THE DIFFERENTIAL IMPACT OF KNOWLEDGE DEPTH AND KNOWLEDGE BREADTH ON CREATIVITY OVER INDIVIDUAL CAREERS

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Abstract

While usually argued to be fostering creativity, the effect of knowledge depth and breadth on creativity is actually mixed. We take a dynamic approach to the knowledge-creativity relationship and argue that the effect of knowledge depth and knowledge breadth is likely to be contingent on career age. We propose that individuals' knowledge structures become increasingly rigid as career age grows and that because of this, knowledge depth and breadth have different effects on creativity at different points of the career. More specifically, we hypothesize that knowledge depth is more beneficial for creativity in earlier stages of one's career, when creators need to increase the complexity of knowledge structures, while knowledge breadth is more beneficial in later stages, when flexibility is most needed. We test and find support for our hypotheses in a longitudinal study set in the context of the Hollywood animation industry, a setting characterized by the presence of a variety of creators involved in knowledge-intensive activities. Theoretical and practical implications of the results are discussed.

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INTRODUCTION

In 1995, John Lasseter was in the early years of his career in the animation industry. In the previous years, he had worked on many animated short movies focusing on inanimate objects, such as *Tin Toy* and *Knick Knack*. This in-depth knowledge proved fruitful: in February 1996, *Toy Story*, an animated movie that he wrote and directed for Pixar Animation Studios, received a Special Achievement Academy Award for its groundbreaking contribution to the art of animation. This recognition followed another nomination at the Academy Awards for Best Original Screenplay, as well as four other nominations and awards from the most prestigious societies in Hollywood. Later in his career, however, that same expertise did not help him: in December 2011 Lasseter's latest work, *Cars 2*, not only did not earn him any nomination but was the first Pixar movie not to be nominated for the Academy Award for Best Animated Feature.

Tim Burton followed a different pattern: in the early years of his career, he experimented with a variety of different genres within the animation medium, broadening his knowledge. His experimental approach resulted in his peers not recognizing his work as particularly creative, earning him only a total of two awards and nominations. However, later in his career, his approach paid off and his animated movies, such as *The Corpse Bride and Frankenweenie*, earned him plaudits for his creative and unique style.

The examples above illustrate an existing conundrum in creativity research: when are depth and breadth of knowledge more or less conducive to creativity? Does their effect on creativity vary over the course of the career? Knowledge represents the fuel that feeds the engine of creative idea generation (Campbell, 1960; Dane, 2010; Simonton, 2003). Within an individual's mind, knowledge is organized in domains, which are in turn organized in schemas – i.e., cognitive structures containing knowledge attributes about a domain and the linkages between these attributes (Dane, 2010; Fiske & Taylor, 1991; Harris, 1994). Scholars have argued that, in theory, idea generation is more effective when individuals' knowledge structures are both complex (i.e., including a large set of schemas rich in knowledge attributes and inter-schema linkages) and flexible (i.e., including weak linkages and thus open to the addition of new domains and schemas) (Amabile, 1983; Campbell, 1960; Dane, 2010; Mednick, 1962).

To this end, two knowledge characteristics have been argued to be conducive to creativity: on one side, individuals should have knowledge depth (i.e., the degree to which an individual is knowledgeable about a specific domain). Knowledge depth increases the complexity of knowledge structures, providing individuals with a greater number of schemas that are richer in terms of attributes and linkages, and thus with a larger ideational sample within the focal domain (Campbell, 1960; Dane, 2010). On the other side, individuals should have knowledge breadth (i.e., the degree to which an individual's knowledge covers multiple domains). Knowledge breadth increases the flexibility of knowledge structures because it provides individuals with exposure to different domains and thus loosens up existing linkages, helping to create new ones within and between domains (Amabile, 1983; De Dreu, Baas, & Nijstad, 2008; Mednick, 1962). Consequently, the knowledge dimensions of depth and breadth affect creativity by shaping knowledge structures within an individual's mind.

Empirical evidence for the effects of these knowledge dimensions, however, has been mixed. Individuals with deep knowledge in a domain have indeed more complex knowledge structures, and are thus able to consider a greater number of knowledge reconfigurations within a domain to generate novel outcomes (Amabile, 1983; Gino et al., 2010; Taylor & Greve, 2006). However, complex knowledge structures are also more susceptible to cognitive entrenchment, which increases the rigidity of linkages within and between schemas, and consequently limits individuals' ability to generate novel combinations (Audia & Goncalo, 2007; Dane, 2010; Mumford & Gustafson, 1988). Conversely, individuals with broad knowledge have more flexible knowledge structures thanks to the exposure to different domains, and in doing so, have a greater ability to recombine knowledge across different domains to generate creative outcomes (Perry-Smith & Shalley, 2003; Simonton, 1988; Sosa, 2011; Taylor & Greve, 2006). However, broad knowledge can also generate cognitive overload, resulting in creativity impairment (Connolly, 1977; Hwang & Lin 1999; O'Reilly 1980; Sparrow, 1999; Wadhwa & Kotha, 2006).

We aim to resolve these mixed findings by taking into account the role of career age. Research suggests that career age increases the strength of inter-domain linkages, thus increasing the rigidity of knowledge structures (Cirillo, Brusoni, & Valentini, 2014; Feldman, 1989; Frensch & Sternberg, 1989; Simonton, 1997). In other words, career age affects individuals' ability to effectively combine different knowledge domains to identify novel combinations. Consequently, there is reason to believe that the effect of knowledge depth and breadth on creativity will vary at different stages of an individual's career. We hypothesize that knowledge depth is more beneficial for creativity in the earlier stages of one's career, when knowledge structures are relatively flexible and there is a need to increase complexity, and less beneficial later in the career, when individuals' knowledge structures become increasingly rigid. Conversely, we hypothesize that knowledge breadth is more beneficial in later phases, when rigidity is high and there is a need to improve flexibility by loosening up knowledge structures.

We test our hypotheses in a setting specifically suited for our research questions: the Hollywood animation industry. This context is particularly promising because it is characterized by the presence of a variety of creators involved in knowledge-intensive activities, and of objective measures to assess the creativity of their outcomes across their professional careers. We collected information on core individual creators for all animated movies produced between 1978 and 2013. In particular, we focused on their knowledge base in terms of domain-specific knowledge and the variety of different domains tackled throughout their career.

This study stands to make three main contributions. First, we provide a possible solution to the contradictory findings on the impact of knowledge depth and breadth on creativity. Specifically, in showing that the two dimensions of knowledge have different effects on creativity at different stages of a career, we stress that studying creativity over the career is important to better comprehend the impact of its antecedents at different points in time. Second, we contribute to research on career age and creativity by elaborating and testing a theory of how and why career age affects the relationship between knowledge dimensions and creativity. The fact that creativity varies over the span of an individual's career has been thoroughly documented in creativity research (e.g., Lehman, 1953, 1954; Simonton, 1975, 1997, 2000). However, we know little about how creativity is best fostered at different stages of the career. In other words, we do not know if the factors that are thought to foster creativity are equally effective at different stages of the career. Our findings indicate that this is not the case, and provide insights into the moderating role of career age as a potential explanation for the existence of different creative trajectories. Finally, our findings suggest that the variation of creativity over the career might be determined by changes in the knowledge structures underlying idea generation, pointing out the need to explore how this process evolves over time in order to understand why creativity varies.

THEORY AND HYPOTHESES

Creativity consists of the generation of ideas, products, or services that are judged to be novel and useful by external observers (Amabile, 1996; Woodman, Sawyer, & Griffin, 1993). While idea generation can take place in teams (e.g., Hargadon & Bechky, 2006; Harvey, 2014; Mannucci, 2017) and is influenced by social and contextual elements (Shalley, Zhou, & Oldham, 2004; Woodman et al., 1993), the very first origin of every creative idea originates from the individual's mind (Amabile, 1983; Campbell, 1960; Simonton, 2003).

Creative idea generation can be described as an associative, quasi-random recombination of the knowledge possessed by each individual (Campbell, 1960; Mednick, 1962; Simonton, 2003). Each individual's knowledge is organized in an array of more or less interlinked domains, with each domain made up of an array of interlinked cognitive schemas (Dane, 2010; Fiske & Taylor, 1991; see Figure 1). Each cognitive schema, in turn, is made up of knowledge attributes and the linkages among these attributes (Fiske & Taylor, 1991; Rousseau, 2001). For example, the domain of an "animation" is made of an array of interlinked schemas such as "animation techniques" and "character designer". In turn, the schema of a "character designer" is made up of interlinked attributes representing the activities that the "character designer" schema entails, such as drawing, coloring, and animating (adapted from Rousseau, 2001).

Insert Figure 1 about here.

The array of domains and the strength of the corresponding linkages, as well as the array of interlinked schemas within each domain, influence how individuals recombine their knowledge into creative outcomes. In particular, research has shown that the complexity and flexibility of knowledge structures affect the probability and speed of generating a creative outcome (Campbell, 1960; Dane, 2010; Mednick, 1962). Complexity represents the number of schemas within a given knowledge domain, as well as the number of knowledge attributes within a schema and their linkages. Flexibility represents the degree to which knowledge structures are open to the addition of new elements and linkages, within and between domains. Complex knowledge structures are characterized by a larger number of schemas, attributes, and linkages within a knowledge domain. These linkages tend to be stable and relatively strong. Individuals with complex knowledge structures can access a larger array of richer schemas within a given domain, and are therefore able to consider a wider range of possible recombinations to generate novel and useful outcomes (Campbell, 1960; Simonton, 2004). At the same time, weaker linkages between and within domains characterize flexible knowledge structures. Individuals with flexible knowledge structures thus possess a greater ability to reorganize schemas in a way that departs from the existing paradigms of each domain (Campbell, 1960; De Dreu, et al., 2008; Mednick, 1962; Mumford & Gustafson, 1988; Simonton, 1999, 2003). In contrast, cognitively rigid individuals are less able to reconfigure and adapt their knowledge structures (Dane, 2010). Overall, this suggests that individuals with knowledge structures that are both complex and flexible should be in the best position to be creative: they have access to a large ideational sample within the domain, and they are able to make new linkages between and within each domain.

An individual's knowledge depth and breadth affects the internal structure of domains and schemas and the linkages between them (Amabile, 1983; Dane, 2010; Katila & Ahuja, 2002; Perry-Smith, 2014). Acquiring knowledge depth in a given domain increases the number of knowledge attributes and the corresponding linkages *within* each schema, thus increasing the number of possible recombinations (Amabile, 1983; Dane, 2010). Moreover, deep knowledge in a specific domain helps individuals to make more proficient use of their knowledge, identifying and selecting new linkages that are more promising for the development of novel and useful outcomes (Haas & Ham, 2015; Taylor & Greve, 2006). Knowledge depth, however, can also have detrimental effects on creativity. Knowledge depth increases the strength of within-schema linkages, thus increasing cognitive rigidity and limiting an individual's ability to modify knowledge structures to generate novel combinations (Audia & Goncalo, 2007; Dane, 2010; Mumford & Gustafson, 1988; Simonton, 2000). The increased strength of within-schema linkages can even hamper individuals' willingness to search for new knowledge, limiting the formation of new linkages between domains and schemas, and further increasing cognitive rigidity (Gavetti, Levinthal, & Rivkin, 2005; Haas & Ham, 2015).

Knowledge breadth represents the diversity of an individual's knowledge, know-how and experiences, i.e. the number of different domains within his or her knowledge (Amabile, 1983; Taylor & Greve, 2006). Individuals with knowledge breadth have greater exposure to diverse perspectives that increase their ability to recombine knowledge (Perry-Smith & Shalley, 2003; Simonton, 1988; Sosa, 2011; Taylor & Greve, 2006). Spanning different knowledge domains helps individuals see problems from a different perspective, increasing the likelihood they will identify and consider new linkages between domains and schemas (Campbell, 1960; Perry-Smith, 2006; Taylor & Greve, 2006). Moreover, diverse knowledge can stimulate individuals to reconfigure knowledge schemas and domains, loosening up their internal structure and increasing flexibility (Gavetti et al., 2005; Mumford & Gustafson, 1988). Knowledge breadth, however, can also generate cognitive overload, resulting in idea-production blocking and creativity impairment (Connolly, 1977; Hwang & Lin 1999; O'Reilly 1980; Sparrow, 1999; Wadhwa & Kotha, 2006). Access to a wide range of potential recombinations can also impair individuals' ability to decide which one to develop from the potential idea stage to the generated idea stage (Haas & Ham, 2015; Rietzchel, Nijstad, & Stroebe, 2010). Moreover, knowledge breadth is likely to lead to the generation of extreme outcomes – i.e., it can lead to the generation of very novel ideas or it can also lead to failures (Taylor & Greve, 2006).

Overall, extant research presents mixed evidence on the effect of knowledge dimensions on creativity. Knowledge depth increases the complexity of knowledge structures in terms of the number and richness of within-domain schemas and the corresponding linkages. Knowledge depth, however, also strengthens within-domain and within-schemas linkages, limiting the creation of new linkages and thus leading to cognitive rigidity. Knowledge breadth increases the flexibility of knowledge structures by exposing individuals to new domains and thus stimulating the creation of new linkages between domains and schemas. However, it also results in excessive cognitive load that can lead to ideation paralysis. We propose that taking into account career age and its effect on knowledge structures can provide an explanation for these inconsistent findings.

Career Age and Knowledge Structures

The variation of individual creativity over the career is one of the oldest topics in the behavioral sciences, and has received a significant amount of attention, especially from authors such as Lehman (e.g., 1953), Dennis (e.g., 1966) and Simonton (e.g., 1977). These studies show that creative productivity (the total number of works) and creative quality (the number of major works) of eminent artists and scientists vary according to a curvilinear trajectory: either an inverted-backward J-curve (Simonton, 1975a, 1975b, 1977, 1984, 1988, 1997) or an inverted U-shape (Lehman, 1953, 1954, 1958, 1960, and 1966). This trajectory has been observed in different fields, such as poetry, mathematics, medicine, novel writing, and composing (see Simonton, 1988, for a complete review). While the peak and exact trajectory patterns vary across different individuals and professions, the general pattern displays a single peak, followed by a decline. This decline is steeper for quality, and more gradual and regular for productivity.

Building on these findings, Simonton developed a model that identifies the process of idea generation and its evolution as central elements to explain the variation of creativity over the career (e.g. Simonton, 1997). According to the model, creativity is a dynamic ability that is a function of the individual's initial creative potential, ideation rate, and elaboration rate. At any given point of the career, the total quantity of potential creative ideas can thus be divided into (1) ideas neither generated or developed , still in the "potential" stage, (2) ideas generated but yet to be developed, and (3) ideas generated and already developed into completed outcomes. While (1) decreases over time, (3) tends to increase, with (2) first increasing and then decreasing. The rate to which ideas are converted from potential to generated is called the ideation rate. Given the creative trajectory observed in extant research, Simonton suggested that creativity variation is due to the increase and subsequent decrease of idea generation, i.e. to the variation of the ideation rate. However, the model is merely descriptive, and can be estimated only ex post (Simonton, 1977, 1997). In other words, Simonton's model states that the idea generation rate declines over time, but does not explain why this happens.

We propose that creativity varies over a career because career age affects the strength of linkages between domains (between-domains flexibility) and, consequently, between schemas (within-domain flexibility). Hence, cognitive linkages become increasingly rigid as career age increases (Cirillo et. al, 2014; Feldman, 1989; Frensch & Sternberg, 1989; March, 1991; McCrae, Arenberg, & Costa, 1987). Individuals in early stages of their career are not yet embedded in the rules and norms of the field, and are open to new perspectives and ways of doing things (Dane, 2010; Perry-Smith & Shalley, 2003). Their knowledge domains and schemas are thus loosely linked and open to modification. As career age increases, individuals become more socialized within their field, mastering its codes, rules and beliefs (March, 1991). This increases the strength of linkages within and between knowledge domains, increasing individuals' ability to effectively connect different domains and schemas. Over time, however, increased mastery also results in a homogenization of knowledge structures and thinking styles that lead to cognitive rigidity (Katz & Allen, 1982; March, 1991). Individuals become increasingly reliant on established linkages between and within knowledge domains, thus resorting to the usual ways of solving problems and approaching tasks (Nelson & Winter, 1982). This is known as negative transfer (Bartlett, 1958), a type of mental block where individuals focus only on those mental pathways and associations that they have already used in the past. This suggests that, as career age increases, the strength of linkages increases while within- and between-domain flexibility decreases. Table 1 provides an illustration of the predicted effect of career age on knowledge structures.

Insert Table 1 about here.

The Moderating Role of Career Age

While knowledge dimensions and career age are often conceptualized as overlapping constructs, extant research suggests that they are independent and follow significantly different trajectories. For example, an individual can quickly become an expert in a given domain through study and practice, while another one might spend years exploring different domains without attaining significant expertise in any (Simonton, 1997, 2000). Moreover, when knowledge depth and career age are considered together, career age has a positive or an inverted U-shaped relationship with creativity, while the relationship between knowledge depth and creativity follows a backward-J function (Simonton, 2000). Thus, Simonton suggests that, "the impact of any given creative product would be a partial function of many prior experiences, both generic and specific, both cumulative years and cumulative products" (Simonton, 2000: p. 312). However, it remains unclear how knowledge and career age would interact to shape creativity.

We argue that, since career age strengthens the linkages between knowledge domains and schemas, it magnifies or hinders the effectiveness of knowledge depth and breadth in fostering creativity. Early in their career, individuals need to acquire deep knowledge about the domain in order to understand its rules and procedures and be able to effectively push its boundaries to generate creative solutions (Perry-Smith & Shalley, 2003; Taylor & Greve, 2006). Without acquiring deep knowledge, their knowledge structures would be overly simple and, despite their flexibility, would not include the building blocks necessary to activate the recombination process that leads to the generation of creative ideas (Amabile, 1983, Dane 2010). Moreover, individuals would be unable to evaluate novel contributions without knowledge depth. Consequently, those early in their careers, with their relatively flexible knowledge structures, should acquire deep knowledge to enhance the number of recombination possibilities (Dane, 2010; Mumford, Blair, Dailey, Leritz, & Osburn, 2006; Perry-Smith & Shalley, 2003; Taylor & Greve, 2006) and thus improve the likelihood of generating creative outcomes.

As career age increases, linkages between domains and schemas become increasingly rigid, eventually leading to cognitive entrenchment (Audia & Goncalo, 2007; Cirillo et al., 2014). Individuals need thus to increase the flexibility of their knowledge structures. Consequently, knowledge depth becomes less beneficial for creativity. The increased rigidity of knowledge structures reduces the likelihood of identifying new linkages between schemas and attributes, thus limiting the benefits of knowledge depth. Moreover, career age exacerbates the negative effect of knowledge depth on cognitive flexibility by increasing the rigidity of inter-schemas or inter-domain linkages. Thus, the ability to exploit the benefits of knowledge depth decreases with increasing career age. That is, individuals are less able to harvest the benefits of possessing a larger set of domain-specific schemas and attributes. Conversely, the cognitive rigidity induced by knowledge depth intensifies with career age, resulting in a steeper associative hierarchy that blinds them to alternatives. Given these arguments, we predict:

Hypothesis 1: As career age increases, the effect of knowledge depth on creativity becomes less positive.

Knowledge breadth is likely to have a less positive effect on creativity early in the career. Early in their career, individuals already have flexible knowledge structures that allow them to make remote recombinations. Thus, increasing the breadth of an individual’s knowledge is likely to be less beneficial, as increasing flexibility adds little to no value to an already flexible knowledge structure. Moreover, neophytes are not able to fully exploit the benefits of knowledge breadth because of their low socialization with the field. They have yet to master the rules and procedures of the domain, and are thus unable to convert diverse, non-redundant knowledge into novel permutations that are also useful and appropriate (Taylor & Greve, 2006). Having spent time within the field is important in order to recognize, process, and apply relevant knowledge to the generation of novel combinations with a non-trivial likelihood of success, thus reducing the risk of generating creative failures (Amabile, 1983; Taylor & Greve, 2006). Finally, for those early in their career, excessive knowledge breadth is likely to result in cognitive overload, as they are less capable of recognizing and effectively processing relevant knowledge (Connolly, 1977; Hwang & Lin 1999; O'Reilly 1980; Sparrow, 1999). In turn, this results in individuals experiencing a reduced ability to recombine knowledge into novel and useful outcomes (Boh, Evaristo, & Ouderkirk, 2014; Wadhwa & Kotha, 2006).

Conversely, with increasing career age a knowledge base that spans different domains is likely to benefit creativity. Knowledge breadth fosters the creation of linkages between existing domains and schemas and new domains and schemas, and thus increases the flexibility of knowledge structures. Increasing breadth means refreshing an individual's knowledge base with new knowledge from different domains, improving the probability of breaking out of existing ways of doing things to find new combinations (Katila & Ahuja, 2002; Taylor & Greve, 2006). This is particularly beneficial for individuals at later stages of their career because they are more likely to reuse previously explored combinations (March, 1991). As the number of combinations that individuals can generate using the same knowledge base is limited (Simonton, 2003), they risk generating outcomes that are decreasingly creative. Broadening their knowledge can thus help individuals in the later stages of their career to come up with new linkages between existing domains and schemas with new domains and schemas, and in doing so, generate novel, previously untried combinations. These arguments lead to the following prediction:

Hypothesis 2: As career age increases, the effect of knowledge breadth on creativity becomes more positive.

METHODS

Setting: The Hollywood Animation Industry

To test our hypotheses, we needed data that allowed us to identify individual creators undertaking the same activities and who had worked on multiple creative outcomes over time. We also needed to objectively measure the creativity of these outcomes. The Hollywood animation industry is a unique setting that provides data meeting our empirical requirements. The Hollywood animation industry is considered one of the most creative and innovative industries. For example, the technical and storytelling innovations introduced by Walt Disney ensured Disney Animation an enduring competitive advantage (Canemaker, 2001), which made the company the uncontested leader of the industry for more than fifty years. Similarly, the extraordinary success of Pixar Animation was based on the innovations of John Lasseter. Lasseter was the first to abandon the classic “fairy tale” stories for more unconventional and mature plots and topics, such as identity crisis, humanism, and marital dysfunction (Burningham, 2000; Hall, 2000; Travers, 2012), thus freeing animation from its label of “children product”.

In general, animated movies are classified according to one main genre defining the major features of the movie, and multiple secondary genres defining minor accessory features (Altman, 1999; Perretti & Negro, 2007). Industry experts and prestigious institutions (e.g., the American Film Institute) make this classification based on established standards and conventions, and dates back to the origins of cinema. Each movie is classified into one or more genres based on the presence of similar and identifiable patterns in terms of setting, content, mood, style, and structure (Dirks, 2017). In other words, each of these genres comes with its own characteristics in terms of themes and expressive style, and genres are profoundly different in terms of structure of dramatic action, characters, visuals, and music (Altman, 1999; Dirks, 2017). Animated movies vary greatly in terms of main genre, ranging from classic fairy tales (e.g., *The Little Mermaid)* to westerns (e.g. *Rango*), horrors (e.g., *Frankenweenie*), sci-fi (e.g., *Wall-E*), super-hero movies (e.g., *The Incredibles*), drama (e.g., *My Dog Tulip*), and many others. Within the same main genre, movies can have different sub-genres: for example, *Wall-E* is classified as sci-fi/comedy, given its happy ending and the presence of comedic elements, while *Star Wars: Clone Wars* is classified as sci-fi/adventure, given its focus on battles and heroic rescue missions.

Animated movies are the sum of the creative efforts of different individual creators, including screenwriters, directors, animators, character designers, editors, and music composers. Each creator contributes specialized knowledge, technical knowledge, and talent. Thus, despite the collective nature of moviemaking, it is possible to identify and isolate each individual's creative contribution, independently from the overall creativity of the movie (Cattani & Ferriani, 2008; Simonton, 2004). For example, a movie can feature outstanding art direction but a poor script. The following description of the creative process in the animation industry illustrates how a movie results from the combination of many separate and distinguishable ideas:

> *People tend to think of creativity as a mysterious solo act, and they typically reduce products to a single idea: this is a movie about toys, or dinosaurs, or love, they'll say. However [...] the initial idea for the movie – what people in the movie business call "the high concept" – is merely one step in a long, arduous process that takes four to five years. A movie contains literally tens of thousands of ideas. They're in the form of every sentence; in the performance of each line; in the design of characters, sets, and backgrounds; in the locations of the camera; in the colors, the lighting, the pacing* (Catmull, 2008).

It is in this rich context, characterized by the presence of a variety of creators, that we ground our research on knowledge dimensions and creativity over the career.

Data and Sample

The sample consists of the entire population of core crew members who worked in at least one of the 231 feature-length animated movies produced in the United States and released in movie theaters from 1978 through 2013, with the movie-creator dyad as the unit of analysis. Data collection involved two main steps. First, we identified all feature-length animated movies produced in the United States and released in theaters between 1978 and 2013. For each movie, we captured the main and secondary genres. Second, we identified the core crewmembers of each of the identified movies. While recognizing that a movie is the result of the creative effort of multiple professionals, we followed a diffused practice in management and creativity research (e.g., Cattani & Ferriani, 2008; Mannucci, 2017; Perretti & Negro, 2007; Simonton, 2004) and concentrated on the creative ideas generated by the restricted group of people that is in charge of the most critical aspects of the creative work in an animated movie, i.e. the “core crew”. This includes the producer, director, writer, editor, cinematographer, art director[1], production designer, and composer of original music score (Goldman 1983). We identified animated movies, movie genres, and the core crew using the Internet Movie Database (IMDB), an online source used by a growing number of studies (e.g., Cattani & Ferriani, 2008; Mannucci, 2017; Sorensen & Waguespack 2006). The reliability of the information on movies and core crew obtained through IMDB was checked with another dataset, the American Film Institute Catalog of Motion Pictures (AFI), as well as with company websites and other online sources. Since IMDB lists genres in alphabetical order, we used the AFI catalog to determine the main genre of the movie. When

[1] While art directors are not included in the original list elaborated by Goldman (1983), in the animation industry their role overlaps and often substitutes the one of the cinematographer. We therefore decided to include them in the sample.

movies span multiple genres, AFI classifies them following a hierarchical logic, with the main genre indicated first and the other listed consecutively in order of relevance.

We then cleaned the data, removing duplicates and checking for other inconsistencies. Since not all crewmembers are involved in a movie in any given year of the observation period, the final sample is an unbalanced panel, with 3409 observations for 2070 creators. On average, each creator in our sample worked on 2 movies during the observation period (M=1.95, s.d. = 1.71). It is worth noting that the number of creators is higher that the number of roles multiplied by the number of movies because multiple creators can cover the same role within a given movie (e.g., a movie can have more than one producer).

Measures

Creativity. We define creativity as the generation of novel and useful outcomes (Amabile, 1983; Woodman et al., 1993). Scholars have come to recognize that novelty and usefulness are not objective properties, but are shaped by the sociocultural context within which the creator is embedded (Amabile, 1996; Csikszentmihályi, 1999; George, 2007; Perry-Smith & Shalley, 2003), and therefore need to be evaluated by appropriate observers. Consistent with this definition, we measured the creativity of core crewmembers using the awards and nominations they received from the two most prominent observers and judges of creativity in the animation field: critics and peers. Awards and nominations have been validated as indicators of creativity in a variety of settings (e.g., Caird, 1994; Cattani & Ferriani, 2008; Hocevar & Bachelor, 1989; Simonton, 2004; Von Nordenflycht, 2007; see Amabile & Mueller, 2008, for a review), as they reflect the socio-cultural expectations of the field regarding the creativity of a given outcome (Cattani & Ferriani, 2008; Simonton, 2004). Furthermore, using a count measure of awards and nominations allows us to account for the continuous nature of creativity. Assessing different degrees of creativity is more precise than distinguishing major from minor creative contributions:

one minor contribution can be more creative than other minor contributions, and even major contributions vary in their degree of creativity (e.g., Amabile, 1996; Amabile & Mueller, 2008; Cattani & Ferriani, 2008; Shalley et al., 2004).

Critics and peers in the movie industry are organized in independent professional associations that provide systematic assessment of individual contributions in the various domains of cinematic creativity (Simonton, 2004). These awards are bestowed on individual creators, and not on the movie as a whole, thus making it possible to assess the creativity of each creator. Accordingly, we collected data on nominations and awards assigned to crew members by at least one of the following professional societies: (1) the Academy of Motion Picture Arts and Sciences; (2) the Directors Guild of America; (3) the Writers Guild of America; (4) the American Society of Cinematographers; (5) the American Cinema Editors; (6) the Producers Guild of America; (7) the Hollywood Foreign Press Association; (8) the National Board of Review; (9) the New York Film Critics Circle; or (10) the Los Angeles Film Critics Association. Moreover, given our focus on the animation industry, we also included the nominations and awards assigned by two associations who have devoted particular attention to animation: (11) the Hollywood branch of the International Animated Film Society (ASIFA Hollywood); and (12) the Academy of Science Fiction, Fantasy & Horror Films. We focused on these associations for several reasons. First, they consistently grant annual awards and nominations to the major roles in moviemaking, particularly with respects to animation. Second, their mission is to identify and recognize creativity in the movie industry. For example, the Directors Guild of America aims to "pass judgment on the creative ability of the director … free from prejudice and unhampered by outside influence" (O'Neil, 2003). Third, the inclusion of different types of awards allows us to minimize the risk of including only awards, like the Oscars, whose assignment is often driven not only by creative merit, but also by commercial or political reasons (Holden, 1993; Wiley & Bona, 1993).

Finally, all considered awards have been in existence for several decades, and their credibility is widely recognized across the industry. This ensures data reliability and comparability across years and creators. Table 2 lists the professional societies and the awards they bestow, along with the year they have been established.

Insert Table 2 about here.

Even if awards and nominations have been validated in many studies as a measure of creativity, we decided to evaluate its convergent validity, i.e. whether the instrument adequately measures the underlying construct it purports to measure. Given the archival nature of our data, we had access to only one type of convergent validity test, what Anastasi and Urbina (1997) refer to as "criterion-prediction validity" (p. 188). This assesses whether the measure is empirically associated with what it is theoretically supposed to capture. If awards and nominations truly measure creativity, crewmembers who receive many of them should be evaluated as more creative than crewmembers who do not receive any awards. To test this, we asked seven expert judges (one for each role in the core crew) to evaluate the individual creativity of each role in movies they have seen[2]. Overall, we collected ratings on 189 individual contributions. This,

[2] We contacted these judges using online forums devoted to animation professionals. Each of the judges had worked in one specific role – of the seven we considered in our dataset – within the animation industry. These expert judges made their assessment independently, and were asked to also rate other dimensions of creativity, such as technical aspects of the work (Amabile, 1982). When rating creativity, they were instructed not to take into account any prior knowledge of the number of awards received by that particular creator. They were presented with the movie titles in random order, and were asked to rate only the role they had experience with (i.e., producers evaluated producers, directors evaluated directors, etc.) and the movies they have seen and could recall well, in order to avoid recall bias. Traditionally, at least two judges are employed to rate each outcome in creativity research, in order to ensure consistency (Amabile, 1982). However, given our focus on individual creativity, this meant we would have had to find at least 14 experienced professionals (two per creative role). Moreover, in order to calculate inter-rater agreement, these judges needed to have watched and remember the same exact set of movies; however, this is a highly unlikely occurrence. Overall, we believe that our measure is the best possible given the circumstances and the fact that it is used as a robustness check.

given the fact that some roles are covered by more than one person, amounted to 383 observations (340 creators), equal to 11.23% (16.43%) of our sample.

Next, we compared creators with above-the-mean expert judge ratings with those with below-the-mean ratings on the number of awards and nominations received. Of the 189 ratings, 87 (46%) were above-the-mean, while the remaining 102 (54%) were below-the-mean. The difference was significant and substantial ($t = 7.75$, $p < .001$, two-tailed): those with an above-the-mean creativity rating received eight times more awards and/or nominations than those with a below-the-mean rating, thus corroborating our choice to use awards to measure creativity.

Career Age. Career age is defined as the amount of time one has spent in a given field (Bader & Kivnick, 1993; Simonton, 1997). First, we identified the year of the creator's first contribution to the field, i.e. the Hollywood animation industry. This contribution could be any nature (e.g., feature film, short) and in any role (core – e.g., director – or non-core – e.g., assistant director). We then operationalized career age as the time elapsed between the year of the first contribution to the field and the observation year. This follows an established practice for studies looking at creative careers (e.g., Simonton, 1992, 2000). Moreover, it allowed us to implicitly consider the time elapsed between each creative contribution, which differs for each creator, providing a more fine-grained assessment of each individual creator's career trajectory.

Knowledge Depth. In order to estimate the two dimensions of knowledge, we first had to identify what constituted the domain for each creative contribution. As mentioned above, each movie genre represents a specific domain, with its rules, procedures, and codes. The main genre defines the key features of the movie, such as narrative style and structure, visual appearance and design, characters, and music (Altman, 1999). We thus identified the domain of each movie with the main genre of the movie. Consequently, we operationalized knowledge depth for a creator at year *t* as the number of movies the creator has worked on that include the main genre of the movie he or she realized in year *t*. For example, consider the case of a creator that, after having already worked on three movies, in year *t* works on a movie whose main genre is “comedy”. If the three movies prior to the movie in year *t* have “comedy” as the main genre, the creator will have a knowledge depth equal to three. However, if only two of the preceding three movies had the main genre “comedy”, the creator will have a knowledge depth equal to two.

Knowledge Breadth. Since movie genres represent different domains, knowledge breadth was measured as the number of different genres an individual has worked on up to the focal year. For example, if a creator has worked on a movie classified as sci-fi/comedy, and in another movie classified comedy/adventure, this creator will have a knowledge breadth equal to three.

Control Variables. We included several control variables to account for factors that can influence the creators’ likelihood of receiving nominations and awards and/or the characteristics of their knowledge base. To account for the relative preference that award voters might have towards rewarding creators that are new to the field, we included a dummy variable that was coded 1 when a creator makes her or his first contribution in a *core* role and 0 otherwise (for a similar approach, see Cattani & Ferriani, 2008). Award voters may prefer newcomers over established creators to show their openness to new artistic voices and perspectives. Conversely, voters may prefer not to award newcomers who still have to “pay their dues”[3].

Second, we included a variable to account for creators’ individual quality and past success, calculated as the number of awards received by the creator prior to the focal year. Including this variable is warranted for several reasons. Research has shown that past success can hinder individuals’ ability to generate creative outcomes (Audia & Goncalo, 2007). Moreover,

[3] It is worth noting that a value of 1 in the “first core contribution” variable did not equate to a value of 0 in career age, or to a value of 1 in knowledge depth. Individuals can have their first core contribution at different stages of their career: for example, John Lasseter had his first core contribution 3 years after he entered the animation industry, while Aaron Blaise, the director of Brother Bear, had his after 13 years. In the same fashion, creators could have already acquired a good degree of knowledge within a given domain (genre) before their first core contribution, thanks to their involvement in other movies where they undertook non-core roles.

past success can also influence knowledge structures, as successful individuals tend to focus on tried and tested ways of doing things, deepening their knowledge instead of broadening it (March, 1991; Ward, 2004). Lastly, individuals with past creative success are likely to stay in the field, while less successful individuals are more likely to select out. Consequently, including this variable allows us to control for the possibility that results are driven by selection due to past accomplishment and skills. Third, we controlled for creators' mobility. Research has showed that mobility positively affects creativity and innovativeness, and is particularly relevant at different stages of the career (e.g., Cirillo et al., 2014). Thus, we created a binary variable coded 1 if the creator has moved to a different production studio since his/her previous movie and 0 if he/she stayed in the same studio. Fourth, we controlled for whether and how often the focal creator has worked with other team members in the past. We identified the team members that each creator has already worked with prior to the focal year. We then calculated the strength of each collaboration as the number of times that the creator has previously worked with that team member. The variable was computed as the average strength of all prior collaborations.

We then controlled for characteristics of the movie and of the creative team that could affect creators' knowledge and/or creativity. First, we controlled for whether the movie was a sequel or not. Sequels risk being perceived as less original by award voters; thus, creators may have a lower probability of receiving an award by working on a sequel. Moreover, creators working on a sequel often also worked on the original movie, and therefore are more likely to focus on the same knowledge domain rather than exploring new ones. Second, we controlled for team quality, expressed as the sum of the number of awards that team members (other than the focal creator) received for the movie they collaborated on. Research has shown that the presence of creative coworkers positively affects one's creativity (Zhou, 2003). Moreover, a creator working in a movie that is judged to be excellent may receive a nomination even if his/her individual contribution was not particularly original. Third, we controlled for the movie budget. Research has shown that abundant resources foster creativity by increasing motivation and risk-taking (Amabile et al., 1996). We thus added the logarithmic transformation of the movie budget to the model. We obtained this information from IMDB, and cross-checked it with other sources such as Box Office Mojo (boxofficemojo.com). Fourth, a creator's likelihood of receiving an award or a nomination could also be affected by critics' ratings. Critics' ratings are released as soon as the movie comes out, while awards are often assigned many months after the release. Consequently, critics' ratings have the potential to influence award voters, especially for awards bestowed by critics' associations. Voters might pay more attention to movies that have received critical acclaim due to social and media influence. Thus, we controlled for critical reception, measured as the average of the critics' ratings for the movie(s) the creator worked on in the focal year. Data on critical reception was obtained from, www.rottentomatoes.com, a well-established online resource that assigns each movie a critical reception score. The score is based on a wide number of movie reviews from accredited media outlets and critics societies. For each review, the quantitative score provided by the critic is converted to an 11-point scale (i.e., 0 to 10). When critics do not provide a quantitative score, internal staff converts each critic's general impression into a score based on that critic's word choice, tone, and authoritativeness. Individual scores are then averaged to produce an overall critics' rating. The same list of critics is used to evaluate each movie, thus mitigating the risk of bias.

Finally, we included dummies for the observation year, production studios, and roles in order to control for the existence of unobserved time-varying factors, studio-specific, and role-specific characteristics. Including a dummy for production studios with only one movie produced in the observation period would have resulted in collinearity problems. Moreover, adding an excessive number of control variables could result in an over-specification of the model with little or no increase in predictive power (Greene, 2011). Thus, we included a dummy for each company that has produced 7 (the median number of movies produced) or more movies in the observation period. These companies accounted for 75% of the total number of movies produced.

Estimation Procedures

Our dependent variable measures individual creativity by computing the number of awards and nominations each creator received in a given year. As this variable is a non-negative integer, the use of linear regression would result in inconsistent, inefficient, and biased estimators. Moreover, our dependent variable is overdispersed, violating the basic assumption of the Poisson estimator of mean equal to variance (Hausman, Hall, & Griliches, 1984). We thus used a panel negative binomial regression model, which allows for overdispersion by relaxing the assumption mean equal to variance (Cameron & Trivedi, 1998). We estimated the final model using the generalized estimating equations (GEE) to control for heterogeneity at the individual level and the existence of any unobserved systematic difference across individuals. GEE fits a population-averaged model that specifies a marginal distribution over the population of individuals. The resulting coefficients can thus be interpreted as the response averaged over the population of individuals (Hardin & Hilbe, 2013). This method accounts for the correlation in the dependent variable across observations over time – generated by the repeated yearly measurements and by other forms of nesting – by estimating the correlation structure of the error terms (Liang & Zeger, 1986; Hardin & Hilbe, 2013). In other words, it controls for the fact that we have repeated observations for the same creators over time.

While the consistency of GEE parameter estimates is not affected by a misspecification of the correlation structure, the efficiency of these estimates depends on choosing the appropriate correlation structure (Hardin & Hilbe, 2013; Liang & Zeger, 1986). The quasi-likelihood under the independence model criterion (QIC) can be used to select the correlation structure that is most appropriate for each dataset (Cui, 2007; Pan, 2001). The QIC statistic revealed that an exchangeable correlation structure – which assumes that the correlations between repeated measurements of the dependent variable are equal across time – had a better fit with the data than other alternatives. Furthermore, our panel was characterized by unequal spacing between observations and by the presence of gaps, making an exchangeable correlation structure methodologically more appropriate (Hardin & Hilbe, 2003). Another advantage of the exchangeable correlation structure is that it yields estimators that are identical to those generated by the quantitative inference function (QIF), a modification of GEE which has been shown to be very robust to the presence of outliers and missing values (Qu, Lindsay, & Li, 2000; Qu & Song, 2004). We report significance levels based on Huber-White robust standard errors to control for any residual heteroscedasticity across panels. Using robust standard errors is equivalent to clustering on the creator, further accounting for the presence of repeated observations (Arellano, 2003; Wooldridge, 2016). STATA 14.0 *xtgee* command was used to estimate all models.

RESULTS

Table 3 presents correlations and descriptive statistics. Overall, 23.86% of creators received their first award for their first contribution in a core role. 24.39% received their first award in the first six years of their career, while 35.5% received it within the first 15 years. We checked for multicollinearity by computing the collinearity diagnostic procedures illustrated by Belsley and colleagues (1980), the most appropriate approach for computing collinearity using GEE (Hill & Adkins, 2003). These procedures examine the "conditioning" of the matrix of independent variables, producing a condition number that is the largest condition index. The condition number for the full model was 26.75, below the value of 30 considered problematic by conventional standards (Belsley, 1991), indicating that collinearity was not an issue.

Insert Table 3 and Table 4 about here.

Table 4 presents the GEE coefficient estimates for the negative binomial regression model. We centered the predictor variables before calculating the interaction terms (Aiken & West, 1991). Model 1 includes all the control variables. The coefficient for the variables *team quality*, *budget*, and *critical reception* is positive and significant ($p < .01$). This indicates that working with creative co-workers, and on movies with greater financial resources and that receive positive critics' reviews increases the likelihood of receiving a nomination and/or an award. Moreover, the coefficient for the variable *individual quality* is positive and significant ($p < .01$), indicating that past success is positively related to current creative performance. Model 2 shows the results after we entered the independent variables and the moderator. Career age has a positive, marginally significant effect ($p < .10$), while depth and breadth have no significant effect on creativity. Model 3 reports the results for the full model, with the inclusion of the interaction variables. As expected, the coefficient for the interaction between knowledge depth and career age is negative and significant ($p < .01$). This indicates that, as career age increases, the effect of knowledge depth becomes less positive. This is consistent with Hypothesis 1. In line with Hypothesis 2, the interaction between knowledge breadth and career age is positively related to creativity ($p < .01$). The overall fit of the model improves as compared to the baseline, but also with respect to Model 2, indicating that the full model better fits the data. The chi-square test for two degrees of freedom shows that Model 3 improves significantly on Model 2 (Pr > chi-square is < 0.01). Figures 2 and 3 plot the marginal average effects, showing that the impact of knowledge depth becomes less positive as career age increases, while the impact of knowledge breadth becomes more positive. Knowledge depth has a positive and significant effect ($p < .05$) in the first ten years of the career that turns progressively less positive as career age increases, becoming negative and significant in later stages (*p* < .05). In contrast, knowledge breadth does not have a significant effect in the early years of the career, and then has a positive and significant effect (*p* < .01). In our dataset, calculating standardized coefficients for Model 3 did not make sense: when the outcome is a count variable, the interpretation of effect sizes cannot be based on the standardized coefficient of the interaction term (Hilbe, 2007). Thus, in order to ensure interpretability, we calculated effect sizes at different levels of career age. We calculated effect sizes in the form of incidence rate ratios (IRR), the most appropriate when the dependent variable is a count (Arellano, 2003; Hilbe, 2007). In the early years of the career, each additional level of knowledge depth is associated with an increase in creativity that starts at 8% and then declines towards 4%. Conversely, in later stages of the career, each additional level knowledge depth is associated with a decrease in creativity that ranges between 7% and 24%. Early in the career, knowledge breadth does not affect creativity. However, later in the career each additional level of knowledge breadth is associated with an increase in creativity between 3% and 27%. Overall, the analysis of marginal effects of knowledge depth and breadth at different levels of career age provides further support for both Hypotheses 1 and 2.

Insert Figure 2 and Figure 3 about here

Robustness Checks

We performed a split sample analysis to further explore our moderation hypotheses, (Shaver, 2007). Since career age was overdispersed, we estimated Model 2 at above-median and below-median levels of career age. Results were consistent with those presented above: at below-median levels, the effect of knowledge depth on creativity is positive and significant (b= .37, *IRR*=1.45, *p* < .01), while the effect of breadth is non-significant; at above-median levels, the effect of knowledge breadth on creativity is positive and significant (b= .04, *IRR*=1.04, $p < .05$), while the effect of depth is non-significant.

Alternative Explanations. We also tested the robustness of the results against potential alternative explanations. First, our results could be explained by selection due to skills and talent. In the long run, skilled individuals are more likely to survive. In other words, it might be that inferior creators would have relatively short careers and capable creators would have longer careers, and this could explain the change in effect of knowledge dimensions on creativity. While controlling for individual quality should account for this, we decided to directly test for the potential effect of selection. We adopted Lee's (1983) modified version of the Heckman model (Heckman, 1979). Since we were looking at individuals dropping out of the sample because of low skill, we used an accelerated failure time (AFT) model with an exponential distribution to estimate the likelihood that a creator will leave the industry (and thus the sample) in year t+2 (see Henderson, Miller, & Hambrick, 2006 for a similar approach)[4]. We chose 2 years as the time lag as it was the average time between each contribution in our sample. Next, we followed the procedure detailed by Henderson and colleagues (Henderson et al., 2006) to calculate the selection parameter, or Inverse Mills ratio (IMR), and then controlled for the Inverse Mills ratio in the full model. Selection bias can be said to be absent when two conditions are simultaneously satisfied: a) the coefficient of the IMR in the full model is not significant; and b) the correlation between IMR and the independent variables is low, indicating the presence of strong exclusion restrictions (Certo, Busenbark, Woo, & Semadeni, 2016). The correlation between IMR and

[4] The predictors in the selection function included the two independent variables, the individual quality variable, and two additional selection conditions. All the variables were calculated at time t. The first selection condition was the stability of the production studio, coded as 1 if the studio was stable (i.e., was not created only for producing that particular movie), and 0 otherwise. Individuals working for stable companies should be less likely to leave the sample. The second selection condition controlled for whether the creator had *just* been promoted to the core role (coded 1, 0 otherwise). A recently promoted individual might be more likely to stay in the sample, rather than being fired and thus leaving the sample. We also tried a specification with only the first exclusion restriction, and it yielded results identical to those reported here.

depth and breadth was low (r_{depth}=0.19; $r_{breadth}$=0.34), thus suggesting that the significance of the IMR could be used as an indicator of the presence of selection bias. Model 4 reports the results of the second stage. The Inverse Mills ratio does not have any significant effect on creativity. Moreover, results are robust and consistent with those presented in Model 3. This provides evidence that sample selection was not driving the results.

Unobserved differences in talent and ability could also influence the effects of knowledge depth and breadth on creativity. It could be that skilled creators would get a greater number of assignments than less skilled ones, thus affecting knowledge depth and breadth, depending on the type of assignment. While controlling for individual quality and longitudinal design should mitigate this possibility, we decided to check whether our results differed for different sub-populations of creators. To this end, we divided our sample into independent freelance professionals and those who have more stable, permanent-hire contracts with the studios. As mentioned, in the animation industry the distinction between independent freelance professionals and those permanently working for studios is less clear-cut than in the movie industry as a whole, and cannot be traced back to specific roles or defined *ex ante*. For example, directors tend to be independent professionals in the movie industry, but they often have permanent-hire contracts within the animation industry. We thus classified our 2070 creators based on their mobility rate. The mobility rate was calculated as the ratio between the total number of mobility episodes of each creator (i.e., the number of times a creator moved to a different animation studio) and the total number of movies he/she has worked on. Creators with above-mean levels of mobility ratio were classified as independent professionals, while creators with below-mean levels were classified as permanent hires within an animation studio. We re-ran model 3 for each sub-sample of creators. The pattern of results for knowledge breadth did not differ between the two samples: the effect of knowledge breadth became increasingly positive over the career, both for independent freelance professionals (non-significant effect in the first 5 years of the career, increasingly positive and significant at $p < .05$ and $p < .01$ afterwards) and for permanent hires (non-significant effect in the first 20 years of the career, increasingly positive and significant at $p < .05$ afterwards). In contrast, results for knowledge depth differed between the two samples. For independent professionals, the effect of knowledge depth became increasingly less positive over the career: depth had a positive and significant effect over the first 10 years of the career (p < .05) that decreased over time (n.s.) and turned negative after 30 years of career (p < .10). For permanent hires, the effect also turned negative over time, but was always non-significant.

Our theory suggests that the effects of knowledge depth and career age on creativity are not curvilinear, but contingent on each other. However, extant literature has suggested that both dimensions have curvilinear effects on creativity. While we argue that this is due to how creativity was measured and to the fact the two are rarely considered in conjunction, we decided to run two separate analyses to control for the presence of a curvilinear effect of depth and career age. Both the linear ($b_{\text{depth}} = .08$, n.s.; $b_{\text{career age}} = .01$, $p < .10$) and squared terms ($b_{\text{depth}} = -.00$, n.s.; $b_{\text{career age}} = -.00$, n.s.) were non-significant, suggesting curvilinear effects were absent.

We also checked for the possibility that effects were not driven by knowledge depth and breadth, but by overall experience in the field. We re-ran models 2 and 3 substituting knowledge depth and breadth with a measure of overall experience, calculated as the total number of movies a creator has worked on up to the given year. Results revealed a positive and significant effect of overall experience ($p < .05$), but no significant interaction effect between experience and career age. This suggests that the effects of knowledge depth and breadth over the career are separate and distinct from the effect of overall experience. We also checked for the possibility that the increasingly positive effect of knowledge breadth is driven by increasing depth, rather than career age, by testing the significance of the interaction between the two knowledge dimensions. The interaction was never significant, neither when it was tested in isolation (b $_{\text{depth-breadth}}$ = .006, n.s), nor when it was tested together with the two hypothesized interactions, which remained significant (b $_{\text{depth-career age}}$= - .005, $p < .05$; b $_{\text{breadth-career age}}$= .004, $p < .01$; b $_{\text{depth-breadth}}$ = .006, n.s).

Finally, we also checked whether nesting at the studio level affected our results. While GEE is robust to misspecifications of the underlying correlation structures (Hubbard et al., 2010), it might be that nesting makes estimations inefficient. Our data was not perfectly nested across levels of analysis: while observations were perfectly nested in individuals, individuals were not perfectly nested in studios, as they did not always work within the same studio (see Cattani, Ferriani & Allison, 2014 for a similar example). Thus, we adopted the procedure described by Miglioretti & Heagerty (2007) to deal with multilevel, non-nested clusters in GEE models, computing standard errors that are robust to this type of data structure. Estimates and the analysis of marginal effects yielded results consistent with those reported in Table 4.

Alternative Specifications of Variables. We also checked the robustness of the results against different specifications of the variables of interest. First, we estimated a logistic regression model where the dependent variable was dichotomized between high and low creativity (coded “1” when the individual received more than one award/nomination in a given year, “0” otherwise). Results were consistent with those presented here, with career age negatively moderating the effect of knowledge depth on creativity ($p < .01$) and positively moderating the effect of knowledge breadth on creativity ($p < .01$). Marginal effects analysis also revealed a pattern similar to the main analysis: knowledge depth had a positive effect early in the career ($p < .05$) and a negative effect in later stages ($p < .01$), while breadth had a marginally negative effect in the early years of the career ($p < .10$) and a positive one in later stages ($p < .01$). Second, we re-estimated Model 3 substituting the continuous measure of career age with a categorical variable measuring career stages. The variable took the value of 1 when career age was low (0-6 years), 2 when career age was middle (7-15 years) and 3 when career age was high (above 15 years). The results were consistent with those obtained with the continuous measure of career age: the effect of knowledge depth becomes less positive as career age increases, ($b_{\text{mid career}} = -.13$, $p < .10$; $b_{\text{late career}} = -.13$, $p < .05$), while the effect of knowledge breadth becomes more positive ($b_{\text{mid career}} = .07$, $p < .05$; $b_{\text{late career}} = .08$, $p < .05$). Third, we checked for whether different early experiences in terms of knowledge depth and breadth had a long-term impact on creativity by running an analysis on the subsample of creators in the mid-to-late stages of their career. Instead of using our cumulative measures of knowledge depth and breadth, we re-ran Model 2 using measures of the knowledge depth and breadth creators had acquired in early years of their career. Results showed that early knowledge depth has no significant effect on creativity later in the career, while early knowledge breadth has a positive and significant effect ($b = .06$, $p < .01$). That we find the same effect in our main analysis suggests the time of knowledge breadth acquisition does not affect its efficacy in stimulating creativity in later stages of the career.

The full results of all robustness analyses are not reported due to space constraints, and are available from the authors upon request.

DISCUSSION AND CONCLUSION

Our goal was to understand if and how the effects of knowledge depth and breadth on creativity vary over an individual's career. In order to be creative, individuals need to possess knowledge structures that balance complexity and flexibility. As career age increases, knowledge structures become increasingly rigid. We hypothesized that, because of this increase in rigidity, different characteristics of individuals' knowledge base will be more conducive to creativity at different stages of the career. Knowledge depth (increasing the complexity and rigidity of knowledge structures) will be more beneficial in early stages of a career, when knowledge structures are less complex and more flexible; and knowledge breadth (increasing the flexibility of knowledge structures) will be more beneficial in later phases of a career, when structures become increasingly rigid and need to be "loosened up" in order for idea generation to take place. We found support for both hypotheses. This suggests that individuals who are able to appropriately restructure their knowledge base across their career should be able to maintain high levels of creativity over time, while individuals with a stable or inappropriately configured knowledge base should experience fluctuations in their creativity.

Overall, we contribute to the creativity literature in several ways. First, considering career age allows us to reconcile existing inconsistencies on the impact of different knowledge dimensions on creativity. Our research suggests that these mixed findings might be due to the role played by career age in influencing how knowledge structures evolve. We show that the effects of knowledge depth and breadth on creativity are contingent on career age because of its effect on the strength of linkages between domains and schemas. Thus, the efficacy of different knowledge dimensions in fostering creativity depends on how knowledge and cognition mutually shape each other (Dane, 2010), rather than knowledge being merely an input that is then elaborated by the human mind. Moreover, our results show that the moderating effect of career age is also significant when outcomes are dichotomized as either "creative" or "non-creative". This suggests that having the appropriate levels of knowledge depth and breadth at the right stage of the career not only determines how creative an individual can be, but also for *whether* he or she is able to generate creative outcomes in the first place. This finding is consistent with phenomena such as the "writer's block" (Rose, 2009), where creators not only experience a decline in their creativity but also become incapable of generating new ideas and outcomes. Thus, an inappropriate configuration of knowledge dimensions leads to a decline in creative performance and the inability to generate ideas. Future studies exploring intra-individual creative cognition should take into account the double-faceted nature of the knowledge-cognition relationship to articulate their joint role in shaping individual creativity. In addition, our results point out that research on knowledge structures and cognition could benefit by examining the linkages *between* domains, in addition to the linkages between schemas *within* domains. Current research has focused mostly on within-domain linkages to explain how knowledge affects creativity (e.g., Dane, 2010). We suggest that looking at how factors such as career age affect between-domain linkages is important to understanding the knowledge-creativity link.

Second, our results contribute to research on career age and creativity. While we know a lot about creativity variation over a career (e.g., Lehman, 1953, 1954; Simonton, 1975, 1997, 2000), we know little about whether individuals' needs in terms of creative stimuli vary across the career (i.e., about the role of career age as a moderator). Our findings provide a first answer by showing that different levels of knowledge depth and breadth are more conducive to creativity at different stages of the career. Future research could further explore this issue, looking at other factors whose impact on creativity might vary over the course of the career. We also contribute to research on career age and creativity by showing that the effects of career age reported in extant literature could be a consequence of how creativity was operationalized. Consistent with extant findings (Dennis, 1958, 1966; Simonton, 1977), we find that career age does not have a direct effect on creativity – neither linear nor curvilinear – when creativity is measured as a continuous variable. The curvilinear trajectory usually described in career trajectories research is thus likely a consequence of how creativity is measured. Many have argued for the superiority of continuous measures of creativity in comparison to count measures of total products or total "highly creative products", as they allow for a more fine-grained assessment of creative outputs (Amabile & Mueller, 2008; Cattani & Ferriani, 2008; Shalley et al., 2004). Thus, a more accurate assessment of how creativity varies over the career requires continuous measures of creativity. Future research looking at creativity variation over time should take this into account, using continuous measures such as awards, accolades, patents, article citations, and critics' evaluations.

Finally, we also contribute to the call for including temporal effects to enhance the quality of creativity research (Amabile et al., 1996; Drazin, Glynn, & Kazanjian, 1999; Perry-Smith & Mannucci, 2017; Woodman et al., 1993), and of organization theory in general (Ancona, Goodman, Lawrence, & Tushman, 2001; George & Jones, 2000). Our focus on the effects of knowledge depth and breadth provides an important micro-foundation for a theory of why creativity varies over time. Specifically, our findings point out the necessity of looking at the dynamic unfolding of creative cognition in order to understand how individuals generate creative outcomes By developing and testing a theoretical framework that encompasses both the cognitive process underlying creativity and the continuous nature of creative outcomes, we suggest that understanding how and why creativity varies over time requires taking into account the evolution of the underlying cognitive process resulting from the variation of knowledge structures. Considering the two in conjunction, rather than in isolation, could enrich future theory development, enabling scholars to better understand creative cognition.

Managerial Implications

Our study has implications for managerial practice. Organizations have been struggling to identify and put in place the measures necessary for fostering employees' creativity, and to sustain it over time (Amabile, 1998; Catmull & Wallace, 2014). Learning and development programs have become popular tools to achieve these goals, as increased knowledge is associated with greater creative performance (Senge, 1990). Our study points out an important caveat to the benefit of learning: fostering creativity of those early in their careers requires different strategies and types of knowledge than those needed to sustain or reinvigorate the creativity of those late in their careers. Learning and development programs for new hires should therefore focus on deepening their knowledge base, getting neophytes acclimated with the rules, norms, and ways of doing things of the domain. Conversely, learning and development programs for those later in their careers should focus on broadening their knowledge base, exposing them to diverse domains and stimulating them to explore novel ways to approach problems. A good example of this approach is Pixar University, the professional development program implemented by Pixar: while neophytes receive job-specific training, those later in their career can take courses in topics such as meditation, creative writing, ballet, and computer programming (Catmull & Wallace, 2014).

Our findings are especially relevant for today's organizations, as the population is aging at unprecedented rates (Kulik, Ryan, Harper, & George, 2014). Our findings suggest that late-career employees benefit greatly from exposure to different knowledge domains. This could also explain why older employees often struggle to be creative: it might be that late-career employees need different resources to be creative. Managers should account for these differences when assigning tasks and projects to late-career employees, finding a way to appropriately foster their creativity.

Limitations and Directions for Future Research

Notwithstanding its contributions, this study has limitations. First, the archival nature of the data does not allow us to explore in-depth the cognitive mechanisms involved. We adopted an archival, longitudinal approach in order to explore the moderating role of career age not only between creators – like it would have been the case with a cross-sectional sample – but also within the same creators, thus providing a robust and reliable test for our hypotheses. However, the archival nature of the sample prevented us from empirically measuring and directly testing the changes in knowledge structures induced by career age. Thus, there is the possibility that there are other mechanisms through which career age could be affecting the knowledge-creativity relationship. For example, it might be that the effect is due to skill building and its dynamics. Individuals need to generate a base of domain-relevant knowledge before being able to generate creative outcomes. However, after some time, increasing knowledge will not provide any further benefit (e.g. Sternberg, 1977). In the same fashion, being exposed to diverse knowledge is unlikely to yield any benefit until a deep knowledge of the domain has been acquired. Our finding on the negative effect of knowledge depth late in the career, as well as the robustness checks on the effects of overall experience and accumulation, provides support for the cognitive schemas mechanism. However, our research design does not allow us to completely rule out alternative explanations, and future research could further explore and clarify this issue.

One alternative explanation is the possibility that career age and knowledge depth are overlapping constructs. However, our findings show that career age and knowledge depth have separate and distinct effects on creativity. Moreover, robustness checks show that depth and career age have different moderating effects on the breadth-creativity relationship, suggesting that the two variables are separate constructs with distinct effects on knowledge structures and creativity. Another mechanism that could provide an alternative explanation to our findings is intrinsic motivation. Research has shown that intrinsic motivation declines as the time spent within a given field increases, due to the attainment of mastery goals and decreasing interest (Gottfried, Fleming, & Gottfried, 2001; Otis, Grouzet, & Pelletier, 2005). Thus, it might be that individuals late in their career are less motivated when they work on a genre where they have attained deep knowledge. Given the importance of intrinsic motivation for creativity (Amabile, 1983), this could result in reduced creativity. Conversely, they could be intrinsically motivated to work on projects in other domains, thus generating more creative outcomes.

Finally, it might be that our theorized effects are not driven by knowledge depth, but by other factors that are affecting both knowledge and creativity. For example, one of our robustness checks showed that knowledge depth does not have any effect for permanent hires. It might be that job stability is the real cause underlying the effects we attributed to knowledge depth, or that it substitutes for knowledge depth in affecting creativity. Job stability might either foster knowledge depth, and consequently creativity, or directly foster individuals' socialization with their task and domain, thus affecting creativity. Unfortunately, the sample size for this analysis (N=314) was too small to draw any meaningful conclusions, and the archival nature of our data prevented us from exploring this issue definitively. Future research could explore how career age and other factors such as job stability affect the knowledge-creativity relationship.

A second limitation is that our findings might not generalize to other settings, given the strong industry focus on creative endeavors and the adoption of project-based structures. Our findings may apply to settings with similar characteristics, such as consulting, scientific research, and new product design, but not to teams that do not require creativity for their tasks. However, there are at least two reasons to believe in the generalizability of our findings to a wide range of settings. First, the animation industry is characterized by a higher stability of working relationships than the movie industry as a whole (Furniss, 2009), with many studios hiring creators on a permanent basis. Second, many of the problems faced by employees in cultural industries are common to other knowledge-intensive industries where creativity and innovation drive success and survival (Lampel, Lant, & Shamsie, 2000). Despite these features, we cannot definitively rule out that the phenomenon of interest plays out differently in other settings. Future research should explore our focal relationships in settings with different conditions.

Notwithstanding these limitations, this paper extends our understanding of the relationship between knowledge dimensions and creativity in general, and of its dynamics across an individual's career in particular. Our study suggests that the differential effect of knowledge depth and breadth on creativity is due to their interplay with career age in shaping individuals' knowledge structures. We hope to provide impetus to research exploring the differential impact of creativity antecedents at different stages of a career.

REFERENCES

Aiken, L.S., & West, S.G. 1991. ***Multiple regression: Testing and interpreting interactions***. Thousand Oaks, CA: Sage.

Altman, R. 1999. ***Film/genre***. London, UK: British Film Institute.

Amabile, T.M. 1982. A consensual assessment technique. ***Journal of Personality and Social Psychology***, 43: 997-1013.

Amabile, T.M. 1983. The social psychology of creativity: A componential conceptualization. ***Journal of Personality and Social Psychology***, 45: 357-376.

Amabile, T.M. 1996. ***Creativity in context***. Boulder, CO: Westview Press.

Amabile, T.M. 1998. ***How to kill creativity***. Boston, MA: Harvard Business School Publishing.

Amabile, T.M., Conti, R., Coon, H., Lazenby, J., & Herron, M. 1996. Assessing the work environment for creativity. ***Academy of Management Journal***, 39: 1154-1184.

Amabile, T. M. & Mueller, J. S. 2008. Studying creativity, its processes, and its antecedents: An exploration of the componential theory of creativity. In J. Zhou & C.E. Shalley (Eds.), ***Handbook of organizational creativity***, 33-64. New York: Lawrence Erlbaum.

Anastasi, A. U., & Urbina, A. S. 1997. ***Psychological testing***. Ann Arbor, MI: Prentice Hall.

Ancona, D. G., Goodman, P. S., Lawrence, B. S., & Tushman, M. L. 2001. Time: A new research lens. ***Academy of Management Review***, 26: 645-663.

Arellano, M. 2003. ***Panel data econometrics***. Oxford: Oxford University Press.

Audia, P.G., & Goncalo, J.A. 2007. Past success and creativity over time: A study of inventors in the hard disk drive industry. ***Management Science***, 53: 1-15.

Bader, J.E., & Kivnick, H.Q. 1993. Career age. In R. Kastenbaum (Ed.), ***Encyclopedia of adult development***: 55-57. Phoenix, AR: Oryx Press.

Bartlett, F. C. 1958. ***Thinking***. London, UK: Allen & Unwin.

Belsley, D.A., Kuh, E., & Welsch, R. 1980. ***Regression diagnostics***. New York: Wiley & Sons.

Belsley, D.A. 1991. ***Conditioning diagnostics, collinearity and weak data in regression***. New York: John Wiley & Sons.

Boh, W. F., Evaristo, R., & Ouderkirk, A. 2014. Balancing breadth and depth of expertise for innovation: A 3M story. ***Research Policy***, 43: 349-366.

Burningham, B. 2000. Walt Disney's Toy Story as Postmodern Don Quixote. ***Cervantes***, 20: 157–174.

Caird, S. 1994. How do award winners come up with innovative ideas? ***Creativity and Innovation Management***, 3: 3–10.

Campbell, D. T. 1960. Blind variation and selective retention in creative thought as in other knowledge processes. ***Psychological Review***, 67: 380–400.

Cameron, A. C., & Trivedi, P. K. 1998. ***Regression analysis of count data***. Cambridge University Press, New York.

Canemaker, J. 2001. ***Walt Disney's Nine Old Men and the art of animation***. New York: Disney Editions.

Catmull, E. 2008. How Pixar fosters collective creativity. ***Harvard Business Review***, 86: 64-72.

Catmull, E., & Wallace, A. 2014. ***Creativity Inc.: Overcoming the unseen forces that stand in the way of true inspiration*****.** New York: Random House.

Cattani, G., & Ferriani, S. 2008. A core/periphery perspective on individual creative performance: Social networks and cinematic achievement in the Hollywood film industry. ***Organization Science***, 19: 824-844.

Cattani, G., Ferriani, S., & Allison, P.D. 2014. Insiders, outsiders, and the struggle for consecration in cultural fields: A core-periphery perspective. ***American Sociological Review***, 79: 258-281.

Certo, S.T., Busenbark, J. R., Woo, H.S., & Semadeni, M. 2016. Sample selection bias and Heckman models in strategic management research. ***Strategic Management Journal***, 37: 2639-2657.

Cirillo, B., Brusoni, S., & Valentini, G. 2014. The rejuvenation of inventors through corporate spinouts. ***Organization Science***, 25: 1764-1784.

Connolly, T. 1977. Information processing and decision making in organizations. In B. M. Staw & G. R. Salancik (Eds.), ***New directions in organizational behavior***: 205–234. Chicago: St. Clair Press.

Csikszentmihályi, M. 1999. Implications of a systems perspective for the study of creativity. In R. J. Sternberg (Eds.), ***Handbook of creativity***: 313-335. New York: Cambridge University Press.

Cui, J. 2007. QIC program and model selection in GEE analyses. ***The Stata Journal***, 7, 209-220.

Dane, E. 2010. Reconsidering the trade-off between expertise and flexibility: A cognitive entrenchment perspective. ***Academy of Management Review***, 35: 579-603.

De Dreu, C.K., Baas, M., & Nijstad, B.A. 2008. Hedonic tone and activation level in the mood-creativity link: toward a dual pathway to creativity model. ***Journal of Personality and Social Psychology***, 94, 739-756.

Dennis, W. 1958. The age decrement in outstanding scientific contributions: Fact or artifact? ***American Psychologist***, 13: 457-460.

Dennis, W. 1966. Creative productivity between the ages of 20 and 80 years. ***Journal of Gerontology***, 21: l-8.

Dirks, T. 2017. ***Film genres***. http://www.filmsite.org/filmgenres.html .

Drazin, R., Glynn, M.A., & Kazanjian, K. 1999. Multilevel theorizing about creativity in organizations: A sensemaking perspective. ***Academy of Management Review***, 24: 286-307.

Feldman D.C., 1989. Socialization, resocialization, and training: Reframing the research agenda. In I.L. Goldstein (Eds.) ***Training and development in organizations***, 376–416. San Francisco: Jossey-Bass.

Fiske, S. T., & Taylor, S. E. 1991. ***Social cognition*** (2nd ed.). New York: McGraw-Hill.

Frensch, P. A., & Sternberg, R.J. 1989. Expertise and intelligent thinking: When is it worse to know better. ***Advances in the Psychology of Human Intelligence***, 5: 157-188.

Furniss, M. (Ed.) 2009. ***Animation: Art and industry.*** London: John Libbey Publishing.

Gavetti, G., Levinthal, D. A., & Rivkin, J. W. 2005. Strategy making in novel and complex worlds: The power of analogy. ***Strategic Management Journal***, 26: 691-712.

George, J.M. 2007. Creativity in organizations. ***Academy of Management Annals***, 1: 439–477.

George, J.M., & Jones, G.R. 2000. The role of time in theory and theory building. ***Journal of Management***, 26 : 657-684.

Gino, F., Argote, L., Miron-Spektor, E., & Todorova, G. 2010. First, get your feet wet: The effects of learning from direct and indirect experience on team creativity. ***Organizational Behavior and Human Decision Processes***, 111: 102-115.

Goldman, W. 1983. ***Adventures in the screen trade***. New York: Scribner.

Gottfried, A. E., Fleming, J. S., & Gottfried, A. W. 2001. Continuity of academic intrinsic motivation from childhood through late adolescence: A longitudinal study. ***Journal of Educational Psychology***, 93: 3-13.

Greene, W.H. 2011. ***Econometric analysis*** (7th ed.). New York: Prentice Hall.

Haas, M., & Ham, W. 2015. Microfoundations of knowledge recombination: Peripheral knowledge and breakthrough innovation in teams. In G. Gavetti, W. Ocasio (Eds.), ***Advances in Strategic Management (Special Issue on Cognition & Strategy)***, 32: 47-87.

Hall, L. K. B. 2000. Toy Stories for humanists? ***The Humanist***, 60: 38.

Hargadon, A. B., & Bechky, B. A. 2006. When collections of creatives become creative collectives: A field study of problem solving at work. ***Organization Science***, 17: 484-500.

Hardin, J.W. & Hilbe, J.M. 2013. ***Generalized Estimating Equations***. Boca Raton, FL: Chapman & Hall/CRC.

Harris, S.G. 1994. Organizational culture and individual sensemaking: A schema-based perspective. ***Organization Science***,5: 309 –321.

Harvey, S. 2014. Creative synthesis: Exploring the process of extraordinary group creativity. ***Academy of Management Review***, 39: 324-343.

Hausman, J., Hall, B., & Griliches, Z. 1984. Econometric models for count data with application to the patents-RD relationship. ***Econometrica***, 52: 909–38.

Heckman, J. J. 1979. Sample selection bias as a specification error. ***Econometrica***, 47: 153-161.

Henderson, A.D., Miller, D., & Hambrick, D.C. 2006. How quickly do CEOs become obsolete? Industry dynamism, CEO tenure, and company performance. ***Strategic Management Journal***, 27: 447-460.

Hilbe, J.M. 2007. ***Negative binomial regression***. London, UK: Cambridge University Press.

Hill, R. C., & Adkins, L. C. 2001. Collinearity. In B.H. Baltagi (Ed.), ***A companion to theoretical econometrics***, 257-78. Chicago, IL: John Wiley and Sons.

Hocevar, D., & Bachelor, P. 1989. A taxonomy and critique of measurements used in the study of creativity. In J. A. Glover, R. R. Ronning, & C. R. Reynolds (Eds.), ***Handbook of creativity***, 53-75. New York: Plenum.

Holden, A. 1993. ***Behind the Oscar: The secret history of the Academy Awards***. New York: Simon and Schuster.

Hubbard, A.E., Ahern, J., Fleischer, N.L., Van der Laan, M., Lippman, S.A., Jewell, N., Bruckner, T., & Satariano, W.A. 2010. To GEE or not to GEE: comparing population average and mixed models for estimating the associations between neighborhood risk factors and health. ***Epidemiology***, 21: 467-474.

Hwang, M. I., Lin, J.W. 1999. Information dimension, information overload and decision quality. ***Journal of Information Science***, 25: 213–218.

Katila, R., & Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. ***Academy of Management Journal***, 45: 1183-1194.

Katz, R., Allen, T.J. 1982. Investigating the not invented here (NIH) syndrome: A look at the performance, tenure, and communication patterns of 50 R&D project groups. ***R&D Management***, 12:7–20.

Kulik, C.T., Ryan, S., Harper, S., & George, G. 2014. Aging populations and management. ***Academy of Management Journal***, 57: 929-935.

Lampel, J., Lant, T., & Shamsie, J. 2000. Balancing act: Learning from organizing practices in cultural industries. ***Organization Science***, 11: 263-269.

Lee, L.F. 1983. Generalized econometric models with selectivity. ***Econometrica,*** 51: 507-512.

Lehman, H.C. 1942. The creative years: oil paintings, etchings, and architectural works. ***Psychological Review***, 49: 19-42.

Lehman, H.C. 1953. ***Age and achievement***. Princeton, NJ: Princeton University Press.

Lehman, H.C. 1954. Men's creative production rate at different ages and in different countries. ***The Scientific Monthly***, 78: 321-326.

Lehman, H.C. 1958. The chemist's most creative years. ***Science***, 127: 1213-1222.

Lehman, H.C. 1960. The age decrement in outstanding scientific creativity. ***American Psychologist***, 15: 128-134.

Lehman, H.C. 1966. The most creative years of engineers and other technologists. ***The Journal of Genetic Psychology***, 108: 263-277.

Liang, K.Y., Zeger, S.L. 1986. Longitudinal data-analysis using generalized linear-models. ***Biometrika***, 73: 13–22.

Mannucci, P.V. 2017. Drawing Snow White and animating Buzz Lightyear: Technological toolkit characteristics and creativity in cross-disciplinary teams. ***Organization Science***, 28: 711-728.

March, J. G. 1991. Exploration and exploitation in organizational learning. ***Organization Science***, 2: 71–87.

McCrae, R.R., Arenberg, D., & Costa, P.T. 1987. Declines in divergent thinking with age: Cross-sectional, longitudinal, and cross-sequential analyses. ***Psychology and Aging***, 2: 130-137.

Mednick, S.A. 1962. The associative basis of the creative process. ***Psychological Review***, 69: 220-232.

Miglioretti, D.L., & Heagerty, P.J. 2006. Marginal modeling of nonnested multilevel data using standard software. ***American Journal of Epidemiology***, 165: 453-463.

Mumford, M.D., Blair, C., Dailey, L., Leritz, L.E., & Osburn, H.K. 2006. Errors in creative thought? Cognitive biases in a complex processing activity. ***The Journal of Creative Behavior***, 40: 75-109.

Mumford, M. D., & Gustafson, S. B. 1988. Creativity syndrome: Integration, application, and innovation. ***Psychological Bulletin***,103: 27–43.

Nelson, R.R., & Winter R.G. 1982. ***An evolutionary theory of economic change***. Cambridge, MA: Harvard University Press.

O'Neil, T. 2003. ***Movie Awards***. New York: Perigee Trade.

O'Reilly, C.A. 1980. Individual and information overload in organizations: Is more necessarily better? ***Academy of Management Journal,*** 23: 684-696.

Otis, N., Grouzet, F. M., & Pelletier, L. G. 2005. Latent motivational change in an academic setting: A 3-Year Longitudinal Study. ***Journal of Educational Psychology***, 97: 170-183.

Pan, W. 2001. Akaike's information criterion in generalized estimating equations. ***Biometrics***, 57: 120–125.

Perretti, F., & Negro, G. 2007. Mixing genres and matching people: a study in innovation and team composition in Hollywood. ***Journal of Organizational Behavior***, 28: 563–586.

Perry-Smith, J.E. 2006. Social yet creative: The role of social relationships in facilitating individual creativity. ***Academy of Management Journal***, 49: 85-101.

Perry-Smith, J.E. 2014. Social network ties beyond nonredundancy: An experimental investigation of the effect of knowledge content and tie strength on creativity. ***Journal of Applied Psychology***, 99: 831-846.

Perry-Smith, J.E., & Mannucci, P.V. 2017. From creativity to innovation: The social network drivers of the four phases of the idea journey. ***Academy of Management Review***, 42: 53-79.

Perry-Smith, J.E., & Shalley, C.E. 2003. The social side of creativity: A static and dynamic social network perspective. ***Academy of Management Review***, 28: 89–106.

Qu, A., Lindsay, B.G., & Li, B. 2000. Improving generalised estimating equations using quadratic inference functions. ***Biometrika***, 87: 823-836.

Qu, A., & Song, P.X.K. 2004. Assessing robustness of generalised estimating equations and quadratic inference functions. ***Biometrika***, 91: 447-459.

Rietzschel, E.F., Nijstad, B.A., & Stroebe, W. 2010. The selection of creative ideas after individual idea generation: Choosing between creativity and impact. ***British Journal of Psychology***, 101: 47-68.

Rodowick, D. N. 2008. ***The virtual life of film***. Cambridge, MA: Harvard University Press.

Rose, M. 2009. ***The writer's block: The cognitive dimension. Studies in writing & rhetoric***. Carbondale, IL: Southern Illinois University Press.

Rousseau, D.M. 2001. Schema, promise and mutuality: The building blocks of the psychological contract. ***Journal of Occupational and Organizational Psychology***, 74: 511-541.

Senge, P. M. 1990. ***The fifth discipline***. New York: Doubleday.

Shalley, C.E., Zhou, J., & Oldham, G.R. 2004. The effects of personal and contextual characteristics on creativity: where should we go from here? ***Journal of Management***, 30: 933-958.

Shaver, J.M. 2007. Interpreting empirical results in strategy and management research. ***Research Methodology in Strategy and Management***,4: 273–93.

Simonton, D.K. 1975a. Sociocultural context of individual creativity: A transhistorical time-series analysis. ***Journal of Personality and Social Psychology***, 32: 1119-1133.

Simonton, D. K. 1975b. Age and literary creativity: A cross-cultural and transhistorical survey. ***Journal of Cross-Cultural Psychology***, 6: 259-277.

Simonton, D. K. 1977. Creative productivity, age, and stress: a biographical time-series analysis of 10 classical composers. ***Journal of Personality and Social Psychology***, 35: 791-804.

Simonton, D. K. 1984. Creative productivity and age: A mathematical model based on a two-step cognitive process. ***Developmental Review***, 4: 77-111.

Simonton, D. K. 1988. Age and outstanding achievement: What do we know after a century of research?. ***Psychological Bulletin***, 104: 251-267.

Simonton, D.K. 1992. Leaders of American psychology, 1879–1967: Career development, creative output, and professional achievement. ***Journal of Personality and Social Psychology***, 62: 5–17.

Simonton, D.K. 1997. Creative productivity: A predictive and explanatory model of career trajectories and landmarks. ***Psychological Review***, 104: 66-89.

Simonton, D.K. 1999. ***Origins of genius: Darwinian perspectives on creativity***. New York: Oxford University Press.

Simonton, D.K. 2000. Creative development as acquired expertise: Theoretical issues and an empirical test. ***Developmental Review***, 20: 283-318.

Simonton, D.K. 2003. Scientific creativity as constrained stochastic behavior: The integration of product, person, and process perspectives. ***Psychological Bulletin***, 129: 475–494.

Simonton, D.K. 2004. Film awards as indicators of cinematic creativity and achievement: A quantitative comparison of the Oscars and six alternatives. ***Creativity Research Journal***, 16: 163–172.

Sorensen, O., & Waguespack, D. M. 2006. Social networks and exchange: Self-confirming dynamics in Hollywood. ***Administrative Science Quarterly***, 51: 560–589.

Sosa, M.E., 2011. Where do creative interactions come from? The role of tie content and social networks. ***Organization Science***, 22: 1-21.

Sparrow, P.R. 1999. Strategy and cognition: Understanding the role of management knowledge structures, organizational memory and information overload. ***Creativity and Innovation Management***, 8: 140–149.

Sternberg, R. J. 1977. ***Intelligence, information processing, and analogical reasoning: The componential analysis of human abilities***. Mahwah, NJ: Lawrence Erlbaum.

Taylor, A., & Greve, H.R. 2006. Superman or the Fantastic Four? Knowledge combination and experience in innovative teams. ***Academy of Management Journal***, 49: 723-740.

Travers, P. 2012. ***10 best movies of the decade: 6. The Incredibles***. Rolling Stone, http://www.rollingstone.com/movies/lists/10-best-movies-of-the-decade-19691231/the-incredibles-20101202. Retrieved June 2016.

Von Nordenflycht, 2007. Is public ownership bad for professional service firms? Ad agency ownership, performance, and creativity. ***Academy of Management Journal,*** 50: 429-445.

Wadhwa, A., & Kotha, S. 2006. Knowledge creation through external venturing: Evidence from the telecommunications equipment manufacturing industry. ***Academy of Management Journal***, 49: 819-835.

Ward, T.B. 2004. Cognition, creativity, and entrepreneurship. ***Journal of Business Venturing***, 19: 173-188.

Wiley, M., & Bona, D. 1993. ***Inside Oscar: The unofficial history of the Academy Awards***. NewYork: Ballantine Books.

Woodman, R.W., Sawyer, J. E., & Griffin, R. 1993. Toward a theory of organizational creativity. ***Academy of Management Review***, 18: 293-321.

Wooldridge, J.M. 2016. ***Introductory econometrics: A modern approach***. Boston: Cengage.

Zhou, J. 2003. When the presence of creative coworkers is related to creativity: Role of supervisor close monitoring, developmental feedback, and creative personality. ***Journal of Applied Psychology***, 88: 413-422.

TABLES AND FIGURES

TABLE 1
Effects of Career Age on Flexibility of Knowledge Structures

Career Stage	Inter-Schema Flexibility	Inter-Domain Flexibility
Early	High	High
Middle	Medium	Medium
Late	Low	Low

TABLE 2
Professional Societies and Awards

Professional Society	Award	Year First Awarded
Academy of Motion Picture Arts and Sciences	Academy Awards (Oscars)	1929 [a]
Academy of Science Fiction, Fantasy and Horror Films	Saturn Awards	1973
American Cinema Editors	Eddie Awards	1951
American Society of Cinematographers	ASC Awards	1986
Art Directors Guild	ADG Awards	1996
Directors Guild of America	DGA Awards	1948
Hollywood Foreign Press Association	Golden Globes	1944
International Animated Film Association	Annie Awards	1972
Los Angeles Film Critics Association	LAFCA Awards	1975
National Board of Review	NBR Awards	1929
New York Film Critics Circle	NYFCC Awards	1935
Producers Guild of America	PGA Awards	1989
Writers Guild of America	WGA Awards	1949

[a]: The Academy Award for Best Animated Feature was introduced in 2001. However, animated movies could compete for other categories before that date (e.g., Beauty and the Beast was nominated for Best movie in 1991).

TABLE 3
Means, Standard Deviations, and Correlations [a]

Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1. Creativity	0.71	1.26	0.0	13.0												
2. Knowledge depth	1.75	1.41	1.0	16.0	.14											
3. Knowledge breadth	4.49	1.86	1.0	12.0	.09	.54										
4. Career age	6.33	7.82	0.0	62.0	.10	.46	.41									
5. First core contribution	0.60	0.49	0.0	1.0	– .10	– .64	– .57	– .50								
6. Individual quality	0.51	1.41	0.0	20.0	.34	.36	.34	.25	– .44							
7. Mobility	0.15	0.35	0.0	1.0	.01	.27	.34	.25	– .50	.11						
8. Repeated collaboration	0.41	0.73	0.0	5.3	.16	.67	.47	.40	– .69	.46	.12					
9. Sequel	0.16	0.37	0.0	1.0	– .05	.17	.02	.09	– .15	.10	– .04	.15				
10. Team quality	4.94	5.49	0.0	27.0	.57	.10	.15	.15	– .13	.19	.04	.13	– .08			
11. Critical reception	6.05	1.31	2.8	9.0	.47	.04	.08	.07	– .07	.14	– .02	.08	– .07	.69		
12. Budget	7.65	0.46	4.8	8.4	.27	.18	.23	.17	– .19	.22	.03	.40	.16	.10	.47	.20

[a] All values greater than |.04| are significant at $p < .01$

TABLE 4
GEE Coefficient Estimates for a Negative Binomial Panel Regression Model Predicting Individual Creativity [a]

Variables	Model 1	Model 2	Model 3	Model 4
First core contribution	0.067	0.133	0.146†	0.155†
	(0.083)	(0.082)	(0.087)	(0.088)
Individual quality	0.082**	0.079**	0.075**	0.075**
	(0.016)	(0.018)	(0.020)	(0.020)
Mobility	0.045	– 0.001	– 0.026	– 0.025
	(0.078)	(0.078)	(0.080)	(0.080)
Repeated collaboration	– 0.021	– 0.069†	– 0.083*	– 0.083*
	(0.038)	(0.041)	(0.040)	(0.040)
Sequel	– 0.119	– 0.119	– 0.112	– 0.111
	(0.073)	(0.075)	(0.074)	(0.074)
Team quality	0.101**	0.100**	0.101**	0.101**
	(0.007)	(0.007)	(0.006)	(0.006)
Critical reception	0.497**	0.505**	0.500**	0.499**
	(0.034)	(0.034)	(0.034)	(0.034)
Budget	0.744**	0.726**	0.733**	0.735**
	(0.083)	(0.085)	(0.084)	(0.084)
Career age		0.007†	0.006	0.005
		(0.004)	(0.004)	(0.004)
Knowledge depth		0.030	0.075*	0.075*
		(0.025)	(0.035)	(0.035)
Knowledge breadth		0.015	– 0.002	0.007
		(0.017)	(0.018)	(0.022)
Depth X career age			– 0.005**	– 0.005*
			(0.002)	(0.002)
Breadth X career age			0.004**	0.004**
			(0.001)	(0.001)
Mills ratio				– 0.100
				(0.134)
Year dummies	Yes	yes	yes	yes
Role dummies	Yes	yes	yes	yes
Wald χ^2	3,074.39**	3,192.02**	3,185.56**	3,176.69**
Observations	3,409	3,409	3,409	3,409
Number of creators	2,070	2,070	2,070	2,070

[a] Unstandardized coefficients. Huber-White robust standard errors are in parentheses.

† $p < .10$
* $p < .05$
** $p < .01$

FIGURE 1
Knowledge Structure: Domains, Schemas, Attributes, and Linkages

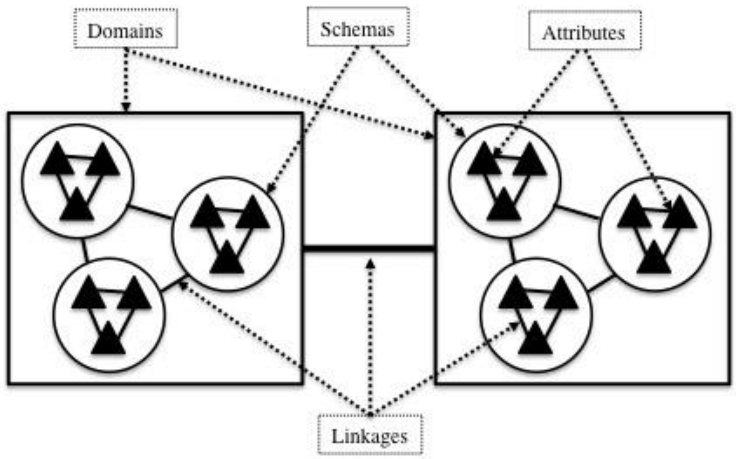


FIGURE 2
Interaction Effect of Knowledge Depth and Career Age on Individual Creativity

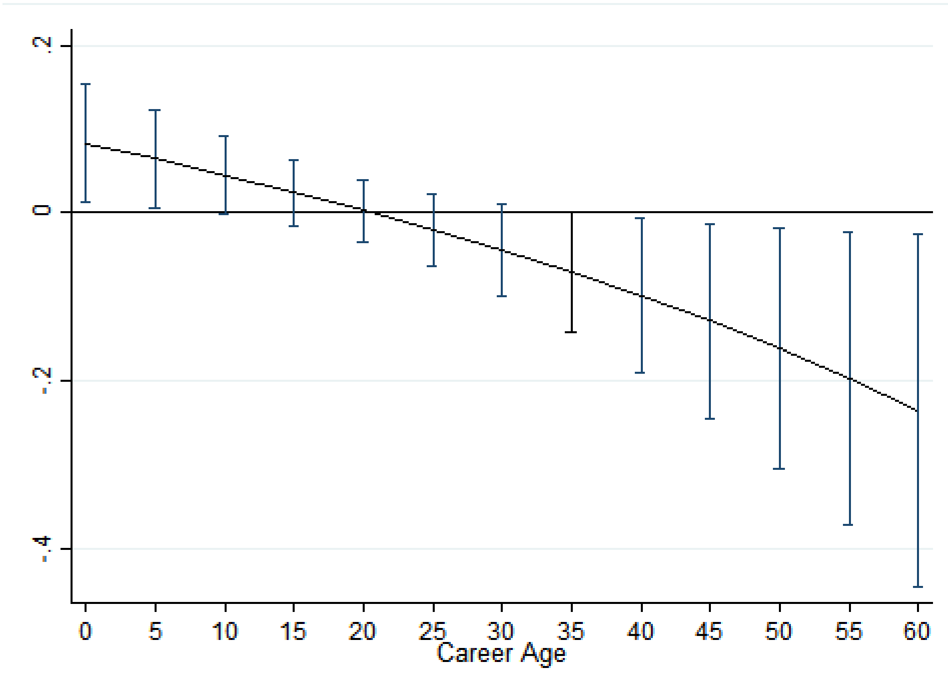
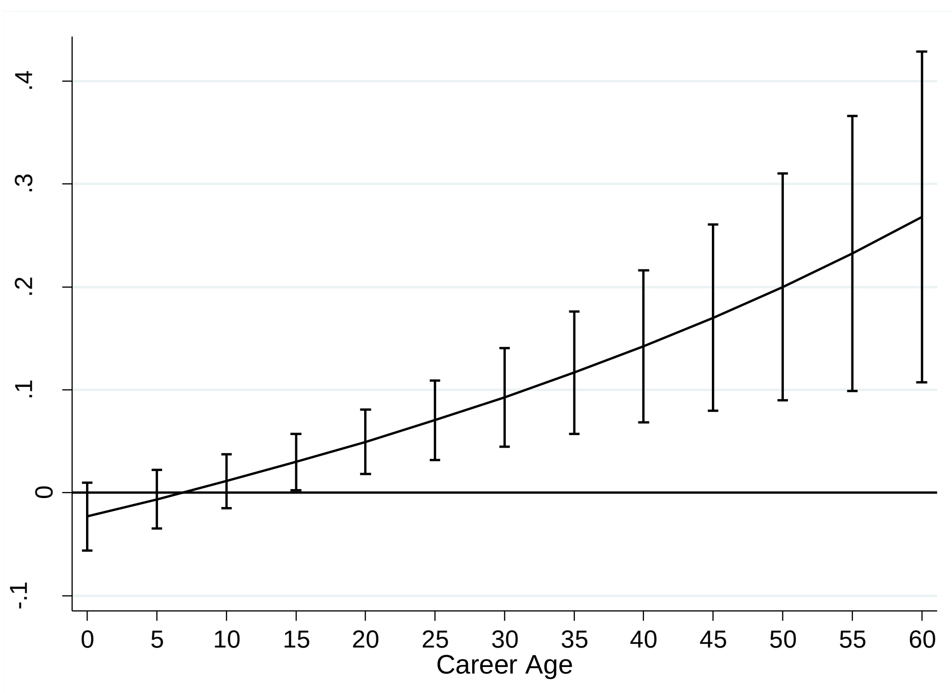


FIGURE 3
Interaction Effect of Knowledge Breadth and Career Age on Individual Creativity



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