One-Hit Wonders versus 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 that 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 a creator's path to sustained success depends on the creativity in their portfolio at the time of 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. I tested the proposed theory using an archival study of the U.S. music industry from 1959–2010, including data on over 3 million songs by 69,050 artists, and the results largely support the hypotheses. Artists who reached their initial hits with relatively creative (novel or varied) portfolios were more likely to generate additional hits, but a novel portfolio was less likely to yield an initial hit than was a typical portfolio. These findings suggest that new creators face a tradeoff between their likelihood of initial versus sustained success, such that building a relatively creative early portfolio is a risky bet that can make or break a creator's career.

Keywords: creativity, innovation, careers, path dependence, creative industries, markets, adaptation

In creative industries, success is notoriously fickle. Film, music, art, theater, publishing, cuisine, gaming, fashion, and other creative industries supply products ''that we broadly associate with cultural, artistic, or simply entertainment value'' (Caves, 2000: 1). A hallmark of creative industries is that the success of new products is highly uncertain (Potts et al., 2008; Flew, 2012). Audience demand and competition produce a constant stream of new products that can quickly render previously successful products outdated (Jones et al., 2016). Although large organizations often handle distribution and marketing,

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new products are usually generated by creators working individually or in teams (Caves, 2000; Perry-Smith and 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 (Hirsch, 1972; Bielby and Bielby, 1994). On rare occasions creators may face radical innovations that fundamentally change their industries (Abernathy and Clark, 1985), but the vast majority of the time the challenge is responding to constant incremental change in what is popular at a given moment (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 (Salganik, Dodds, and Watts, 2006; Potts et al., 2008). 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 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, and Chung, 1995; Fox and Kochanowski, 2004), visual 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 not only to creators but also to the people who manage them and the organizations that employ them (Elsbach and 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 scholars have rarely examined the relationship between creativity and market success over time (cf. Audia and Goncalo, 2007), prior research has yielded valuable knowledge on how creativity relates to market success at a given moment in 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 that novelty on average reduces the likelihood of market success, as typical products tend to outperform more-novel ones (Ward, Bitner, and Barnes, 1992; Veryzer and Hutchinson, 1998; Fleming, 2001; Uzzi et al., 2013; Liu et al., 2017), even in so-called creative industries (Becker, 1982; Martindale, 1990; Interiano et al., 2018). 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 variety and market success, as 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 moment 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, research on creativity and innovation more broadly reflects this assumption. 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, and 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; Staw, 1990; West, 2002; Perry-Smith and Mannucci, 2017). The assumption is that once the final product is implemented in the market, creators move on to their next project, and the process starts anew. This assumption 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., Rosenbaum, 1979; Arthur, 1989; Carroll and Harrison, 1994; Sydow, Schreyögg, and Koch, 2009). 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. When creators achieve an initial hit, they and their product 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.

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 article, 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, such as artists, writers, designers, inventors, chefs, architects, filmmakers, choreographers, social media influencers, and game developers, build portfolios of products that audiences and gatekeepers associate with them. To test the theory, I assembled an archival dataset of the U.S. music industry from 1959–2010, which includes data on over 3 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, I suggest 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. I theorize how two self-reinforcing mechanisms—internal learning and external expectations—can work together to tether creators' odds of sustaining success to the creativity (novelty and variety) in their portfolios at the time of their initial hits. 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 expectation applies only to creators' *current* products at a given time. The path-dependent view 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. My research illustrates that path independence tells only half the story; path dependence is also needed for understanding how creativity and market success are related over time. This study also sheds light on important boundary conditions for evolutionary theories of creativity and innovation. In the dataset, the benefits of variety implied by an evolutionary perspective were limited to the variety that creators generated before their initial hits, 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 (David, 1985; Arthur, 1989), competition between organizational populations (Carroll and Harrison, 1994), firm-level competitive advantage (Barney, 1991; Teece, Pisano, and Shuen, 1997), between-firm alliances (Lavie and Rosenkopf, 2006), entrepreneurial success (Beckman and Burton, 2008), employee promotions (Rosenbaum, 1979), and job mobility (Dlouhy and 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, and Koch, 2009). A strength of path dependence theory is that it explains 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).

My theorizing adapts and builds on Sydow and colleagues' (2009) theory of organizational path dependence. Rather than organizations, my focus is on creators—the primary individuals or groups responsible for generating given portfolios of products in creative industries 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, path-dependent situations 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. The point at which the situation turns from path independent toward path dependent is called the ''critical juncture.'' After the critical juncture, self-reinforcing mechanisms 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, ultimately locking the actor into a relatively limited range of viable options.

   In my proposed theory, a 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 two self-reinforcing mechanisms that make their quest for sustained success path dependent: 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 at the time of their 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 and also keep 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 viable options for weathering this double bind over time. Creators who reach initial success with relatively creative (novel or varied) portfolios maintain a wider path, increasing their odds of sustaining success. See Figure 1 for a visual summary of the theory and hypotheses.

The Benefit of Relatedness for Sustaining Success

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, both of which are common self-reinforcing mechanisms in the literature on path dependence (Arthur, 1988; Sydow, Schreyögg, and Koch, 2009). 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, compared to gaining new capabilities (Levinthal and March, 1993; Argote, 1999; Audia and Goncalo, 2007). When learning yields success, the benefits of such learning can become self-reinforcing: leveraging one's existing repertoire becomes increasingly rewarding, while expanding one's repertoire becomes increasingly costly (March,

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[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. A creator who has never achieved a hit product is relatively unknown in the market and may not encounter the path dependencies faced by a creator who has had at least one hit.

Figure 1. Visual Summary of Proposed Theory and Hypotheses
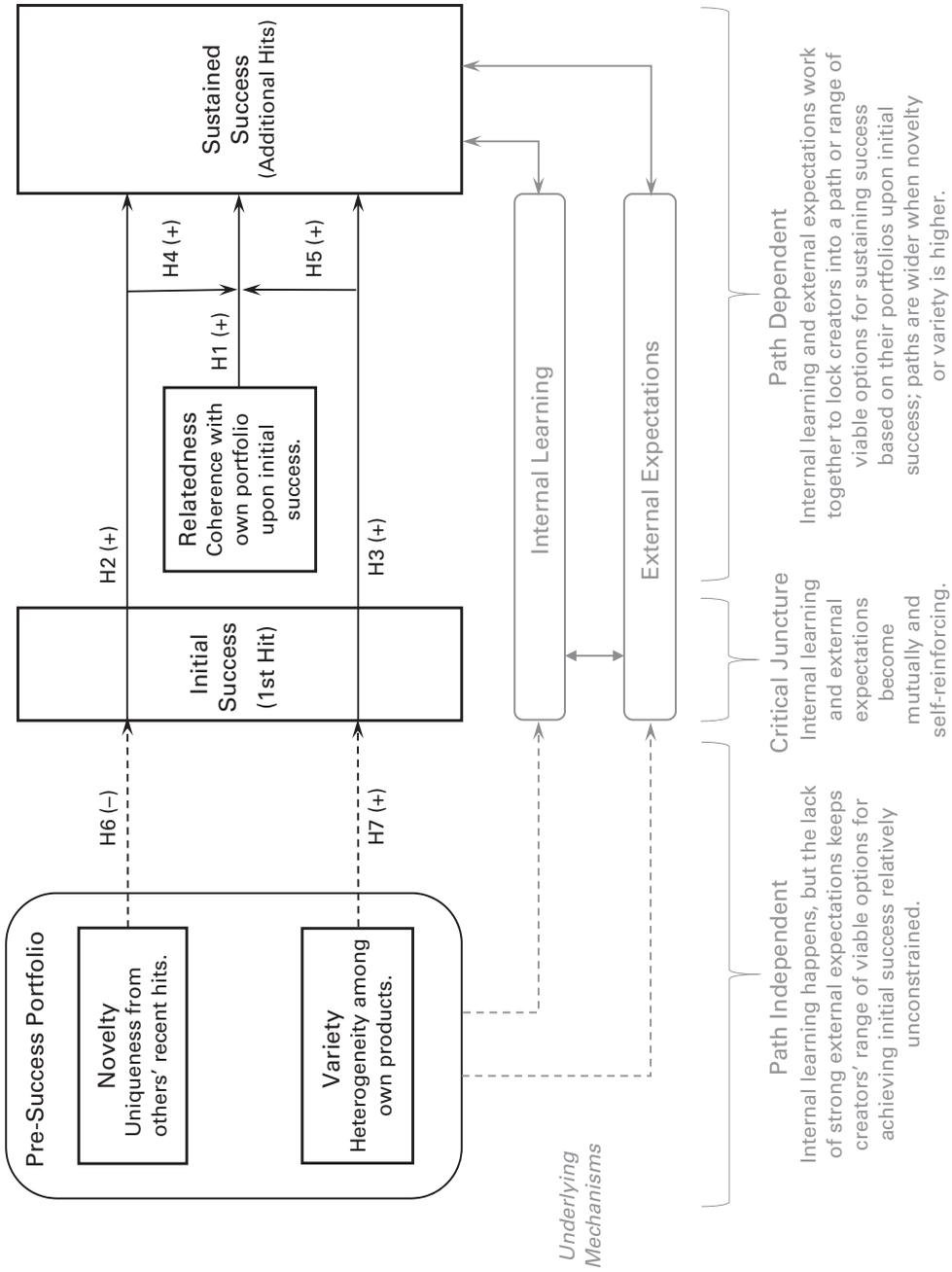
1991). Second, the external expectations mechanism is based on the notion that expectations can be self-fulfilling prophecies (Sydow, Schreyögg, and Koch, 2009). The audience and gatekeepers are more likely to reward products that fit what they expect from a creator (and reject products that violate their expectations), thereby reinforcing their initial expectations (Zuckerman, 1999; Hsu, 2006).

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 of the initial hit. 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 (Bunderson and Sutcliffe, 2003; Arts and Fleming, 2018). The concept of relatedness follows the same logic as theories of related diversification at the firm level, which highlight the benefits of adding new products that maintain coherence with one's existing capabilities and reputation (e.g., Bettis, 1981; Singh and Montgomery, 1987; Markides and Williamson, 1994).

The internal learning and external expectations mechanisms exist before creators achieve initial success, but prior to that success they may not limit creators' viable options. As new creators build their portfolios, they learn new capabilities tailored to their particular products (March, 1991), but they are relatively free to learn a wide range of such capabilities because they do not yet know which ones will benefit them the most. Likewise, before achieving initial hits, creators are relatively unknown in the market. They may experience some external expectations from gatekeepers and audience members, but such expectations are not strong or widespread, so creators are relatively free to diversify their portfolios with little or no downside. Once creators achieve initial success, however, the two mechanisms may become mutually reinforcing and self-reinforcing, making relatedness key to sustaining success.

When a creator achieves their first hit, the audience and gatekeepers are likely to form strong expectations for the creator to deliver more hits that are consistent with their portfolio at the time of the initial hit. 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 often appear in exhibitions with other works by the artist. Thus the audience and gatekeepers may categorize and form strong expectations about creators based on both their initial hits and broader portfolios at the time. These strong expectations could help creators sustain success but only if their new products fit the expectations by staying related to their portfolios at the time of initial success. If creators' new products deviate from their portfolios upon initial success, this difference may violate what the audience and gatekeepers expect from them, reducing their odds of success (Zuckerman, 1999; Hsu, 2006).

Thus when a creator achieves an initial hit, the two underlying mechanisms—internal learning and external expectations—may work together to form a path to sustained success, as the creator is more likely to achieve additional hits when their new products are closely related to their portfolio upon initial success. Of course, creators may not follow their paths to sustained success; they may stray 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. If creators do follow their paths to sustained success, they are more likely to achieve additional hits that are closely related to their portfolios upon initial success. In turn, this additional success should 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 at the time of 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 at the time of initial success, their portfolios may become outdated over time. Creators' portfolios upon initial success remain static, but market preferences in creative industries constantly change (Caves, 2000). 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 (Hirsch, 1972; Bikhchandani, Hirshleifer, and Welch, 1992). New trends may be impossible to predict in advance (Caves, 2000; Salganik, Dodds, and Watts, 2006), but after they emerge, creators may be more likely to sustain success if they incorporate elements of such 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. But the width of creators' paths over time—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, as scholars tend to consider creators' output (ideas or products) independently at one moment or in one window of time. An important exception is Sternberg and Lubart's (1991, 1995) investment theory of creativity, which emphasizes the value of considering a creator's whole portfolio of projects, analogous to how considering a financial investor's whole portfolio is 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 with others' recent hit products in the market. Variety captures the heterogeneity among the products in a creator's own portfolio. Novelty and variety require different forms 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; Torrance, 1962; Runco, 1991). In addition, scholars have used similar conceptual distinctions to describe related matters, including audience members' tastes (Goldberg, Hannan, and Kovács, 2016) and types of artistic deviance (Stamkou, van Kleef, and Homan, 2018). In practice, novelty and variety may be positively correlated, but the two dimensions are conceptually distinct and should have plenty of independent variance. As such, my proposed theory treats novelty and variety as independent dimensions of creativity and assumes the other dimension is held constant, which is also how the hypotheses are tested.[2]

The benefit of prior novelty and variety. Reaching initial success with relatively novel or varied portfolios may position creators to pursue relatedness and adapt to market changes at the same time, increasing their odds of sustained success. The two mechanisms (learning and expectations) may be less constraining in terms of locking them into their portfolios upon initial success, enabling them to incorporate new trends into their new products and receive a relatively warm market reception for such products. Creators with more-typical or homogenous portfolios upon initial success may benefit from relatedness but struggle to adapt as the market changes, narrowing their range of viable options for sustaining success.

Regarding internal learning, building a novel or varied portfolio prior to initial success may endow a creator with a more flexible repertoire of capabilities, helping them generate new products that keep up with new market trends. As creators build novel portfolios prior to initial success, they develop repertoires that are distinct from the current milieu. In contrast, as creators build typical portfolios, they are surrounded by salient exemplars of creators and products that are similar to their own style. The latter situation 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 (March, 1991; Audia and Goncalo, 2007; Dane, 2010; Bayus, 2013). By building novel portfolios prior to initial success, creators may avoid this extra entrenchment and fixation, preventing their repertoires from becoming as rigid. In turn, creators should be better positioned to expand their repertoires to accommodate new trends, allowing them to generate new products that reflect relatedness and new trends at the same time.

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[2] Scholars frequently assess creativity or creative potential based on three dimensions (Guilford, 1956; Runco, 1991): novelty, variety, and quantity (often labeled originality, flexibility, and fluency, respectively). I treat quantity as a control in this 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., Simonton, 1997, 1999, 2011; Liu et al., 2018). Much of this prior research uses quantity 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 to one another or few products that are all quite dissimilar. By focusing on variety (and novelty) with quantity held constant, my research complements prior work that treats variety and quantity as one and the same.

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. By building more-varied portfolios prior to initial success, creators should develop more-diverse repertoires (Amabile, 1996; Bartel and Garud, 2009; Conti, Gambardella, and Mariani, 2014; Mannucci and Yong, 2018). As new trends emerge, creators with more-diverse repertoires should have more options for generating new products that keep up with the latest trends, without substantially expanding their existing capabilities (Ashby, 1956; Weick, 1976; Cohen and Levinthal, 1990; Baker and Nelson, 2005; Harrison and Klein, 2007). 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).

For these reasons, reaching initial success with novel or varied portfolios should relax the internal learning mechanism such that creators can better generate new products that reflect relatedness and new trends at the same time. And external expectations may work in tandem with internal learning to make it easier for creators who reach initial success with novel or varied portfolios to succeed with new products that mix relatedness and new market trends. 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 do not fit the current mainstream (and thus feature novelty) or that contain a broad range of elements (and thus feature 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 (Zuckerman, 1999; Hsu, 2006). Thus creators who reach initial success with novel or varied portfolios may be better positioned to generate new products that reflect both relatedness and new trends, and they may also find a warmer market reception for such products. As such, they should enjoy a wider path or range of viable options for sustaining success, compared to creators with more-typical or homogenous portfolios upon initial success.

> **Hypothesis 2 (H2):** 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 3 (H3):** Creators who have varied portfolios upon initial success are more likely to sustain success than creators who have less-varied portfolios upon initial success.

Prior novelty and variety strengthening the benefit of relatedness. The hypotheses thus far posit that relatedness (H1), prior novelty (H2), and prior variety (H3) each predict sustained success independently. Building on these arguments, I suggest that prior novelty and variety may also strengthen the benefit of relatedness in predicting sustained success. Creators with relatively novel or varied portfolios upon initial success may be better positioned to successfully pursue relatedness, contributing to their overall advantage in sustaining success.

First, when creators reach initial success with relatively novel portfolios, they may create their own niche reputations that are tailored to their existing repertoires (Carroll, 1985; Laland, Odling-Smee, and Feldmam, 2000). This should help creators find a warmer reception for new products that are closely related to their niche reputations. As long as their new products remain relatively high in relatedness, they should be able to integrate elements of new trends into their new products without losing their niche reputations over time. In contrast, relatedness may be less beneficial for creators who reach initial success with more-typical portfolios, as their repertoires and reputations are likely tied to trends that will soon become outdated.

Second, creators with varied portfolios upon initial success should have a wider array of options for how they can leverage their existing repertoires and reputations to weather an ever-changing market (Liu et al., 2021). Their diverse portfolios should give them more options for pursuing relatedness in ways that complement the latest trends. Creators with more-homogenous portfolios upon initial success may have fewer options for how they can leverage their relatively narrow repertoires and reputations as the market changes, making relatedness less effective.

> **Hypothesis 4 (H4):** Prior novelty enhances the benefit of relatedness for sustained success such that relatedness is a stronger positive predictor of sustained success for creators who have novel portfolios upon initial success than for creators who have more-typical portfolios upon initial success.

> **Hypothesis 5 (H5):** Prior variety enhances the benefit of relatedness for sustained success such that relatedness is a stronger positive predictor of sustained success for creators who have varied portfolios upon initial success than for creators who have less-varied portfolios upon initial success.

In sum, when creators reach initial success with novel or varied portfolios, they may enjoy a wider path or range of viable options for leveraging relatedness while adapting to market changes, giving them an overall advantage in sustaining success. The renowned painter Georgia O'Keeffe provides an illustration of the dynamics proposed in H1–H5. 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-1920s, trends toward modernism were gaining momentum in the art world. O'Keeffe incorporated elements of the latest trends in her new work while maintaining relatedness with her novel and varied portfolio upon initial success, helping her sustain success for several decades (Randolph, 2017). Two decades after her initial success, for instance, a critic remarked that her latest paintings, which were done in Hawaii, ''testify to Miss O'Keeffe's ability to make herself at home anywhere'' (McBride, 1940: 10).

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

In the proposed theory, creators' pursuit of initial success is path independent, as the two underlying mechanisms are not restrictive until creators achieve their initial hits. Whereas prior research has largely overlooked a path-

dependent view of the relationship between creativity and market success, ample research speaks to how novelty and variety relate to market success from a path-independent standpoint, suggesting that new creators who build novel portfolios are less likely to achieve initial success, while those who build varied portfolios are more likely to achieve initial success. Although these path-independent arguments are straightforward applications of existing 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 out-perform more-novel ones in the marketplace (Ward, Bitner, and Barnes, 1992; Veryzer and Hutchinson, 1998; Fleming, 2001; Uzzi et al., 2013; Liu et al., 2017), including in so-called creative industries (Becker, 1982; Martindale, 1990; Interiano et al., 2018). Generating an initial hit may be a long shot for all new creators, but the odds may be even lower when one's portfolio comprises relatively novel products. Second, in contrast to novelty, variety should be a positive predictor of initial success. This view 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 (Campbell, 1960; Simonton, 1984, 1997, 1999, 2011; Staw, 1990; Aldrich, 1999).

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

> **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 United States 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 nineteenth century (Gronow, 1983). Estimates of revenue from recorded music in the United States have been over $4.4 billion (inflation-adjusted to 2020 dollars) every year from 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 a common thread among the creative industries on which the proposed theory focuses.

Third, artists build portfolios of songs throughout their careers, which the audience and gatekeepers attribute primarily to them. Although some artists may exert more control over their portfolios than others, most artists have substantial agency to shape their own portfolios. 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 and O'Mahony, 2010). As in most creative industries, people in many supporting roles may have a hand in building artists' portfolios, e.g., producers, songwriters, and engineers. 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 and O'Mahony, 2010: 59–60). Thus people in the supporting roles inherit the implications of the focal artist's portfolio such that they should experience the proposed theoretical mechanisms (learning and expectations) in much the same way as the focal artist does. This characteristic makes the music industry representative of the many other creative industries—such as book publishing, film, art, cuisine, architecture, theater, and video games—in which portfolios are likely to have enduring implications for both the focal creators and their supporting teams over time.

Fourth, although music distribution has evolved over the years, the dominant design (Abernathy and 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: whether they appear on Billboard's Hot 100 chart, which has listed the 100 most successful songs every week since 1958 (Anand and 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 virtually all songs released by each artist from 1959–2010, including whether each song was a hit or not. All artists in the dataset were signed by a label that produced one or more hits. Of the 69,050 artists, 4,857 (7 percent) had at least one hit, and the other 93 percent 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 collaboration, hereafter I use ''we'' instead of ''I'' in describing our data collection effort.) Although many sources of music data existed, no single source adequately provided 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 data sources were crowdsourced platforms in which music enthusiasts and retailers upload information on their music collections: Discogs (see Montauti and Wezel, 2016) and MusicBrainz (see Interiano et al., 2018). These 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' databases were less redundant than those from 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 when the artist originally released the song. To avoid duplicates and identify the original release year of each song, we cross-referenced the four sources. Our

approach involved four main steps, each of which I summarize below.
See Online Appendix A (http://journals.sagepub.com/doi/suppl/10.1177/
00018392221083650) for more-detailed descriptions of each step. We devel-
oped our approach using artists with at least one hit (steps 1–3) and then
applied the same basic approach to non-hit artists (step 4).

Step 1: Identifying hit artists. Our first step was to create a list of artists
who had at least one hit song in their careers. 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 and Mauskapf, 2017). Billboard
launched the Hot 100 chart in 1958, and it has remained the industry standard
for classifying whether songs are hits (Anand and Peterson, 2000). We identi-
fied all 6,771 artists who had at least one hit song from 1958 through 2010 and
then applied four exclusion criteria to this list to ensure the dataset was appro-
priate for testing the hypotheses. First, the artist had to be a primary artist on
at least one hit, which excluded artists with only cameo/secondary roles.
Second, to ensure that artists' careers were captured from inception, we
excluded artists who released any song before 1959. We used the cutoff of
1959 because it was the earliest year for which novelty could be calculated (as
I describe in the upcoming ''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, we omitted artists if they did not
have any songs in Spotify through their first hit year, as the independent
variables required data from Spotify. After we applied 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. We next assembled 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 these artists and then to filter out redundant and incorrect songs.
We gathered data on all songs released by each artist in each of the four
sources: 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 geo-
graphic territories. To determine whether song titles were duplicates, we used
edit distance, which is a common technique in approximate text matching
(Navarro, 2001). We clustered duplicates within each of the four data sources
and then merged duplicate clusters between the four sources. This effort
yielded a dataset with 741,761 rows, each row representing an artist–song pair
to possibly include in the final dataset. This dataset was tentative because it
still included many redundant song titles.

Step 3: Finalizing dataset for hit artists. Next, we devised a set of selec-
tion 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 in

multiple independent sources, then 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 we implemented the selection criteria, the dataset included 356,826 artist–song pairs (351,493 unique songs, as some songs were recorded 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. We selected these artists because they released one or more songs on a label that had at least one hit from 1958–2010. This effort created a meaningful comparison group for 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 our treatment of the hit artists, we targeted only non-hit artists whose careers began from 1959–2005, meaning they had at least six years to generate a hit (2005–2010 for artists whose careers 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 we followed 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 percent matched across two or more sources. Having multiple sources per song helped identify the correct release year, and we used the earliest release year provided across sources.

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 used 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 its 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 percent of songs overall and 94 percent 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, meaning the 11 sonic features were captured with a total of 22 variables. See Online Appendix B for

a visual summary of the three independent variable measures (Figure B1), as well as examples illustrating how we calculated novelty and variety (Table B1).

Relatedness. Relatedness focused on songs that artists created after their initial success, particularly how coherent these songs were with their portfolios at the time of initial success. For each song released after an artist's initial success (after their 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 measure captured the extent to which each song created after an artist's initial success drew on elements of their portfolio upon initial success.

Novelty. Following past research on market novelty (versus typicality), we measured novelty in terms of how unique songs were compared to prototypical songs at the time they were released (e.g., Veryzer and 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 approach 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 percent of them (23,173) in Spotify. Seventy-nine percent of these hits were by artists in the main dataset, but we also collected sonic features for the 21 percent 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 (S.D. = 120.18). To provide a general sense of how hit songs may change over time, Figure 2 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 Figures B2 and B3 in Online Appendix B for representations of how similar hits were to one another over time.

For each song in our dataset, we first calculated a typicality value and 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 fact, we weighted bigger hits more heavily, calculating a weight 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 we summed all scores for each hit within each year and divided the summed scores by the maximum score any hit had in that year. This way, the

Figure 2. Example Sonic Features of Hit Songs by Year*
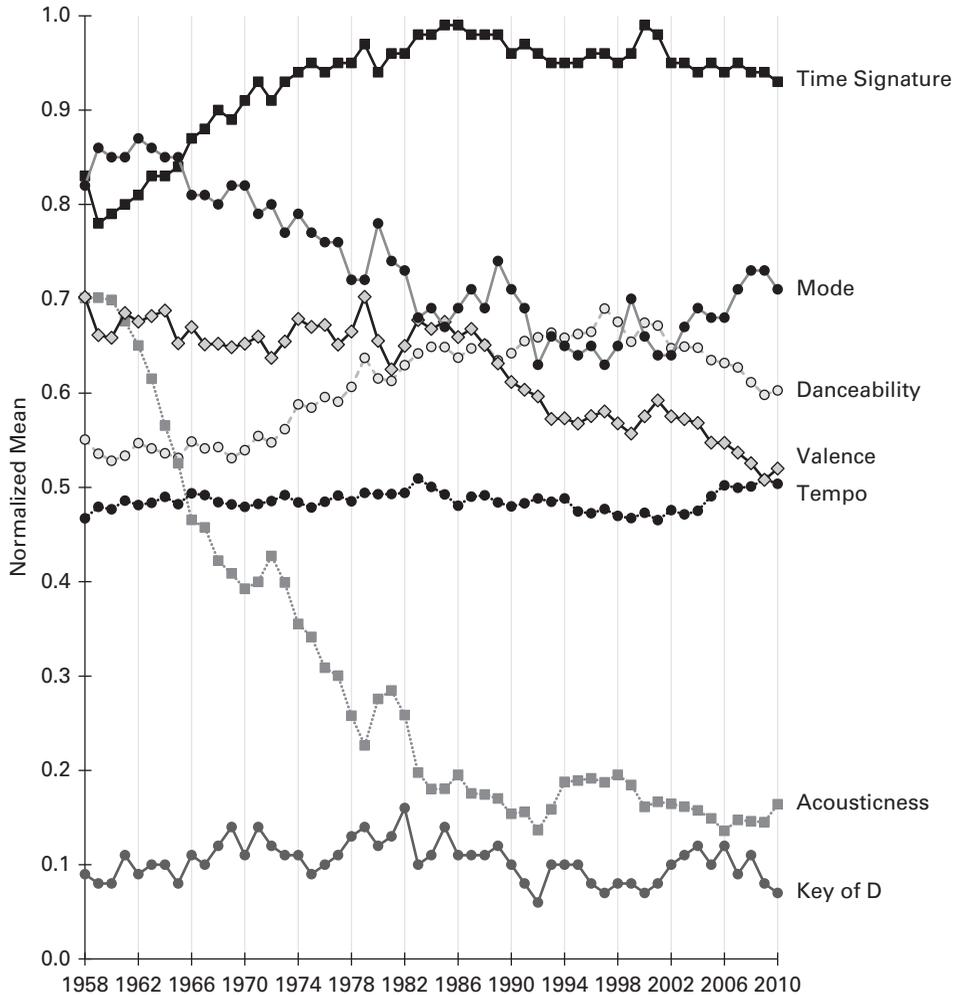
* For brevity, 7 of the 22 variables used to measure the sonic features are shown as examples.

weights ranged 0–1, with the biggest hit of the year having a weight of 1 (mean weight = .23, S.D. = .23).

To summarize, we calculated novelty for each song in four steps. First, we calculated the cosine similarity between the song and each hit from the year before the song was released, excluding any hits by the artist(s) of the focal song. Second, we multiplied each cosine similarity value 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).

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 1). 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 released only one or two songs total, variety was 0 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 ($r = .30$, $p < .001$), which is conceptually logical because 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 to the number of them.

Success. The core measure of market success was whether artists' songs were hits or not. A song was deemed a hit if it appeared in Billboard's Hot 100 chart, the industry standard for classifying hits (Anand and Peterson, 2000). But 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 (92.97 percent) had no hits. 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 percent) or two hits (16.49 percent) over-all, while a relatively small group of artists (10.75 percent) had 10 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 an artist 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 fact 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 percent) had one hit in their first year on the charts, while the rest (39.39 percent) had multiple hits in their first year, usually from the same album. As for sustained success, most artists (57.71 percent) had zero hits after their first year on the charts, but plenty of artists (42.29 percent) did manage to garner additional hits after their initial success.

To provide a rough sense of the practical significance of hit songs, we obtained sales data from Nielsen SoundScan, which has provided the raw data underlying the Hot 100 since 1991 (Anand and 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 3 and 4, 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.

Table 1. Percentage of Artists by Hit Count

| 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) | | |
	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%

Figure 3. Total Single Sales by Hot 100 Peak Rank (1994–2004)*
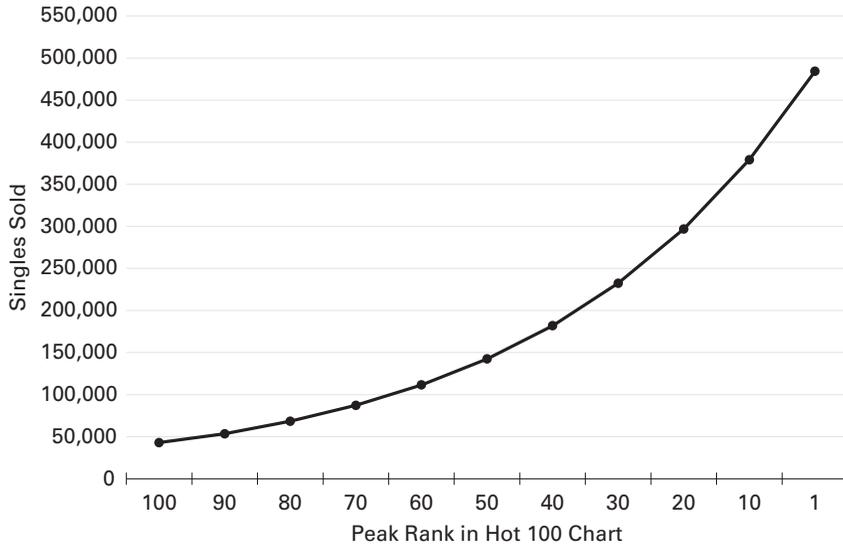
* Singles sold refers to the total number sold through 2004. To ensure that the sales life cycle of songs was mostly complete, only songs that entered the Hot 100 from 1994–2002 were included, as the vast majority of sales occur in the two years after entry into the Hot 100.

Figure 4. Total Sales by Artist Hit Count (1994–2004)*
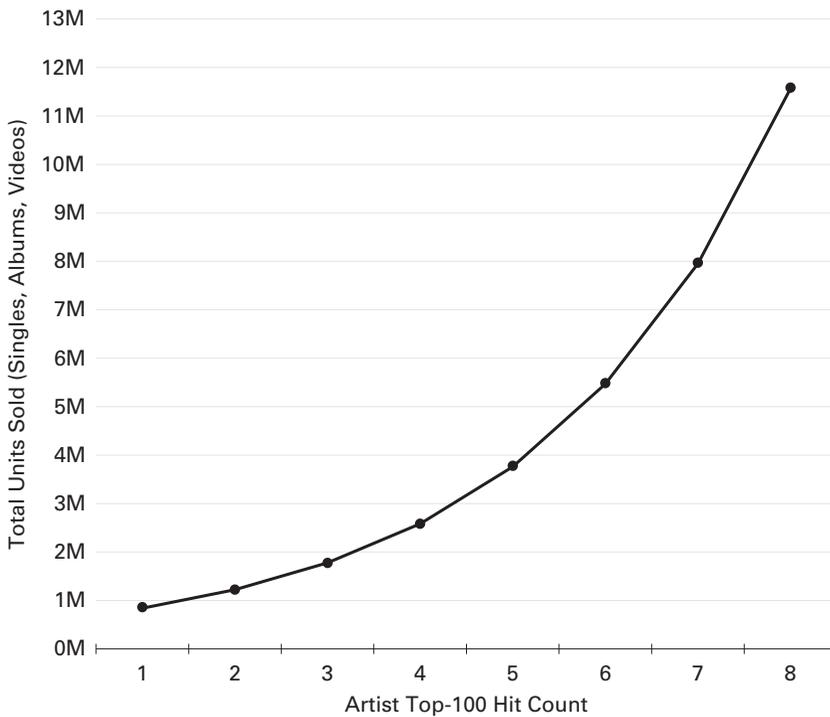
* Total units sold refers to the total number of units sold through 2004. Only artists who had their first hits from 1994–2002 were included, allowing two years for sales cycles to complete.

Controls. We collected data to create several 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 dummy variables for the 15 different genres and a ''genre crossover'' dummy that was 1 if a song belonged to more than one genre (0 if only one). Label data were available for 80 percent 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 each song by multiple labels, we selected a representative label. To do so, we first ranked all 76,994 labels in the dataset based on the number of hits they had; ties were broken by the total number of weeks in the top 100, 40, and 10, and then (for labels without any hits) by the number of songs the label had in the dataset. For the 11 percent of songs by multiple labels, we selected the highest-ranking label as the representative label. This approach reduced the number of different labels in the dataset to 60,159 (2.60 percent, or 1,566 of which produced one or more hits).

We created several time-varying controls at the artist level, which were calculated for each year 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 that had 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 variable for artist type (1 = soloist, 0 = group). Second, of the 37,272 solo artists in the dataset, 5.97 percent were in groups that had one or more hits before the individuals became soloists. We created a dummy variable 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 percent of the songs in our dataset and producer data for 51 percent (68 percent and 75 percent for hit artists, respectively). At the artist level, we had at least partial data for 88 percent of artists in terms of writing and 84 percent in terms of producing (98 percent and 95 percent 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.

Table 2. Correlations and Descriptive Statistics for Song-Level Variables*

		1	2	3	4	5	6	7	8	9	10	11	12	13
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
15.	Genre pop	−.01	−.12	.01	.01	.01	−.08	−.02	−.01	.03	−.04	−.02	.01	.00
16.	Genre jazz	−.09	.02	−.02	−.01	−.01	.00	.04	.01	−.02	.00	−.05	−.03	.09
17.	Genre Latin	.01	−.08	−.02	−.01	−.01	−.03	−.02	.00	.00	−.03	−.06	.05	.01
18.	Genre non-music[†]	−.03	.02	−.01	−.01	.00	.01	.00	.00	.05	.01	−.01	.01	−.01
19.	Genre reggae	.04	−.05	−.01	−.01	−.01	.01	−.01	.00	−.01	−.03	−.03	−.04	.00
20.	Genre rock	.05	−.15	.02	.02	.01	−.15	.07	−.02	−.04	−.11	−.09	−.10	−.07
21.	Genre stage/screen	−.10	.07	−.01	.00	.00	.05	−.01	.02	.05	.12	.02	−.01	.00
22.	Genre crossover	−.06	−.05	.00	.00	.00	−.03	.19	.04	.09	.10	.24	.27	.26
23.	Release year	−.06	.50	−.06	−.04	−.03	.04	−.03	−.04	−.04	−.04	.14	−.15	−.14
	Mean	.67	.14	.01	.00	.00	1.53	.02	.00	.01	.04	.14	.12	.07
	Standard deviation	.09	.04	.08	.06	.04	1.50	.15	.04	.10	.19	.34	.33	.25
	Minimum	.00	.01	0	0	0	1	0	0	0	0	0	0	0
	Maximum	1.00	.26	1	1	1	106	1	1	1	1	1	1	1

		14	15	16	17	18	19	20	21	22	23
14.	Genre hip hop	1.00									
15.	Genre pop	−.06	1.00								
16.	Genre jazz	−.05	−.03	1.00							
17.	Genre Latin	−.02	.04	.03	1.00						
18.	Genre non-music[†]	−.02	.00	.00	−.02	1.00					
19.	Genre reggae	.01	−.06	−.04	−.01	−.02	1.00				
20.	Genre rock	−.11	.05	−.10	−.10	−.04	−.08	1.00			
21.	Genre stage/screen	−.04	.01	.05	−.03	.06	−.03	−.07	1.00		
22.	Genre crossover	.08	.28	.23	.24	.12	.02	.09	.22	1.00	
23.	Release year	.16	−.12	−.11	−.10	−.04	.00	−.04	−.05	−.08	1.00
	Mean	.06	.20	.08	.06	.02	.03	.29	.04	.22	1992
	Standard deviation	.23	.40	.27	.24	.12	.17	.46	.19	.41	13.37
	Minimum	0	0	0	0	0	0	0	0	0	1959
	Maximum	1	1	1	1	1	1	1	1	1	2010

* 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 $p < .001$.

[†] 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
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) with 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
14. Hit count (overall)	.05	.16	.26	.50	.17	−.13	.09	.13	.02	.10	−.05	−.04
15. Hit count (pre)	.00	.17	.21	.21	.09	−.09	.00	.04	.00	.02	−.02	−.04
16. Hit count (post)	.06	.14	.24	.50	.17	−.12	.09	.14	.02	.11	−.06	−.04
17. Hit weeks (overall)	.05	.16	.25	.43	.06	−.14	.10	.13	.08	.15	.10	−.02
18. Hit weeks (pre)	.02	.19	.23	.15	−.09	−.14	.03	.04	.13	.12	.26	−.01
19. Hit weeks (post)	.05	.13	.22	.44	.09	−.12	.10	.14	.05	.13	.04	−.03
20. Career age at 1st hit	.01	.23	.08	.32	.16	−.05	.16	.11	.07	.09	−.02	.04
21. Year of 1st hit	.06	.16	.18	−.03	−.59	−.28	.10	.05	.38	.27	.97	.09
Mean	0.13	0.16	10.25	46.22	18.58	2.79	0.54	0.03	0.87	0.77	1983	1.55
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
Minimum	0.01	0	1	1	1	0	0	0	0	0	1959	1
Maximum	0.24	1.03	309	1,215	52	46.67	1	1	1	1	2005	31.67

	13	14	15	16	17	18	19	20	21
Hit artists only:									
13. Relatedness	1.00								
14. Hit count (overall)	−.05	1.00							
15. Hit count (pre)	.02	.50	1.00						
16. Hit count (post)	−.06	.98	.34	1.00					
17. Hit weeks (overall)	−.05	.94	.45	.93	1.00				
18. Hit weeks (pre)	−.01	.42	.79	.30	.51	1.00			
19. Hit weeks (post)	−.06	.93	.30	.96	.98	.31	1.00		
20. Career age at 1st hit	−.08	−.04	−.04	−.04	−.02	.00	−.02	1.00	
21. Year of 1st hit	−.06	−.06	−.03	−.06	.09	.26	.03	.22	1.00
Mean	0.68	4.18	1.7	2.47	50.74	20.49	30.24	3.30	1981
Standard deviation	0.06	6.36	1.23	5.84	87.28	19.94	78.95	3.20	13.39
Minimum	0.32	1	1	0	1	1	0	1	1959
Maximum	1.00	74	38	64	1,040	285	1,021	34	2005

* ''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 $p < .05$.

RESULTS

Note that supplementary analyses, including robustness checks, are reported after the main results. 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)

I tested the hypotheses on sustained success (H1–H5) with mixed-effects logistic regression, which leveraged the granularity of the song-level data while accounting for cross-nesting in labels and artists (Raudenbush and Bryk, 2002). Specifically, I used random-intercept models, 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. 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. Hereafter, I use the prefix ''pre'' to convey that pre-novelty and pre-variety refer to the novelty and variety in artists' portfolios before and during their initial success.

Main effects of relatedness, pre-novelty, and pre-variety (H1–H3).
Models 1–6 in Table 4 test H1–H3. In support of these hypotheses, relatedness (H1), pre-novelty (H2), and pre-variety (H3) were all significant positive predictors of sustained success across all three hit levels (top 100, 40, and 10). These significant results held when relatedness was in the models alone (Models 1–3) and with pre-novelty and pre-variety included (Models 4–6). Figure 5 shows estimated marginal means from Models 4–6 at high and low levels of each dimension (holding the other dimensions constant). High and low refer to one standard deviation above and below the mean, respectively. 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%). 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%).

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

Table 4. Logistic Regression Models for H1–H5: Hit Artists' Sustained Success (All Songs Released after First Hit Year)*

DV (Song Hit vs. Miss):	Model 1 Top 100	Model 2 Top 40	Model 3 Top 10	Model 4 Top 100	Model 5 Top 40	Model 6 Top 10	Model 7 Top 100	Model 8 Top 40	Model 9 Top 10
Relatedness (H1)	.200•••	.199•••	.155•••	.209•••	.212•••	.178•••	.213•••	.214•••	.179•••
	(.013)	(.018)	(.026)	(.014)	(.018)	(.027)	(.014)	(.018)	(.027)
Pre-novelty (H2)				.120•••	.159•••	.185•••	.119•••	.154•••	.181•••
				(.024)	(.031)	(.041)	(.024)	(.031)	(.041)
Pre-variety (H3)				.053•	.066•	.099•	.053•	.066•	.102•
				(.025)	(.033)	(.042)	(.025)	(.033)	(.042)
Relatedness × Pre-novelty (H4)							.007	.019	.014
							(.013)	(.018)	(.026)
Relatedness × Pre-variety (H5)							.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•	.143••	.185••	.203•
	(.052)	(.068)	(.086)	(.052)	(.067)	(.086)	(.052)	(.067)	(.086)
Prior hit(s) with group	.286•••	.366•••	.272••	.290•••	.370•••	.277••	.288•••	.368•••	.276••
	(.067)	(.085)	(.104)	(.067)	(.085)	(.104)	(.067)	(.084)	(.104)
Self-write %	–.143•••	–.155•••	–.073	–.149•••	–.164•••	–.083	–.152•••	–.167•••	–.087
	(.029)	(.038)	(.050)	(.029)	(.038)	(.050)	(.029)	(.038)	(.050)
Self-produce %	.167•••	.218•••	.215•••	.172•••	.222•••	.215•••	.174•••	.225•••	.218•••
	(.027)	(.035)	(.045)	(.027)	(.034)	(.044)	(.027)	(.034)	(.045)
Career age at 1st hit	.499•••	.523•••	.529•••	.496•••	.523•••	.525•••	.495•••	.522•••	.525•••
	(.037)	(.050)	(.071)	(.038)	(.050)	(.071)	(.038)	(.050)	(.071)
Year of 1st hit	–.492•••	–.614•••	–.750•••	–.506•••	–.636•••	–.785•••	–.508•••	–.639•••	–.789•••
	(.065)	(.083)	(.128)	(.065)	(.083)	(.128)	(.065)	(.083)	(.128)
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†	226,191	226,191	225,525†	226,191	226,191	225,525†
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

• $p < .05$; •• $p < .01$; ••• $p < .001$.

* Standard errors are in parentheses. All continuous variables were standardized.

† 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.

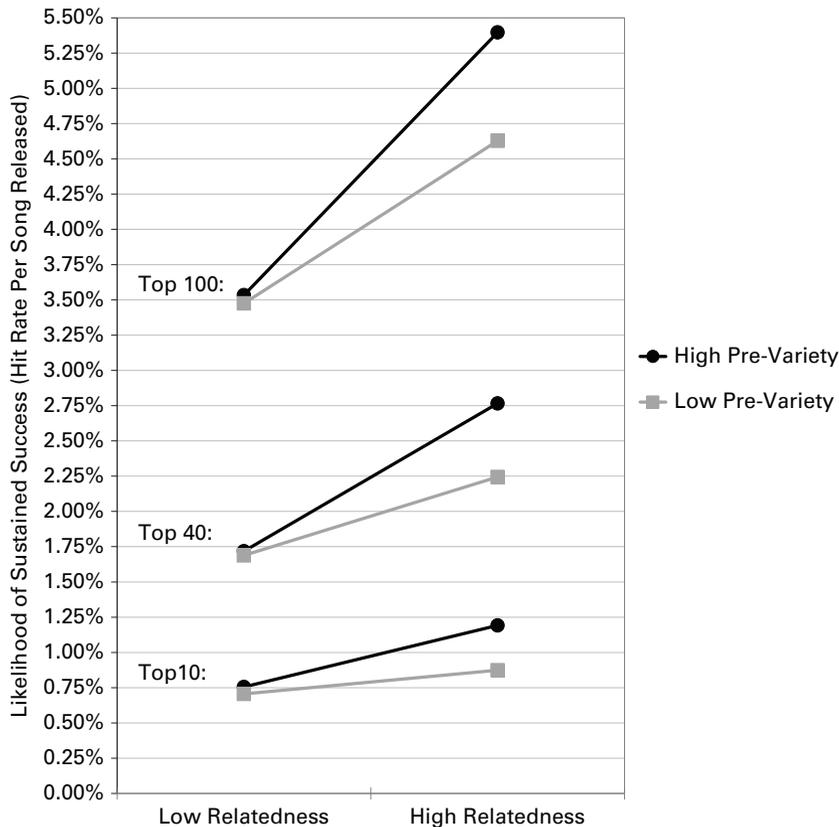**Figure 5. Estimated Marginal Means for H1–H3***
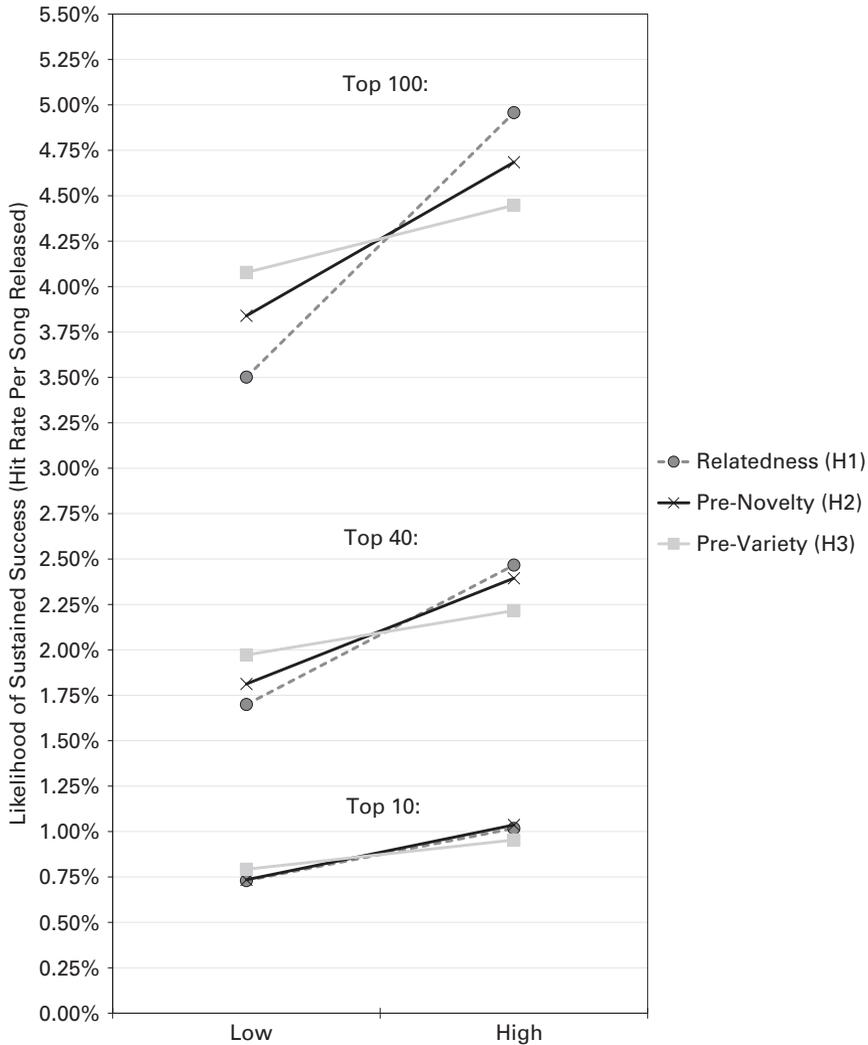
* High and low refer to one standard deviation above and below the mean, respectively. The estimates are based on Models 4–6 in Table 4.

additional hits from 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.

   Pre-novelty and pre-variety moderating relatedness (H4 and H5).
Models 7–9 in Table 4 test whether pre-novelty (H4) and pre-variety (H5) enhanced the benefit of relatedness. Results did not support H4, as the interaction between relatedness and pre-novelty was not significant in any models. The null results for H4 suggest that artists high in pre-novelty did not benefit from relatedness more than artists low in pre-novelty. Results did support H5, as the predicted interaction between relatedness and pre-variety was

Figure 6. Estimated Marginal Means for H5: Relatedness $\times$ Pre-Variety*

* 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.

significant across all three hit levels (top 100, 40, and 10). As shown in Figure 6, artists high in pre-variety benefited significantly more from related-ness than artists low in pre-variety.[3] Artists low in pre-variety still benefited 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 still positive for all three hit levels, but they were signifi-cantly lower than when pre-variety was high: top 100 [$b = .17$, SE $= .02$, $p < .001$], top 40 [$b = .16$, SE $= .02$, $p < .001$], and top 10 [$b = .11$, SE $= .04$, $p = .001$]. 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

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[3] Another way to interpret this interaction is that the benefit of pre-variety depended on related-ness: reaching initial success with a varied portfolio was beneficial only when artists then leveraged that portfolio with related songs.

more likely 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 Village Stompers provides an archetypal example of low pre-variety limiting the benefit of relatedness. Their portfolio scored .58 standard deviations below the mean in pre-variety at the time of their first hit in 1963. Although their new songs scored 1.30 standard deviations above the mean in relatedness, they had just two more hits in 1964 and zero thereafter.

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). Cox regression was appropriate given that the dependent variable was new artists' odds of achieving an initial hit (or not) over time (Cox and Oakes, 1984). These models include all 69,050 artists—those with zero hits and those with one or more hits. Cox regression accounted for the possibility of right-censoring, which was important because 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, including novelty and variety, were entered as time-varying covariates and are marked with "[X Time]" in Table 5. I entered all other controls 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. I determined artists' labels and genres on a rolling basis based on the songs released by each artist up through each year. (I used artists' highest-ranking label through each year— see the "Measures" section for ranking criteria.) Given that a small percentage of labels produced hits (2.22 percent 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.

In support of H6 and H7, across all models novelty was a negative predictor and variety was a positive predictor of new artists achieving an initial hit (see 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 7 for a representation of the estimated likelihood of new artists achieving initial success over time when novelty and variety were high versus low (Ruhe, 2016). New artists' likelihood of achieving initial success increased the most early in their careers and flattened in later years. At 10 years into their careers, artists low in novelty had an 11.04 percent likelihood of achieving an initial hit, while those high in novelty had a 5.43 percent likelihood, meaning low-novelty artists were 2.03 times more likely than

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

DV (Artist Hit vs. Miss):	Model 1 Top 100	Model 2 Top 100	Model 3 Top 100	Model 4 Top 40	Model 5 Top 10
Novelty [× Time] (H6)	−.061•••		−.068•••	−.080•••	−.086•••
	(.005)		(.005)	(.007)	(.010)
Variety [× Time] (H7)		.012•	.031•••	.048•••	.073•••
		(.005)	(.005)	(.007)	(.010)
Time-varying artist controls:					
Song count year (log) [× Time]	.089•••	.076•••	.088•••	.119•••	.126•••
	(.005)	(.005)	(.005)	(.009)	(.012)
Song count total (log) [× Time]	.078•••	.085•••	.072•••	.064•••	.068•••
	(.008)	(.008)	(.008)	(.012)	(.017)
Mean # of artists on songs (log) [× 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) with 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)†	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

• $p < .05$; •• $p < .01$; ••• $p < .001$.
* Standard errors are 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).
† 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).

high-novelty artists to achieve initial success. Conversely, artists high in variety had a 9.99 percent likelihood of achieving an initial hit, while those low in variety had a 5.97 percent likelihood, meaning high-variety artists were 1.67 times more likely than low-variety artists to achieve initial success. 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 than high-novelty artists to achieve a top-40 initial hit (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 than low-variety artists to achieve a top-40 initial hit (5.89% vs. 3.01%) and 2.24 times more likely to achieve a top-10 initial hit (3.03% vs. 1.35%).

Figure 7. Likelihood of New Artists Achieving Initial Success by Career Age (H6 and H7)*
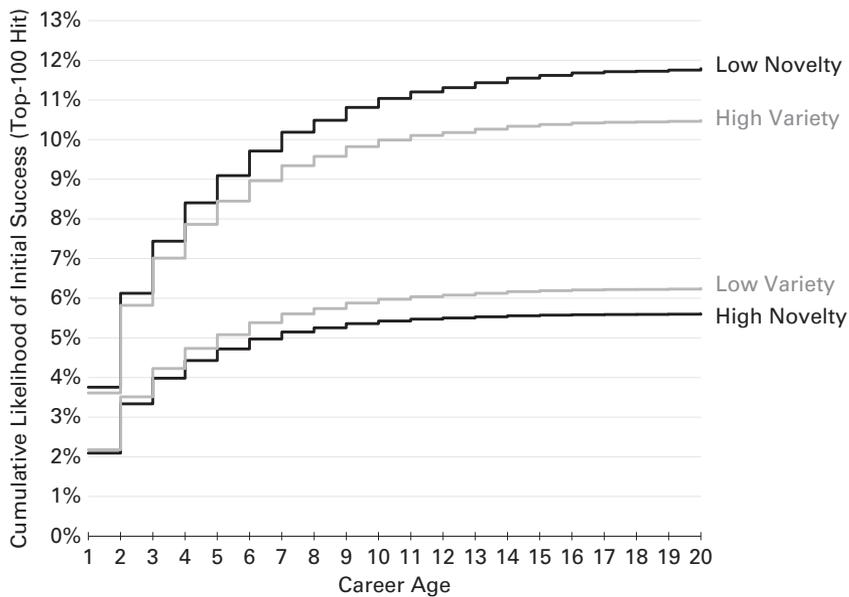
* High and low refer to one standard deviation above and below the mean, respectively (with the other dimension held at its mean). The estimates are based on Model 3 in Table 5.

Supplementary Analyses

I ran additional models to test the mediating role of market adaptation, serve as robustness checks, explore 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 (along with relatedness) is adaptation to changes in the market. To test whether market adaptation can help explain the results, I conducted mediation analyses for H2–H5. (Although H4 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 approach 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 H2, H3, and H5 but not H4. Broadly, these results suggest that artists higher in prenovelty (H2) or pre-variety (H3 and H5) were more likely to adapt to market changes after their initial success and that this adaptation contributed to their advantage in sustaining success.

Hit counts. Whereas I tested the hypotheses on sustained success (H1–H5) in terms of artists' hit *rate* (the likelihood of a hit per song released after initial success), I ran supplementary analyses to address artists' hit *count* (the

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 explore the practical significance of the hypotheses for artists' careers, I ran models on artists' overall hit counts—the total number of hits they garnered in their careers (Table C4). Estimated overall hit counts were calculated for artists with the best-case versus worst-case portfolios (i.e., high versus low in relatedness, pre-novelty, and pre-variety). Compared to the worst-case artists, best-case artists could expect 105 percent more top-100 hits (6.07 vs. 2.96), 151 percent more top-40 hits (3.29 vs. 1.31), and 173 percent 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. When the aforementioned model of total sales is used to derive estimates (see Figure 3), the difference between best- and worst-case artists in expected top-100 hits (6.07 vs. 2.96) would translate into a difference of roughly 3.8 million more units sold (5.6 vs. 1.8 million).

   Robustness checks. I conducted several robustness checks. 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 by 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 was 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 versus 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 percent of hit artists and 2.25 percent of all artists. These artists' initial hits may have been driven more by random chance or other external influences than the outcomes of 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 it was with the full sample.
   Second, to run analyses on the role of underlying ability or innate talent, I created measures of post-novelty and post-variety, which capture the novelty and variety that creators generated after their initial success. It seems plausible that more-talented artists were able to succeed by 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 by 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 were. This explanation 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 I controlled for prior success in all tests of the hypotheses on sustained success, the results could still be influenced by cumulative advantage effects (Merton, 1968; DiPrete and Eirich, 2006). I examined this possibility 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, the results for relatedness could be driven entirely by audience and gatekeepers' expectations rather than by 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). This finding suggests 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 sustained versus short-lived market success. The results largely support the proposed hypotheses, indicating that initial success may act as a critical juncture that locks in important implications of creators' portfolios going forward. The artists in this dataset were relatively free to build novel and varied portfolios until their initial hits, 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 hits with relatively novel or varied portfolios were more likely to garner additional hits, a novel portfolio was less likely than a typical portfolio to yield an initial hit. Thus path dependencies meant that artists' portfolios could not be optimized 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. This 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 pre-cursor to innovation (idea implementation) in the context of one project at a time (Amabile, 1988; Staw, 1990; West, 2002; Perry-Smith and Mannucci, 2017). Such theorization implies a path-independent view: once a final product is implemented at the end of a 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).

My research introduces a path-dependent view of creativity and innovation: once a product is implemented in the market, the creativity that creators exercised to generate the product may have enduring implications for the suc-cess of their future innovations. Thus each cycle of creativity and innovation has the potential to enable or constrain future cycles of creativity and innova-tion. The proposed theory highlights how two self-reinforcing mechanisms, internal learning and external expectations, may work together to drive this path-dependent dynamic. In my dataset, the creativity (novelty and variety) that creators exercised in building their early portfolios predicted their capacity to produce hit innovations in the future, if they were able to achieve an initial hit. This finding suggests a more-dynamic, reciprocal relationship between cycles of creativity and innovation than what prior research has usually assumed.

I also show 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, this study uncovers a tradeoff between initial and sustained success based on the novelty (versus typicality) in creators' early portfolios, and this tradeoff becomes visible only in light of path dependencies at the career level. Typical portfolios in this dataset were more conducive to initial success, but reaching initial success with a novel portfolio was more con-ducive to sustained success. This combination of results means that it was impossible for new artists' portfolios to maximize their likelihood of both initial and sustained success, presenting a thorny tradeoff. Variety may help artists compensate for this tradeoff to some extent, as variety in this study predicted both initial and sustained success, but variety did not eliminate the tradeoff. Thus creativity is potentially conducive to market success in the long run, but pursuing creativity with a novel portfolio may backfire and increase the risk of never achieving a hit. In short, creativity is a high-risk, high-reward investment that could make or break an artist's career. Building a typical portfolio is a safer bet in terms of having at least some success, but the upside is limited as this success may be short-lived. Revealing this important tradeoff demonstrates the theoretical value of a path-dependent view of creativity and innovation, which complements the path-independent view 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 moment in time) have revealed a consistent finding: after creators' initial success, the creativity of their subsequent work declines, as they tend to generate ideas or products that are similar to their initial successes

(Audia and Goncalo, 2007; Bayus, 2013). But these studies offer conflicting results on the net impact of this decline. Audia and Goncalo (2007) showed that despite the decline in creativity, past success predicted subsequent success; Bayus (2013) found the opposite. My study may help reconcile these mixed findings. The 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 my research 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, the effectiveness of this pursuit 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 provide a fuller picture of how creativity and success relate to one another over time. I encourage future research to adopt 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. This study 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, as scholars tend to focus on how organizations balance exploitation and exploration in their portfolios of products (e.g., Fernhaber and Patel, 2012), activities (e.g., Anand, Mesquita, and Vassolo, 2009), or alliances (e.g., Lavie, Kang, and Rosenkopf, 2011). Portfolio perspectives are rare in the literature on creativity and innovation at the individual and team levels even though individuals and teams of creators often work for or with multiple organizations as they build their product portfolios throughout their careers (Caves, 2000; Mollick, 2012). As Sternberg and Lubart (1995: 291) lamented, creativity scholars rarely consider creators' product portfolios 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." My research elaborates on this basic insight by developing theory on creators' portfolios as potent "carriers of history" (David, 1994: 205).
   The proposed theory shows how two underlying mechanisms—internal learning and external expectations—may turn creators' portfolios into important carriers of history after their initial success. My results suggest that the creativity (novelty and variety) in creators' early portfolios may indicate their readiness to sustain success should they achieve initial success. However, path dependencies may make creative industries suboptimal in terms of allowing creators to prepare their portfolios for sustained success. The path of less resistance to initial success in the music industry was also a path to less creativity and short-lived success. The industry churned through one-hit wonders with typical portfolios 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. Creators and those who manage them likely hold various lay theories of what drives success, which may or may not align with what actually drives success in the industry (Levinthal and March, 1993). My research lays the groundwork for future research on how creators may deliberately shape their portfolios in more- or less-strategic ways. For instance, scholars 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 and Mumford, 2007; Mueller, Wakslak, and Krishnan, 2014), resource requirements (e.g., Dailey and Mumford, 2006), and likely market success (e.g., Girotra, Terwiesch, and Ulrich, 2010; Berg, 2016). But 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 view 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, this 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. This 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., Campbell, 1960; Staw, 1990; Aldrich, 1999; Simonton, 1999). Such theories construe creativity and innovation as part of a Darwinian process in which multiple variants are generated and then relatively few are selectively retained based on their fitness in the environment. These theories suggest that given the uncertainty about how new products may be received in the marketplace, generating a greater variety of products should increase the odds of a hit. In my research, this evolutionary perspective was quite useful for predicting whether new creators would ever achieve initial hits but less useful for predicting whether creators would garner additional hits after their initial ones.

My 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 not beneficial, as artists were more likely to sustain success when their new songs were related to their pre-success portfolios. This finding suggests that in creative industries, the benefits of variety implied by evolutionary theories may be limited to the variety that creators generate before their initial success. Thus the present research highlights both the value and limits of evolutionary perspectives, with achieving a hit product 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 is fairly representative of the creative industries on which the proposed theory focuses, 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—e.g., books, movies, and games— are pulled by consumers. 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 included only 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 in which 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, although the sample of artists was relatively broad, the fact that all the artists were signed by successful labels may have created selection effects that cannot be ruled out. Future research could address these limitations by 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 approach 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 present study also raises new questions that future research could explore. 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 (Paulus and Nijstad, 2003; Harvey and Kou, 2013). Second, artists who wrote their own songs were less likely to sustain success, but artists who produced their own songs were more likely to sustain success. Studying this pattern 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, and writing). Future research could explore the drivers of sustained success across multiple creative industries, which could reveal interesting forms of brokerage (Fleming, Mingo, and Chen, 2007).

Practical Implications and Conclusion

In recent years, many famous artists have sold rights to their song portfolios for impressive sums, underscoring the outsize success enjoyed by hit makers.

For example, Bruce Springsteen sold his portfolio for $500 million, Stevie Nicks sold a majority stake in her portfolio for $100 million, and the Red Hot Chili Peppers sold their portfolio for $140 million (Cross, 2022). My study may offer useful insights for creators—and managers of creators—looking to increase the odds of becoming hit makers, particularly in the music industry but perhaps in other creative industries as well. Creators and their managers could potentially use the results of this study to construct their portfolios in strategic ways. The results suggest that creators ought to base their portfolio strategies on their career stage. As creators begin their careers, 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 the 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. If they do manage to achieve initial success, creators should then switch their strategy to focus on balancing relatedness and adaptation. This balancing act should be easier and more successful for creators who built novel or varied portfolios before their initial success.

In concert with the results, the methods used in this study may provide managers with actionable tools to help them select and cultivate hit makers. Using data and measures like those in the study, managers could score emerging creators' portfolios on novelty and variety to gauge their likelihood of initial and sustained success. Such scores could inform high-stakes decisions about which creators to sign and how to manage them. For instance, managers could hedge risky bets on novel creators with safer bets on more-typical creators. In addition, managers could use variety scores to assess emerging creators' readiness to achieve success. If creators score low in variety, managers can give them time to generate more variety before they are widely marketed, helping them prepare to sustain success even before they reach initial success. After initial success, creators and their managers could generate prototypes for new products and use data to assess how well they balance relatedness and adaptation. Based on these assessments, creators could make revisions to improve relatedness, adaptation, or both before the prototypes are finalized and released to the market.

Although these data-driven methods could yield competitive advantages for managers and creators who use them wisely, this approach could also backfire if taken too far. Much more goes into building successful creative products than what can be readily captured with quantitative data. For this reason, the measures in this study should be used as a complement to more-subjective, qualitative considerations in guiding how creators build their portfolios over time. One such consideration is creators' own appreciation for their products, especially the products they generate early in their careers. After all, they may need to live with these products for their whole careers, as their paths to sustained success will likely be paved with products that resemble their early portfolios. Maintaining enthusiasm for their early portfolios should facilitate the pursuit of relatedness later in their careers. As they build their early portfolios, creators may want to strive for products that are likely to hold their interest, pride, and appreciation for the long term. Managers may support this aim by helping creators realize their own creative aspirations, which may require managers to limit how much they impose their preferences on creators.

Broadly, creators and their managers ought to think carefully about the products they build in pursuit of initial success, as their success in the end may depend on how it began.

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Supplemental Material

Supplemental material for this article can be found in the Online Appendix at http://journals.sagepub.com/doi/suppl/10.1177/00018392221083650.

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