One-Hit-Wonders vs. Hit-Makers:
Sustaining Success in Creative Industries

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Abstract

Creative industries produce many "one-hit-wonders" who struggle to repeat their initial success and fewer "hit-makers" who sustain success over time. To develop theory on the role of creativity in driving sustained market success, I propose a path dependence theory of creators' careers. The theory considers creators' whole portfolios of products over time and how their early portfolios shape their later capacity to sustain success. The main idea is that creators' paths to sustained success depend on the creativity in their portfolios upon their initial hit—relatively creative portfolios give creators more options for leveraging their past portfolios while adapting to market changes, increasing their odds of additional hits. The proposed theory was tested using an archival study of the U.S. music industry from 1959-2010, including data on over three million songs by 69,050 artists. Results largely supported the hypotheses. Artists who reached their initial hit with relatively creative (novel or varied) portfolios were more likely to generate additional hits, but novel portfolios were less likely to yield an initial hit than typical portfolios. This meant that artists faced a tradeoff between their likelihood of initial vs. sustained success. This research uncovers important theoretical insights on creativity and innovation over time.

Online Appendix:
https://drive.google.com/file/d/13dyG9XIPPD7asyEMjyqnYxRvhi4W_i05/view?usp=sharing

In creative industries, success is notoriously fickle. Creative industries supply products "that we broadly associate with cultural, artistic, or simply entertainment value" (Caves, 2000: 1). Examples of creative industries include film, music, art, theater, publishing, cuisine, gaming, and fashion. A hallmark of creative industries is that the success of new products is highly uncertain (Flew, 2012; Potts et al., 2008). Audience demand and competition produce a constant stream of new products, which can quickly render previously successful products outdated (Jones et al., 2016). Although large organizations often handle distribution and marketing, new products are usually generated by creators working individually or in teams (Caves, 2000; Perry-Smith & Mannucci, 2017). Sustaining success in these fast-paced markets requires creators to generate new products that suit the ever-changing tastes of the audience—and the gatekeepers who control access to the audience (Bielby & Bielby, 1994; Hirsch, 1972). Creators may face radical innovations that fundamentally change their industries on rare occasions (Abernathy & Clark, 1985). But the vast majority of the time, the challenge is responding to constant incremental change in what is popular at a given time (Klepper, 1997). Changes in what types of products are popular may be difficult or impossible to predict any more than a short time into the future, complicating the challenge of sustaining success over time (Simonton, 2011).

Furthermore, creative industries are often dominated by hits—highly successful products that garner a disproportionate share of the market (Potts et al., 2008; Salganik, Dodds, & Watts, 2006). Hits are by definition rare, and so are creators who consistently produce them. In most creative industries, the majority of creators who produce any hits have just one or two in their careers, while only a handful of creators are able to achieve more hits over time (Simonton, 1984). This pattern has come to be known as Lotka's Law, named for the scholar who first observed it (Lotka, 1926). Scholars have since observed this pattern in many different creative industries, including among film directors (De Vany, 2003), musicians (Cox, Felton, & Chung, 1995; Fox & Kochanowski, 2004), artists (Fraiberger et al., 2018), and book authors (Yucesoy et al., 2018). As creative industries mature, Lotka's Law typically emerges—some creators become "hit-makers" who generate several or more hits in their careers, but more creators remain "one-hit-wonders" who struggle to repeat their initial success. Given the outsize value generated by hit-makers and the costs of churning through one-hit-wonders, understanding the predictors of sustained success in creative industries could be useful to creators, the people who manage them, and the organizations that employ them (Elsbach & Kramer, 2003; Mollick, 2012).

In so-called creative industries, creativity would presumably be key to sustaining market success. One might assume that hit-makers sustain success by continually generating more creative products than one-hit-wonders. Yet, the relationship between creativity and market success may not be this straightforward over the course of creators' careers. Although past research has rarely examined the relationship between creativity and market success over time (cf. Audia & Goncalo, 2007), prior research has yielded valuable knowledge on how creativity relates to market success at a given snapshot of time. This work has revealed that different dimensions of creativity predict market success in opposite ways. On one hand, scholars have built a body of research on how the novelty or uniqueness of products in the market relates to success. This work has uncovered a negative relationship between creativity and market success: novelty on average reduces the likelihood of market success, as typical products tend to outperform more novel ones (Fleming, 2001; Liu et al., 2017; Uzzi et al., 2013; Veryzer & Hutchinson, 1998; Ward, Bitner, & Barnes, 1992), even in so-called creative industries (Becker, 1982; Interiano et al., 2018; Martindale, 1990). On the other hand, a separate body of research has advocated for an evolutionary view of creativity, focusing on a different dimension of creativity: the variety among creators' own products (e.g., Campbell, 1960; Simonton, 1997, 1999, 2011). This work highlights a positive relationship between creativity and market success: generating a wider variety of products increases creators' odds of a hit

Taken together, this prior work explains how these two core dimensions of creativity predict creators' odds of achieving a hit product at a given snapshot in time: novelty decreases the odds of a hit, while variety increases the odds of a hit. An assumption underlying this prior work is that each product is its own independent attempt at a hit. Indeed, this assumption is reflected in research on creativity and innovation more broadly. Scholars have usually treated creativity as a precursor to innovation, defining creativity as the generation of novel and useful ideas and innovation as the successful implementation of creative ideas (Anderson, Potočnik, & Zhou, 2014). Past research on creativity has tended to construe creative projects as their own separate endeavors, focusing on what contributes to the creativity of the final product in a given project (Amabile, 1988, 1996; Perry-Smith & Mannucci, 2017; Staw, 1990; West, 2002). The assumption is that once the final product is implemented in the market, creators move to their next project, and the process starts anew. This paints a path-independent picture of the relationship between creativity and market success, in which the creativity of creators' *current* products is what matters for predicting whether those products will become hits. Complementing this perspective, I propose a path-dependent view in which the creativity of creators' *past* products can also matter for predicting whether their current products become hits.

Simply put, path dependence implies that history matters (David, 2007). Scholars use path dependence theory to explain situations in which early events unintentionally narrow the set of viable options available to actors over time, locking actors into a particular path or range of viable options going forward (e.g., Arthur, 1989; Carroll & Harrison, 1994; Rosenbaum, 1979;

Sydow, Schreyögg, & Koch, 2009). Path dependencies are driven by positive feedback loops: patterns of behavior get positively reinforced such that other options become increasingly difficult or costly to pursue (Sydow, Schreyögg, & Koch, 2009). Creativity is likely to govern positive feedback loops in creators' careers, as the creativity that creators exercise in generating their past products should have enduring effects on the capabilities they learn (Ericsson, 1999; March, 1991) and the expectations that the audience and gatekeepers have for them (Hsu, 2006; Zuckerman, 1999). Learning and expectations tend to form positive feedback loops—when initial learning and expectations are positively reinforced, it becomes increasingly difficult to succeed with products that stray from one's initial capabilities and reputation (Sydow, Schreyögg, & Koch, 2009).

In creators' careers, achieving an initial hit product is likely to trigger such positive feedback loops, locking creators into the capabilities and reputations associated with the creativity—or lack thereof—in their product portfolios at the time. In creative industries, creators do not generate each of their new products in a vacuum. Rather, they build portfolios of products throughout their careers (Caves, 2000), and each product is released at a specific time in an ever-changing market. To build a relatively creative (novel and varied) portfolio before their initial hit, creators must generate products that diverge from the market and their own products over time, making creativity the path of more resistance, at least in the short run (Sternberg & Lubart, 1991, 1995). When creators achieve an initial hit, their broader portfolios at the time may be catapulted from relative obscurity to being known by a large swath of the market. In turn, their portfolios may serve as "carriers of history" (David, 1994: 205), such that the creativity (novelty and variety) in their portfolios shapes their possible paths to sustained success. If creators have a relatively uncreative (typical and homogenous) portfolio when they achieve their initial hit, their capabilities and reputation may be inextricably tied to a narrow range of products that are typical for the current milieu (Audia & Goncalo, 2007; Bayus, 2013; Dane, 2010; Hsu, 2006; Zuckerman, 1999). These creators may struggle to sustain success as the ever-changing market inevitably leaves this milieu behind. In contrast, when creators build a relatively creative (novel and varied) portfolio prior to their initial hit, their capabilities and reputation should be more adaptable, giving them more viable options for sustaining success as the market evolves. In this way, creators' paths to sustained success likely depend on the creativity in their portfolios upon their initial hit, such that creators who build relatively creative (novel and varied) portfolios before their initial hit are more likely to generate additional hits.

Despite the likely prevalence of key path dependencies in creators' careers, this notion has been largely overlooked in prior theory and research on creativity and innovation. In this paper, I develop a path dependence theory of success in creative industries, focusing on how the creativity in creators' early portfolios predicts their likelihood of short-lived versus sustained market success. The goal is a middle-range theory (Weick, 1974) that applies to the many creative industries in which creators build portfolios of products that audiences and gatekeepers associate with them, such as artists, writers, designers, inventors, chefs, architects, filmmakers, choreographers, social media influencers, and game developers. To test the theory, I assembled an archival dataset of the U.S. music industry from 1959-2010, which includes data on over three million songs by 69,050 artists, of whom 4,857 had one or more hit songs.

This research uncovers important theoretical insights for understanding how creativity and innovation unfold over time. Prevailing theories of creativity and innovation suggest that creators start over fresh each time they implement a product and move to their next project. In contrast, the present research suggests that creativity and innovation can become path dependent, such that the creativity of creators' prior products can have enduring implications for their capacity to produce successful innovations going forward. This path-dependent perspective reveals temporal dynamics that would be impossible to see with just a path-independent view of creativity and innovation. For instance, the path-independent view adopted in prior research suggests that creators are more likely to generate hits when their products are relatively typical, but this only applies to creators' *current* products at a given snapshot in time. The path-dependent view in the present research brings creators *past* products into the picture, revealing that when creators build relatively novel portfolios before their initial hits, they are more likely to generate additional hits going forward. This illustrates how path independence only tells half the story—path dependence is also needed for understanding how creativity and market success are related over time. Furthermore, the present study helps shed light on important boundary conditions for evolutionary theories of creativity and innovation. The benefits of variety implied by an evolutionary perspective were limited to the variety that creators generated before their initial hit, suggesting that achieving a hit product is a key boundary condition for evolutionary theories of creativity and innovation.

PATH DEPENDENCE, SUCCESS, AND CREATIVITY IN CREATORS' CAREERS

Scholars have invoked path dependence to explain a wide array of temporal processes and outcomes, including technological inertia (Arthur, 1989; David, 1985), competition between organizational populations (Carroll & Harrison, 1994), firm-level competitive advantage (Barney, 1991; Teece, Pisano, & Shuen, 1997), between-firm alliances (Lavie & Rosenkopf, 2006), entrepreneurial success (Beckman & Burton, 2008), employee promotions (Rosenbaum, 1979), and job mobility (Dlouhy & Biemann, 2018). The ultimate outcome of path dependence is "lock-in" to a particular path or range of viable options. Path dependencies are driven by positive feedback and self-reinforcing mechanisms: patterns of behavior get positively reinforced such that other options become increasingly difficult or costly to pursue (Arthur, 1988; Sydow, Schreyögg, & Koch, 2009). The most famous example of path dependence is the persistence of the QWERTY keyboard (Arthur, 1989; David, 1985). This keyboard layout was originally designed to minimize typewriter jamming while also allowing salespeople to impress customers by quickly keying "TYPE WRITER." Largely by chance, the QWERTY layout gained early traction in the market and typists increasingly became accustomed to it. Despite the presence of technically superior alternatives, QWERTY continued to be positively reinforced in the market and ultimately became locked in, persisting as the dominant keyboard layout for over 115 years. As this example illustrates, a strength of path dependence theory is explaining how actors become constrained by past events—often a mix of deliberate choices and chance occurrences—in ways that would be impossible for them to predict in advance (David, 2007).

Sydow and colleagues' (2009) integrated ideas from multiple literatures to build a relatively comprehensive theory of path dependence. They focus on path dependence at the organizational level, but they encourage scholars to adapt their general framework to suit other levels and contexts of interest. My theorizing adapts and builds on their framework. Rather than organizations, my focus is on creators, or the primary individual or group responsible for generating a given portfolio of products in a creative industry over time. Because ideas or prototypes that have not been released to the market are unlikely to drive path dependencies in the same way as finished products that have reached the market, I define a portfolio as all products by the focal creator that have been released to the market.

In Sydow and colleagues' (2009) framework, an important defining feature of path-dependent situations is that they do not start as path dependent. Rather, they start as path-independent situations in which the focal actor has a relatively unrestricted range of viable options. Path dependencies emerge when events inadvertently trigger self-reinforcing mechanisms that narrow one's path or range of viable options going forward. The point at which the situation turns from path independent toward path dependent is called the "critical juncture." Following the critical juncture, self-reinforcing mechanisms begin to drive positive feedback loops that privilege the actor's existing patterns of behavior over alternative options. In turn, the actor's path or range of viable options narrows at an increasing rate, ultimately locking the actor into a relatively limited range of viable options.

In my proposed theory, creator's initial success (first hit product) is the critical juncture, an unpredictable event that triggers the formation of the creator's path or range of viable options for sustained success (any additional hits after their first one).[1] New creators' pursuit of initial success is path independent, as they have a relatively unconstrained range of viable options for achieving initial success. If creators do achieve initial success, this triggers self-reinforcing mechanisms that make their quest for sustained success path dependent. Two self-reinforcing mechanisms drive this path-dependent process: internal learning and external expectations. These mechanisms work together to narrow creators' path or range of viable options for sustaining success based on their portfolios upon initial success. The mechanisms place creators in a double bind: to maximize their odds of sustained success, creators need to generate new products that are related to their portfolios upon initial success while also keeping up with inevitable changes in market preferences. The creativity (novelty and variety) in creators' portfolios upon initial success governs how much the mechanisms narrow their path or range of

[1] Although simply releasing a product to the market is a form of success, the proposed theory defines success using a much higher bar—achieving a hit product—because hits account for the vast majority of consumption in creative industries. For this reason, creators who have never achieved a hit product are relatively unknown in the market and may not encounter the path dependencies faced by creators who have had at least one hit.

viable options for weathering this double bind over time—creators who reach initial success with relatively creative portfolios maintain a wider path, increasing their odds of sustaining success. In the sections that follow, I elaborate this proposed theory and corresponding hypotheses. See Figure 1 for a visual of the theory and hypotheses, and see Figure 2 for a diagram illustrating example paths for an archetypal hit-maker and one-hit-wonder.

[Insert Figures 1 and 2 about here]

The Benefit of Relatedness for Sustaining Success

Self-reinforcing mechanisms are the engines of path dependencies, and these engines are fueled by positive feedback (Sydow, Schreyögg, & Koch, 2009). The proposed theory focuses on two self-reinforcing mechanisms that are especially relevant to success and creativity in creators' careers: internal learning and external expectations. Learning and expectation effects are among the most central self-reinforcing mechanisms in the literature on path dependence (Arthur, 1988), including in Sydow and colleagues' theory (2009). In my proposed theory, these two mechanisms work together to make creators' quest for sustained success path dependent.

First, the internal learning mechanism is based on the notion that exploiting existing capabilities tends to be more efficient, reliable, and actionable than gaining new capabilities (Argote, 1999; Audia & Goncalo, 2007; Levinthal & March, 1993). When learning yields success, it can become self-reinforcing: leveraging one's existing repertoire becomes increasingly rewarding, while expanding one's repertoire becomes increasingly costly (March, 1991). Second, the external expectations mechanism is based on the notion that expectations can be self-fulfilling prophecies. The audience and gatekeepers are more likely to reward products that fit what they expect from a given creator (and reject products that violate their expectations), thereby reinforcing their initial expectations (Hsu, 2006; Zuckerman, 1999).

Once creators achieve an initial hit, these two mechanisms may work together to make it increasingly difficult for creators to sustain success with products that diverge from their portfolios at the time. To maximize their odds of sustaining success, creators may need to pursue relatedness—generating new products that are coherent with the products in their portfolios upon initial success (Arts & Fleming, 2018; Bunderson & Sutcliffe, 2003). The concept of relatedness follows the same logic as theories of related diversification at the organizational level, which highlight the benefits of adding new products that maintain coherence with one's existing capabilities and reputation (e.g., Bettis, 1981; Markides & Williamson, 1994; Singh & Montgomery, 1987).

Before creators achieve initial success, the two mechanisms may be relatively dormant. Once creators achieve initial success, however, the two mechanisms may become mutually- and self-reinforcing, making relatedness key to sustaining success. As new creators build their portfolios, they learn capabilities tailored to their particular products (March, 1991). Thus, internal learning happens from the start of creators' careers. However, before achieving an initial hit, creators are relatively unknown in the market. Without strong or widespread expectations from the audience and gatekeepers, creators are relatively free to diversify their portfolios with little or no downside. But when they achieve their first hit, the audience and gatekeepers are likely to form strong expectations for creators to deliver more hits that are consistent with their portfolios at the time. Although creators' hit products may be most important in determining these expectations, hits tend to draw attention to creators' broader portfolios. For example, hit songs are a key driver of album sales, and hit artworks are often in exhibitions with other works by the artist. Thus, the audience and gatekeepers may categorize and form strong expectations about creators based on their initial hits and broader portfolios at the time. These strong expectations could help creators sustain success, but only when their new products fit the expectations by staying related to their portfolios upon initial success. If creators’ new products deviate from their portfolios upon initial success, this may violate what the audience and gatekeepers expect from them, reducing their odds of success (Hsu, 2006; Zuckerman, 1999).

In sum, the proposed theory suggests that when creators achieve an initial hit, the two underlying mechanisms (internal learning and external expectations) work together to form creators’ paths to sustained success, in which they are more likely to generate additional hits when their new products are closely related to their portfolios upon initial success. However, the proposed theory does not assume that creators will necessarily follow their paths to sustained success. Creators may stray from their paths to sustained success by generating only new products that deviate from their portfolios upon initial success. In this case, the presumed outcome would be reduced odds of sustaining success and thus increased risk of losing relevance in the industry. However, if creators do follow their paths to sustained success, they are likely to achieve additional hits that are closely related to their portfolios upon initial success. In turn, this should only reinforce the internal learning and external expectations associated with their portfolios upon initial success, further locking creators into paths in which maintaining relatedness with their portfolios upon initial success is key to sustaining success.

> **Hypothesis 1 (H1):** After creators’ initial success, relatedness predicts sustained success, such that creators are more likely to sustain success when their new products are related to their portfolios upon initial success.

The Challenge of Relatedness and Benefit of Prior Creativity for Sustaining Success

Although creators may maximize their odds of sustained success when their new products stay related to their portfolios upon initial success, their portfolios may become outdated over time. In creative industries, market preferences constantly change (Caves, 2000), but creators’ portfolios upon initial success remain static. Creative industries tend to be dominated by a mainstream of hit products (Becker, 1982). Waves of similar products become hits in the same stretch of time and shape what is typical in the market, until new trends emerge that make what was previously typical outdated (Bikhchandani, Hirshleifer, & Welch, 1992; Hirsch, 1972). New trends may be impossible to predict in advance (Caves, 2000; Salganik, Dodds, & Watts, 2006). However, after new trends emerge, creators may be more likely to sustain success if they incorporate elements of the trends into their new products. If they do not adapt to new trends, they risk losing market share to the latest mainstream hits. Thus, creators may face a double bind as they seek sustained success: their new products must stay related to their prior portfolios but also keep up with an ever-changing market. This double bind may narrow the paths that creators have for sustaining success as the market moves away from their portfolios upon initial success. However, the width of creators' paths over time, meaning the range of viable options for sustaining success, may depend on the creativity in their portfolios upon initial success.

Portfolio-level perspectives are relatively rare in theory and research on creativity, in which scholars tend to consider creators' output (ideas or products) independently at one snapshot or window of time. One important exception is Sternberg and Lubart's (1991, 1995) investment theory of creativity. Their theory emphasizes the value of considering creators' whole portfolio of projects, analogous to how considering a financial investor's whole portfolio would be more informative than examining only a subset of their investments. Whereas their theory implies a path-independent view, I build on key tenets of their theory to help theorize a path-dependent view of creativity and market success over time. Their theory highlights how creators' portfolios may differ in two core dimensions of creativity: novelty and variety. Novelty captures how unique or statistically rare a given creator's portfolio of products is compared to others' recent hit products in the market. Variety captures the heterogeneity among the products in a creator's own portfolio. Novelty and variety each require a different form of divergence. To build a novel portfolio, creators must diverge from others' popular products in the market. To build a varied portfolio, creators must diverge from their own products over time.

Creativity scholars have long conceptualized novelty and variety as separate core dimensions of creativity (Guilford, 1956; Runco, 1991; Torrance, 1962). In addition, scholars have used similar conceptual distinctions to describe related matters, including audience members' tastes (Goldberg, Hannan, & Kovács, 2016) and types of artistic deviance (Stamkou, van Kleef, & Homan, 2018). Although novelty and variety are conceptually distinct, they may be positively correlated in practice. On average, creators with novel portfolios may score higher in variety, and creators with typical portfolios may score lower in variety. But the two dimensions should also have plenty of independent variance. Creators may generate products that are novel for the market but similar to one another (e.g., creating multiple paintings in the same avant-garde style). Conversely, creators may generate products that are typical for the market but different from one another, as mature markets usually have multiple popular products at a given time, meaning products can be typical in a range of different ways (e.g., making films in several different genres, but each film is typical for its genre). As such, the proposed theory treats novelty and variety as independent dimensions of creativity and assumes that the other dimension is held constant, which is also how the hypotheses are tested.[2]

[2] Scholars frequently assess creativity or creative potential based on three dimensions (Guilford, 1956; Runco, 1991): novelty, variety, and quantity (often labelled originality, flexibility, and fluency respectively). Quantity is treated as a control in the present research because a large body of evidence demonstrates that greater quantity increases the odds of a hit, and that this relationship remains fairly consistent throughout creators' careers (e.g., Liu et al., 2018; Simonton, 1997, 1999, 2011). In much of this prior research, quantity is used as a proxy for variety. But quantity may be a noisy indicator of variety, as creators could generate many products that are all quite similar or few products that are all quite dissimilar from one another. By focusing on variety (and novelty) with quantity held constant, the present research complements prior work that treats variety and quantity as one in the same.

Prior Creativity and Benefitting from Relatedness. Although H1 posits that relatedness is key to sustaining success for all creators, creators who reach initial success with novel or varied portfolios may benefit more from relatedness than creators who reach initial success with more typical or homogenous portfolios. The two underlying mechanisms (internal learning and external expectations) may be more restrictive for creators with relatively typical or homogenous portfolios upon initial success, as they may fall behind the ever-changing market when they try to succeed with new products that are related to their existing portfolios. In contrast, creators with more novel or varied portfolios upon initial success may be better positioned to succeed with new products that are related to their existing portfolios and keep up with the ever-changing market at the same time. This should give them a wider path or range of viable options—and thus better overall odds—to sustain success.

Regarding internal learning, building a novel or varied portfolio prior to initial success may endow creators with a more flexible repertoire of capabilities, helping them generate new products that are both related to their portfolios upon initial success and keep up with new market trends. As creators build novel portfolios prior to initial success, they learn how to generate products that diverge from salient exemplars in the market. In contrast, as creators build typical portfolios, they are surrounded by salient exemplars of creators and products that are similar to their own style. This may exacerbate the cognitive entrenchment and fixation processes that tend to occur as individuals gain expertise and success in their domains, making their repertoires overly rigid going forward (Audia & Goncalo, 2007; Bayus, 2013; Dane, 2010; March, 1991). Building a novel portfolio prior to initial success may prevent creators' repertoires from becoming as rigid. In turn, after creators reach initial success with novel portfolios, they may be better positioned to expand their repertoires based on new trends, giving them more options for pursuing relatedness while keeping up with market changes.

Whereas creators who build *novel* portfolios before initial success may be better positioned to expand their repertoires to incorporate new trends, creators who build *varied* portfolios before initial success may be better positioned to keep up with new trends using their existing repertoires. New products come from recombining elements of existing products (Welch, 1946). By building more varied portfolios prior to initial success, creators may develop more diverse repertoires that afford them a wider range of options for making new combinations (Amabile, 1996; Bartel & Garud, 2009; Conti, Gambardella, & Mariani, 2014; Mannucci & Yong, 2018). As new trends emerge, creators with more diverse repertoires may have more options for generating new products that keep up with the latest trends without substantially expanding or reinventing their existing repertoires (Ashby, 1956; Baker & Nelson, 2005; Harrison & Klein, 2007; Weick, 1976). In this way, they may be able to utilize their diverse repertoires to generate new products that reflect relatedness and new market trends at the same time. In contrast, creators who build portfolios with little variety prior to initial success may struggle to reflect new trends using their relatively narrow repertoires (March, 1991).

Along with internal learning, external expectations may work in tandem to make it easier for creators who reach initial success with novel or varied portfolios to succeed with new products that reflect both relatedness and new market trends. Creators with novel or varied portfolios upon initial success may find a warmer reception in the market for this mix of old and new. The audience and gatekeepers should have more accommodating expectations for creators who reach initial success with novel or varied portfolios, as these expectations are based on portfolios that already diverge from the mainstream (novelty) or contain a broad range of elements (variety). In contrast, the audience and gatekeepers may be more likely to "pigeonhole" creators who have more typical or homogenous portfolios upon initial success, imposing a more restrictive set of expectations on them going forward (Hsu, 2006; Zuckerman, 1999). Thus, creators who reach initial success with novel or varied portfolios may have a dual advantage: they may be better positioned to generate new products that simultaneously reflect relatedness and new market trends, and they may also find a warmer reception for such products in the market. As a result, these creators should benefit more from relatedness than creators who reach initial success with less novel or varied portfolios.

> **Hypothesis 2 (H2):** Novelty enhances the benefit of relatedness for sustained success, such that creators who have novel portfolios upon initial success are more likely to succeed with related products than creators who have more typical portfolios upon initial success.

> **Hypothesis 3 (H3):** Variety enhances the benefit of relatedness for sustained success, such that creators who have varied portfolios upon initial success are more likely to succeed with related products than creators who have less varied portfolios upon initial success.

The Overall Advantage of Prior Creativity for Sustaining Success. Given that creators who have novel or varied portfolios upon initial success are well positioned to adapt to market changes while still benefitting from relatedness, they should enjoy an overall advantage in sustaining success. Creators with more typical or homogenous portfolios upon initial success may benefit from relatedness but not adaptation, narrowing their range of viable options for sustaining success. Their options may narrow even more as the market moves away from their portfolios upon initial success and/or they fail to generate more hits and thus lose relevance in the industry. In contrast, creators with novel or varied portfolios upon initial success may benefit from relatedness *and* adaptation, giving them a wider range of options for sustaining success. As they achieve additional hits that reflect market changes, the two mechanisms (internal learning and external expectations) may be less constraining in terms of locking them into their portfolios upon initial success. In turn, their path or range of viable options for balancing relatedness and adaptation may remain wider for longer, giving them better odds to sustain success.

The renowned painter Goergia O'Keeffe provides an illustration. Prior to her first hit, O'Keeffe built a highly novel and varied portfolio, including abstract drawings, precisionist portrayals of the New York City skyline, and large-scale depictions of flowers for which she is most famous (Georgia O'Keeffe Museum, 2020). After her initial hit in the mid 1920's, trends toward modernism were gaining momentum in the art world. O'Keeffe incorporated elements of the latest trends in her new work while maintaining her own signature style, helping her sustain success for several decades (Randolph, 2017). Two decades after her initial success, for instance, a critic remarked that her latest collection of paintings, which were done in Hawaii, "testify to Miss O'Keeffe's ability to make herself at home anywhere" (McBride, 1940: 10). In sum, when creators reach initial success with novel or varied portfolios, they may enjoy a wider path or range of viable options for adapting to market changes while still leveraging relatedness, giving them an overall advantage in sustaining success.

> **Hypothesis 4 (H4):** Creators who have novel portfolios upon initial success are more likely to sustain success than creators who have more typical portfolios upon initial success.

> **Hypothesis 5 (H5):** Creators who have varied portfolios upon initial success are more likely to sustain success than creators who have less varied portfolios upon initial success.

Reaching Initial Success: The Risk of Novelty and Benefit of Variety

The hypotheses thus far have focused on the path-dependent stage of the proposed theory, particularly how the novelty and variety in creators' portfolios upon initial success predicts their odds of sustaining success. This raises the important question of how novelty and variety may predict creators' odds of ever achieving an initial hit in the first place. In the proposed theory, creators' pursuit of initial success is path independent, as the two underlying mechanisms do not become mutually- or self-reinforcing until creators achieve their initial hit. Whereas prior research has largely overlooked a path-dependent view of the relationship between creativity and market success, plenty of prior research speaks to how novelty and variety relate to market success from a path-independent standpoint, in which each product is an independent attempt at a hit. This prior research suggests that new creators who build novel portfolios should be less likely to ever achieve initial success, while those who build varied portfolios should be more likely to achieve initial success. Although these path-independent arguments are straightforward applications of existing theory and research, I hypothesize them here because they help clarify the importance of the path-dependent hypotheses.

First, past research has demonstrated that on average, typical products outperform more novel ones in the marketplace (Fleming, 2001; Liu et al., 2017; Uzzi et al., 2013; Veryzer & Hutchinson, 1998; Ward, Bitner, & Barnes, 1992), including in so-called creative industries (Becker, 1982; Interiano et al., 2018; Martindale, 1990). Relatively novel products may become hits on rare occasions (Becker, 1982), but gatekeepers and audience members are likely to prefer typical products over more novel ones (Montoya et al., 2017; Winkielman et al., 2006; Zajonc, 1968). Generating an initial hit may be a longshot for all new creators, but the odds may be even lower when one's portfolio is comprised of relatively novel products. This reveals a tradeoff: if novelty negatively predicts initial success but positively predicts sustained success (as posited in H2 and H4), this suggests that creators' early portfolios cannot optimize for both initial and sustained success at the same time—one must come at the expense of the other.

> **Hypothesis 6 (H6):** New creators who build novel portfolios are less likely to achieve initial success than new creators who build more typical portfolios.

Second, in contrast to novelty, variety should be a positive predictor of initial success. This is consistent with evolutionary theories of creativity and innovation, which posit that given the uncertainty in how new products will perform in the market, generating a wider variety of products should increase the odds of a hit (Aldrich, 1999; Campbell, 1960; Simonton, 1984, 1997, 1999, 2011; Staw, 1990). All creators face irreducible uncertainty regarding what products will be hits (Caves, 2000), but the uncertainty is likely even higher for creators who have yet to achieve an initial hit. Without a widely or firmly established reputation, creators who have yet to achieve a hit should be relatively free to release a wide range of products without violating expectations from the audience or gatekeepers (Hsu, 2006; Younkin & Kashkooli, 2020; Zuckerman, 1999). By building portfolios with a variety of products, new creators may increase the odds that any one of their products will be a hit (Sternberg & Lubart, 1991, 1995). Although variety may predict initial success, generating further variety after initial success would be antithetical to pursuing relatedness (H1). This suggests that variety is only beneficial for success until creators achieve their first hit, at which point they may be better off focusing on relatedness.

> **Hypothesis 7 (H7):** New creators who build varied portfolios are more likely to achieve initial success than new creators who build less varied portfolios.

METHODS

Context: The Case of the Music Industry

I tested the hypotheses using an archival dataset of the music recording industry, focusing on popular music in the U.S. from 1959-2010. The music industry was an appropriate context for four main reasons. First, the industry for recorded music has remained a large and culturally important marketplace since it began in the late 19th Century (Gronow, 1983). Estimates of revenue from recorded music in the U.S. have been over $4.4 billion (inflation-adjusted to 2020 dollars) every year 1959-2010, reaching as high as $22 billion in 1999 (Gronow, 1983; RIAA, 2018). On average, Americans listen to 24 hours of music per week, making it a substantial part of many people's daily lives (Nielsen, 2016). The size, longevity, and cultural importance of the music industry offer a compelling set of incentives for creators to achieve and sustain success. Second, new music constantly replaces older music (Interiano et al., 2018), making it challenging for creators to keep up with the market and sustain success over time. This churn of new trends is representative of the creative industries that are the focus of the proposed theory.

Third, artists build portfolios of songs throughout their careers that the audience and gatekeepers primarily attribute to them. Although artists differ in the degree of control they have over their portfolios, most have substantial agency in shaping their own portfolio. Many artists write and produce their own songs, and those who do not usually have at least some say in which songs they record and how they perform them (Lingo & O'Mahony, 2010). Like most creative industries, many supporting roles may have a hand in building artists' portfolios (e.g., producers, songwriters, engineers, etc.). Importantly, these supporting roles are embedded in the artists' existing portfolios. For instance, when producers try to find promising songs for specific artists to record, they seek songs that are "sufficiently consistent to support a coherent artist identity" and "highlight the artist's unique performance strengths" (Lingo & O'Mahony, 2010: 59-60). Thus, the supporting roles inherit the implications of the focal artist's portfolio. This makes the music industry representative of the many other creative industries in which portfolios are primarily attributed to the focal creator, such that portfolios are likely to have enduring implications for the focal creator and their supporting teams over time (e.g., book publishing, film, art, cuisine, architecture, theater, video games, etc.).

Fourth, although music distribution has evolved over the years, the dominant design (Abernathy & Utterback, 1978) of the most basic product—a song—has remained the same. Also, the industry has an agreed upon standard for whether songs are considered hits: if they make Billboard's Hot 100 chart, which has listed the 100 most successful songs every week since 1958 (Anand & Peterson, 2000). Thus, the music industry enables comparisons of creators' entire portfolios over a long historical period, making it suitable for testing the hypotheses.

Data Collection

To test the hypotheses, I assembled an archival dataset that includes data on 3,092,927 songs by 69,050 artists. The dataset captures all songs released by each artist from 1959-2010, including whether each song was a hit or not. All of the artists in the dataset were signed by a label that produced one or more hits. Of the 69,050 artists, 4,857 had at least one hit (7%), and the other 93% did not have any hits. To build the dataset and measures, I collaborated with a research assistant who was highly skilled in software engineering (to reflect this, from hereafter I use "we" instead of "I" in describing our data collection effort). Although many sources of music data existed, any one source was not adequate in providing comprehensive data on artists' complete song portfolios. We devised an approach that involved cross-referencing four different sources to leverage the advantages—and offset the limitations—of each source.

Two of the four data sources were crowdsourced platforms in which music enthusiasts and retailers upload information on their music collections: Discogs (see Montauti & Wezel, 2016) and MusicBrainz (see Interiano et al., 2018). These crowdsourced databases were relatively comprehensive, but often had many duplicates of the same song. The other two data sources were the two companies with the largest digital collections of music: Spotify and Apple's iTunes. These companies had less redundancy in their databases than the crowdsourced platforms but were also less comprehensive. Moreover, the years assigned to songs often indicated when the company released the song digitally, rather than the year the artist originally released the song. To avoid duplicates of the same song and identify the original release year of each song, we cross-referenced the four sources. Our approach involved four main steps, which are each summarized below. See Online Appendix A for more detailed descriptions of each step. We developed our approach using artists with at least one hit (Steps 1-3 below), and then applied the same basic approach to non-hit artists (Step 4 below).

Step 1: Identifying Hit Artists. Our first step was creating a list of artists who had at least one hit song in their career. To do so, we obtained data on the complete history of Billboard's Hot 100 charts from a crowdsourced effort known as "The Whitburn Project" (see Askin & Mauskapf, 2017). Billboard launched the Hot 100 chart in 1958, and it has remained the industry standard for classifying whether songs are hits (Anand & Peterson, 2000). We first identified all artists with at least one hit song from 1958 through 2010, which included 6,771 artists. We then applied four exclusion criteria to this list of artists to ensure the dataset was appropriate for testing the hypotheses. First, the artist had to be a primary artist on at least one hit, excluding artists with only cameo/secondary roles. Second, to ensure artists' careers were captured from inception, artists who released any song before 1959 were excluded. The cutoff of 1959 was selected because it was the earliest year for which novelty could be calculated (as described in the *Measures* section). Third, artists needed to have their first hit by 2005, ensuring that all artists had at least five years after their first hit to potentially gain more hits. Fourth, artists were omitted if they did not have any songs in Spotify through their first hit year, as the independent variables required data from Spotify. After applying these criteria, 4,857 hit artists qualified for the dataset. From 1959-2010, these artists had a combined 19,046 hit songs.

Step 2: Compiling Song Data for Hit Artists. Our next step was assembling data on all songs released from 1959-2010 by the 4,857 artists identified in Step 1. Our general strategy was to cast a wide net at the start to make sure we captured all songs by the artists, and then filter out redundant and incorrect songs. We gathered data on all songs released by each artist in each of the four sources. This included data on 7.6 million songs from Discogs, 2.8 million songs from MusicBrainz, 1.1 million songs from Spotify, and 597,386 songs from iTunes. The same song often appeared many times within each of the four sources, as songs may be released multiple times on different albums/compilations or to different geographic territories. To determine whether song titles were duplicates, we used edit distance, which is a common technique in approximate text matching (Navarro, 2001). We first clustered duplicates within each of the four data sources, and then merged duplicate clusters between the four sources. This yielded a dataset with 741,761 rows, each row representing an artist-song pair to possibly include in the final dataset. This was a tentative dataset because it still included many redundant song titles.

Step 3: Finalizing Dataset for Hit Artists. Next, we devised a set of selection criteria to remove redundant and incorrect songs from the tentative dataset. Our approach focused on matching across the four data sources, leveraging the notion that if the same song title for a given artist was found in multiple independent sources, this was a strong signal of quality. Song titles that matched across three or four sources were almost always actual songs that belonged in the final dataset. Most song titles without a match did not belong in the final dataset, usually because they were incorrect or idiosyncratic titles for songs that were in the dataset under better titles that matched across more sources. After implementing the selection criteria, the dataset included 356,826 artist-song pairs (351,493 unique songs, as some songs were by multiple artists).

Step 4: Repeating Steps 1-3 for Non-Hit Artists. Lastly, we repeated our approach to collect data on artists without any hits, which added 64,193 artists to the dataset. These artists were selected because they released one or more songs on a label that had at least one hit from 1958-2010. This provided a meaningful comparison group to the hit artists, as all the non-hit artists were signed by labels with the resources to produce a hit song/artist. To be consistent with the hit artists, we targeted only non-hit artists whose careers began 1959-2005. This meant that all non-hit artists had at least six years to generate a hit (2005-2010 for artists whose career began in 2005). We gathered data on all songs by the non-hit artists from the four sources, which included 18.9 million songs from Discogs, 8.6 million songs from Spotify, 5.4 million songs from MusicBrainz, and 4.4 million songs from iTunes. After following the same procedures used with the hit artists, the non-hit artist dataset included 2,834,875 artist-song pairs (2,746,233 unique songs). The finalized dataset, with the hit and non-hit artists compiled together, included 3,191,701 artist-song pairs (3,092,927 unique songs) by 69,050 artists. Among the artist-song pairs, 88% matched across two or more sources. Having multiple sources per song helped identify the correct release year, as the earliest release year across sources could be used.

Measures

To create our independent variables (relatedness, novelty, and variety), we drew on Askin and Mauskapf's (2017) method of measuring similarity between songs. This approach utilized data on 11 sonic features of songs from Spotify's database: danceability, acousticness, energy, instrumentalness, key, liveness, mode, speechiness, tempo, time signature, and valence. Each of these 11 features quantifies an important aspect of how a song sounds. The algorithms used to automatically measure these features were developed with machine learning techniques by a company called EchoNest. Spotify acquired EchoNest in 2014 and integrated the sonic features into their database and recommendation system. We collected the 11 sonic features for all songs in our dataset that were in Spotify's database, which was 78% of songs overall and 94% of hit songs. Following Askin and Mauskapf (2017), we measured the similarity between two songs using cosine similarity, with the 11 sonic features as the vector for each song. We followed their procedures for normalizing the data, such that all features were scaled 0-1 and the key feature was measured using 12 separate dummy variables, one for each key. See Online Appendix B for a visual summary of the three independent variable measures (Figure B1), as well as examples illustrating how novelty and variety were calculated (Table B1).

Relatedness. Relatedness focused on songs that artists created after their initial success, particularly how coherent these songs were with their portfolios upon initial success. For each song released after an artist's initial success (first year with a hit), relatedness was the average cosine similarity between the song and all the songs that the artist had released from the start of their career through the year of their first hit. This captured the extent to which each song created after artists' initial success drew on elements of their portfolios upon initial success.

Novelty. Following past research on market novelty (vs. typicality), we measured novelty in terms of how unique songs were compared to prototypical songs at the time they were released (e.g., Veryzer & Hutchinson, 1998). Whereas Askin and Mauskapf (2017) compared how similar hit songs were to other concurrent hits, we adapted their measure to capture how dissimilar each song in our dataset was to the hits from the year before the song was released. This accounted for the fact that novelty constantly changes over time in the music industry (Interiano et al., 2018). Using hits from the year before songs came out—as opposed to the same year—ensured that songs had not influenced the prototypes with which they were compared.

From 1958-2010, a total of 24,733 songs entered the Hot 100, and we found sonic features for 94% of them in Spotify (23,173). Seventy-nine percent of these hits were by artists in the main dataset, but we also collected sonic features for the 21% of hits by artists excluded from the main dataset to serve as prototypes in the novelty measure. Each year had an average of 531.60 hits to serve as prototypes (*SD* = 120.18). To provide a general sense for how hit songs may change over time, Figure 3 displays the mean of several sonic features for each year. Although the features follow long- and medium-term trends, a churn of more temporary trends created substantial variance year to year. See Online Appendix B for visuals of how similar hits were to one another over time (Figures B2 and B3).

For each song in our dataset, we first calculated a typicality value, then reverse scored it to reflect novelty. Typicality was the average cosine similarity between the song and each of the hits from the year before the song was released, excluding any hits by the same artist(s) as the focal song. However, some hits spent much more time on the charts—and at higher ranks—than other hits, meaning bigger hits were more representative of what was typical at the time. To account for this, bigger hits were weighted more heavily. A weight was calculated for each hit based on how high it was ranked each week during a given year. The weights were calculated by subtracting each weekly ranking from 101 (e.g., if a song was ranked 35 in a given week, the score would be 66 for that week; a number one ranking would be a score of 100). Then, all scores were summed for each hit within each year, and the summed scores were divided by the maximum score any hit had in that year. This way, the weights ranged 0-1, with the biggest hit of the year having a weight of one (mean weight = .23, *SD* = .23).

To summarize, we calculated novelty for each song in four steps. First, we calculated the cosine similarity between the song and each of the hits from the year before the song was released, excluding any hits by the artist(s) of the focal song. Second, each cosine similarity value was multiplied by the hit's 0-1 weight to yield a weighted cosine similarity value. Third, these weighted cosine similarity values were averaged to yield the song's typicality. Lastly, to have the measure reflect novelty, we reverse scored the typicality values by subtracting each from .27 (because the maximum typicality value was .26).

[Insert Figure 3 about here]

Variety. We calculated the variety in an artist's portfolio for each year they released one or more songs. For example, if an artist released their first 12 songs in 1970, 13 more songs in 1972, and 11 more songs in 1975, their portfolio would be 12 songs in 1970, 25 songs in 1972, and 36 songs in 1975. For each release year, we calculated the cosine similarity between each pair of songs in the artist's portfolio at the time (excluding a song paired with itself, which would always be a cosine similarity of one). Thus, the number of cosine similarity values calculated was $[(n-1)^2 + (n-1)] / 2$, where n was the number of songs in the artist's portfolio at the time. We measured variety using the coefficient of variation (standard deviation divided by the mean) for the artist's portfolio. If an artist had 50 songs in their portfolio in a given year, 1,225 cosine similarity values would be calculated, one for each unique pair among the 50 songs. Variety would be the standard deviation divided by the mean for these 1,225 values. When artists only released one or two songs total, variety was zero for that year.

Using the coefficient of variation provided a normalized measure of variety that offered more meaningful information than just the mean or standard deviation alone (Mukherjee et al., 2017). The higher the mean similarity between an artist's songs, the higher the standard deviation had to be to increase variety. For instance, if two artists had the same standard deviation (e.g., 0.15), but their similarity means were 0.50 and 0.90, the 0.50 artist would have a higher variety score (0.30 vs. 0.17). This makes conceptual sense, as the artist with more dissimilar songs (the one with a 0.50 similarity mean) should have a higher variety score.

Song quantity was positively correlated with variety ($r = .30$, $p < .001$). This is logical from a conceptual standpoint, as variety should increase to some extent as more songs are added to a portfolio. However, the correlation was low enough to suggest that much of the variance in variety was independent of quantity. Thus, the nature of artists' songs mattered, not just the quantity of them. Furthermore, song quantity was controlled for in all analyses, helping to isolate the variety that was attributable to the nature of artists' songs and not the number of them.

Success. The core measure of market success was whether an artist's song was a hit or not. A song was deemed a hit if it appeared in Billboard's Hot 100 chart, the industry standard for classifying hits (Anand & Peterson, 2000). However, given that some hits enjoyed substantially more success than others, the analyses differentiate between three hit levels based on the peak rank reached: top 100, top 40, and top 10. These three levels have been important in the industry since the inception of the Hot 100 and are designed to reflect meaningful differences in market success. Rankings have always been based on a combination of sales and radio airplay, plus additional criteria that have evolved over time to reflect changes in how music is consumed (e.g., formerly Jukebox play, then digital downloads and streaming).

Table 1 shows the percentage of artists who reached various hit counts. The vast majority of artists had no hits (92.97%). The results on artists with at least one hit are largely consistent with Lotka's Law (Lotka, 1926). Most of these artists had either one hit (44.10%) or two hits (16.49%) overall, while a relatively small group of artists (10.75%) had ten or more hits. As expected, it was rarer for artists to garner top-40 hits, and even rarer for top-10 hits.

Initial success included the hit(s) that artists had in their first year on the charts, and sustained success included any hits after this first year. Artists sometimes had multiple songs from the same album become hits, but artists rarely released more than one album in a given year. This helped ensure that initial success reflected songs that artists created before their first hit, while sustained success reflected songs they created after their first hit. In terms of initial success, most artists (60.61%) had one hit in their first year on the charts, while the rest (39.39%) had multiple hits in their first year, usually from the same album. In terms of sustained success, most artists (57.71%) had zero hits after their first year on the charts, but plenty of artists (42.29%) did manage to garner additional hits after their initial success.

To provide a rough sense of the practical significance of hit songs, sales data were obtained from Nielsen SoundScan, which has provided the raw data underlying the Hot 100 since 1991 (Anand & Peterson, 2000). The sales data available in Nielsen's archive spanned from 1994-2004. These data were used to conduct analyses on two relationships: hit songs' peak rank and single sales, as well as artists' overall hit count and total sales. Estimates from these analyses are in Figures 4 and 5 respectively, and details of these analyses are reported in Online Appendix B. The patterns in the figures highlight how hits are related to market success in an exponential fashion, suggesting that seemingly small differences in the chart performance or quantity of artists' hits likely represent relatively large differences in market success.

[Insert Table 1, Figure 4, and Figure 5 about here]

Controls. We collected data to create a number of controls (see Tables 2 and 3 for descriptive statistics). For each song in the dataset, we collected data on release year, genre, label, and the number of artists who collaborated on the song. These data were used to create controls at the song or artist level, depending on the analysis (Tables 4 and 5 specify the level of each control). We collected genre and label data from Discogs, which was the most comprehensive source for such data. Following Askin and Mauskapf (2017), we created dummies for the 15 different genres and also a "genre crossover" dummy that was 1 if a song belonged to more than one genre (0 if only one), unless the two genres were pop and rock, as they were often used interchangeably. Label data was available for 80% of songs in the dataset. All songs missing label data were treated as if they were on the same label, and thus had their own intercept or hazard function in the analyses. For songs by multiple labels, a representative label was selected by ranking all 76,994 labels in the dataset. Rankings were based on the number of hits labels had, and ties were broken by the total number of weeks in the top 100, 40, and 10, and then by the number of songs the label had in the dataset (for labels without any hits). For the 11% of songs by multiple labels, the highest-ranking label was selected as the representative label. This reduced the number of different labels in the dataset to 60,159 (2.60% or 1,566 of these labels produced one or more hits).

We created several time-varying controls at the artist level, which were calculated for each year that artists released one or more songs. First, we created controls for artists' quantity of songs, including their song count within the focal year and the cumulative number of songs they released through the focal year. Second, career age was calculated as the number of years that had passed since the artist's first song, beginning at one (e.g., Kozbelt, 2008). Third, we calculated the number of years passed since the artist's previous release. Fourth, to control for past success, we calculated artists' cumulative number of prior hits and the cumulative number of weeks their hits had spent on the Hot 100.

We also created controls capturing static characteristics of artists. First, we created a dummy for artist type (1 = soloist, 0 = group). Second, of the 37,272 solo artists in the dataset, 5.97% were in groups that had one or more hits before the individuals became soloists. We created a dummy to control for the potential effects of this prior experience (1 = had prior hit with group, 0 = no prior hit with group). Third, we calculated the frequency with which artists wrote and produced their own songs. We collected all available writer and producer data from Discogs, the most comprehensive source for this information. We found writer data for 48% of songs in our dataset, and producer data for 51% (68% and 75% for hit artists, respectively). At the artist level, we had at least partial data for 88% of artists in terms of writing and 84% in terms of producing (98% and 95% for hit artists, respectively). Because the artist level had better coverage than the song level, we created controls at the artist level to capture the percentage of artists' songs for which they were credited as a writer or producer. Groups were given credit if any of the group members were credited. For the small number of artists with no writer or producer data, the sample mean was used in the analyses.

[Insert Tables 2 and 3 about here]

RESULTS

Overview of Analytical Approach

To match the specific needs of the hypotheses, the type of model used depended on whether the hypothesis focused on sustained or initial success. The hypotheses on sustained success (H1-H5) were tested with Mixed-Effects Logistic Regression, which leveraged the granularity of the song-level data while accounting for cross-nesting in labels and artists (Raudenbush & Bryk, 2002). These analyses included only artists who achieved at least one hit in their career. The hypotheses on initial success (H6 and H7) were tested with Cox Regression, which was appropriate given that the dependent variable was new artists' odds of achieving an initial hit (or not) over time (Cox & Oakes, 1984). These analyses included all 69,050 artists—

those with zero hits and those with one or more hits. Note that supplementary analyses are reported after the main results, including robustness checks. Across all analyses, novelty and variety (or pre-novelty and pre-variety) did not significantly interact; their relationship in predicting success was additive, not multiplicative.

Sustained Success (H1-H5)

The hypotheses on sustained success were tested with Mixed-Effects Logistic Regression. Specifically, random-intercept models were used, which accounted for the fact that the observations were individual songs (level 1) that were cross-nested within labels (level 2) and artists (level 3)—label was level 2 and artist was level 3 because the number of labels exceeded the number of artists (Raudenbush & Bryk, 2002). These models included the 4,310 artists who achieved at least one hit and then released one or more songs that could be scored on relatedness. The observations included all the songs that these artists released after their initial hit year, and the dependent variable was whether each song was a hit or not. Thus, the results of these analyses speak to artists' hit rates after their initial success, or their likelihood of a hit for each song released after their initial success. This approach enabled song-level controls for genre, label, release year, and number of artists on each song (and for relatedness to be measured at the song level), while also allowing for controls and tests of the hypotheses at the artist level. From hereafter, I use the prefix "pre" to convey that pre-novelty and pre-variety refer to the novelty and variety in artists' portfolios before/during their initial success.

Relatedness (H1). Models 1-6 in Table 4 test whether relatedness predicts sustained success (H1). Consistent with H1, relatedness was a significant positive predictor of all three hit levels (top 100, 40, and 10). This held when pre-novelty and pre-variety were excluded (Models 1-3) or included (Models 4-6) in the models. Figure 6 shows estimated marginal means from

Models 4-6. Compared to artists' songs that were low in relatedness, songs high in relatedness were 1.42 times more likely to be top-100 hits (4.96% vs. 3.52%), 1.45 times more likely to be top-40 hits (2.47% vs. 1.70%), and 1.40 times more likely to be top-10 hits (1.02% vs. .73%). These results suggest that artists were more likely to sustain success when they released new songs that were related to their portfolios upon their initial success, supporting H1.

Pre-Novelty and Pre-Variety as Moderators of Relatedness (H2 and H3). Models 7-9 in Table 4 test whether pre-novelty (H2) and pre-variety (H3) enhance the benefit of relatedness. The results support H3 but not H2. The interaction between relatedness and pre-novelty was not significant in any models, and thus H2 was not supported. The null results for H2 suggest that artists higher in pre-novelty did not benefit more than average artists when they drew on their pre-success portfolios. However, results did support H3, as the interaction between relatedness and pre-variety was significant across all three hit levels. Consistent with H3, artists high in pre-variety benefitted significantly more from relatedness than artists low in pre-variety in terms of all three hit levels. Artists low in pre-variety still benefitted from relatedness, just not as much as those high in pre-variety. The simple slopes were positive and significant when pre-variety was high for all three hit levels: top 100 [$b = .26$, $SE = .02$, $p < .001$], top 40 [$b = .27$, $SE = .03$, $p < .001$], and top 10 [$b = .24$, $SE = .04$, $p < .001$]. When pre-variety was low, the simple slopes were lower than when pre-variety was high, but still positive and significant for all three hit levels: top 100 [$b = .17$, $SE = .02$, $p < .001$], top 40 [$b = .16$, $SE = .02$, $p < .001$], and top 10 [$b = .11$, $SE = .04$, $p = .001$]. As shown in Figure 7, compared to artists who scored high in relatedness but low in pre-variety, songs by artists who scored high in both relatedness and pre-variety were 1.17 times more likely to be top-100 hits (5.40% vs. 4.63%), 1.23 times more like to be top-40 hits (2.77% vs. 2.24%), and 1.36 times more likely to be top-10 hits (1.19% vs. .87%).

The band *Poison* provides an archetypal example of pre-variety strengthening the benefit of relatedness. They had their first hit in 1987, and their portfolio scored .51 standard deviations above the mean in pre-variety. After their initial success, their new songs scored .91 standard deviations above the mean in relatedness, and they garnered nine more hits from 1988 to 1993. The band *The Islanders* provides an archetypal example of not capitalizing on pre-variety combined with relatedness. Their portfolio scored 1.37 standard deviations above the mean in pre-variety upon achieving their first hit in 1959. However, after their initial success, their new songs often deviated substantially from their prior songs, scoring 1.62 standard deviations below the mean in relatedness, and they failed to generate any more hits.

[Insert Table 4, Figure 6, and Figure 7 about here]

Main Effects of Pre-Novelty and Pre-Variety (H4 and H5). Models 4-6 test whether pre-novelty (H4) and pre-variety (H5) predict sustained success. Across all three hit levels, both pre-novelty and pre-variety were significant positive predictors of sustained success, supporting H4 and H5. Figure 6 shows estimated marginal means at high and low levels of each dimension (holding relatedness constant). Compared to artists low in pre-novelty, songs by artists high in pre-novelty were 1.22 times more likely to be top-100 hits (4.68% vs. 3.84%), 1.32 times more likely to be top-40 hits (2.39% vs. 1.81%), and 1.42 times more likely to be top-10 hits (1.04% vs. .73%). Compared to artists low in pre-variety, songs by artists high in pre-variety were 1.09 times more likely to be top-100 hits (4.45% vs. 4.08%), 1.13 times more likely to be top-40 hits (2.22% vs. 1.97%), and 1.20 times more likely to be top-10 hits (.95% vs. .79%).

These results suggest that artists higher in pre-novelty (H4) or pre-variety (H5) had an overall advantage in sustaining success. However, the results for H3 suggest that the advantage of pre-variety was also moderated by relatedness. As shown in Figure 7, at high levels of relatedness, pre-variety was quite beneficial, but at low levels of relatedness, pre-variety had little benefit. In contrast, artists benefitted from pre-novelty and relatedness independently.

An archetypal one-hit-wonder was the artist Coro, who had his first and only hit in 1991. He scored 1.35 standard deviations below the mean in relatedness, 1.42 standard deviations below the mean in pre-novelty, and .29 standard deviations below the mean in pre-variety. An archetypal hit-maker was Shania Twain, who had her first hit in 1995, and then sustained success with 14 additional hits 1996-2004. She scored .35 standard deviations above the mean in relatedness, .81 standard deviations above the mean in pre-novelty, and .40 standard deviations above the mean in pre-variety.

Initial Success (H6 and H7)

The Cox Regression models in Table 5 test H6 (novelty negatively predicts initial success) and H7 (variety positively predicts initial success). These models are survival analyses: the focal event was an artist's first hit, thus "survival" meant not having a first hit. Cox Regression accounted for the possibility of right-censoring, which was important because it is possible some artists could have hits after 2010 that would not be captured in the data. To enable meaningful comparisons between novelty and variety over time, both novelty and variety were measured at the artist-year level. This meant that the observations captured artists' average novelty and variety for all their songs from the start of their career through each year they released one or more songs, until the first year they had a hit (if any).

Continuous variables that changed over time were entered as time-varying covariates, including novelty and variety, which are marked with "[X Time]" in Table 5. All other controls were entered as regular covariates. All models were stratified by label, meaning each label had its own hazard function, which is the equivalent of a random intercept in a mixed-effects model.

Artists' labels and genre dummies were determined on a rolling basis, based on the songs released by the artist up through each year (artists' highest-ranking label through each year was used—see *Measures* section for ranking criteria). Given that a small percentage of labels produced any hits (2.22% for the songs in these models), this approach was stronger than including a label for each separate release year, which would just add more labels with zero hits and spread the number of observations per label unreasonably thin.

In support of H6 and H7, novelty was a negative predictor and variety was a positive predictor of new artists achieving an initial hit across all models (Table 5). Results were significant when novelty and variety were entered separately (Models 1 and 2), and together (Model 3). Results remained significant for both novelty and variety when hits were restricted to only the top 40 (Model 4) and top 10 (Model 5). See Figure 8 for a visual of the estimated likelihood of new artists achieving initial success over time when novelty and variety were high vs. low—these estimates were calculated using Ruhe's (2016) procedures.

As displayed in Figure 8, new artists' likelihood of achieving initial success increased the most early in their careers and flattened in later years. At ten years into their careers, artists low in novelty had an 11.04% likelihood of achieving an initial hit, while those high in novelty had a 5.43% likelihood, meaning low-novelty artists were 2.03 times more likely to achieve initial success than high-novelty artists. Conversely, artists high in variety had a 9.99% likelihood of achieving an initial hit, while those low in variety had a 5.97% likelihood, meaning high-variety artists were 1.67 times more likely to achieve initial success than low-variety artists. Estimates when hits were restricted to the top 40 and top 10 followed a similar pattern, just with lower base rates than top-100 hits. Low-novelty artists were 2.12 times more likely to achieve a top-40 initial hit than high-novelty artists (6.14% vs. 2.90%), and 2.25 times more likely to achieve a top-10 initial hit (3.04% vs. 1.35%). High-variety artists were 1.95 times more likely to achieve a top-40 initial hit than low-variety artists (5.89% vs. 3.01%), and 2.24 times more likely to achieve a top-10 initial hit (3.03% vs. 1.35%). These results support both H6 and H7.

[Insert Table 5 and Figure 8 about here]

Supplementary Analyses

Additional models were run to test the mediating role of market adaptation, serve as robustness checks, shed light on the practical significance of the hypotheses, and address alternative explanations. The full models and more detailed descriptions of the results are in Online Appendix C. Below, I highlight some key takeaways from these supplementary analyses.

Market Adaptation Mediation. The theorizing for H2-H5 suggests that a key driver of sustained success is adapting to changes in the market (along with relatedness). To test whether market adaptation can help explain the results in this way, I conducted mediation analyses regarding H2-H5 (although H2 was not supported in the main results, indirect effects were still possible). To measure market adaptation as the mediator, I used the typicality (novelty reverse scored) of artists' songs after their initial success, controlling for relatedness at the song level (Table C1). This captured how much artists' songs incorporated new trends that emerged in the market after their initial success. Consistent with the main results, mediation results were significant for H3-H5, but not H2. Broadly, these results suggest that artists higher in pre-novelty (H4) or pre-variety (H3 and H5) were more likely to adapt to market changes after their initial success, and that this contributed to their advantage in sustaining success.

Hit Counts. Whereas the hypotheses on sustained success (H1-H5) were tested in terms of artists' hit *rate* (likelihood of a hit per song released after initial success), supplementary analyses were run to address artists' hit *count* (quantity of hits after initial success). Results for hit count were largely consistent with the corresponding results for hit rate, suggesting that higher hit rates translated into higher hit counts (Tables C2 and C3). To shed light on the practical significance of the hypotheses for artists' careers, models were run on artists' overall hit counts, meaning the total number of hits they garnered in their careers (Table C4). Estimated overall hit counts were calculated for artists with the best-case vs. worst-case portfolio (i.e., high vs. low in relatedness, pre-novelty, and pre-variety). Compared to the worst-case, best-case artists could expect 105% more top-100 hits (6.07 vs. 2.96), 151% more top-40 hits (3.29 vs. 1.31), and 173% more top-10 hits (1.42 vs. .52)—absolute differences of 3.11 more top-100 hits, 1.98 more top-40 hits, and .90 more top-10 hits in one's career. Using the aforementioned model of total sales (see Figure 4), the difference in expected top-100 hits (6.07 vs. 2.96) would translate into a difference of roughly 3.8 million more units sold (5.6M vs. 1.8M).

Robustness Checks. Several robustness checks were conducted. First, results for all seven hypotheses were largely consistent without any controls (Tables C5 and C6). Second, results held when pre-novelty (H4) and pre-variety (H5) were entered separately and/or without relatedness in the model (Tables C7-C9), and when pre-novelty was measured using only artists' initial hit songs (Table C10). Third, analyses with specific subsets of artists showed that results were not substantially biased by left- or right-censoring, or the inclusion of artists with relatively little control over their portfolios or relatively few songs in their pre-success portfolios (Tables C11-C14). Fourth, results for sustained success (H1-H5) were consistent when Linear or Cox Regression were used in place of Logistic Regression (Tables C15-C17), and results for initial success (H6 and H7) were consistent when Logistic Regression was used in place of Cox Regression (Table C18). Lastly, results for sustained success were consistent when the dependent variable was number of weeks on the Hot 100, as opposed to the binary dependent variable (hit vs. miss) used in the main analyses (Tables C19-C21).

Alternative Explanations. Supplementary analyses also helped rule out key alternative explanations. First, to address "beginner's luck" as a potential confound, the hypotheses were tested without the 1,557 artists who had their initial hit(s) in their first career year, which was 32.06% of hit artists and 2.25% of all artists. These artists' initial success may have been driven more by random chance or other external influences than artists who did not enjoy such early success. Results were generally consistent with the full sample (Tables C22 and C24), with the caveat that the support regarding pre-variety (H3 and H5) was not as strong as the full sample.

Second, analyses were run to address the role of underlying ability or innate talent. It seems plausible that more talented artists were able to succeed through generating novelty and variety because of the talent with which they started. If innate talent drove the results in this way, then artists high in pre-novelty or pre-variety should be more likely to succeed through generating novelty or variety after their initial success. But the data suggest just the opposite: artists higher in pre-novelty were *less* likely to sustain success when they generated more novel songs after initial success (Table C25), and artists higher in pre-variety were *less* likely to sustain success when they generated further variety after initial success (Table C26). If pre-novelty and pre-variety were just proxies for innate talent, these results would suggest that after initial success, the more talented artists were somehow less capable of succeeding with novelty or variety than their less talented peers, even though they were able to achieve initial success with novelty or variety in the first place. This seems relatively implausible, suggesting that innate talent was likely not the main driver of the results. The results are more consistent with the notion that initial success triggered path dependencies that were shaped by the novelty and variety in artists' portfolios at the time. However, innate talent presumably played a role that cannot be measured or completely ruled out in this study.

Third, although prior success was controlled for in all tests of the hypotheses on sustained success, results could still be influenced by cumulative advantage effects (DiPrete & Eirich, 2006; Merton, 1968). This was examined by testing H1-H5 with subsets of artists with varying degrees of initial success (Tables C27-C29), which helped rule out cumulative advantage as a confound. Lastly, it seems plausible that the results for relatedness could be driven entirely by expectations from the audience and gatekeepers, as opposed to both mechanisms (learning and expectations) together. If external expectations were solely responsible for the results, then artists should be rewarded more for staying consistent with their initial hits than their non-hit songs, as the audience and gatekeepers should be less familiar with their non-hits. However, the benefit of relatedness was approximately equal when artists' songs drew on their hits or non-hits (Tables C30 and C31). These results suggest that the results for relatedness were likely driven by more than just expectations from the audience and gatekeepers, allowing for the possibility that both proposed mechanisms (learning and expectations) were at play.

DISCUSSION

Using an archival dataset of the music industry, I tested a path dependence theory of success in creators' careers, focusing on how the creativity (or lack thereof) in creators' portfolios may predict short-lived versus sustained market success. Results largely supported the proposed hypotheses. Initial success acted as a critical juncture that "locked in" important implications of creators' portfolios going forward. Artists were relatively free to build novel and varied portfolios until their initial hit, at which point they were better off creating songs that were related to their prior portfolios and more typical for the market. Although artists who reached their initial hit with relatively novel or varied portfolios were more likely to garner additional hits, novel portfolios were less likely to yield an initial hit than typical portfolios. Thus, path dependencies meant that artists' portfolios could not optimize for both initial and sustained success at the same time—one came at the expense of the other.

Theoretical Implications

The Path Dependence of Creativity and Innovation. The present research provides a new theoretical perspective on how creativity and innovation may unfold over time. Prevailing theories tend to construe creativity (idea generation) as a precursor to innovation (idea implementation) in the context of one project at a time (Amabile, 1988; Perry-Smith & Mannucci, 2017; Staw, 1990; West, 2002). This implies a path-independent view, such that once a final product is implemented at the end of the project, creators leave the product—and the creativity they exercised to build it—behind. This path-independent view is usually taken for granted in research on creativity and innovation, including in the literature on creative industries, in which scholars tend to emphasize "a lot more path creation and less path dependence" when characterizing creators' careers (Jones et al., 2016: 756).

The present research introduces a path-dependent view of creativity and innovation, such that once a product is implemented in the market, the creativity that creators exercised to generate the product may carry enduring implications for the success of their future innovations. From this path-dependent view, each cycle of creativity and innovation has the potential to enable or constrain future cycles of creativity and innovation. In the present study, the creativity (novelty and variety) that creators exercised in building their early portfolios predicted their capacity to produce hit innovations in the future, assuming they were able to achieve an initial hit. This suggests a more dynamic, reciprocal relationship between cycles of creativity and innovation than what is usually assumed in prior research.

Furthermore, the present research shows how a path-dependent view of creativity and innovation can reveal temporal dynamics that would be impossible to see with just a path-independent view. For instance, the present study uncovered a tradeoff between initial and sustained success based on the novelty (vs. typicality) in creators' early portfolios. This tradeoff only becomes visible in light of path dependencies at the career level. The results showed that typical (and thus uncreative) portfolios were more conducive to initial success, but reaching initial success with a novel (and thus creative) portfolio was more conducive to sustained success. This made it impossible for new artists' portfolios to maximize their likelihood of both initial and sustained success, presenting a thorny tradeoff. Variety could help artists compensate for this tradeoff to some extent, as variety predicted both initial and sustained success, but variety could not eliminate the tradeoff. Thus, creativity was potentially conducive to market success in the long run, but pursuing creativity with a novel portfolio could also backfire and increase the risk of never achieving a hit. In short, creativity was a high-risk, high-reward investment that could make or break an artist's career. Building a typical portfolio was a safer bet in terms of having at least some success, but with limited upside, as this success was likely to be short-lived. Revealing this important tradeoff demonstrates the theoretical value of a path-dependent view of creativity and innovation, which is complementary to the path-independent view that is often taken for granted in the literature, as both views are necessary for understanding how creativity and market success are related over time.

A path-dependent view of creativity and innovation may also help resolve conflicting findings in prior research. The small number of prior studies that have examined the relationship between creativity and success over time (rather than at one snapshot in time) have revealed a consistent finding: after creators' initial success, the creativity of their subsequent work declines (Audia & Goncalo, 2007; Bayus, 2013). But results on the net impact of this decline have been mixed. One study showed that despite the decline in creativity, past success predicted subsequent success (Audia & Goncalo, 2007), while the other study found the opposite (Bayus, 2013). The present study may help reconcile these mixed findings. The two prior studies focused on creators' creativity *after* their initial success, as opposed to how their creativity *before* initial success may shape their path or range of viable options for sustaining success. Results from the present study suggest that to sustain success, the creativity (novelty and variety) of creators' products may need to decline some after their initial success, as they pursue relatedness and try to keep up with market changes. However, their effectiveness in doing so may depend on the novelty and variety in their portfolios when they achieve initial success. Thus, accounting for the path-dependent implications of creators' creativity (or lack thereof) before their initial success may help reconcile the mixed results from prior studies, providing a fuller picture of how creativity and success may relate to one another over time. More broadly, the present research invites future research that adopts a path-dependent view of creativity and innovation, in which earlier cycles of creativity and innovation may enable or constrain later cycles.

Product Portfolios as Carriers of History. The present research advances theory on product portfolios as a powerful lens for analyzing creativity and innovation over time. Portfolio perspectives are relatively common in research at the organizational level, in which scholars tend to focus on how organizations balance exploitation and exploration in their portfolios of products (e.g., Fernhaber & Patel, 2012), activities (e.g., Anand, Mesquita, & Vassolo, 2009) or alliances (e.g., Lavie, Kang, & Rosenkopf, 2011). Portfolio perspectives are rare in the literature on creativity and innovation at the individual and team levels, despite the fact that individuals and teams of creators often work for or with multiple organizations as they build their portfolios of products throughout their careers (Caves, 2000; Mollick, 2012). As Sternberg and Lubart (1995) lament, creativity scholars rarely consider creators' portfolios of products, despite the insight that "In the world of art and music, readiness for various kinds of training has traditionally been assessed via portfolios of products" (p. 291). The present research elaborates on this basic insight by developing theory on creators' portfolios as potent "carriers of history" (David, 1994: 205).

More specifically, the present study suggests that the creativity (novelty and variety) in creators' early portfolios may indicate their readiness to sustain success should they achieve an initial hit. However, the results suggest that path dependencies may make creative industries like the music industry sub-optimal in terms of allowing creators to prepare their portfolios for sustained success. The path of less resistance to initial success was also a path to uncreative and short-lived success. One-hit-wonders with typical portfolios were churned through before they could build more varied portfolios that may have facilitated sustained success. Meanwhile, many artists who built novel portfolios that may have positioned them to sustain success failed to ever achieve an initial hit, and thus were never given the opportunity to sustain success.

These results reflect the path-dependent implications of creators' portfolios, but the results (and proposed theory) are agnostic about whether or how creators may deliberately shape their portfolios in pursuit of success. It is likely that creators and those who manage them hold various lay theories of what drives success, which may or may not align with what actually drives success in the industry (Levinthal & March, 1993). The present research lays the groundwork for future research on how creators may deliberately shape their portfolios in more or less strategic ways. For instance, future research could explore idea evaluation and selection from a portfolio perspective. Prior research has addressed individuals' accuracy in evaluating new product ideas in terms of creativity (e.g., Blair & Mumford, 2007; Mueller, Wakslak, & Krishnan, 2014), resource requirements (e.g., Dailey & Mumford, 2006), and likely market success (e.g., Berg, 2016; Girotra, Terwiesch, & Ulrich, 2010). However, prior work has largely overlooked these matters in the context of creators' broader portfolios of products. Given scarce time and resources, creators cannot fully develop and release every new product idea they generate. A portfolio perspective suggests that when selecting which new product ideas to pursue, creators (and those who manage them) may benefit from evaluating how the products fit into their broader portfolios at the time. This opens up opportunities for future research on creators' skill in managing their portfolios, such as their accuracy in assessing how new product ideas would contribute to the novelty, variety, relatedness, and/or likely success of their portfolios. In general, the present research paves the way for using portfolio perspectives in future theory and research on creativity and innovation at the individual and team levels.

The Value and Limits of Evolutionary Theories of Creativity and Innovation. The present research both supports and challenges evolutionary theories of creativity and innovation. Evolutionary theories posit that variety is the key dimension of creativity in predicting market success (e.g., Aldrich, 1999; Campbell, 1960; Simonton, 1999; Staw, 1990). Evolutionary theories construe creativity and innovation as a Darwinian process, in which multiple variants are first generated and then relatively few are selectively retained based on their fitness in the environment. These theories suggest that given the uncertainty in how new products may be received in the marketplace, generating a greater variety of products should increase the odds of a hit. This evolutionary perspective was quite useful for predicting whether new creators would ever achieve an initial hit, but less useful in predicting whether creators would garner additional hits after their initial one.

Thus, the present study suggests that initial success may be a turning point that changes the relationship between variety and market success. Results showed that generating variety early in one's career predicted both initial and sustained success. In this sense, variety was an unmitigated good, unlike the thorny tradeoff between novelty and typicality. But after initial success, generating further variety was detrimental, as artists were more likely to sustain success when their new songs were related to their pre-success portfolios. This suggests that in creative industries like the music industry, the benefits of variety implied by evolutionary theories may be limited to the variety that creators generate before their initial success. In this way, the present research highlights both the value and limits of evolutionary perspectives, with achieving a hit product serving as an important boundary condition. These findings also encourage further research to better understand the conditions under which evolutionary perspectives are more or less useful for explaining and predicting creativity and innovation.

Limitations and Future Directions

This study has key limitations that may be addressed in future research. First, although the music industry was fairly representative of the creative industries that are the focus of the proposed theory, it may be idiosyncratic in ways that limit generalizability. For instance, the music industry may be more fast-paced and competitive than other creative industries, making sustained success more difficult and unpredictable. Also, songs are often "pushed" to consumers by radio stations, whereas products in many other creative industries are "pulled" by consumers—e.g., books, movies, and games. These differences could have produced more extreme results than in other industries, in which creators may have more leeway and time to develop products that keep up with the market. Future research could test whether the results hold in other contexts. Second, the dataset only included songs that were widely distributed, as comprehensive data on unreleased songs did not exist at the time of the study. Although the proposed theory focuses on products that reach the market, including unreleased songs may have provided a more complete view of artists' capabilities. Future research could explore the effects of including released and unreleased products in contexts where such data are available.

Third, due to the cross-sectional nature of the data, alternative explanations could not be completely ruled out, nor could the proposed mechanisms be precisely tested. Moreover, the dataset only included artists who were signed by a label that produced one or more hits. Although this was a fairly broad sample, the fact that all the artists were signed by a successful label may have created selection effects that cannot be ruled out in this study. Future research could address these limitations using longitudinal field experiments in which the independent variables are manipulated. Fourth, this study focused on a particular form of market success—having a hit song appear in the Hot 100 chart. Although this provided a persistent and meaningful measure of success over a long time, ranking charts of this sort may be subject to biases that more raw measures might avoid. Future research could explore other measures of success, such as raw sales or downloads.

The study results also raise new theoretical questions that could be explored in future research. First, soloists had better sustained hit rates than groups. Research that unpacks this finding may speak to theoretical conversations on group versus individual creativity and innovation (Harvey & Hou, 2013; Paulus & Nijstad, 2003). Second, artists who write their own songs were less likely to sustain success, but artists who produce their own songs were more likely to sustain success. Studying this pattern further may yield insights on role effects in creative collaborations. Third, this study focused on success only within the music industry, but some creators work across multiple creative industries in their careers (e.g., film, theater, writing, etc.). Future research could explore the drivers of sustained success across multiple creative industries, which could afford interesting forms of brokerage (Fleming, Mingo, & Chen, 2007).

Practical Implications and Conclusion

Results from this study may provide useful insights for creators, and managers of creators, who wish to sustain success over time. As creators begin their careers, they may face a tradeoff as they build their portfolios of products. Focusing on products that reflect what is popular at the time may be the most likely and efficient path to initial success. But taking this path may undermine their likelihood of sustaining success. If the goal is sustained success, creators may need to resist the temptation to achieve initial success quickly or easily. Instead, they may position themselves for sustained success by investing their time into generating a variety of novel products early in their careers. Broadly, the results suggest that creators should think about the long term in deciding which products to pursue, as the nature of their current products may impact the success of their future products.

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TABLE 1
Percentage of Artists by Hit Count

	All Artists (N = 69,050)	Hit Artists Only (n = 4,857)								
	Overall (All Years)	Overall (All Years)			Initial Success (1st Hit Year)			Sustained Success (Post 1st Hit Year)		
Hit Count	Top 100	Top 100	Top 40	Top 10	Top 100	Top 40	Top 10	Top 100	Top 40	Top 10
0	92.97%	n/a	40.64%	66.83%	n/a	48.10%	75.31%	57.71%	75.05%	84.06%
1	3.10%	44.10%	29.69%	19.33%	60.61%	35.91%	19.39%	13.05%	7.41%	6.96%
2	1.16%	16.49%	9.84%	5.09%	21.78%	9.47%	3.48%	6.69%	4.51%	3.29%
3	0.69%	9.78%	4.55%	2.70%	10.46%	3.69%	1.07%	4.22%	2.86%	1.61%
4	0.41%	5.83%	3.27%	1.50%	4.08%	1.79%	0.51%	2.53%	2.04%	0.95%
5	0.27%	3.89%	2.22%	0.97%	1.89%	0.58%	0.10%	2.47%	1.44%	0.68%
6	0.21%	2.92%	1.67%	0.97%	0.60%	0.14%	0.06%	2.31%	1.11%	0.47%
7	0.19%	2.64%	1.11%	0.47%	0.23%	0.23%	0.04%	1.44%	0.54%	0.49%
8	0.15%	2.08%	1.09%	0.41%	0.27%	0.06%	0.00%	1.17%	0.86%	0.21%
9	0.11%	1.52%	0.89%	0.39%	0.02%	0.02%	0.00%	0.82%	0.66%	0.21%
10+	0.76%	10.75%	5.03%	1.34%	0.06%	0.02%	0.02%	7.59%	3.52%	1.07%

TABLE 2
Correlations and Descriptive Statistics for Song-Level Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Relatedness	1.00																						
2. Novelty	-.39	1.00																					
3. Top 100 (Hit vs. Miss)	.04	-.05	1.00																				
4. Top 40 (Hit vs. Miss)	.03	-.04	.70	1.00																			
5. Top 10 (Hit vs. Miss)	.01	-.03	.45	.64	1.00																		
6. # of Artists	-.02	.15	-.03	-.02	-.01	1.00																	
7. Genre Blues	-.02	-.03	-.01	-.01	.00	-.02	1.00																
8. Genre Brass/Military	-.01	.00	.00	.00	.00	.01	.00	1.00															
9. Genre Children	.00	-.03	-.01	-.01	.00	.01	-.01	.00	1.00														
10. Genre Classical	-.08	.11	-.02	-.01	-.01	.15	-.02	.04	-.01	1.00													
11. Genre Electronic	-.01	.01	.00	.00	.00	.01	-.05	-.01	-.03	-.04	1.00												
12. Genre Folk/Country	.08	-.06	-.01	-.01	-.01	-.03	.03	.02	.00	.00	-.11	1.00											
13. Genre Funk/Soul	-.05	-.09	.06	.04	.02	-.04	.05	-.01	-.02	-.04	.01	-.05	1.00										
14. Genre Hip Hop	.02	.03	.04	.03	.02	.00	-.03	-.01	-.02	-.05	.03	-.08	.04	1.00									
15. Genre Pop	-.01	-.12	.01	.01	.01	-.08	-.02	-.01	.03	-.04	-.02	.01	.00	-.06	1.00								
16. Genre Jazz	-.09	.02	-.02	-.01	-.01	.00	.04	.01	-.02	.00	-.05	-.03	.09	-.05	-.03	1.00							
17. Genre Latin	.01	-.08	-.02	-.01	-.01	-.03	-.02	.00	.00	-.03	-.06	.05	.01	-.02	.04	.03	1.00						
18. Genre Non-Music[a]	-.03	.02	-.01	-.01	.00	.01	.00	.00	.05	.01	-.01	.01	-.01	-.02	.00	.00	-.02	1.00					
19. Genre Reggae	.04	-.05	-.01	-.01	-.01	.01	-.01	.00	-.01	-.03	-.03	-.04	.00	.01	-.06	-.04	-.01	-.02	1.00				
20. Genre Rock	.05	-.15	.02	.02	.01	-.15	.07	-.02	-.04	-.11	-.09	-.10	-.07	-.11	.05	-.10	-.10	-.04	-.08	1.00			
21. Genre Stage/Screen	-.10	.07	-.01	.00	.00	.05	-.01	.02	.05	.12	.02	-.01	.00	-.04	.01	.05	-.03	.06	-.03	-.07	1.00		
22. Genre Crossover	-.06	-.05	.00	.00	.00	-.03	.19	.04	.09	.10	.24	.27	.26	.08	.28	.23	.24	.12	.02	.09	.22	1.00	
23. Release Year	-.06	.50	-.06	-.04	-.03	.04	-.03	-.04	-.04	-.04	.14	-.15	-.14	.16	-.12	-.11	-.10	-.04	.00	-.04	-.05	-.08	1.00
Mean	.67	.14	.01	.00	.00	1.53	.02	.00	.01	.04	.14	.12	.07	.06	.20	.08	.06	.02	.03	.29	.04	.22	1992
Standard Deviation	.09	.04	.08	.06	.04	1.50	.15	.04	.10	.19	.34	.33	.25	.23	.40	.27	.24	.12	.17	.46	.19	.41	13.37
Minimum	.00	.01	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1959
Maximum	1.00	.26	1	1	1	106	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2010

Notes:
N = 3,191,701 artist-song pairs for all variables except relatedness (*n* = 226,191; includes only songs released after an artist's first hit) and novelty (*n* = 2,500,221; excludes songs missing from Spotify). Correlations greater than .005 or less than -.005 were significant at $p < .001$.
[a]The non-music genre includes songs that have both music and speaking elements (e.g., comedy routines or speeches set to music).

TABLE 3
Correlations and Descriptive Statistics for Artist-Level Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Novelty (Pre for hit artists)	1.00																				
2. Variety (Pre for hit artists)	.30	1.00																			
3. Song Count Year (Mean)	.16	.29	1.00																		
4. Song Count Total	.07	.30	.53	1.00																	
5. Overall Career Age	.04	.21	.11	.37	1.00																
6. Years Since Last Song (Mean)	.10	.04	.03	-.09	.50	1.00															
7. Soloist (vs. Group)	.14	.05	.01	.09	.15	.04	1.00														
8. Prior Hit(s) w/ Group	-.03	.02	.02	.06	.08	.02	.17	1.00													
9. Self-Write %	.09	.06	-.03	-.02	-.07	-.01	.35	.02	1.00												
10. Self-Produce %	.14	.02	-.03	.01	-.01	.01	.49	.05	.61	1.00											
11. Career Start Year	.29	.06	.02	-.09	-.60	-.31	-.05	-.04	.14	.10	1.00										
12. Mean # of Artists on Songs	.16	-.05	.02	-.02	.08	.04	.19	.00	.06	.14	-.02	1.00									
Hit Artists Only:																					
13. Relatedness	-.19	-.36	-.09	-.14	-.06	.00	-.12	-.07	-.04	-.07	-.04	-.07	1.00								
14. Hit Count (Overall)	.05	.16	.26	.50	.17	-.13	.09	.13	.02	.10	-.05	-.04	-.05	1.00							
15. Hit Count (Pre)	.00	.17	.21	.21	.09	-.09	.00	.04	.00	.02	-.02	-.04	.02	.50	1.00						
16. Hit Count (Post)	.06	.14	.24	.50	.17	-.12	.09	.14	.02	.11	-.06	-.04	-.06	.98	.34	1.00					
17. Hit Weeks (Overall)	.05	.16	.25	.43	.06	-.14	.10	.13	.08	.15	.10	-.02	-.05	.94	.45	.93	1.00				
18. Hit Weeks (Pre)	.02	.19	.23	.15	-.09	-.14	.03	.04	.13	.12	.26	-.01	-.01	.42	.79	.30	.51	1.00			
19. Hit Weeks (Post)	.05	.13	.22	.44	.09	-.12	.10	.14	.05	.13	.04	-.03	-.06	.93	.30	.96	.98	.31	1.00		
20. Career Age at 1st Hit	.01	.23	.08	.32	.16	-.05	.16	.11	.07	.09	-.02	.04	-.08	-.04	-.04	-.04	-.02	.00	-.02	1.00	
21. Year of 1st Hit	.06	.16	.18	-.03	-.59	-.28	.10	.05	.38	.27	.97	.09	-.06	-.06	-.03	-.06	.09	.26	.03	.22	1.00
Mean	0.13	0.16	10.25	46.22	18.58	2.79	0.54	0.03	0.87	0.77	1983	1.55	0.68	4.18	1.7	2.47	50.74	20.49	30.24	3.30	1981
Standard Deviation	0.03	0.09	7.62	53.98	14.37	3.78	0.50	0.18	0.29	0.38	13.76	1.03	0.06	6.36	1.23	5.84	87.28	19.94	78.95	3.20	13.39
Minimum	0.01	0	1	1	1	0	0	0	0	0	1959	1	0.32	1	1	0	1	1	0	1	1959
Maximum	0.24	1.03	309	1,215	52	46.67	1	1	1	1	2005	31.67	1.00	74	38	64	1,040	285	1,021	34	2005

Notes:
Pre refers to songs released before/during first hit year (initial success); Post refers to songs released after first hit year (sustained success).
Correlations greater than .03 or less than -.03 were significant at $p < .05$.

TABLE 4
Logistic Regression Models for H1-H5: Hit Artists' Sustained Success
(All Songs Released After First Hit Year)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
DV (Song Hit vs. Miss):	Top 100	Top 40	Top 10	Top 100	Top 40	Top 10	Top 100	Top 40	Top 10
Relatedness (H1)	.200***	.199***	.155***	.209***	.212***	.178***	.213***	.214***	.179***
	(.013)	(.018)	(.026)	(.014)	(.018)	(.027)	(.014)	(.018)	(.027)
Pre-Novelty (H4)				.120***	.159***	.185***	.119***	.154***	.181***
				(.024)	(.031)	(.041)	(.024)	(.031)	(.041)
Pre-Variety (H5)				.053*	.066*	.099*	.053*	.066*	.102*
				(.025)	(.033)	(.042)	(.025)	(.033)	(.042)
Relatedness X Pre-Novelty (H2)							.007	.019	.014
							(.013)	(.018)	(.026)
Relatedness X Pre-Variety (H3)							.043***	.056***	.066**
							(.012)	(.017)	(.024)
Time-Varying Artist Controls:									
Song Count Year (log)	-.248***	-.167***	-.064*	-.243***	-.160***	-.054	-.243***	-.159***	-.053
	(.014)	(.020)	(.030)	(.014)	(.020)	(.030)	(.014)	(.020)	(.030)
Song Count Total (log)	-.239***	-.184***	-.309***	-.271***	-.228***	-.374***	-.275***	-.234***	-.380***
	(.036)	(.050)	(.068)	(.037)	(.051)	(.069)	(.037)	(.051)	(.070)
Prior Hit Count (log)	-.139*	-.196*	-.077	-.128*	-.184*	-.058	-.126*	-.182*	-.056
	(.061)	(.081)	(.115)	(.062)	(.081)	(.115)	(.062)	(.081)	(.115)
Prior Hit Weeks (log)	.966***	1.059***	1.052***	.964***	1.060***	1.048***	.962***	1.059***	1.047***
	(.057)	(.078)	(.114)	(.057)	(.078)	(.114)	(.057)	(.078)	(.114)
Career Age	-1.924***	-2.230***	-2.199***	-1.900***	-2.203***	-2.175***	-1.898***	-2.201***	-2.172***
	(.077)	(.105)	(.156)	(.077)	(.105)	(.156)	(.077)	(.105)	(.156)
Years Since Last Song	-.109*	-.017	-.079	-.111*	-.021	-.090	-.111*	-.021	-.089
	(.052)	(.073)	(.114)	(.052)	(.073)	(.114)	(.052)	(.073)	(.114)
Static Artist Controls:									
Soloist (vs. Group)	.164**	.214**	.235**	.140**	.182**	.201*	.288***	.368***	.276**
	(.052)	(.068)	(.086)	(.052)	(.067)	(.086)	(.067)	(.084)	(.104)
Prior Hit(s) w/ Group	.286***	.366***	.272**	.290***	.370***	.277**	-.152***	-.167***	-.087
	(.067)	(.085)	(.104)	(.067)	(.085)	(.104)	(.029)	(.038)	(.050)
Self-Write %	-.143***	-.155***	-.073	-.149***	-.164***	-.083	.174***	.225***	.218***
	(.029)	(.038)	(.050)	(.029)	(.038)	(.050)	(.027)	(.034)	(.045)
Self-Produce %	.167***	.218***	.215***	.172***	.222***	.215***	.495***	.522***	.525***
	(.027)	(.035)	(.045)	(.027)	(.034)	(.044)	(.038)	(.050)	(.071)
Career Age at 1st Hit	.499***	.523***	.529***	.496***	.523***	.525***	-.508***	-.639***	-.789***
	(.037)	(.050)	(.071)	(.038)	(.050)	(.071)	(.065)	(.083)	(.128)
Year of 1st Hit	-.492***	-.614***	-.750***	-.506***	-.636***	-.785***	.288***	.368***	.276**
	(.065)	(.083)	(.128)	(.065)	(.083)	(.128)	(.067)	(.084)	(.104)
Song Controls:									
# of Artists on Song (log)	-.039**	-.012	.069**	-.040**	-.013	.068**	-.040**	-.014	.068**
	(.015)	(.019)	(.025)	(.015)	(.019)	(.025)	(.015)	(.019)	(.025)
Genre Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Release Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed Intercept	-4.911***	-5.829***	-7.177***	-4.930***	-5.856***	-7.215***	-4.916***	-5.836***	-7.190***
	(.117)	(.155)	(.248)	(.117)	(.155)	(.248)	(.117)	(.155)	(.248)
Random Intercept (Artist)	.588***	.791***	.740***	.570***	.760***	.708***	.569***	.758***	.709***
	(.047)	(.073)	(.090)	(.046)	(.071)	(.089)	(.046)	(.071)	(.088)
Random Intercept (Label)	.502***	.558***	.530***	.501***	.556***	.530***	.501***	.555***	.528***
	(.039)	(.056)	(.081)	(.039)	(.055)	(.081)	(.039)	(.055)	(.081)
Observations (Songs)	226,191	226,191	225,525[a]	226,191	226,191	225,525[a]	226,191	226,191	225,525[a]
Artists	4,310	4,310	4,309	4,310	4,310	4,309	4,310	4,310	4,309
Labels	6,575	6,575	6,553	6,575	6,575	6,553	6,575	6,575	6,553
Log-Likelihood	-36,826	-22,332	-11,012	-36,808	-22,315	-10,997	-36,802	-22,308	-10,993

Notes: *$p < .05$, ** $p < .01$, *** $p < .001$. Standard errors in parentheses. All continuous variables were standardized.
[a]No songs from the children genre made it to the top 10, omitting 666 songs within this genre from Models 3, 6, and 9, which omitted one artist whose songs were all in this genre.

TABLE 5
Cox Regression Models for H6 and H7: New Artists' Likelihood of Initial Success (Career Start Through First Hit Year, If Any)

	Model 1	Model 2	Model 3	Model 4	Model 5
DV (Artist Hit vs. Miss):	Top 100	Top 100	Top 100	Top 40	Top 10
Novelty [X Time] (H6)	-.061***		-.068***	-.080***	-.086***
	(.005)		(.005)	(.007)	(.010)
Variety [X Time] (H7)		.012*	.031***	.048***	.073***
		(.005)	(.005)	(.007)	(.010)
Time-Varying Artist Controls:					
Song Count Year (log) [X Time]	.089***	.076***	.088***	.119***	.126***
	(.005)	(.005)	(.005)	(.009)	(.012)
Song Count Total (log) [X Time]	.078***	.085***	.072***	.064***	.068***
	(.008)	(.008)	(.008)	(.012)	(.017)
Mean # of Artists on Songs (log) [X Time]	-.375***	-.374***	-.366***	-.320***	-.331***
	(.021)	(.021)	(.021)	(.027)	(.040)
Static Artist Controls:					
Soloist (vs. Group)	.439***	.438***	.434***	.400***	.368***
	(.039)	(.039)	(.039)	(.053)	(.076)
Prior Hit(s) w/ Group	.631***	.641***	.625***	.625***	.721***
	(.053)	(.053)	(.053)	(.072)	(.100)
Self-Write %	-.256***	-.260***	-.258***	-.260***	-.253***
	(.014)	(.014)	(.014)	(.019)	(.028)
Self-Produce %	-.476***	-.482***	-.476***	-.452***	-.441***
	(.017)	(.017)	(.017)	(.023)	(.034)
Career Start Year Dummies	YES	YES	YES	YES	YES
Genre Dummies	YES	YES	YES	YES	YES
Observations (Artist Release Years)[a]	346,608	346,608	346,608	346,608	346,608
Total Career Years Under Observation	1,047,681	1,047,681	1,047,681	1,047,681	1,047,681
Artists	69,050	69,050	69,050	69,050	69,050
Labels	14,924	14,924	14,924	14,924	14,924
Log-Likelihood	-20,414	-20,499	-20,397	-11,154	-5,386

Notes: $*p < .05$, $** p < .01$, $*** p < .001$
Standard errors in parentheses. All continuous variables were standardized.
All models were stratified by label. Artists' labels and genre dummies were determined on a rolling basis, based on the songs released by the artist up through each year (artists' highest-ranking label through each year was used).
[a] The observations in all models include each year artists released one or more songs, from their first career year through the year of their first hit (if any).

FIGURE 1
Visual Summary of Proposed Theory and Hypotheses

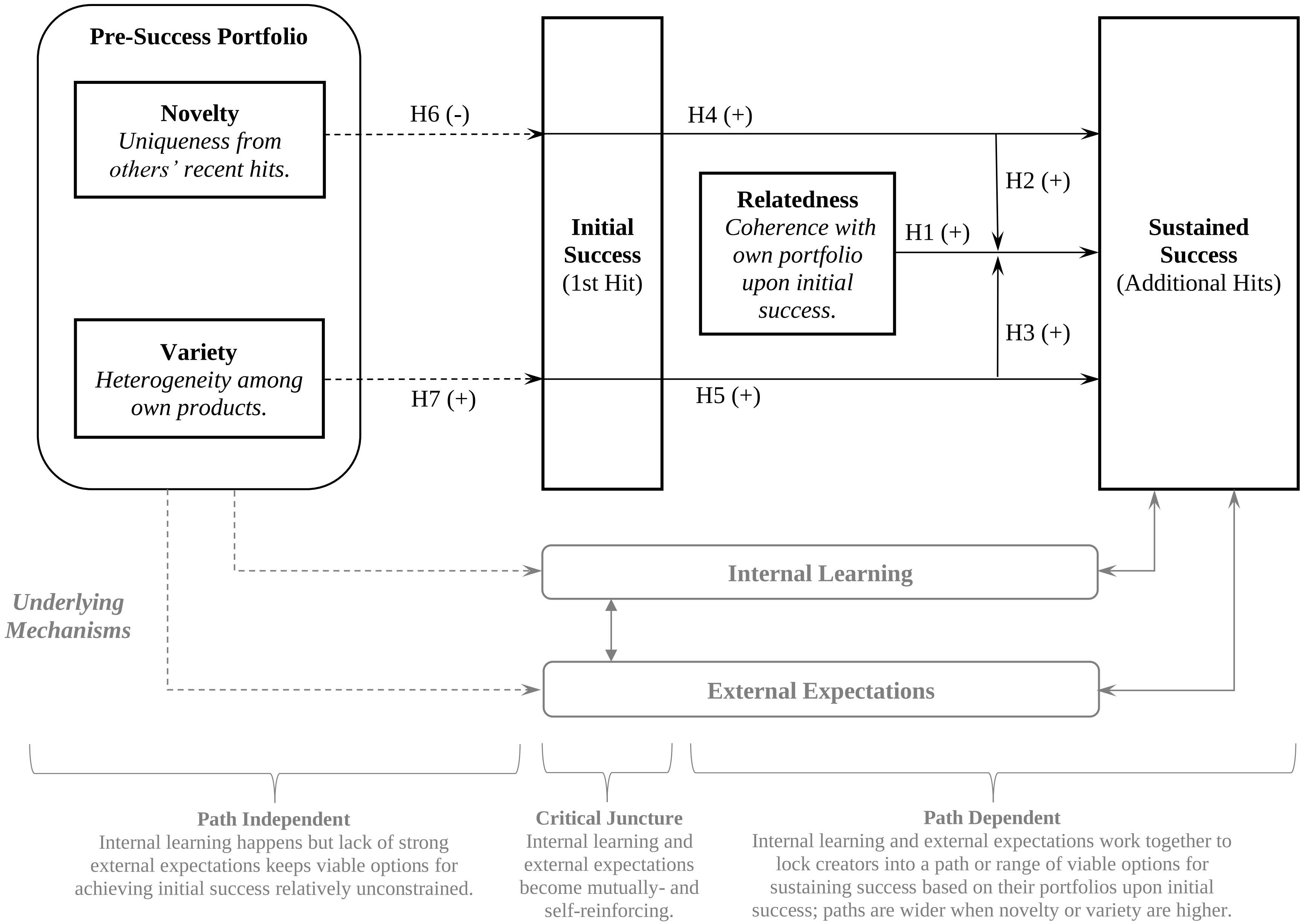
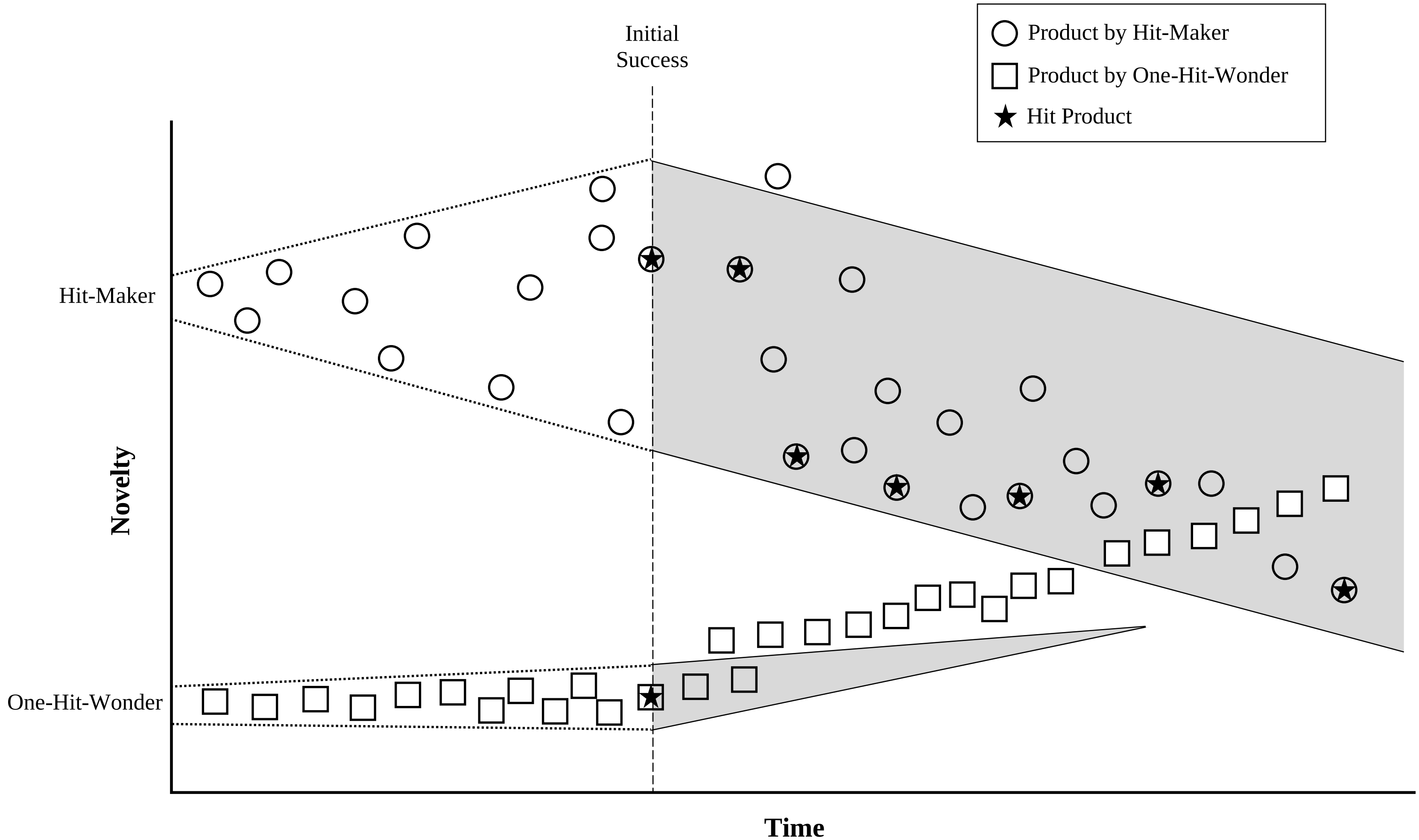


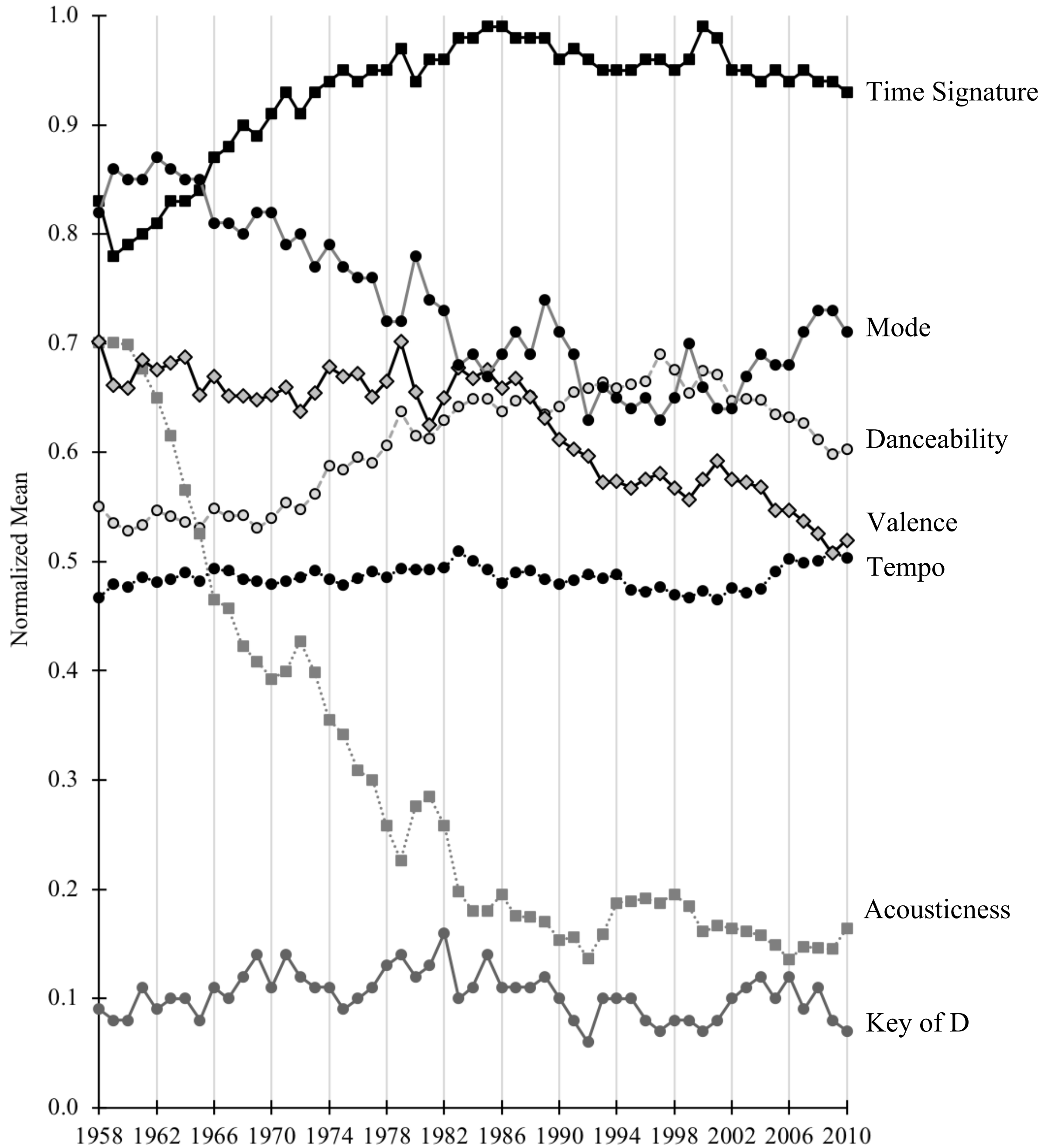
FIGURE 2
Diagram of Example Paths for Archetypal Hit-Maker and One-Hit-Wonder



(Dotted lines represent variety in portfolio.)

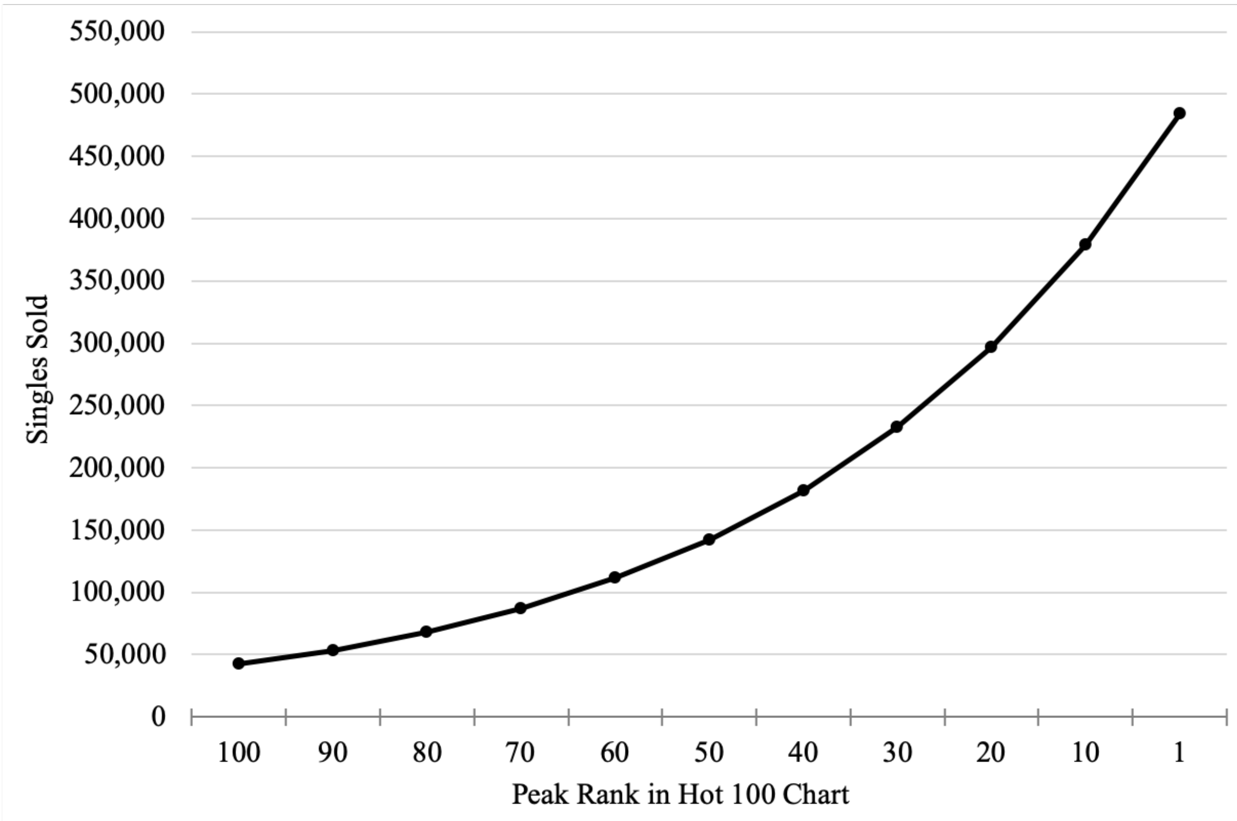
(Shaded areas represent the creator's path or range of viable options for sustaining success. Path width depends on the novelty and variety in creators' portfolios upon initial success, as these dimensions predict their capacity to simultaneously benefit from relatedness and adapt to market changes.)

FIGURE 3
Example Sonic Features of Hit Songs by Year



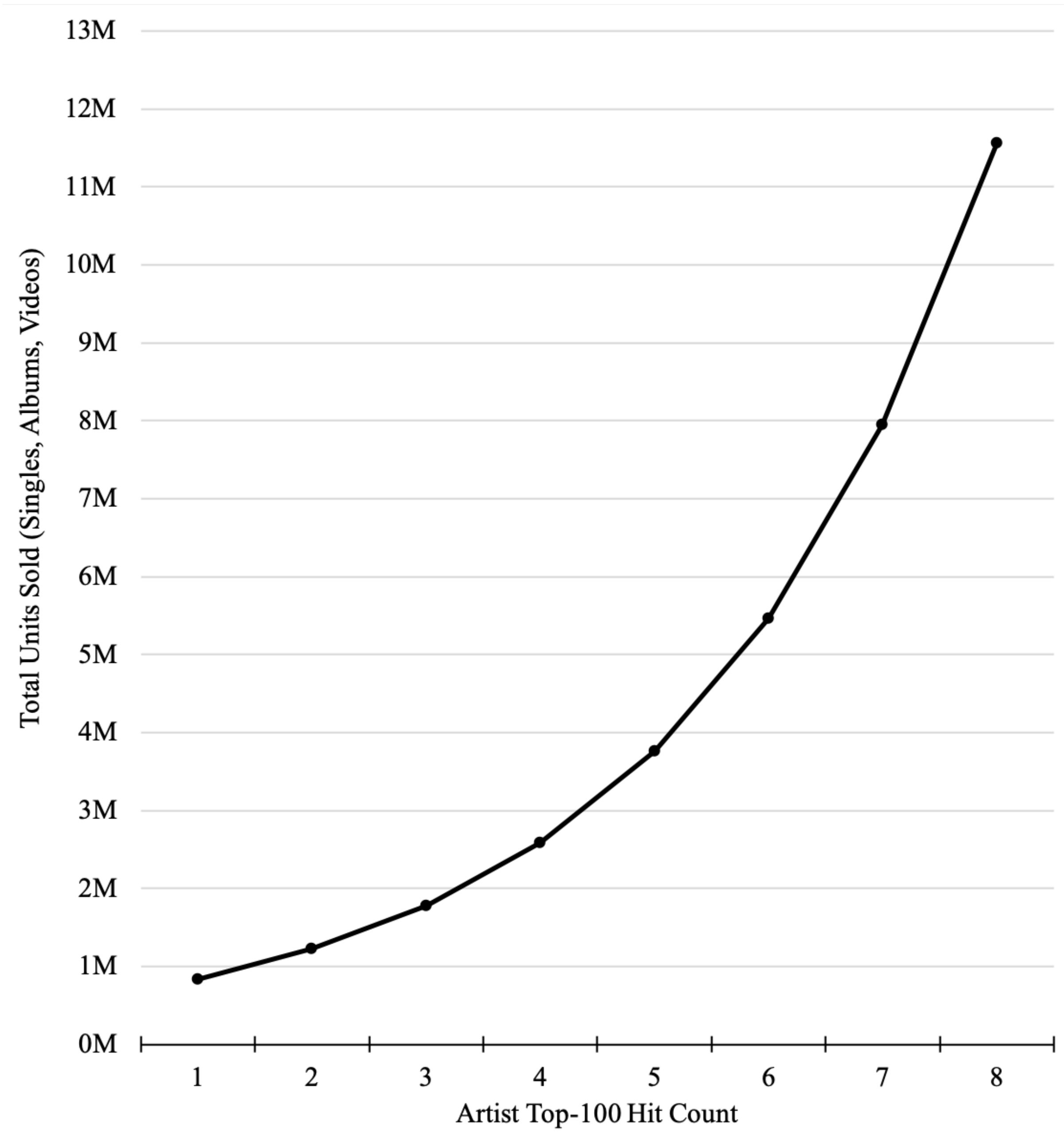
Note: For brevity, seven of the 22 variables used to measure the sonic features are shown as examples.

FIGURE 4
Total Single Sales by Hot 100 Peak Rank (1994-2004)



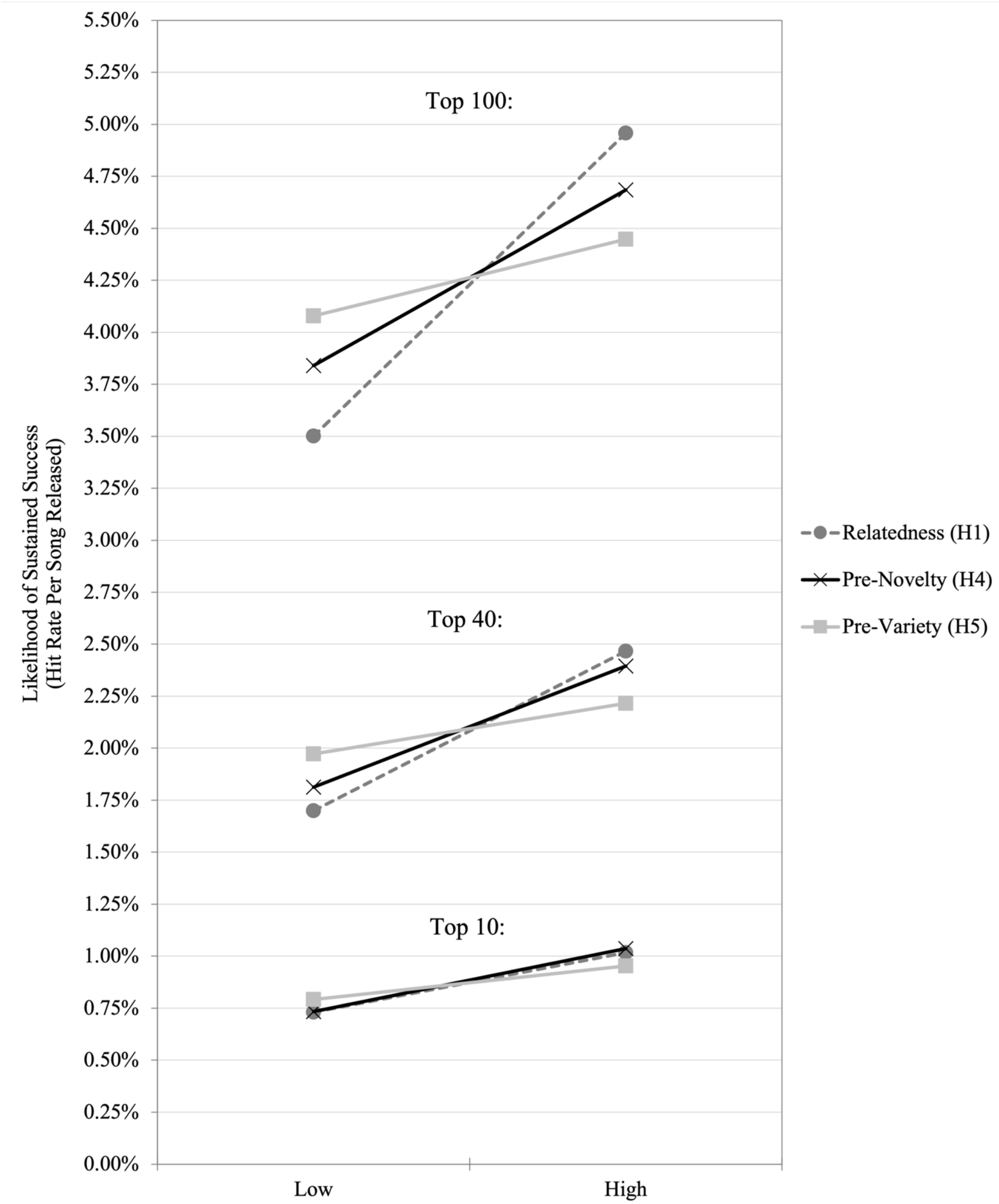
Note: Singles sold refers to the total number sold through 2004. To ensure the sales life cycle of songs was effectively complete, only songs that entered the Hot 100 from 1994-2002 were included, as the vast majority of sales occur in the two years after entry into the Hot 100.

FIGURE 5
Total Sales by Artist Hit Count (1994-2004)



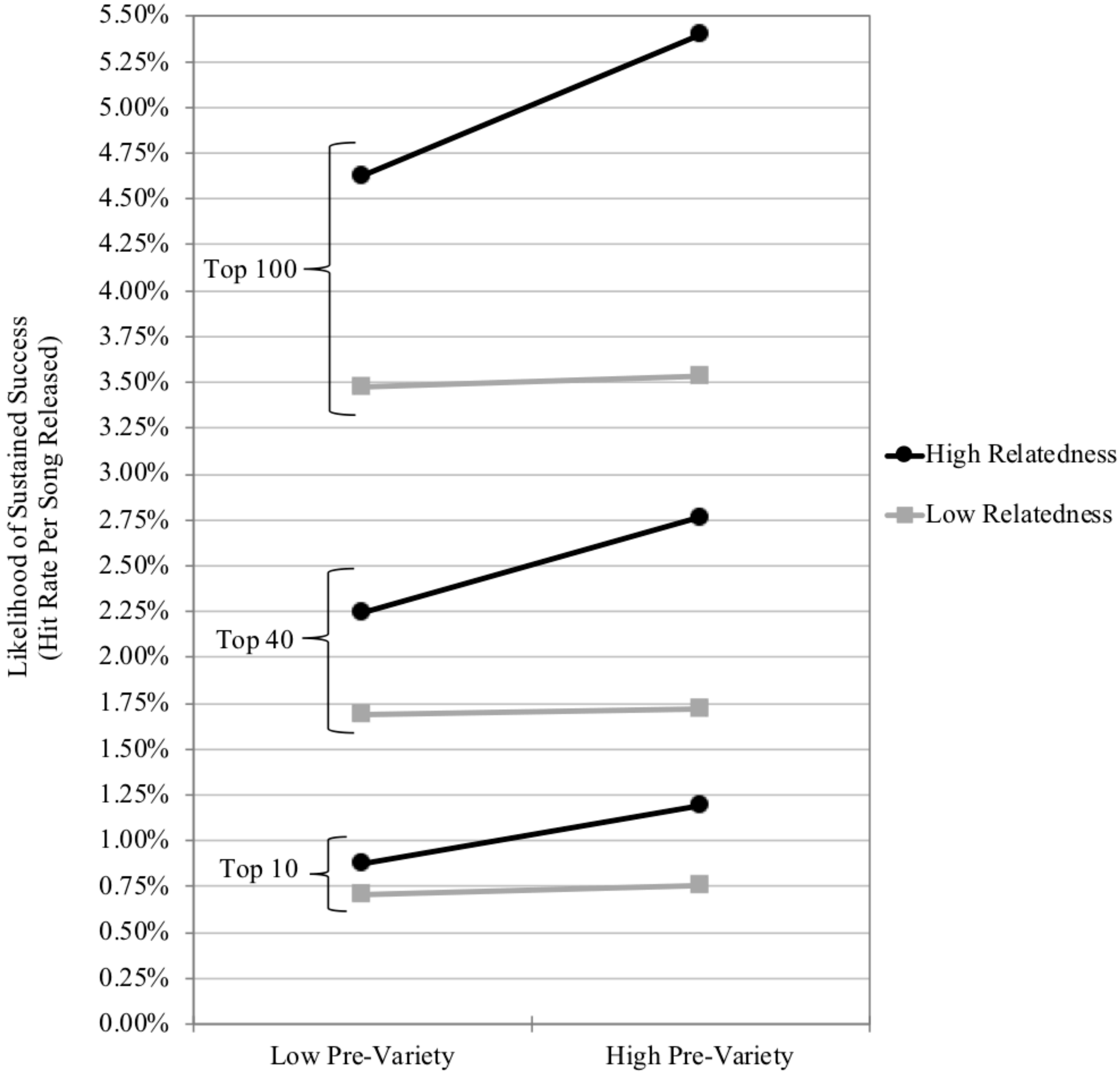
Note: Total units sold refers to the total number of units sold through 2004. Only artists who had their first hits 1994-2002 were included, allowing two years for sales cycles to complete.

FIGURE 6
Estimated Marginal Means for H1, H4, and H5



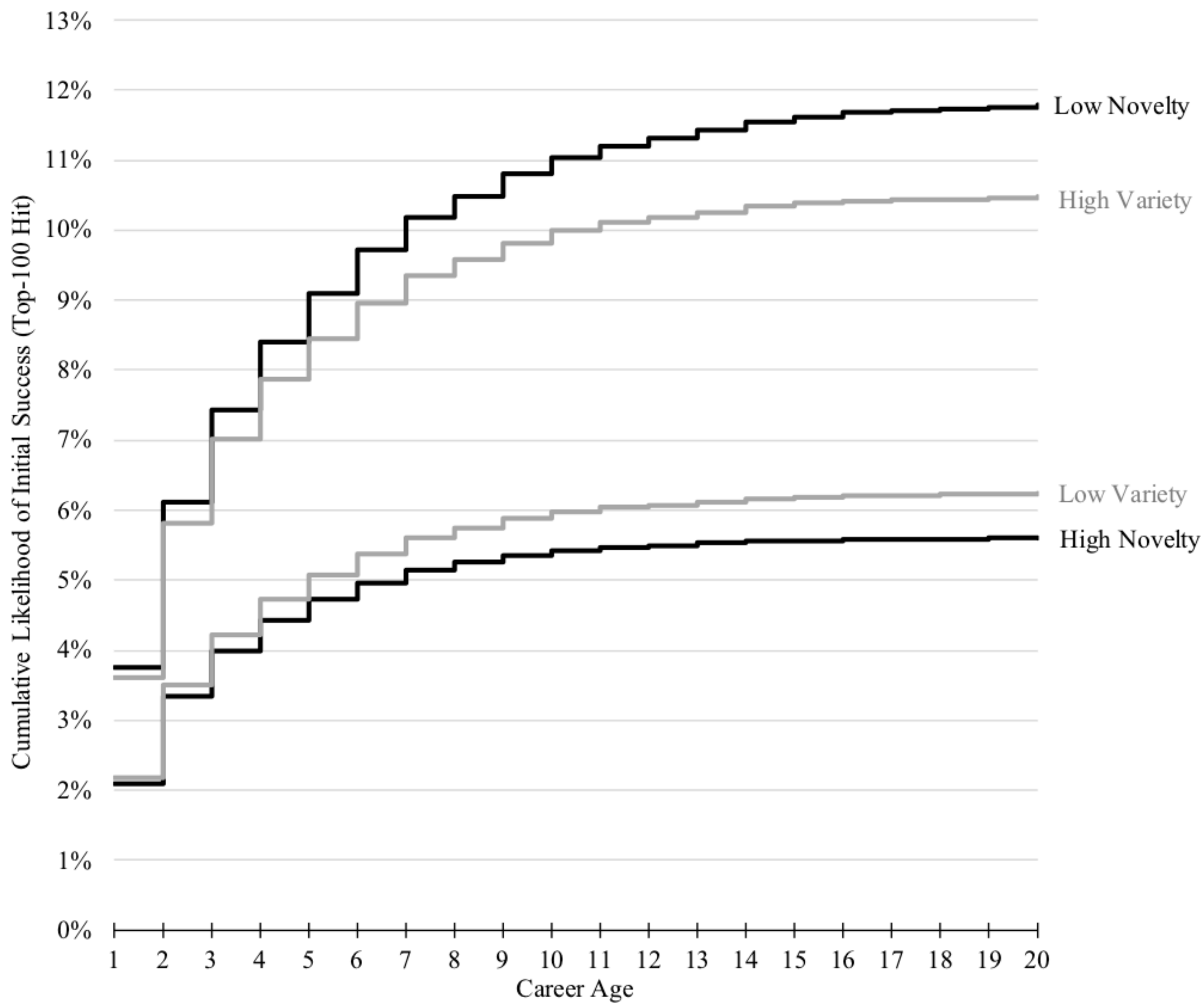
Note: High and low refer to one standard deviation above and below the mean respectively. The estimates are based on Models 4-6 in Table 4.

FIGURE 7
Estimated Marginal Means for H3: Relatedness X Pre-Variety



Note: High and low refer to one standard deviation above and below the mean respectively. The estimates are based on Models 7-9 in Table 4.

FIGURE 8
Likelihood of New Artists Achieving Initial Success by Career Age (H6 and H7)



Note: High and low refer to one standard deviation above and below the mean respectively (with the other dimension held at its mean). The estimates are based on Model 3 in Table 5.