	0	
7	Cézanne	0	0	0	2	1	1	3	2	3	2	9				
8	Chagall	0	9	9	6	2	0	0	1	2	1	0	0	0	0	1
9	Degas	0	0	1	2	4	9	3	4	1	1	0	0	0	0	
10	Delaunay R.	0	1	9	0	0	0	0	0	0						
11	Derain	0	0	9	0	0	0	0	0	1	0	0	0			
12	Duchamp M.	0	1	9	4	4	0	0	0	0	0	0	0	0	0	
13	Dufy R.	0	0	9	0	0	0	0	9	0	0	0	3	0		
14	Gauguin	0	0	0	0	0	9	4	1	0						
15	Gris	0	1	9	1	1	0									
16	Guillaumin	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0
17	Herbin	0	0	0	0	0	0	0	0	9	9	9	0	0		
18	Léger	0	0	1	6	9	8	1	1	6	1	0	0			
19	Manet	0	0	1	9	5	3	1	9							
20	Masson	0	0	2	9	0	2	7	0	0	0	0	0	0	0	0
21	Matisse	0	0	0	1	9	6	3	2	1	1	0	0	1	2	2
22	Miró	0	1	2	9	2	7	4	0	0	0	1	0	0	0	0
23	Modigliani	0	0	1	9	0										
24	Monet	0	0	9	9	5	1	1	9	1	1	1	0	1	4	1
25	Morisot	0	0	1	9	5	1	4	0							
26	Picabia	0	0	0	3	9	5	2	0	0	0	0	0			
27	Picasso	0	4	9	8	1	5	2	2	3	0	0	0	0	0	0
28	Pissarro	0	0	0	0	5	9	5	1	7	0	5	2			
29	Redon	0	0	0	0	2	5	8	0	2	9	5	5	2		
30	Renoir	0	0	6	4	9	8	4	2	1	0	1	1	1		
31	Rouault	0	1	0	4	9	1	2	1	2	2	9	1	0	0	0
32	Rousseau H.	0	0	0	0	0	1	4	9	0	4	9				
33	Seurat	0	0	9	4											
34	Sisley	0	0	0	9	9	0	0	3	0	0					
35	Soutine	0	0	9	9	2	0	0	0							
36	Tanguy	0	0	9	0	6	6	0	4	0						
37	Toulouse-Lautrec	0	1	9	3	0										
38	Van Gogh	0	0	0	2	9										
39	Vlaminck	0	1	3	9	0	0	0	0	1	0	1	0	0	0	
40	Vuillard	0	4	9	7	1	3	0	0	0	0	0	0			
41	Whistler	0	0	4	2	6	9	1	0	0	0	0				

[a] For each artist, indices of creativity were first calculated for each of her 5-year periods, with the reference index 100 being attributed to the period with highest average annual number of illustrations. In this table, the latter indices have been approximated by discrete numbers, according to the following schedule: [0; 5[= 0; [5;15[= 1; [15; 25[= 2; [25; 35[= 3; [35; 45[= 4; [45; 55[= 5; [55; 65[= 6; [65; 75[= 7; [75; 85[= 8 ; [85; 100] = 9.

Appendix C

This is not the place to give a detailed account of optimal matching methods. To put things briefly, they consist into measuring pairwise distances between sequences made up of common elements, or states, by assessing, for each pair of sequences, the minimum number of operations, weighted by their respective "cost", necessary to transform one sequence into the other. The operations involved can be of two kinds: substituting an element for another within a sequence, or merely inserting (or deleting) an element in (from) the sequence. Let us for example imagine sequences formed of states represented by the letters A, B and C. How, then, can one transform the sequence ABABAC into the sequence ABBAB? There are actually several solutions: one might want to keep the first two states, then substitute a B for an A, an A for a B, another B for an A, and delete the remaining C. Or one could simply delete the second A, and substitute a B for a C at the end of the sequence. A cost is associated with each of these operations.[26] Measuring the distance between two sequences comes down to selecting the set of elementary operations of which the total cost is lowest.

Assigning costs suited to the researcher's ultimate purpose is an important step, since obtained pairwise distances between sequences may significantly vary for various cost specifications. Parameters of the algorithm measuring distances have therefore to be set in a fashion consistent with the kind of patterns or regularities one seeks to uncover (Abbott, 2000).

In the present instance, positions individuals can occupy at any point in time (at any 5-year period of creativity) are ordered along a linear scale ranging from 0 to 9 (see Appendix B). As a consequence, setting the relative value of various substitution costs should not raise much difficulty. Indeed, for a given point in time, the closer the positions two sequences occupy on the scale, the more alike these sequences.[27] In other words, one can logically assign to the substitution of element x for element y the cost: $S_{xy} = |x - y|$. Substitution costs therefore range from 1 to 9.

Setting the cost of insertions and deletions (so-called "indel") now amounts to tackling the thorniest issue, namely specifying the relative weight of indel and substitution costs. If still problematic, this issue has been explored by several scholars, and one can here rely on a number of guidelines.

1. Early studies implementing sequence analysis in sociology tended to set the indel cost at fairly high values (typically larger than that of the largest possible substitution cost (*e.g.* Abbott and Hrycak, 1990)). This strategy partly rested on the following observation: setting the indel cost at a value under half the greatest substitution cost would imply systematically avoiding such an expensive substitution, because the algorithm would always prefer to get round the latter by instead using in turn one deletion and one insertion. On the other hand, it has been objected

[26] There should indeed be as many costs as there are possible insertions and deletions of elements, and replacements of one element by another. This, in case an element can take n different values, would amount to n insertion/deletion costs and $n \times (n-1)/2$ substitution costs (for logical reasons costs are symmetrical: inserting an element ought to cost exactly as much as deleting it, and substituting x for y has to be just as expensive as substituting y for x). However, when there are no logical reasons to do otherwise, insertions (or deletions) of different elements are usually given the same cost. This is the option I adopt here as well.

[27] An alternative strategy consists in defining substitution costs from observed longitudinal transitions across states, *i.e.* from a transition matrix (Stovel *et al.*, 1996; Lemercier, 2005; Stark and Vedres, 2006). This strategy would here have implied not taking advantage of the continuous nature of the data when setting the substitution costs. This is the reason why it was not adopted.

that, if sequences are of equal length, the indel cost *cannot be larger* than half the largest substitution cost. Because it would take two of them to replace any single possible substitution, indels would never be used. If on the contrary sequences are of unequal length, an indel cost larger than half the greatest substitution cost only prevents the algorithm from using any more indel once the length gap has been filled in, which is less problematic than using no indel at all (Abbott and Tsay, 2000). Subsequent studies thus turned to using lower indel costs, typically close to half the largest substitution cost (*e.g.* Blair-Loy, 1999). In the context of this article, I shall retain the guideline that the indel cost should not be smaller than half the greatest substitution cost. Since the sequences at stake are of various lengths, there is no necessity to keep the indel cost smaller than half the greater substitution cost.[28] Abiding by this first guideline restricts the range of possible costs for indel to values strictly above 4.5.

2. Optimal matching techniques have also been criticized for not clearly taking into account the direction of the progression from state to state within a sequence, in other words for being insensitive to the directionality of time (Wu, 2000; Stark and Vedres, 2006). This at first glance can be seen as a weakness. But suppose we have an idea of the level of time directionality sensitivity that best suits the pattern we expect to observe in the data. Then, provided we can measure such sensitivity for various cost specifiations, the alleged shortcoming of the method actually becomes an advantage. It provides a second guideline for setting the relative value of costs. In particular, since I am mostly interested here in the relationship between artistic creativity and the life cycle, or age, of artists, it seems reasonable to favor parameters that will coerce the algorithm into sharply differentiating sequences that follow reverse orders, and minimizing the differences between sequences that follow the same order. The following paragraphs further illustrate what is meant by sensitivity to the directionality of time, and present the method I used to draw conclusions from this second guideline in terms of cost setting.

Optimal matching methods' insensitivity to the directionality of time does not mean that the algorithm they rest on is unable to distinguish between reverse sequences (as could mistakenly be inferred from Stark and Vedres (2006)). Rather, one should say that for some specifiations of indel and substitution costs, the algorithm will tend to find smaller distances between sequences exactly reverse than between sequences unfolding in the same order but marginally differing from each other. Let us for instance focus on the following sequences, which, though fictional, mimic the ones examined in the present article:

Sequence i	1	0	1	6	0	0	9
Sequence j	9	0	0	6	1	0	1
Sequence k	1	0	1	6	0	9	0

Sequences *i* and *j* are exactly reverse. On the contrary, sequences *i* and *k* seem to unfold similarly across time. There is only one slight difference between them towards the end. Suppose the substitution costs have been set as the value of the absolute difference between elements, as is the case in this article. Also suppose that the indel cost is 10 (which is the highest substitution cost, plus the absolute difference between the two highest substitution costs, as recommended by Abbott and Hrycak (1990)). Distances computed by the optimal matching algorithm between *i* and *j* on the one hand, *i* and *k* on the other, will actually both amount to 18. This can be considered inappropriate *given our purpose*—which deals with the

[28] Sequences' lengths range between 4 and 15 periods (mean = 11.4, standard deviation = 3.3, median = 12).

relationship between creativity and the life cycle. We would rather like to mark a sharper difference between artists whose creativity evolves in an exactly reverse fashion over time (*i* and *j*) than between artists with a similar pattern of creativity along their life cycle, except for a little difference in the end (*i* and *k*). As a consequence, one might want to try another indel cost, that is, another specification of the relative levels of indel and substitution costs. Indeed, an indel cost of 3 would yield a distance of 14 between *i* and *j*, and a distance of 6 between *i* and *k*. This is more consistent with our idea of how we would like the algorithm to compute distances between careers. Now, this approach does not really tell precisely what indel cost we should choose.

In order to solve that problem, Stark and Vedres (2006) suggest an empirical method, which I also use here to set an appropriate indel cost. It basically consists of three steps. In the first step, measures of directional similarity and reverse directional similarity between any pair of sequences are generated, by respectively counting the number of exact matches (the same element at the same time) between two sequences and between one sequence and the other's reverse. In the second step, pairwise optimal matching distances between sequences are calculated for various cost specifications. Finally, the optimal matching distance between two sequences is regressed on the measures of directional similarity and reverse directional similarity between them. This is done as many times as there are optimal matching distances obtained from different cost settings. The overall idea is ''to find cost parameters for optimal matching that reward similarity in temporal ordering and punish similarity in reverse temporal ordering'' (Stark and Vedres, 2006:1405). The cost specification yielding the greatest difference between coefficients of respectively the reverse directional similarity predictor and the directional similarity one (with the latter smaller than the former) can be considered the one most sensitive to the directionality of time. In the simple example above, exact matches amount to 3 beween *i* and *j*, and 5 between *i* and *k*. There are also 7 exact matches between *i* and the reverse of *j*, and only 2 between *i* and the reverse of *k*. The proposed strategy would tend to favor costs that yield a great distance between *i* and *j*, and a small one between *i* and *k*.

I applied Stark and Vedres' method to the 41 creativity careers in order to uncover the cost structure that most ''respects'' the directionality of time when computing the optimal matching distance between sequences. The substitution costs were set once and for all as explained before, and the variation of cost structure rested on the variation of the indel cost only. Table C.1 reports, and Fig. C.1 diagrams, the values of coefficients associated to the

Table C.1
Coefficients of variables Matches and Reverse Matches for various indel costs.

Model	Dep. Var. = optimal matching distance								
Indel cost	2	3	4	5	6	7	8	9	10
Subst costs	$\lvert x-y\rvert$	$\lvert x-y\rvert$	$\lvert x-y\rvert$	$\lvert x-y\rvert$	$\lvert x-y\rvert$	$\lvert x-y\rvert$	$\lvert x-y\rvert$	$\lvert x-y\rvert$	$\lvert x-y\rvert$
Matches (*a*)	−12.3	−14.17	−14.89	−14.86	−14.16	−13.06	−11.72	−10.19	−8.56
Constant	21.83	28.49	34.09	38.81	42.78	46.35	49.7	52.9	56
N	820	820	820	820	820	820	820	820	820
R^2	0.17	0.12	0.08	0.05	0.03	0.02	0.01	0.01	0.002
Reverse matches (*b*)	−5.88	−7.03	−7.6	−7.89	−8.56	−9.41	−10.27	−11.18	−12.21
Constant	18.95	25.25	30.75	35.58	40.04	44.33	48.49	52.59	56.67
N	820	820	820	820	820	820	820	820	820
R^2	0.04	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.01
$[(b-a)/\lvert a\rvert](\times 10)$	5.22	5.04	4.90	4.69	3.95	2.79	1.24	−0.97	−4.26

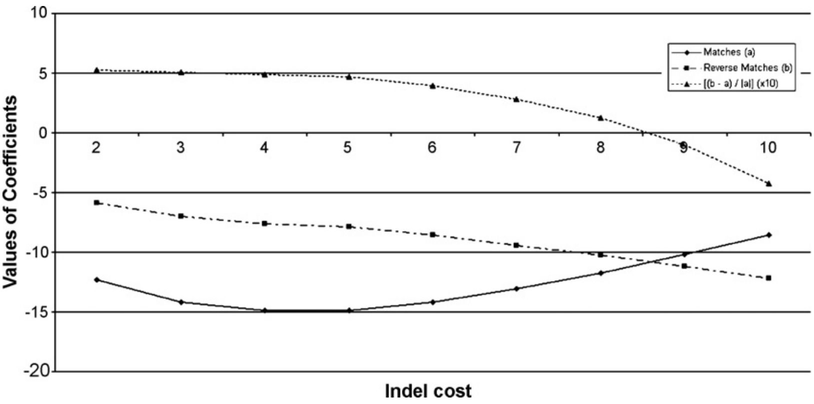

Fig. C.1. Coefficients of variables Matches and Reverse Matches for various indel costs.

directional similarity (''Matches (a)'') and reverse directional similarity (''Reverse Matches (b)'') predictors for dependent variables generated with various indel costs (all coefficients are significant at the $p < 0.05$ level except that of a when indel cost = 10 ($p < 0.1$ level)).

As can be seen, for no indel cost does the algorithm actually *punish* reverse directional similarity, but it rewards it more or less. It also always rewards directional similarity–though again more or less. To set the appropriate indel cost value I rely on the difference $(b - a)$, divided by $|a|$ in order to discount for scale effects (not only the level, but also the range of optimal matching pairwise distances vary from one indel cost value to another). Values of $(b - a)/|a|$ for various indel costs are reported in Table C.1 and Fig. C.1. Sensitivity of the algorithm to time directionality seems maximum for low values of the indel cost, and slowly decreases till this cost reaches the vicinity of 5. Sensitivity then seems to decrease more dramatically, and the algorithm eventually comes to finding smaller distances between sequences with reverse directional similarity than with directional similarity (for indel costs above 9). Given the first guideline presented before, this restricts the range of possible indel costs to values between 4.5 and about 5. Refined analyses involving stepwise increases of the indel cost by 0.1 steps show that 5.2 can actually be considered a bend and the largest appropriate indel cost. Beyond this point, the algorithm's sensitivity to time directionality decreases at a higher rate. (Note that indel cost values of 5, 5.1 and 5.2 ultimately all yield the exact same partition of the set of sequences.)

3. Finally, a third guideline helps to decide on a suitable value of the indel cost. Provided one follows the first two constraints, there is a benefit to setting a relatively high indel cost, namely, that the algorithm will then better separate short sequences from long ones. Indeed, comparing creativity careers of individuals who died at very different ages is uncomfortable. (For example, artists who died young necessarily have an early creativity peak, and should therefore be considered conceptual innovators in Galenson's view; yet they might well be experimental innovators whose later peaks were just not given the opportunity to occur.) Specifying an indel cost as large as possible within the previously delimited range should enable us to cope with that issue, by first setting aside short careers, and then focusing on differences in shape between long ones. Accordingly, the indel cost was eventually set to 5.2. As explained earlier, substitution costs take the value of the absolute difference between the elements substituted.

References

Abbott, A., 2000. Reply to Levine and Wu. Sociological Methods and Research 29, 65–76.

Abbott, A., Hrycak, A., 1990. Measuring resemblance in sequence data: an optimal matching analysis of musicians' careers. American Journal of Sociology 96, 144–185.

Abbott, A., Tsay, A., 2000. Sequence analysis and optimal matching methods in sociology. Sociological Methods and Research 29, 3–33.

Baxandall, M., 1985. Patterns of Intention: On the Historical Explanation of Pictures. Yale University Press, New Haven.

Blair-Loy, M., 1999. Career patterns of executive women in finance: an optimal matching analysis. American Journal of Sociology 104, 1346–1397.

Bloom, H., 1975. The Anxiety of Influence. A Theory of Poetry. Oxford University Press, London.

Bourdieu, P., 1996. The Rules of Art. Genesis and Structure of the Literary Field. Stanford University Press, Stanford.

Bruegel, M., Galenson, D.W., 2002. Measuring masters and masterpieces: French ranking of French painters and paintings from realism to surrealism. Histoire et Mesure 17, 47–85.

Csikszentmihalyi, M., 1996. Creativity: Flow and the Psychology of Discovery and Invention. HarperCollins Publishers, New York.

Czujack, C., 1997. Picasso paintings at auction, 1963–1994. Journal of Cultural Economics 21, 229–247.

DeNora, T., 1995. Beethoven and the Construction of Genius: Musical Politics in Vienna, 1792–1803. University of California Press, Berkeley.

Ekelund, R.B., 2002. Book Review: David W. Galenson, "Painting Outside the Lines: Patterns of Creativity in Modern Art" Journal of Cultural Economics 26, 325–327.

Elias, N., 1991. Mozart: sociologie d'un génie. Seuil, Paris.

Farrell, M.P., 2001. Collaborative Circles. Friendship Dynamics and Creative Work. The University of Chicago Press, Chicago.

Galenson, D.W., 2001. Painting Outside the Lines. Patterns of Creativity in Modern Art. Harvard University Press, Cambridge.

Galenson, D.W., 2002a. Quantifying artistic success: ranking French painters – and paintings – from impressionism to cubism. Historical Methods 35, 5–19.

Galenson, D.W., 2002b. Masterpieces and markets: why the most famous modern paintings are not by American artists. Historical Methods 35, 63–75.

Galenson, D.W., 2004. The life cycles of modern artists: theory and implications. Historical Methods 37, 123–136.

Galenson, D.W., 2008. Analyzing artistic innovation. The greatest breakthroughs of the twentieth century. Historical Methods 41, 111–118.

Galenson, D.W., Jensen, R., 2002. Careers and canvases: the rise of the market for modern art in the nineteenth century. NBER Working Paper Series no. 9123.

Galenson, D.W., Weinberg, B.A., 2001. Creating modern art: the changing careers of painters in France from impressionism to cubism. American Economic Review 91, 1063–1071.

Gardner, H., 1993. Creating Minds. An Anatomy of Creativity Seen through the Lives of Freud, Einstein, Picasso, Stravinsky, Eliot, Graham and Gandhi. Basic Books, New York.

Ginsburgh, V., Weyers, S., 2006. Creativity and life cycles of artists. Journal of Cultural Economics 30, 91–107.

Kousser, J.M., 2004. The forms and means of creativity. Historical Methods 37, 108.

Lemercier, C., 2005. Les carrières des membres des institutions consulaires au XIXème siècle. Histoire et Mesure 20, 59–95.

Lesnard, L., 2006. Optimal matching and social sciences. INSEE Working Paper no. 2006-1.

Martindale, C., 1990. The Clockwork Muse. The Predictability of Artistic Change. Basic Books, New York.

Montias, J.M., 1989. Vermeer and his Milieu: A Web of Social History. Princeton University Press, Princeton.

Moulin, R., 1986. Le marché et le musée. La constitution des valeurs artistiques contemporaines. Revue française de sociologie 27, 369–395.

Stark, D., Vedres, B., 2006. Social times of network spaces: network structures and foreign investment in Hungary. American Journal of Sociology 111, 1347–1411.

Stovel, K., 2001. Local sequential patterns: the structure of lynching in the Deep South, 1882–1930. Social Forces 79, 843–880.

Stovel, K., Savage, M., Bearman, P., 1996. Ascription into achievement: models of career systems at Lloyds Bank, 1890–1970. American Journal of Sociology 102, 358–399.

Uzzi, B., Spiro, J., 2005. Collaboration and creativity: the small world problem. American Journal of Sociology 111, 447–504.

Van Rees, C.J., 1983. How a literary work becomes a masterpiece. Poetics 12, 397–417.

Van Rees, C.J., 1987. How reviewers reach consensus on the value of literary works. Poetics 16, 275–294.

White, H., White, C., 1965. Canvases and Careers. Institutional Change in the French Painting World. John Wiley and Sons, New York.

Wu, L., 2000. Some comments on "Sequence analysis and optimal matching methods in sociology: review and prospects". Sociological Methods and Research 29, 41–64.

Fabien Accominotti is a Ph.D. candidate in sociology at Columbia University and the Ecole des Hautes Etudes en Sciences Sociales. His dissertation uses cultural markets to study socio-economic processes such as reputation and inequality construction, status management by economic actors, and the dynamics of collaboration and creativity. Besides his doctoral work, his areas of interest include social networks and the study of reciprocity. A former visiting scholar and Fulbright fellow at Columbia, he holds a M.A. from the EHESS and a B.A. from the Ecole Normale Supérieure of Cachan.