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Continuity, Change, and New Product Performance: The Role of Stream Concentration*

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Product development teams often face the challenge of designing radically new products that cater at the same time to the revealed tastes and expectations of existing customers. In new product development projects, this tension guides critical choices about continuity or change concerning product attributes and team composition. Research suggests these choices interact, but it is not clear whether they are complements or substitutes and if the level of change in one should match or not the level of change in the other. In this article, we examine the interaction between product attribute change, team change, and a new team-level factor, which we term stream concentration, as it captures differences among team members in terms of familiarity with the knowledge domain of the new product being developed. We measure stream concentration as team members' prior NPD experience within a given set of products and assess its impacts on the management of change in new product development projects using longitudinal data from the music industry. We analyze 2621 new product development projects between 1962 and 2008 involving 34,265 distinct team members. Results show that stream concentration is a critical factor in new product development projects that, together with product attributes and team composition, affects new product performance. We discuss implications for research and practice.

Introduction

Developing and launching new products is an imperative for most businesses, but existing successful products might still significantly contribute to profitability, pressuring product development teams to design new products that cater at the same time to the tastes and expectations of existing customers (Eling, Griffin, and Langerak, 2016; Song and Montoya-Weiss, 2003). In other words, new products often join an existing set of products. A new car from the same brand, a new video game in the same franchise, a new music album from the same artist, or a new dish in a popular restaurant chain provide typical examples. This has implications in terms of what product features will be perceived as appropriate or not by an organization and its customers (Ravasi, Rindova, and Stigliani, 2019; Stigliani and Ravasi, 2018). Hence, product development teams are challenged to manage trade-offs between something old and something new. They may opt for continuity, re-using tried and tested product attributes, or for change, introducing new ones, eliminating others, or designing completely different new products (Carbonell and Rodríguez Escudero, 2019; Eggers, 2012; Eling et al., 2016; Heath, Chatterjee, Basuroy, Hennig-Thurau, and Kocher, 2015; Spanjol, Xiao, and Welzenbach, 2018).

In new product development (NPD) projects, this tension is typically reflected in critical structuring decisions about continuity or change concerning product attributes and team composition. Product attributes are tangible (e.g., color, shape, flavor) or intangible features (e.g., style, theme, design) that define a particular product (Evanschitzky, Eisend, Calantone, and Jiang, 2012; Henard and Szymanski, 2001). Existing theory and empirical evidence show

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that product attributes and their degree of novelty are essential decisions in NPD projects. New products that include a moderate amount of new attributes tend to perform better (Askin and Mauskapf, 2017; Uzzi, Mukherjee, Stringer, and Jones, 2013) than those including a higher amount (e.g., Hannan, 2010; Kovacs and Hannan, 2010; Negro and Leung, 2013). Team composition is a second crucial structuring decision in NPD projects. In particular, team change (vs. stability) is a long-studied practice to balance the competence requirements of NPD projects. A common finding is that team stability improves efficiency, but hampers creativity and generates resistance to out-group ideas (Carbonell and Rodríguez Escudero, 2019; Katz, 1982). In contrast, team change offers opportunities to produce more innovative outcomes at the price of reduced efficiency (Brockman, Rawlston, Jones, and Halstead, 2010; Guimera, 2005).

In this article, we contribute to NPD research by theorizing and testing the role of a previously overlooked team-level factor, which we call *stream concentration*. It focuses on team members' familiarity with the knowledge domain of the new product being developed and can be operationalized with team members' prior NPD experience within a given set of products. Studying stream concentration as a structural dimension of NPD projects is important because individual team members often manage careers which are embedded in a more or less extensive network of NPD projects (Evans, Kunda, and Barley, 2004; Tasselli, Kilduff, and Menges, 2015). Stream concentration is low when team members have accumulated NPD experience by working on many unrelated projects. Conversely, stream concentration is maximum when team members' NPD experience is concentrated exclusively on a given set of products.

Our conceptualization of this construct reflects the observation that the distinct subsets of NPD projects that a team member contributes to are often characterized by distinct NPD knowledge. In other words, the NPD experience of individual team members can span distinct streams of NPD projects, each characterized by a common NPD knowledge domain, corresponding to the idiosyncratic knowledge elements that characterize a given set of products (Björk, 2012). For example, the French designer Constance Guisset and the Argentinian designer Francisco Gomez Paz are both known for the furniture products they developed in collaboration with various major brands. Gomez Paz's collaborations are relatively concentrated on pieces developed with the famous Italian brand Luceplan. In contrast Guisset's NPD experience in the field is not dominated by any collaboration with any particular brand. If Luceplan were considering Gomez Paz and Guisset as candidates for a NPD team, the latter would offer a lower level of stream concentration.

Our theoretical framework builds on an established research tradition which has identified individual and organizational knowledge as distinct knowledge structures which affect NPD (e.g., Argote, 2013; Dane, 2010; Song and Montoya-Weiss, 2003; Yayavaram and Ahuja, 2008). These structures have been often described as sets of elements representing the content of what an individual or organization knows (Fleming, 2001), as well as individual and organizational memory (Walsh, 1995; Walsh and Ungson, 1991) about which elements work well together (Ravasi et al., 2019; Yayavaram and Ahuja, 2008). Stream concentration captures differences between team members' knowledge which are likely to affect the management of change in NPD projects. Hence, our empirical study aims to assess (1) the effect of the interaction between product attribute change and team change on new

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product performance and (2) the moderating effect of stream concentration.

We use data on a sample of 2621 NPD projects in the global music industry involving 34,265 unique team members who worked during their career on 684,690 other product development projects in the industry. We measure new product performance as the growth in the number of an artist's listeners. Results show that product attribute change and team change are complementary choices and that performance is higher for projects in which the levels of change in both product attributes and team members are moderate. However, as stream concentration increases, this performance premium is reduced.

Our study offers theoretically and empirically founded reasons to consider stream concentration as a previously overlooked structural dimension in NPD projects, together with the level of change in product attributes and team composition. Our contributions are both novel and important as they address factors that shape the tension between continuity and change in NPD projects.

Theory and Hypotheses

The Tension Between Continuity and Change in New Product Development Projects

In many industries, businesses develop new products that join an existing portfolio of products connected by a shared identity (Ravasi et al., 2019). However, this challenges NPD teams to strike a balance between continuity and change. Continuity focuses on satisfying the preferences of existing customers and includes such things as repetition and incrementalism. Change focuses on novelty and radicalness (Eling et al., 2016; Rosenkopf and McGrath, 2011; Shane and Ulrich, 2004). The tension between continuity and change affects in different ways two critical decisions on how to structure the work of NPD projects.

The first decision is related to the design briefs identifying the relevant product attributes and their relationships with those used in the existing set of products (Seidel, 2007). Product attributes are tangible (e.g., color, shape, flavor) or intangible (e.g., style, theme, design) features that define a particular product and affect consumers' purchasing decisions (Evanschitzky et al., 2012; Henard and Szymanski, 2001). New products are created as bundles of attributes by leveraging existing and new ideas in a variety of ways, ensuring that the output meets the expectations of the market (Fleming, 2001).

A second decision is related to the composition of NPD teams. They are often assembled within a constrained set of candidates and must combine individual member characteristics with interpersonal dynamics for the success of their endeavor (Brockman et al., 2010; Carbonell and Rodríguez Escudero, 2019). Research on constructs such as group longevity (Katz, 1982), team internal density (Reagans, Zuckerman, and McEvily, 2004), team familiarity (Huckman, Staats, and Upton, 2009), and team experience (Reagans, Argote, and Brooks, 2005) shows that team stability increases efficiency, but at the price of resistance to change and ingroup dynamics. The level of team change is thus a critical decision when assembling a NPD team (Schwab and Miner, 2008; Skilton and Dooley, 2010).

We contend that there is a third and under-investigated decision related to the level of experience of team members within a given set of products—i.e., a given NPD knowledge domain. Team members operate both as sources and assemblers. They generate stocks of ideas on product attributes over time and combine them to generate new products (Ancona and Caldwell, 1992; Edmondson and Nembhard, 2009; Seidel, 2007; Taylor and Greve, 2006). In this process, differences between individual and organizational memory can arise because individual team members accumulate knowledge over time through their participation to distinct NPD projects within and outside a given NPD knowledge domain. In contrast, organizational memory is accumulated only over the NPD projects within the focal NPD knowledge domain (Evans et al., 2004; Tasselli et al., 2015). Hence, at the individual level, team members carry with them expectations regarding what product attributes are appropriate for a given set of products which are shaped, at least in part, by their stock of different types of knowledge (Ravasi et al., 2019). For example, inductive research on designers shows how the stocks of aesthetic knowledge—i.e., understanding about the look, feel, smell, taste and sound of certain product attributes (Ewenstein and Whyte, 2007), which designers accumulate through their experiences—affect their choices when searching for new solutions (Stigliani and Ravasi, 2018). Hence, the way team members contribute to a NPD project is shaped by separate knowledge structures—individual and organizational knowledge—which affect in different ways how individuals and teams operate for a given task (Argote, 2013; Dane, 2010; Song and Montoya-Weiss, 2003; Walsh, 1995). Importantly, since these differences in the type of knowledge that a NPD team relies upon arise independently from team change, this should be considered as a separate dimension affecting the design of NPD teams. We term this team-level construct stream concentration because it captures how differences in team members' familiarity with the knowledge domain of the new product being developed may affect NPD outcomes. In the following paragraphs we will explore in greater depth these three dimensions and develop a set of hypotheses on their performance implications in NPD projects.

Product Attribute Change and New Product Performance

NPD teams are called to mix existing and new attributes (Henard and Szymanski, 2001; Urban, Weinberg, and Hauser, 1996) with the tension between continuity and change unfolding both on the supply and the demand side of NPD projects. On the supply side, the higher the number of new product attributes, the more challenging product development becomes (Chandy, Hopstaken, Narasimhan, and Prabhu, 2006; Eling et al., 2016). Significantly departing from previous generations of products requires specific investments in building new competencies and capabilities and in managing the resistance to change generated by existing norms and practices (Calantone and Rubera, 2012; Zahra and George, 2002). On the demand side, modifying product attributes influences consumer evaluations and inferences about a product (e.g., Correll et al., 2017; Hauser and Simmie, 1981; Negro, Koçak, and Hsu, 2010; Newman, Gorlin, and Dhar, 2014). For high levels of novelty, customers sometimes either refrain from purchasing at all or else resort to simple selection heuristics based on familiarity (Henard and Szymanski, 2001). Thus, NPD teams are pressured to adjust their output to the product attribute combinations expected by existing customer bases.

Several industries particularly value innovativeness as a way to generate occasional hits, but at the same time desire consistency in product attributes, especially when an existing set of products is performing well or has unique elements of differentiation (Askin and Mauskapf, 2017; Zuckerman, 2017). For example, studies of NPD in the comics industry (Taylor and Greve, 2006) and the Broadway musical industry (Uzzi and Spiro, 2005) warn that for high levels of novelty, the resulting outcomes may be poorly defined, inconsistent, or inappropriate. Similarly, studies on scientific works show that impact is higher when combinations of new and prior research are anchored in substantial conventionality, rather than novelty (Uzzi et al., 2013; Wu, Wang, and Evans, 2019). New product attributes can increase the likelihood to match changing consumer preferences (Askin and Mauskapf, 2017), to create impactful innovations (Uzzi et al., 2013), and to enlarge the size of the market that a set of products can appeal to. However, new attributes can complicate categorization processes, resulting in products that are considered as less appealing and fail to match existing customer expectations (Newman et al., 2014; Zuckerman, 2017).

In summary, products that balance new and familiar attributes tend to perform better (Barlow, Verhaal, and Angus, 2019; Zhao, Ishihara, Jennings, and Lounsbury, 2018). Hence, based on existing research on the relationship between change in product attributes and new product performance, we advance the following baseline hypothesis:

> *H1: Product attribute change has an inverted U-shaped relationship with new product performance such that moderate levels of change will perform better than low or high levels of change.*

Team Change and New Product Performance

The extent to which NPD teams change over time has significant implications on new product performance (for a review, see Rink, Kane, Ellemers, and Van Der Vegt, 2013). A set of studies focuses on the costs of team change, emphasizing the efforts required to integrate new and existing team members (Solinger, van Olffen, Roe, and Hofmans, 2013) and align team members' skills (Taylor and Greve, 2006) as well as inefficient transactive memory systems (Lewis, Lange, and Gillis, 2005). A robust finding is that stable teams perform better than newly assembled ones (Huckman et al., 2009; Reagans et al., 2004) because shared working experience makes knowledge combination more straightforward (Argote and Miron-Spektor, 2011; Brockman et al., 2010; Carbonell and Rodríguez Escudero, 2019).

Familiarity among members influences how effectively NPD teams coordinate in two ways. Repeated interactions between members gives teammates insight into one another's preferences, styles, and idiosyncrasies (Deming, 2017). Furthermore, shared experience gives teammates insight into a given NPD knowledge domain—e.g., the subtleties, difficulties, and the opportunities associated with NPD in a given field or working for a particular brand. Though conceptually distinct, both dimensions of familiarity impact team coordination in similar ways (Ching, Forti, and Rawley, 2019).

Another set of studies focuses on the advantages of team change. Collaboration has become ubiquitous in creative work and team change can increase the diversity or appropriateness of the team's knowledge base (Carley, 1992). New team members can transfer their tacit knowledge from different contexts (Argote and Miron-Spektor, 2011). Team change can enhance creativity through a broader discussion of issues and alternatives (Choi and Thompson, 2005; Skilton and Dooley, 2010), which can result in more innovative and successful products (Taylor and Greve, 2006). Furthermore, research on social categorization (Zuckerman, 2017) and intergroup bias in the evaluation of novelty (Criscuolo, Dahlander, Grohsjean, and Salter, 2017) considers membership change as an opportunity for NPD teams to develop a better understanding of customers' needs and wants, which can positively affect the adoption of new products (Heath et al., 2015; Spanjol et al., 2018).

Hence, based on existing research on the relationship between team change and new product performance, we advance the following baseline hypothesis:

> *H2: Team change has an inverted U-shaped relationship with new product performance, such that moderate levels of change will perform better than low or high levels of change.*

The Moderating Effect of Stream Concentration

A critical contingency for the interaction between product attribute change and team change arises due to differences in individual team members' experience within or outside the set of products that the NPD project belongs to. More specifically, some team members accumulate NPD experience only within a given NPD knowledge domain whereas other members engage in a more varied set of NPD projects (Tasselli et al., 2015).

These experiences contribute to define not only individual expertise and the opportunity for team members to span organizational boundaries (Carbonell and Rodríguez Escudero, 2019; Carley, 1992), but also individual identities and expectations about what is deemed to be appropriate or not for a given knowledge domain, such as a specific organization's identity (Ravasi et al., 2019). In other words, NPD projects are shaped by distinct knowledge structures: individual and organizational knowledge (Argote, 2013; Dane, 2010; Song and Montoya-Weiss, 2003; Yayavaram and Ahuja, 2008). These structures are often characterized as sets of elements representing the content of what an individual or an organization knows (Fleming, 2001), as well as individual and organizational memory (Walsh, 1995; Walsh and Ungson, 1991) about which elements are most likely to fit well together (Ravasi et al., 2019; Yayavaram and Ahuja, 2008). Knowledge structures evolve over time based on the variance of experiences of different team members across distinct NPD projects, and therefore across different knowledge domains. Hence, in a given project, the knowledge of some team members is likely to differ with respect to the knowledge of others that have been relatively less involved in that product's domain, and more involved in other types of NPD projects. Our central argument is that these differences between members of NPD teams are likely to affect the management of change in NPD projects.

We call this new construct stream concentration as it captures team members' familiarity with the knowledge domain of the new product being developed (e.g., Apple products, movies in the Star Wars franchise, videogames in the Horizon Zero Dawn franchise). Stream concentration is high when the focal set of products is career-defining for many team members. Conversely, stream concentration is low when team members are involved in other unrelated NPD projects, so that their careers are more varied and diverse. We contend that different levels of stream concentration will have distinct implications on new product performance.

In principle, high levels of stream concentration can complement the positive effects of repeated collaboration among team members. It can help the team to converge more efficiently on a product concept through retained members' shared understanding of desirable product attribute combinations

(Ravasi et al., 2019), improving a group's ability to coordinate shared activities (Schwab and Miner, 2008; Solinger et al., 2013) and to negotiate more effectively a course of action with new team members. Members whose careers are defined by the focal NPD knowledge domain implicitly signal to newcomers an ability to execute specific options, providing direction amid the ambiguity spurred by the conflicting demands for novelty and conventionality in NPD and the open-ended nature of the task (Zuckerman, 2017). We would therefore expect that NPD projects characterized by low levels of change in product attributes and team members should benefit from high stream concentration.

However, high stream concentration implies that the individual knowledge of team members overlaps with organizational knowledge, which arises from team members' memory about previous NPD projects in the same knowledge domain (Walsh, 1995; Walsh and Ungson, 1991). Redundancy across the two knowledge structures enhances some of the drawbacks of stable teams, such as rigidities in crucial initial NPD phases like idea disclosure, advocacy, and convergence (Skilton and Dooley, 2010). It also favors the emergence of a collective understanding about a desirable product concept (Stigliani and Ravasi, 2018), influencing new team members to "buy into" existing mental models (Lewis et al., 2005). Hence, teams with high levels of stream concentration will tend to redeploy product concepts that were already successful in previous projects rather than try alternative options. Research on cognitive framing supports this view, suggesting that when people have experienced success with a strategy in the past, they often become narrowly focused on implementing that particular "template" over time (Gavetti, Levinthal, and Rivkin, 2005). Moreover, as NPD team members become more involved in a similar set of experiences, they become risk-averse and favor increases in mean performance rather than increases in the variance of outcomes (Dane, 2010; Taylor and Greve, 2006). Low, rather than high, levels of stream concentration should thus be desirable if the goal of the NPD project is to implement moderate to high levels of change. We therefore propose the following hypothesis:

H3: Stream concentration negatively moderates the interaction between attribute change and team change.

Taken together, our hypotheses make two simple, broad predictions. First, that product attribute change and team change are complementary choices affecting NPD performance. Second, that stream concentration reduces the benefit of such complementarity. We take these predictions to the data after describing the empirical context in more detail below.

Empirical Strategy

The Setting: New Product Development in the Music Industry

Assembling longitudinal data to link decisions about continuity and change and the performance of new products is a significant challenge. We merge transactional and behavioral tracking data to create a consistent and unique dataset on NPD project characteristics and new product performance. We focus on the music industry, which provides an especially suitable setting to test our hypotheses.

First, it is characterized by portfolios of products connected by the brand identity of an artist, which are developed by temporary NPD teams. Artists and record labels aim to create a series of successful albums. The artist's name serves as a brand, around which musical styles can be attached and varied (Hesmondhalgh, 1998).

Second, this setting offers a unique opportunity to observe a stream of products from the same artist because record labels tend to cross-collateralize sequentially, with advances under a recording deal for an artist cross-collateralized with royalties under past and future deals, and vice versa. In other words, a record label funds an artist to create a new album and then keeps the artist's proceeds from current and future NPD projects until the advance is recovered. The artist has a contractual relationship with the label, from which the artist receives in advance a production budget, and has full control in assembling the production team (Passman, 2014, p. 136). Accordingly, artists effectively act as product managers in charge of releasing a set of new products and face concurrent pressures for consistency and novelty (exploring familiar or unfamiliar styles or hiring old or new team members) because each new product will join their existing products.

Third, due to piracy and limited price dispersion across recorded music, the price has little to no effect upon consumers' choices. Success is almost exclusively

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determined by the appeal of the unique characteristics of the recordings (Askin and Mauskapf, 2017; Elberse, 2010).

Sample and Data Sources

Two dynamics connect producers and audiences in the music industry: authorship and musical style. Both dynamics have creative and commercial functions. They allow the organization and understanding of codes and conventions of meaning, as well as publicity and promotion, to signal consumers about the potential experience underlying a product (Hesmondhalgh, 1998). Similar to other studies using data from the music industry (Askin and Mauskapf, 2017; Bhattacharjee, Gopal, Lertwachara, Marsden, and Telang, 2007), we construct our sample by focusing on music charts. Specifically, we collect data on all artists appearing at least once in Last.fm's weekly "top 400 charts" during the period 2004–2008 and all the albums they released between 1962–2008. Last.fm is a branch of CBS Interactive and one of the first and largest music social networks. During the period of our study, the firm used a unique technology to track details of all the songs that its users were listening to across a variety of devices and web applications (e.g., smartphones, computers, mp3 players, game consoles). The system generated weekly global charts of the artists and tracks listened to by all Last.fm users, providing a longitudinal measure of the number of individual listeners for all the artists in our sample.

Similar to other studies on cultural products (Askin and Mauskapf, 2017; Negro et al., 2010), we collected data on the NPD teams, and the product attributes associated with music products by using classification data by Rovi, the world leader in music data services providing catalog data, credits, genre, style, and other information to Apple Music, Amazon, Spotify, and others. Rovi's content is created by professional editors, including over 1500 music critics who review albums and songs. This is considered to be the most extensive database about music recordings, based on coverage and reliability across all genres and formats, and provides for each release an extensive classification of music styles (e.g., Madonna's music is classified using elements such as pop, electronic, and dance as well as energetic and playful). Using the Rovi AMG database, we also retrieved information about the artists' releases and all members of their production teams. To make sure that a team member listed in the credits of an album was consistently the same person over time and across different albums, and prevent generating unreliable matches, we based our data collection on unique person identifiers created by Allmusic.com, which tracks individuals by their unique numerical IDs, rather than by first and last name (or pseudonym). Ultimately, we used this information to identify all the professionals that worked with all the artists in our sample and to match them to specific albums.

Our final sample includes 2621 albums developed by 271 artists in the time frame 1962–2008, along with 34,265 individual team members. Based on this data, we measured product attribute change for each album released by each artist by considering the musical styles associated with the album. We then measured team change by considering the album credits. To measure stream concentration, we further collected additional data on all the 684,690 albums released in the music industry involving at least one of the team members who participated in the development of each album in our sample. While all independent variables are measured using the full sample of projects released in the time frame 1962–2008, our dependent variable is only available between 2004 and 2008. Hence, we estimate our econometric models on a subsample of 491 albums, released by 270 artists between 2004 and 2008, as units of observation. This is required to ensure consistency in the unit of analysis and reliability in the measurement of new product performance based on Last.fm data. First, the "Audioscrobbler" system for tracking the listening habits of its user became fully integrated in the Last.fm platform from 2004. Second, after 2008, the advent of streaming sites such as Spotify and other changes in the music industry (e.g., the popularization of "360 deals") significantly reduced the extent to which artists and record labels relied on albums and sequential cross collateralization as a feature of their NPD contracts, and begun siphoning off tracked users from the Last.fm platform (Passman, 2014). To ensure comparability, we also exclude from our analysis singles and other releases not classified as "brand new" (i.e., re-mastered versions, compilations, remixes, reissues).

Dependent Variable: Product Performance

We measure new product performance as the growth in an artist i's number of listeners when releasing a new album j. We take the difference between the natural logarithm of the moving average of the number unique listeners of artist *i*'s tracks during the four months after the release of album *j* and the correspondent logarithm of the moving average of number unique listeners (of the same artist *i*) during the four months before the release. Consistent with previous studies on entertainment industries, we focus on the size of artists' audience as a measure of performance (Askin and Mauskapf, 2017; Oberholzer-Gee and Strumpf, 2007; Rosen, 1981). Unlike other studies that have used charts or surveys as proxies for new product performance, we directly measure it by counting the unique number of actual listeners using data from Last.fm. As the Last.fm system measured actual product consumption, making no distinction between legally purchased and pirated music, our data do not suffer from an underestimation of the number of listeners.

Independent Variables

Attribute change. We measure the extent to which the attributes of a new product differ from those of the other existing products of an artist by using the classification data provided for each album by the Rovi AMG database, the world leader in music data services providing catalog data, genre, style, and other information to Apple Music, Amazon, Spotify, and others. It is considered to be the most extensive database about music recordings, based on coverage and reliability, and provides for each release an extensive classification of music styles. This content is created by professional editors, including over 1500 music critics who classify albums using keywords that describe their sound and feel (e.g., the album "Confessions on a Dancefloor" by Madonna is classified using elements such as pop, electronic, and dance as well as energetic and playful). To measure *Attribute Change*, we consider all the styles that are present in a new album *j*, released by artist *i*, which are not in the list of styles associated with the previous albums released by the same artist *i*. We then compute the ratio of the number of new styles present in album *j* (*New Attributes*) over the total number of styles attributed to album *j*. This variable ranges between 0 to 1, where 0 represent complete continuity with the existing set of products of the artist and 1 complete change.

$$Attribute\ Change_{ij} = \frac{New\ Attribute_{ij}}{Total\ Attributes_j} \tag{1}$$

Team change. We retrieved information about albums and members of the production teams from the Rovi AMG database. To make sure that a team member listed in the credits of an album was consistently the same person over time and across different albums, and to avoid generating unreliable matches, we based our data collection on unique person identifiers created by Allmusic.com, which tracks individuals by their unique numerical IDs, rather than by first and last name (or pseudonym). Ultimately, we used this information to identify all the professionals that worked with all the artists in our sample and to match them to specific albums. We measure *Team Change* (ranging between 0 and 1) as the ratio of the number of team members appearing in the credits of a new album *j* released by artist *i* who did not collaborated with the artist *i* on previous albums (*New Members*) over the total number of team members in album *j* (excluding the leading artist(s) *i*).[1]

$$Team\ Change_{ij} = \frac{New\ Members_{ij}}{Total\ Members_j} \tag{2}$$

Stream concentration. The variable measures how much (on average) team members that are retained in the transition between one NPD project to the next were involved in the past in other NPD projects with the same artist rather than in other projects with other artists. In other words, stream concentration measures, for each single album *j,* to what extent team members that repeatedly collaborate with an artist *i* are (more or less) involved in *j.* For each artist-release observation *ij*, this variable is defined as the ratio of the number of times that each team member *k* (excluding the leading artist(s) *i*) appearing in the credits of album *j* was also present in the previous albums of artist *i* (*Repeat Collaboration*), over the total number of *k*'s other projects in the industry (*Other Projects*). This index is then averaged over all the members of album *j* by artist *i*.

$$Stream\ Concentration_{ij} = \frac{\sum_{k=1}^{Total\ Members_j} \left(\frac{Repeat\ Collaboration_{ik}}{Other\ Projects_k} \right)}{Team\ Members_j} \tag{3}$$

[1]Results are robust to different operationalizations where we consider only certain types of team members (i.e., producers, musicians, and sound engineers vs. photographers, lawyers, and administrative assistants).

Control Variables

We considered various time-variant, artist-, and product-specific factors that may influence product performance in the music industry.

Independent label. Artists backed by major labels tend to have a large marketing budget and experience wider audience exposure. Independent labels, conversely, for the most part, are private companies with few employees and limited resources (Bhattacharjee et al., 2007). To account for unobserved differences between releases by major vs. independent labels, we used a dummy variable set to 0 if the record label is owned by Universal Music, EMI, Warner, or Sony–BMG and 1 if the label is "independent." To distinguish precisely between "major" and "independent" labels, we reconstructed the corporate hierarchies, accounting for the associated companies together with the dissolved entities, as reported by the Recording Industry Association of America (2009).

Superstar. Consumers' perceptions toward music are affected by artists' popularity and analyses of music sales indicate that a relatively small number of stars tend to dominate the market (Rosen, 1981). Since the concept of "stardom effect" is typically referred to in the literature as multi-dimensional (i.e., driven by a combination of several factors such as sales, number of fan clubs, airplays, advertising, etc.) and skewed, as it triggers only for very high levels of popularity (Kehoe, Lepak, and Bentley, 2018), we use a binary variable denoting the reputation of the artist in terms of sales and airplay. If artist i appeared on the Billboard Top100 yearly charts for at least 100 weeks between 1990 and 2008, the dummy variable is set to 1 (Bhattacharjee et al., 2007; Kehoe et al., 2018).

Google popularity. Research showed that aggregated Google Search data correspond closely to demand and sales of a particular product or brand and that the addition of search-trends to econometric models improves the accuracy of estimates (Da, Engelberg, and Gao, 2011; Du and Kamakura, 2012). Building on this research, we used Google Trends to account for artists' popularity on the Internet. More specifically, we compute the variable as the monthly log number of Google searches worldwide for the artist's name in the category "entertainment" and sub-category "music."

Awards. Award-winning artists benefit from boosts in subsequent album sales and increased media coverage. Hence, we controlled for the most important artistic achievement in the music industry: the Grammy Award. The variable measures for each artist-release observation the cumulative number of awards at the time of release.

Artist geo-location. The supply side of music shows significant differences among countries, so that artists originating from specific locations may benefit from market dynamics that are not available to artists based in other regions of the world. We included dummy variables to account for the macro geographical area of each artist (i.e., North America, Northern Europe, UK and Ireland, and Others).

Main genre. The demand and supply of music shows significant differences across macro genres (Hesmondhalgh, 1998). Hence, we introduced a series of dummy variables (Pop-Rock, Metal, Dance, Rap, and Others) to account for main genre of the album.

Winter release. Consumers tend to increase the amount of music they purchase and listen to between December and January. To check for potential seasonality effects, we included a dummy variable, which is set to 1 if the album was released in December or January and 0 otherwise (Bhattacharjee et al., 2007).

Other controls. To account for differences in the expertise and release pace of artists, we included for each artist-release observation the log of the number of months since the artist's debut album (*Past Experience*) and the log of the number of months since the last release (*Release Lag*). We introduced the dummy variables *Year* to control for potential fixed effects associated with the years in our sample. Finally, to capture most of the latent persistent factors affecting artists' performance, we included several variables: the log of the average four months pre-release audience level (*L.Performance*); the average of the four months pre-release Internet popularity index (*L.Google Popularity*); the dummy variable *Group*,

Table 1. Summary of Variables and Measures

Variable	Formula	Description
Product performance	$log\left(\frac{\sum_{t_{ij}}^{t_{ij}+3} Listeners_{it}}{\sum_{t_{ij}-4}^{t_{ij}-1} Listeners_{it}}\right)$	Growth of artist *i*'s audience when releasing a new album *j* (in month *t*): Difference (in log) between the 4-months moving average of the number of artist *i*'s unique *Listeners* after the release of album *j* and the correspondent 4-months moving average of artist *i*'s unique *Listeners* before the release of album *j*. Data source: Last.fm
Attribute change	$\frac{New\ Attributes_{ij}}{Total\ Attributes_j}$	Ratio of the number of new styles (for artist *i*) present in album *j* (*New Attributes*) over the total number of styles attributed to the same album *j*. Data source: AllMusic
Team change	$\frac{New\ Members_{ij}}{Total\ Members_j}$	Ratio of the number of team members appearing in the credits of a new album *j* (released by artist *i*) who did not collaborate with the same artist *i* on previous albums (*New Members*) over the total number of team members in album *j*. Data source: AllMusic
Stream concentration	$\frac{\sum_{k=1}^{Total\ Members_j}\left(\frac{Repeat\ Collaboration_{ik}}{Other\ Projects_k}\right)}{Total\ Members_j}$	Ratio of the number of times that each individual team member *k* (excluding the main artist(s) *i*) appearing in the credits of album *j* was also present in the credits of the previous albums of artist *i* (*Repeat Collaboration*), over the total number of *k*'s other product development projects in the industry (*Other Projects*). This index is then averaged among all the members of the product development team of album *j* by artist *i*. Data source: AllMusic
Independent label	Binary variable	= 1 if the label is "independent"; = 0 if the record label is owned by Universal Music, EMI, Warner, or Sony–BMG. Data source: RIIA
Superstar	Binary variable	= 1 if artist *i appeared on the Billboard Top100 yearly charts for at least 100 weeks between 1990 and 2008; = 0 otherwise. Data source: Billboard Top100*
Google popularity	$\log\left(Search\ Interest_{it_j}\right)$	Popularity of artist *i* = logarithm of the average search interest on Google (*Search Interest*) worldwide for the name of artist *i* in the category "entertainment" and sub-category "music" during the release month of album *j* (t_j). Data source: Google Trends
L.Google popularity	$log\left(\frac{\sum_{t_{ij}-4}^{t_{ij}-1} Search\ Interest_{it}}{4}\right)$	Latent persistent popularity = logarithm of the average search interest on Google (*Search Interest*) worldwide for the artist *i* name in the category "entertainment" and sub-category "music," during four months pre-release of album *j*. Data source: Google Trends
Artist geo-location	Vector of binary variables	Series of dummy variables to account for the macro geographical area of each artist: North America, Northern Europe, UK and Ireland, and Others (excluded category in the regression models). Data source: AllMusic
Main genre	Vector of binary variables	Series of dummy variables to account for main genre of album *j*: Pop-Rock, Metal, Dance, Rap, and Others (excluded category in the regression models). Data source: AllMusic
Winter release	Binary variable	= 1 if album *j* was released in December or January; = 0 otherwise. Data source: Last.fm
Past experience	$log(t_{ij}-t_{i1})$	log of the number of months since the artist's debut album. Data source: Last.fm
Release lag	$log(t_{ij}-t_{ij-1})$	log of the number of months since the last release of artist *i*. Data source: Last.fm
L.Performance	$log\left(\frac{\sum_{t_{ij}-4}^{t_{ij}-1} Listeners_{it}}{4}\right)$	Latent persistent performance = logarithm of the average four months pre-release audience level of artist *i*. Data source: Last.fm
Group	Binary variable	= 1 if artist *i* is a group (e.g., U2, Daft Punk) = 0 otherwise; Data source: AllMusic
Gender	Binary variable	= 1 if *i* is a solo male artist or a group with more than 50% of male members; = 0 otherwise. Data source: AllMusic

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Table 2. Descriptive Statistics and Correlations (for Continuous Variables)

Variable	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8
1. Product performance	.31	.22	−.13	1.34	1							
2. Attribute change	.35	.28	0	1	.15	1						
3. Team change	.64	.24	0	1	.19	.15	1					
4. Stream concentration	.05	.12	0	1	−.10	.04	−.10	1				
5. Release lag	2.80	.82	0	4.14	.18	.23	.21	−.06	1			
6. Past experience	2.17	.75	0	3.78	−.22	.02	−.23	−.06	−.06	1		
7. L.Product performance	9.06	.82	6.97	11.10	−.49	−.16	−.08	−.01	.00	.12	1	
8. Google popularity	1.73	4.45	−.84	27.00	.16	−.07	.11	−.01	−.06	−.47	.06	1
9. L.Google popularity	1.09	3.66	−.89	28.52	−.03	−.13	.07	.01	−.13	−.42	.08	.88

$N = 491$. All Pearson correlation coefficients above |.09| are significant at .05 level.

which is set to 1 for releases by groups (e.g., U2, Daft Punk) and 0 for releases by solo artists; and the dummy variable *Gender*, which is set to 1 for releases by solo male artists and 0 for solo female artists, while in the case of groups is set to 1 if more than 50% of the group members are male and 0 otherwise. Table 1 summarizes all variables, measures, and sources while Table 2 reports descriptive statistics and correlations for the continuous variables included in the analyses.

Analysis and Results

We begin our analyses by estimating the main effects of change in product attributes (H1) and change in team composition (H2) on product performance as a test of the baseline hypotheses suggested by existing research. We then assess the interaction between attribute change and team change as well as the moderating effect of stream concentration (to test H3).

Model Selection

For each artist-release observation i, we estimate the following model, where the post-release audience growth rate is as a function of changes in product attributes, in team composition, and the level of stream concentration.

$$Product\_Performance_i = f(Attribute\_Change_i, Team\_Change_i, Stream\_Concentration_i, X) \tag{4}$$

Since the artist's performance expectations may drive the levels of change in product attributes and team members for a new album, raising potential concerns for a “simultaneity” bias in our estimates, we begin by assessing the exogeneity of the independent variables with a two stages least squares (2SLS) instrumental variable (IV) approach (Hamilton and Nickerson, 2003). We considered as instruments the lagged values of our set of independent variables (i.e., the degree of team and attribute change of the previous album release and the one-year lagged value of stream concentration) along with other exogenous regressors. Similarly to other studies that adopted lagged independent variables as instruments (Cachon and Olivares, 2010), our IV strategy relies on the assumption that, conditional on the current set of independent and control variables X, the lagged values of changes of product attributes and team members in previous projects do not directly affect the current level of product performance. We can, therefore, exclude the set of instrumental variables Z from the set of right-hand side variables of equation (4).

Table 3 reports the first stage estimates (columns 1–4) along with the relevancy test results for our set of instruments Z considering different specifications. In column 2, we assume only *Attribute Change* to be endogenous; conversely, in column 4, we assume only *Team Change* to be endogenous. Columns 1, 3, and 5 report the first stage and the IV estimate when considering both *Attribute Change* and *Team Change* as endogenous. The Hansen-Sargan tests do not reject the null hypothesis that all the instruments Z are valid, and the Durbin-Wu-Hausman tests do not reject the null hypothesis that both the independent variables are jointly exogenous. These results are confirmed even after taking into account the possible weakness of some of our instruments (i.e., the lagged values of *Attribute Change*), and they suggest that our set of independent variables do not suffer from endogeneity issues (Mikusheva, 2010).

The IV analysis allows us also to test whether changes in team members' composition and product

Table 3. Preliminary Analyses: Antecedents of New Product Performance

Dependent Variable	Attribute Change	Attribute Change	Team Change	Team Change	New Product Performance
Independent Variables	(1)	(2)	(3)	(4)	(5)
Attribute change				.07*	−.30
				(.04)	(.95)
Team change		.09*			.46
		(.05)			(1.09)
Stream concentration	.18*	.19*	−.09	−.10	.01
	(.10)	(.10)	(.09)	(.09)	(.27)
L.Attribute change	.04	.04	.01	−.01	
	(.04)	(.04)	(.03)	(.03)	
L.Team change	.10*	.09*	.12**	.11**	
	(.06)	(.06)	(.05)	(.05)	
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Constant	.37*	.32	.55***	.52***	.65*
	(.21)	(.22)	(.18)	(.18)	(.36)
Mean variance inflation factor (VIF)	2.40	2.35	2.40	2.36	
R-squared	.19	.20	.18	.19	
Hansen-Sargan J statisic [*p*-value]		.78 [.38]		.42 [.52]	.19 [.98]
Durbin-Wu-Hausman test [*p*-value]		.13 [.71]		.45 [.50]	2.67 [.26]

Two stage least squares (Obs. = 497). Standard errors in parentheses.
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

attributes can be considered as cross (or mutual) antecedent factors. Our results provide weak support to this view since the lagged values of attribute change (L1 *Attribute Change*) do not significantly affect its current values nor the current values of *Team Change*. Conversely, past levels of team change (L1 *Team Change*) significantly affect its current values (i.e., we find evidence of persistence in the team change strategies) and the current values of *Attribute Change*. Furthermore, *Stream Concentration* has a weak positive correlation with *Attribute Change*.

Hypothesis Testing

Having assessed the exogeneity of our independent variables with the 2SLS-IV analysis and the Durbin-Wu-Hausman test, we test H1 and H2 using a GLS estimator, which is more efficient in terms of lower mean squared error (MSE), than 2SLS-IV in presence of exogenous regressors (Mikusheva, 2010). We account for correlations of latent factors within releases by the same artist by using clustered robust standard errors.

Table 4 shows the results of the GLS regression models with different specifications for the quadratic relationship between the level of change in product attributes (H1), team members (H2), and product performance. The statistically significant increase of the R-squared in the models with quadratic and interaction terms (columns 2, 3, and 4) suggests that the effect of *Attribute_Change* on the performance of a new product follows an inverted-U shape, supporting H1: moderate change in product attributes is associated with the highest product performance. The quadratic effect of *Team_Change* is instead not significant (hence, not supporting H2), but we find a significant and positive interaction between attribute change and team change (columns 3 and 4) indicating a complementarity between the two. Estimates of the fully saturated model in column 5 are more difficult to interpret since they include all the quadratic terms as well as the two-way and three-way interaction terms. Furthermore, the efficiency of these estimates is likely to be affected by the high pair-wise correlations among the independent variables, which reduces the statistical inference power when multiple quadratics and interaction terms are present in the same model (Cortina, 1993). This is also evidenced by the variance inflation factor (VIF) index, which is close to the commonly adopted rule-of-thumb threshold of 5 in columns 2, 3, and 4, but increases to 13.65 in column 5 (we address this potential problem in the analyses presented in Table 5).

In Table 5 we test our arguments on the moderating effect of stream concentration (H3) by studying how

Table 4. Preliminary Analyses: Quadratic and Interaction Effects

Dependent Variable: Product Performance	(1)	(2)	(3)	(4)	(5)
Attribute change	.03	.39***	.27***	.26***	.35***
	(.02)	(.08)	(.10)	(.10)	(.11)
Attribute change^2		−.48***	−.50***	−.51***	−.51***
		(.09)	(.09)	(.09)	(.09)
Team change	.06*	.13	.10	.11	.18
	(.03)	(.11)	(.11)	(.12)	(.12)
Team change^2		−.07	−.10	−.11	−.13
		(.10)	(.11)	(.11)	(.11)
Attribute change × Team change			.22**	.23**	.12
			(.10)	(.10)	(.12)
Stream concentration	−.07	−.06	−.06	−.04	.50
	(.07)	(.07)	(.07)	(.20)	(.35)
Stream concentration × Attribute change				.09	−.97
				(.17)	(.64)
Stream concentration × Team change				−.11	−.94*
				(.27)	(.53)
Stream concentration × Attribute change × Team change					1.56*
					(.92)
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Constant	.60***	.57***	.61***	.61***	.59***
	(.14)	(.14)	(.14)	(.15)	(.14)
Mean variance inflation factor (VIF)	2.62	4.45	4.93	5.87	13.65
R-squared	.55	.57	.57	.58	.58

(Obs. = 497). Clustered robust standard errors in parentheses.
***$p < .01$, **$p < .05$, *$p < .1$.

product performance changes for low/moderate/high levels of change in both team composition and product attributes (as illustrated in Figure 1). Following Lin, Yang, and Demirkan (2007), we capture these theoretically relevant combinations using three categories reflecting the sample tertiles of the variables Attribute Change and Team Change.[2] This allows us to examine distinct project profiles, resulting from combinations of different levels of change in product attributes and team members (Figure 1, the Appendix).

Table 5 (column 1) reports the GLS estimates using as explanatory variables a set of dummy variables corresponding to distinct combinations of different levels of change in product attributes and team members (illustrated in Figure 1), and using profile [1,1] (i.e., Low Attribute Change + Low Team Change) as the baseline category. Results show that the largest positive and significant coefficient is associated with profile [2,2] (i.e., Moderate Attribute Change + Moderate Team Change), followed by profile [3,3] (i.e., High Attribute Change + High Team Change) and profile [2,3] (i.e., Moderate Attribute Change + High Team Change). Figure 2 reports the predicted performance for each profile along with standard errors and estimated 95% confidence intervals to provide a fully comparable picture of the estimated effects. These effects are computed using the estimates of column 2 in Table 5, by averaging the marginal effects of the other regressors and computing the standard errors using delta methods (Bartus, 2005).

Project profiles [2,2] and [3,3] are associated with the highest predicted new product performance. Respectively, new products resulting from NPD projects with profile [2,2] generate a performance increase of +37.7% ($p < 0.01$) while product performance is only slightly lower for profiles that show high levels of change in both products attributes and team members ([3,3] +35.7%; $p < 0.01$). Moderate and high levels of change in both product attributes and team members significantly increase the performance of new products suggesting that change in product attributes and team composition should be managed jointly. In contrast, projects with low levels of change in both product attributes and team members (profile [1,1]) do not

[2]Testing different sets of threshold values (0.2, 0.8 and 0.3, 0.7 respectively) led to similar results.

Table 5. Main Results: Project Profiles and Moderating Effect of Stream Concentration

Dependent Variable: Product Performance	(1)		(2)	
Independent Variables	Coeff.	S.E.	Coeff.	S.E.
Project profiles				
[2,1] Moderate Attribute Change, Low Team Change	.07***	(.02)	.09***	(.03)
[3,1] High Attribute Change, Low Team Change	.02	(.03)	.05	(.03)
[1,2] Low Attribute Change, Moderate Team Change	.03	(.03)	.06*	(.03)
[1,3] Low Attribute Change, High Team Change	.00	(.03)	.03	(.03)
[2,2] Moderate Attribute Change, Moderate Team Change	.12***	(.03)	.16***	(.03)
[2,3] Moderate Attribute Change, High Team Change	.07***	(.03)	.10***	(.03)
[3,2] High Attribute Change, Moderate Team Change	.03	(.02)	.05*	(.03)
[3,3] High Attribute Change, High Team Change	.10***	(.03)	.12***	(.03)
Moderating effects of stream concentration				
Stream concentration	−.08	(.07)	.23	(.18)
Stream concentration*				
[2,1] Moderate Attribute Change, Low Team Change			−.33	(.22)
[3,1] High Attribute Change, Low Team Change			−.43**	(.21)
[1,2] Low Attribute Change, Moderate Team Change			−.48	(.35)
[1,3] Low Attribute Change, High Team Change			−.75	(.55)
[2,2] Moderate Attribute Change, Moderate Team Change			−.69**	(.28)
[2,3] Moderate Attribute Change, High Team Change			−.47**	(.22)
[3,2] High Attribute Change, Moderate Team Change			−.23	(.19)
[3,3] High Attribute Change, High Team Change			−.22	(.23)
Controls				
Independent label	.02	(.02)	.02	(.02)
Release lag	.03***	(.01)	.03***	(.01)
Past experience	−.03**	(.01)	−.03**	(.01)
Awards	.05	(.04)	.05	(.04)
Main genre: Pop-Rock	.02	(.02)	.02	(.02)
Main genre: Metal	.05*	(.03)	.05*	(.03)
Main genre: Dance	.02	(.03)	.02	(.03)
Main genre: Rap	.01	(.03)	.01	(.03)
Artist geo-location: North America	.07**	(.03)	.06**	(.03)
Artist geo-location: Northern Europe	.13***	(.04)	.13***	(.04)
Artist geo-location: UK + Ireland	.08**	(.03)	.07**	(.03)
Group	.00	(.04)	.00	(.04)
Gender	−.01	(.04)	−.01	(.04)
Superstar	.02	(.02)	.02	(.02)
Winter release	.05*	(.03)	.05	(.03)
L.Performance	−.04**	(.02)	−.04**	(.02)
Google popularity	.04***	(.01)	.04***	(.01)
L.Google popularity	−.04***	(.01)	−.04***	(.01)
Year FE	INCLUDED		INCLUDED	
Constant	.60***	(.14)	.62***	(.14)
Mean variance inflation factor (VIF)	2.52		3.47	
R-squared	.57		.58	

(Obs. = 497). Clustered robust standard errors in parentheses.
***$p < .01$, **$p < .05$, *$p < .1$.

perform as well (+25.01%, $p < 0.02$). Interestingly, profile [1,1] is also among the worst-performing types of NPD projects. Figure 2 displays the predicted performance for all the project profiles. Overall, results are broadly suggestive that product attribute change and team change are complementary and that moderate change is associated with the highest performance. Moreover, another relevant result coherent with our predictions is that profiles displaying extreme changes in product attributes and small changes in team members or minimal change in product attributes paired with a significant change in team members underperform.

In H3, we maintained that stream concentration negatively moderates the relationship between change and performance. To test this hypothesis, we assess the magnitude and the statistical significance of the interaction terms between stream concentration and all the project

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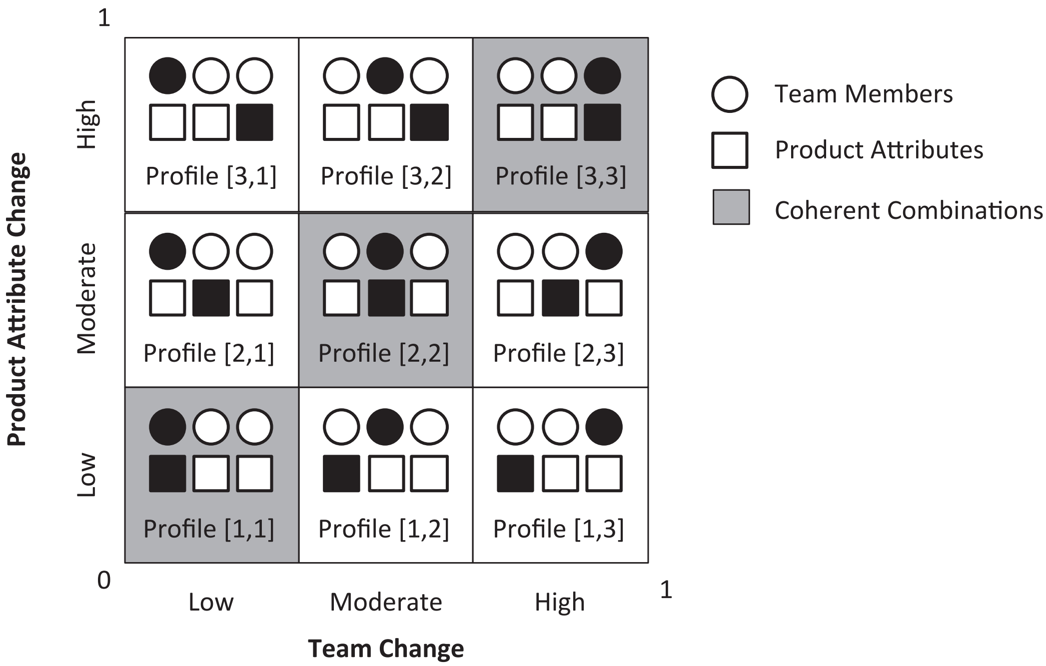

Figure 1. Distinct Patterns of Change in New Product Development Projects.
The figure illustrates how each NPD project can be characterized by low, moderate, or high levels of change in product attributes and team members. Accordingly, projects can be classified in terms of nine distinct types, or NPD project "profiles." Profile [1,1] describes teams that experienced low turnover—i.e., composed in majority by existing members—developing a product very similar to those released by the team in the past. Profile [2,1] includes teams that remain largely intact, but develop a product where about half product attributes are new. Profile [1,2] describes teams that replaced about half of their members with new members and introduce minimal changes to product attributes. In profile [3,2] products are characterized for the most part by new attributes, half of the team members have been retained from past projects, and the remaining members are new. Profile [2,3] describes teams that experienced high turnover—i.e., composed in majority by new members—developing a product where about half of the product attributes were already used by the team in the past and half are new. In profile [3,3] a team composed almost entirely by new members develops a product markedly different from the previous ones. In profile [3,1] an almost intact team develops a product characterized for the most part by new attributes. Profile [2,2] includes teams that have replaced about half of their members with new members and develop a product where about half of the product attributes are new and half are the same that characterized past products. Finally, in profile [1,3] a team composed almost entirely by new members develops a product very similar to those released by the team in the past

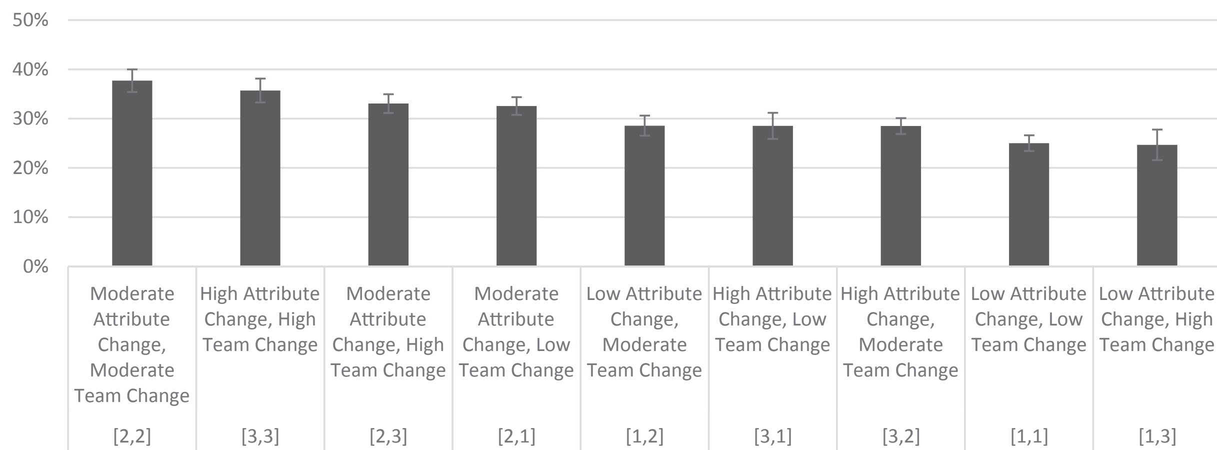

Figure 2. Predicted New Product Performance for Different Types of New Product Development Projects.
Obs. = 497. Vertical axis = % change in artist *i*'s audience after releasing a new album j. The predicted performance is computed using the estimated coefficients of Table 5 column 2. For the individual NPD project profiles the corresponding [..., ...] dummy variable (see Figure 1) is set to 1 and all the other dummies to 0. All remaining variables from Table 5 are included in the model. Error bars display twice the standard error, which is computed using the delta method (Bartus, 2005)

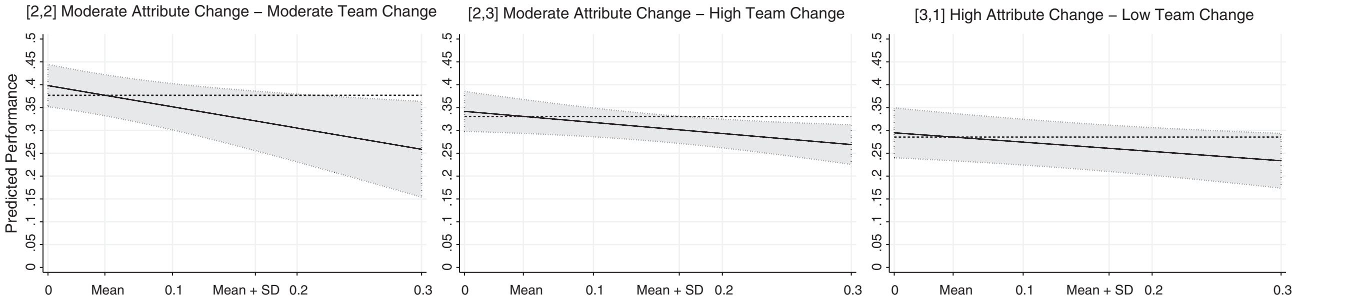

Figure 3. Moderating Effect of Stream Concentration for Different Types of New Product Development Projects.
The moderating effect of Stream Concentration is displayed as a solid black line and is computed using the statistically significant interaction terms of Table 5 column 2 (all remaining variables from Table 5 are included in the model). 95% confidence intervals are displayed in light gray and are computed using the delta method (Bartus, 2005). The average predicted performance with no moderating effect of Stream Concentration is displayed as a dotted line

profile dummies (Table 5, Column 2). Notably, the coefficient of the interaction between the variable *Stream Concentration* and the indicator variable that identifies profiles with moderate amounts of change in both product attributes and team components (profile [2,2]) is negative and statistically significant, suggesting that performance is reduced if the product development experience of team members is largely confined to the focal set of products. Figure 3 illustrates the dynamics and intensity of this moderating effect, which significantly decreases the predicted performance only for relatively large values of *Stream Concentration*.[3] Overall, we can conclude that we find support for H3 in NPD projects characterized by moderate amounts of change in both product attributes and team members.

Looking at the effect of the control variables (Table 5), artists who wait longer before releasing a new album (*Release Lag*) tend to benefit from higher bumps in the number of listeners; conversely, new products by long-tenured artists (*Past Experience*) generate smoother bumps. The estimated negative coefficients of *L.Product_Performance* and *L.Google Popularity* in Table 5 are strongly significant, confirming larger bumps in performance for less popular artists. Additional controls for artistic quality (*Awards*), *Gender*, *Group*, and seasonality (*Winter Release*) do not show any significant effect.

Discussion

We study the management of change in NPD projects. We find that the change of product attributes and of team composition are complementary choices, and model the countervailing effect on new product performance of a new team-level factor that we term stream concentration.

Existing research suggests that attribute change and team change interact (e.g., Carbonell and Rodríguez Escudero, 2019; Evanschitzky et al., 2012), but does not provide clear insights on whether they are complements or substitutes for new product performance and whether the level of change in one domain should match or not the level of change in the other. Our results contribute to this research by showing they are complementary choices and that performance is higher for projects characterized by moderate change in both product attributes and team composition. Most notable, we also report the negative moderating effect of a previously overlooked team-level factor capturing differences among team members arising from prior product development experience. We call this new construct stream concentration because it is low when team members have accumulated NPD experience by working on many unrelated NPD projects. Conversely, stream concentration is high when members have been so exclusively involved in a given type of NPD projects that, for them, it may become career-defining. Overall, our results expand NPD research by highlighting the complementarity between attribute change and team change as well as the role of stream concentration as an important factor for the management of change in NPD projects.

Implications for Research on New Product Development

The literature on NPD projects has seen a steady growth in recent years, paralleling a diffusion of

[3]We include plots for the NPD project profiles where the moderating effect is statistically significant. The moderating effect is negative and statistically significant, though weaker, also for profile [3,1] (High Attribute Change, Low Team Change), and profile [2,3] (Moderate Attribute Change, High Team Change).

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project-based organizing across a wide range of different industries. In such contexts, NPD activities are executed by teams of workers that often come together and disband after task completion (Cattani, Ferriani, Frederiksen, and Täube, 2011; Patanakul, Chen, and Lynn, 2012). The increasingly temporary and often episodic nature of such organizations poses questions regarding the management of change in project-based settings and the embeddedness of team members in broader knowledge structures. Our results have major implications for both lines of inquiry.

Studies on the impact of team change on team processes and outcomes broadly support curvilinear effects, but do not provide specific evidence on interactions with other dimensions of change in NPD projects (e.g., Eling et al., 2016; Mathieu, Maynard, Rapp, and Gilson, 2008; Rink et al., 2013). Our findings on the complementarity between team change and product attribute change and our results on the benefits of coherence in the levels of change across both dimensions add to this stream of research. At the same time, recognizing that organizations can face limits to manipulate continuity vs. change in NPD projects, our study also highlights the importance of identifying and assessing factors that may constrain the manipulation of change in NPD projects. Our study attempts a first step in this direction by identifying stream concentration as a previously overlooked team-level constraint that negatively affects new product performance. Most notably, we find that the more team members have been working exclusively in the knowledge domain of the focal NPD project, the lower is new product performance.

Studies on the management of turnover in creative teams explored the effects of retaining a more or less intact core of team members developing a sequence of new products for a given producer (Brockman et al., 2010; Hollenbeck, Beersma, and Schouten, 2012; Skilton and Dooley, 2010). However, existing research has generally treated new products within a stream of related NPD projects as discrete entities (Carbonell and Rodríguez Escudero, 2019; Huckman et al., 2009; Reagans et al., 2005; Ren and Argote, 2011) and no empirical studies have investigated the consequences of repeat collaborators becoming more or less involved in a given NPD knowledge domain. Furthermore, previous research indicates that repeat collaborators can hamper creativity by influencing other members to "buy into" existing mental models (Carbonell and Rodríguez Escudero, 2019; Skilton and Dooley, 2010; Taylor and Greve, 2006). In contrast, our results suggest that the potential drawbacks of repeated collaboration are not only related to the sheer number of old-timers in a new project team (Katz, 1982) or how many times they have been collaborating together (e.g., Huckman et al., 2009), but to how much retained team members' careers concentrate on a given knowledge domain. Overall our results suggest that stream concentration represents a previously unexplored constraint contributing to our understanding of the conditions that affect the dynamics of NPD teams.

Implications for the Management of Change in New Product Development Projects

Our results focus on elements that managers of NPD teams can shape through their decisions: product attributes and team composition. It thus offers actionable insights to organizations that wrestle with tensions between continuity and change when developing new products that must join an existing successful portfolio. Star Trek producers, for instance, must reinvent their universe to appeal to younger audiences, but have to meet the occasionally unreasonable expectations of the existing "trekkies." Similarly, Activision Blizzard—a top video game publisher in the United States and one of the largest in the world—bases its fortunes on a few increasingly successful product franchises like the billion-dollar Call of Duty military shooter (Bradshaw and Lewis, 2019). Each year, developing a new instalment in the game franchise exposes the NPD team to tensions between continuity and change. Steering the next Call of Duty game away from previous editions may help the firm reach out to new audiences, but at the risk of upsetting hardcore fans. At the same time, continuity with past products may be perceived as complacency.

Our results suggest three specific recommendations for these types of businesses. First, organizations developing new products that join an existing set of products characterized by a strong identity and distinctive product attributes should aim for moderate change. This is consistent with the results obtained by Heath et al. (2015), in a study on the success factors of sequels in the movie industry. Second, product attributes and team composition are complementary choices that should be jointly managed. Third, some team members can become so much involved in a given knowledge domain that, for them, it becomes career defining. Firms should be aware of the possible negative implications of employing such team members. The acquisition of the *Star Wars* franchise and George Lucas's reaction to Disney's decision to avoid employing him in the production of *Star Wars* 7 provide a colorful example of the relevance of stream concentration for NPD projects: "They decided they didn't want to use [my] stories, they decided they were gonna go do their own thing. They weren't that keen to have me involved anyway. But at the same time, if I get in there, I'm just going to cause trouble. Because they're not going to do what I want them to do. All I would do is muck everything up. So, I said, 'Okay, I will go my way, and I'll let them go their way'" (Sandwell, 2015). The *Star Wars* franchise is career-defining for Lucas and his NPD experience is highly concentrated within this domain. Not employing potential team members that have a high level of stream concentration is therefore a core implication of our theory and findings for managers of NPD projects.

Limitations and Future Research Directions

Our study suffers from some limitations that open opportunities for future research. First, we might not have adequately accounted for the potential role of environmental turbulence in relation to decisions about change. The contemporary music industry presents both very low switching costs for artists and customers and a relatively stable landscape of genres and styles. Hence, artists and record labels must continue to introduce new products, primarily due to perceived opportunities for revenue (Askin and Mauskapf, 2017) and, to a lesser extent, to address the concern that existing products will become obsolete. In other industries, organizations may be under pressure to introduce new products and change product attributes because existing ones are quickly rendered obsolete (e.g., Eisenhardt, 2000). This could be a promising area for future research.

We also believe that more analysis is needed to explore the impact of change and stream concentration across organizational roles. Recent research suggests that core and peripheral roles can affect organizational performance directly (Brockman et al., 2010; Cattani and Ferriani, 2008) and indirectly (Carbonell and Rodríguez Escudero, 2019; Fonti and Maoret, 2016). One of the advantages of our analysis is that it allowed us to create complete individual-level profiles of team members and their career in the industry. We see this as an important condition to study additional contingencies such as the potential impact of the degree of specialization of individual team members. We hope our study will inspire future research in this direction.

Furthermore, behavioral tracking allowed us to assess actual product performance on a global scale in terms of unique listeners. However, this data could not be disaggregated according to consumer characteristics and therefore our results do not account for age or other individual traits that may reveal heterogeneity in the market response to change in new products. A potentially revealing study would be to examine whether the effects of change and stream concentration vary depending on the evolution of demand preferences.

Following prior research on the music industry, we measure NPD performance as the growth in the number of an artist's listeners. This is a direct measure of consumer response to a new product released by an artist and is related both directly to actual sales and indirectly to compensation (Passman, 2014). Moreover, rankings based on measures of consumption, such as the number of listeners, readers, reviews, or citations have been extensively used by scholars across management, marketing, psychology, and sociology (for a review see Rindova, Martins, Srinivas, and Chandler, 2018). Rankings are commonly used in various organizational settings to determine the relative standing of firms, products, and producers with direct financial implications. It is important to note that, although our measure may be interpreted as an indicator of the adoption of a new product, our study does not capture the dynamic perspectives typical of adoption and diffusion models. Further work in this area could focus on bridging the organization theory perspective on change in NPD projects that we propose with the literature that has focused on product adoption and diffusion (Spanjol et al., 2018). Studies focusing on consumer reactions to product upgrades could also offer further insights on the role of different organizational structures for NPD in the context of sequences of products connected by a common identity, or "iterated offerings" (Heath et al., 2015).

Finally, limiting the empirical context of our study to one specific industry eliminates cross-industry factors as possible explanations for differences in performance and reduces concerns about internal validity. At the same time, our empirical setting is characterized by low entry barriers, such as market intermediaries, which are more relevant

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in other industries and can impact NPD decisions. While additional research would be required to fully establish the applicability of our findings to other industries, we believe that some of the fundamental issues tied to the management of change in NPD projects and stream concentration are not inherently limited to our setting.

Overall, we believe that our study provides particularly valuable insights for NPD in contemporary industries characterized by project-based production and repeated collaboration among team members.

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Appendix Distinct Patterns of Change in New Product Development Projects: Examples

Type of New Product Development Project		Artist	Album
1_1	*Low Attribute Change, Low Team Change*	Bjork	Volta
		Nightwish	Amaranth
		Van Morrison	Keep It Simple
1_2	*Low Attribute Change, Moderate Team Change*	Kanye West	808s & Heartbreak
		Madonna	Hard Candy
		Snoop Dogg	Ego Trippin'
1_3	*Low Attribute Change, High Team Change*	Bloc Party	Intimacy
		Kylie Minogue	X
		Panic at The Disco	Pretty. Odd.
2_1	*Moderate Attribute Change, Low Team Change*	Coldplay	X & Y
		Prince	3121
		The Chemical Brothers	We Are the Night
2_2	*Moderate Attribute Change, Moderate Team Change*	50 Cent	Curtis
		Bon Jovi	Have a Nice Day
		Goldfrapp	Supernature
2_3	*Moderate Attribute Change, High Team Change*	Beck	Guerolito
		Franz Ferdinand	You Could Have It So Much Better
		Ladytron	Velocifero
3_1	*High Attribute Change, Low Team Change*	Bruce Springsteen	Devils & Dust
		Radiohead	In Rainbows
		The Cardigans	Super Extra Gravity
3_2	*High Attribute Change, Moderate Team Change*	Bon Jovi	Lost Highway
		Ludacris	Release Therapy
		Prince	Planet Earth
3_3	*High Attribute Change, High Team Change*	DJ Shadow	The Outsider
		Madonna	Confessions on a Dance Floor
		Rihanna	Good Girl Gone Bad

This table is intended to be a companion to Figure 1. It provides examples of specific new products to illustrate how each NPD project can be characterized by low, moderate, or high levels of change in product attributes and team members.