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RESEARCH ARTICLE

Two faces of decomposability in organizational search: Evidence from singles versus albums in the music industry 1995–2015

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Abstract

Research Summary: This study proposes that decomposability may generate a trade-off in search. This study compares a decomposed search (i.e., producing and evaluating a decomposed module) and an integrated search (i.e., producing and evaluating a full-scale product). While the former can allow firms to experiment with more alternatives than can the latter, it may be more vulnerable to imperfect evaluation because a larger number of promising alternatives could be omitted after the initial evaluation. The reason for this is that not only do more alternatives face an unlucky draw in their initial evaluation but also a decomposed search may lead firms to set a higher performance target for giving a second-chance opportunity. I test this theory and mechanisms by comparing singles (i.e., decomposed modules) and albums (i.e., full-scale products) in the music industry.

Managerial Summary: This study highlights a hidden cost of experimentation-oriented practices: an increased chance of terminating investment in promising business options (e.g., resources, technologies, and new business projects) after initial small-scale experimentation. A growing number of technological innovations (e.g., software development kits, cloud computing, and e-commerce platforms) have enabled firms to experiment with new business options by producing modules rather than full-scale products. These innovations benefit management practices for experimentation, such as lean start-up or design thinking, and have thus gained popularity among practitioners. This study suggests that while producing and evaluating a module enables firms to experiment with more options, it may increase the chance of terminating investment in promising business options because firms may set a higher performance target for subsequent investment after initial small-scale experimentation.

KEYWORDS

alternative evaluation, aspirations, behavioral theory of the firm, decomposability, evolutionary perspective on organizational search

1 | INTRODUCTION

Simon's (1962) work on the architecture of complexity provides building blocks for analyzing how the properties of complex systems affect the discovery of promising alternatives (e.g., resources, technologies, or products). He emphasizes that one of the fundamental features of complex systems is decomposability, the fact that patterns of interactions among elements of a complex system are not diffuse but tend to be tightly clustered into nearly isolated subsets of interactions (i.e., modules). Subsequent theoretical studies have shown that decomposability helps firms discover a promising option by facilitating module-level experimentations (i.e., producing more variations) (Baldwin & Clark, 2000; Ethiraj & Levinthal, 2004; Fang & Kim, 2018; Kogut & Bowman, 1995; Marengo, Dosi, Legrenzi, & Pasquali, 2000; Schilling, 2000). As Knudsen and Levinthal (2007) note, a critical facet has been largely underexplored in this tradition, namely, how firms select and retain the promising ones among experimented options. To advance the understanding of this topic, I explore the roles of decomposability in the discovery of new promising alternatives in the different stages of organizational search. I argue that decomposability may facilitate experimentation in the variation generation stage but can decrease the efficacy of selection and retention.

The evolutionary perspective on search (e.g., Knudsen & Levinthal, 2007; Posen & Levinthal, 2012; Zollo & Winter, 2002) provides useful insights into how decomposability can create a trade-off across different stages of the discovery of new alternatives. First, some possible alternatives are experimented in the variation generation stage. The realization from these draws is then evaluated, and some of the highly evaluated alternatives will be selected and retained. Across the different stages, I compare the two modes of search: (a) the case in which firms experiment with and evaluate an alternative by producing a full-scale product (i.e., integrated search) and (b) the case in which firms experiment with and evaluate an alternative by producing a decomposed module (i.e., decomposed search). For example, in the music industry, firms can experiment with a new artist and evaluate talent of the new artist by either producing an album (i.e., a release of multiple songs—an integrated search) or producing a single (i.e., a release of a single song—a decomposed search). Integrated search has been the base mode of search in many real-world settings. For example, over the past two decades, a large number of music companies (about 60.7% of the music companies in the world) have produced only albums, but other companies have produced singles.[1]

First, I argue that a decomposed search may be beneficial during the variation generation stage. March and Simon (1958) note that as choice sets are not available ex ante to firms but must be constructed, experimenting with new alternatives is the first step of a search. I emphasize that decomposability lowers the cost of generating an alternative (Ethiraj & Levinthal, 2004; Marengo et al., 2000; Schilling, 2000) because a decomposed search helps managers focus on a subset (i.e., a smaller number of attributes) of the whole search space (i.e., all possible attributes). If firms experiment with more new alternatives, firms will benefit because it increases the chance of discovering promising alternatives with higher upside potentials.

However, the gains from a decomposed search may hurt the discovery of promising alternatives in the selection and retention stage. Knudsen and Levinthal (2007) note that the evaluation of alternatives is likely to be imperfect. A promising option that faces an unlucky failure in the initial evaluation may be mistakenly considered unpromising by firms and lose future chances in these firms. Under the condition of noise in evaluation (e.g., Caves, 2000; Fang, Kim, & Milliken, 2014; Knudsen & Levinthal, 2007), it is challenging for firms to infer an alternative's true quality from a one-shot experimentation result. As Simon (1955) notes, if the evaluated performance of an alternative satisfies a performance target (i.e., a minimum performance criterion), the firm will select and retain the option for future use. Otherwise, firms will search for other alternatives. I argue that when firms implement a decomposed search, they are likely to miss out on a larger number of promising options after initial evaluations than when firms implement an integrated search. This is because of the following two reasons.

First, when firms implement a decomposed search, they will experiment with more new alternatives than when firms implement an integrated search only. In the presence of noise, as firms experiment with more alternatives, more alternatives will face an unlucky draw in their initial evaluation. Promising alternatives are not exceptions to this tendency; some will also face an unlucky draw and be evaluated as unpromising despite their underlying quality. Second, I argue that a decomposed search may increase the performance target because implementing a decomposed search increases the number of outside options that firms can experiment with, resulting in a higher expected quality of the best option among these outside options. The higher performance target may lead to an early termination of investment in each alternative. Thus, firms that implement a decomposed search are more likely to make omission errors in giving second chances to promising options.

I demonstrate the dual roles of decomposability in organizational search based on the recorded music industry, where (a) artists' talent (i.e., each artist is an alternative in the music industry) is the most important source of creativity and profit and (b) singles (i.e., decomposed modules) have coexisted with albums (i.e., full-scale integrated products) since the early 20th

[1]Among single-producing music firms, 61.5% firms produced singles as well as albums; 38.5% firms produced singles only.

century. In particular, I compare (a) music firms that implemented integrated search only (i.e., album-only producing firms) with (b) music firms that implemented decomposed search (i.e., single-producing firms). I collect and match multiple databases: MusicBrainz, AcousticBrainz, Spotify APIs, and Discogs. The sample covers 114,488 artists; 1,026,309 songs; and 9,667 music firms in 29 countries from 1995 to 2015. The results from OLS models, instrumental variable estimators, and matching estimators support my prediction. First, single-producing firms experiment with 35.22% more new artists, some of whom may turn out to be talented artists. However, single-producing firms are 58.89% more likely to miss out on top-tier artists who experience failure with their first releases. Approximately 80% of the increase in neglecting top-tier artists came from the increases in the number of new artists experimented, and the other 20% of the increase came from a higher performance target.

This study contributes to the core tenets of the behavioral theory of the firm. This study's theory and findings have useful implications regarding the roles of decomposability in search by bridging the three strands of the behavioral theory of the firm: (a) the literature on the architecture of complexity (e.g., Baldwin & Clark, 2000; Ethiraj, Levinthal, & Roy, 2008; Simon, 1962); (b) the literature on performance targets and aspirations (e.g., Cyert & March, 1963; Greve & Gaba, 2017; Keum & Eggers, 2018); and (c) the literature on the role of imperfect evaluation and noise (e.g., Cyert & March, 1963; Fang et al., 2014; Knudsen & Levinthal, 2007).

First, strategy scholars have examined the role of experimentation in the discovery of new solutions (e.g., Eggers, 2012; Eggers & Green, 2012; Posen, Martignoni, & Levinthal, 2013). Little attention has been given to how decomposability shapes experimentation with new alternatives such as new resources, technologies, assets, or workers. Specifically, this study contributes to the burgeoning empirical literature on decomposability and complexity (e.g., Ethiraj & Zhou, 2019; Ganco, 2013; Piazzai & Wijnberg, 2019; Zhou, 2011). As Baumann, Schmidt, and Stieglitz (2019) note, to date, the theoretical work has been only incidentally complemented by empirical research, and the theoretical and empirical studies remain rather disconnected. I attempt to tighten the link between theoretical and empirical work by analyzing an unusual setting to measure decomposability and its role in discovering new promising alternatives.

Second, this study speaks to the literature on performance targets and aspiration levels (e.g., Cyert & March, 1963; Greve, 2003). Changes in search behavior in response to performance below a performance target have been actively researched (Greve & Gaba, 2017). Firm behavior is guided by the discrepancy between the performance target and actual performance (e.g., Bromiley, 1991; Keum & Eggers, 2018). Although there are numerous studies on the consequences of financial performance aspirations (e.g., ROS, ROA, or ROE), little attention has been given to how organizational performance targets are determined (Bascle & Jung, 2022; Greve & Teh, 2018). In particular, little empirical research has been done on this topic. As Shinkle (2012) notes, "the literature lacks robust empirical evidence on the antecedents of aspirations[performance targets]. Most studies rely on the formal theoretical model of behavioral theory to infer aspiration levels[performance targets]." This study provides empirical evidence as well as a theoretical argument that decomposability plays an important role in shaping the performance target.

Third, this study advances our understanding of the ramifications of imperfect evaluation in complex problem-solving. As Zollo and Winter (2002) note, a search is primarily carried out through efforts aimed at generating the necessary range of new options as well as selecting the most appropriate ones. In selecting appropriate options, while prior studies have examined heterogeneity in forecasting ability and its origin (e.g., Adner & Helfat, 2003;

Denrell & Fang, 2010; Makadok & Walker, 2000), this study views a decomposed search as a heuristic to complement forecasting abilities. Theoretically, I pinpoint a hidden drawback of decomposed search (i.e., the omission error in giving a second chance to the existing option) in search.

2 | THEORY AND HYPOTHESES

Studies on the behavioral theory of the firm have long recognized the multi-phased nature of the innovation process (e.g., Keum & See, 2017; Knudsen & Levinthal, 2007; Zollo & Winter, 2002). This process starts with a search for new options (i.e., variation generation), followed by an evaluation of those new options, then concludes with selection and retention. This perspective on search provides important insights into how decomposability can create trade-offs across different phases of the innovation process.

2.1 | Decomposability in the variation generation stage

Since Simon (1955) characterized much of the discovery process as a sequential search process, management scholars have explored the problem that arises with the discovery of new alternatives. The optimal solution to the discovery problem draws on the "bandit" literature (e.g., Denrell & March, 2001; Kogut & Kulatilaka, 1994; Lee & Puranam, 2016; Posen & Levinthal, 2012). This tradition describes experimentation as a trial-and-error process (e.g., Kulkarni & Simon, 1990; Thomke, Von Hippel, & Franke, 1998). Through experimentation, firms can reveal information about new alternatives; if one or more new options outperform existing options, the new ones will replace the old. Leiponen and Helfat (2010) note that the likelihood of obtaining a favorable draw from a distribution of payoffs increases as the number of draws increases. Therefore, the benefits of experimentation are derived from information on whether new choices have upside potential.

An integrated search incurs a higher cost of experimenting with new alternatives because an integrated search requires developing a full-blown product with more elements. In particular, a full-blown product increases inputs such as resources and time for design and development (Ethiraj & Levinthal, 2004). Moreover, the production of a full-blown product is more complex than that of a module (Baldwin & Clark, 2000). In reality, many firms implement integrated search only. For example, in the music industry, for a long time (especially in the 1980s and 1990s), many music firms produced albums only (i.e., integrated search); these album-only-producing firms experimented with a new artist (i.e., a new-to-the-world artist) by producing an album, which is a costly option. The high cost of experimentation limits the number of alternatives that firms can experiment with (Baldwin & Clark, 2000; Loch, Terwiesch, & Thomke, 2001). Because of this limitation, firms that implement integrated search only will be less likely to engage in multiple alternatives.

In contrast to the integrated search-only approach, if firms implement a decomposed search, they can experiment with more options than when firms implement an integrated search only. A decomposed search greatly reduces the costs of experimenting with new alternatives because experimenting with a partial product (e.g., a module) generates useful information on the potential of an alternative (Baldwin & Clark, 2000; Ethiraj & Levinthal, 2004; Schilling, 2000). With the application of a decomposed search, it is possible to test an alternative without producing a whole system. The low cost of experimentation allows firms to experiment with more new options. Indeed, a decomposed search slashes costs, freeing up experimentation capacity and enabling what-if experiments that, in the past, have been either prohibitively expensive or nearly impossible to carry out. In contrast, the high cost of experimentation has long put a damper on companies' attempts to test a new alternative (Thomke, 2003). Empirical research has demonstrated that the low cost of experimentation facilitates testing for more new products, technologies, and start-ups where the outcome of success follows a highly skewed distribution. For example, Ewens, Nanda, and Rhodes-Kropf (2018) provide evidence that the low cost of experimentation encourages venture capitalists to invest in more new start-ups, in an investment strategy called "spray and pray."

In summary, decomposition reduces the cost of experimenting with new alternatives. Firms that implement a decomposed search will experiment with more options. Therefore, I hypothesize the following:

Hypothesis (H1). *When firms implement a decomposed search, they will experiment with more new alternatives than when firms implement an integrated search only.*

2.2 | Decomposability in the selection and retention stages

I argue that under imperfect evaluation, the gains from a decomposed search in the variation generation stage may encounter a trade-off with disadvantages in the selection and retention stages. Nelson (1961) notes that the problem of choosing among alternatives is a difficult one, and it is easy to make choices which, ex post, turn out to be the wrong ones in the presence of noise. Behavioral models of selection can be distinguished from conventional economic models of selection, in part, because evaluating alternatives is likely to be imperfect (e.g., Fang et al., 2014; Knudsen & Levinthal, 2007). In the presence of noise, firms may erroneously reject a superior alternative. For example, talented artists who face an unlucky failure from their initial releases may mistakenly be considered untalented by firms and lose future production opportunities.

Second, as Simon (1955) notes, if the evaluated performance of an option satisfies a minimum performance criterion, the firm will select and retain the option for future use. Otherwise, firms will search for other alternatives. Subsequent literature has christened such minimum criterion as the performance target or aspiration level (e.g., Audia & Greve, 2006; Cyert & March, 1963; Gaba & Joseph, 2013; Greve, 2003; Lant & Shapira, 2008).[2] Here, I focus on a type of omission error in the selection and retention stages: missing out on promising alternatives after the first evaluation of those alternatives. This type of error is especially likely to occur when the alternative faces an unlucky draw in its initial evaluation, and the evaluated performance does not satisfy the performance target. In the presence of noise in performance evaluations, no matter whether firms implement a decomposed search or an integrated search, this type of omission error is inevitable. I argue that when firms implement a decomposed search, more alternatives will be likely to be missed out on after its first evaluation than when firms implement an integrated search. This is because of the following two reasons.

[2]Regarding studies on performance targets (or aspiration levels), Shinkle (2012) and Greve and Gaba (2017) provide comprehensive reviews of this topic.

The first reason is rather straightforward. As I derive in Hypothesis (H1), when firms implement a decomposed search, firms will experiment with more new alternatives than when firms implement an integrated search only. In the presence of noise, as firms experiment with more alternatives, more alternatives will face an unlucky draw in their first evaluation. Promising alternatives are not exceptions to this tendency; some of these alternatives will also face an unlucky draw and be evaluated as unpromising despite their underlying quality. Therefore, the observed performance of more alternatives in the first evaluation will fall below the performance target, and these alternatives will not be selected for future use.

Second, I argue that a decomposed search may increase the performance target necessary for being selected and retained, resulting in a higher chance of missing out on promising alternatives that were evaluated as unpromising ones in their initial evaluations (i.e., not giving a second evaluation chance to a promising alternative). In the presence of noise, if the performance target becomes higher, firms will be more likely to miss out on promising alternatives after the first evaluation. Why could a decomposed search lead to a higher performance target? I argue that the formation of the performance target relies on the expected quality of the best option among outside options. As I explained in deriving the first hypothesis, a decomposed search increases the number of new alternatives that firms can experiment with. The distribution of outcomes in many settings, such as the discovery of talent, new technologies, start-up ideas, and new business opportunities, tends to be highly skewed (Ewens et al., 2018; Nelson & Winter, 1978). Under such a skewed distribution, the expected quality of the most promising option that firms can discover will matter. If the number of options firms can experiment with increases, the expected quality of the most promising option will increase. More formally, for a random variable x_i from any distribution, the expected quality of the most prominent option of the firm is $E(max(x_1, x_2, ...x_k))$ when the number of new options that the firm can experiment with is k. When $k<n$, $E(max(x_1, x_2, ...x_k))$ is smaller than $E(max(x_1, x_2, ...x_n))$. Therefore, more options will lead to a higher expected quality of the most prominent outside option.

Even if two alternatives show the same evaluated performance in their initial evaluations, if firms implement a decomposed search, they will be less likely to give a second evaluation chance than firms that implement an integrated search only. Figure 1 visualizes this mechanism by comparing a decomposed search and an integrated search. In Figure 1, the true quality of an alternative is 5, and the evaluated performance is a random draw from the normal distribution, $N(5, 1)$. Let me assume that 5 is high enough to be a promising alternative. A decomposed search has a higher performance target (i.e., a higher expected quality of the most promising outside option); for example, in Panel (a), the performance target of the decomposed search is 4, and the chance of missing out on promising options with the quality five will be 15.85%. However, in Panel (b), an integrated search has a lower performance target (i.e., a lower expected quality of the most promising outside option). As the performance target is 3, the chance of missing out on promising options with the quality level 5 will be 2.27%, which is lower than that of a decomposed search.

In summary, under imperfect evaluation, a decomposed search may increase the chance of missing out on promising alternatives after an initial evaluation. Thus, I hypothesize the following:

> **Hypothesis (H2).** *When firms implement a decomposed search, they will be more likely to miss out on promising alternatives after an initial evaluation than when firms implement an integrated search only.*

3 | EMPIRICAL CONTEXT: THE RECORDED MUSIC INDUSTRY

3.1 | The discovery of new artists in the recorded music industry

Music firms are called record labels or, more simply, labels. In this study, I focus on music firms that conduct the talent scouting and development of new artists (i.e., an artist is a type of alternative), called "artists and repertoire (A&R)," and that maintain contracts with recording artists or bands. The International Federation of Phonographic Industry (2015, p. 9) describes music as an investment-intensive business, as the first major activity that music firms have traditionally undertaken is the discovery of new artists (i.e., new-to-the-world artists). Indeed, music firms' investment in A&R and marketing in 2014 totaled more than $4.3 billion, which accounts for more than 10% of global music sales (IFPI, 2015). According to the IFPI, in 2014, it cost at least $500,000 and an average of $1 million to experiment with a new artist. Common features of contracts signed with artists include the payment of advances, recording costs, tour support, video production, and marketing and promotion costs, as shown in Table 1. In comparison with music firms, online music providers, including online music service providers such as Spotify, iTunes, YouTube, or SoundCloud, spend no money on an upfront investment for talent discovery. This phenomenon indicates that music firms remain the largest upfront investors in artists' careers.

Many would-be artists seek to make their music available to consumers. These potential music artists differ substantially in both their ex ante promise (how broadly appealing the artist would be if their work were produced) and in their ex post success in commercialization (how successful they become) (Benner & Waldfogel, 2016). Caves (2003, p. 74) emphasized that "nobody knows," which refers to "the fundamental uncertainty that faces the producer of a creative good. All inputs must be incorporated and the good presented to its intended customers before the producer learns their reservation prices." This is the main reason why this study focuses on commercialization rather than the pre-commercialization process as experimentation. Moreover, it is almost impossible to collect data on pre-commercialization experimentations (either artists or songs).

Even artists cannot accurately assess their own talent to achieve commercial success (Caves, 2000; Tervio, 2009). For example, Elvis Presley is one of the most significant cultural icons of the 20th century and is referred to as "the King of Rock and Roll." Guralnick (2012) notes that Elvis did not understand his talent, and he chose Sun Records, a small independent music firm in the 1950s, in the hope of being discovered. After he finished his audition with Sun Records, the CEO, Sam Phillips, and his secretary wrote Elvis' name, and the secretary added her own commentary: "Good ballad singer. Hold." Today, Sun Records is known as the music firm where a music genre, "rock and roll," was born because it discovered Elvis Presley. This anecdote evidently shows that it is challenging for firms to evaluate artists' talent ex ante.

Even after having a chance to produce and release music, artists may face unlucky commercial results with their first release. The talent of an artist partially determines the odds of the success of their music. After failures with their first releases, many artists experience terminations in their contracts. They are forced to seek new opportunities with other music firms. My data analysis indicates that, from 1960 to 2015, only 17% of artists had a second production chance with the same firm. The other 83% had to leave their first music firm. Some of the artists who left the first firm became top-notch, talented artists. One of the key informants, from Sony Music Entertainment, introduced Mumford & Sons, a music group that experienced failure with

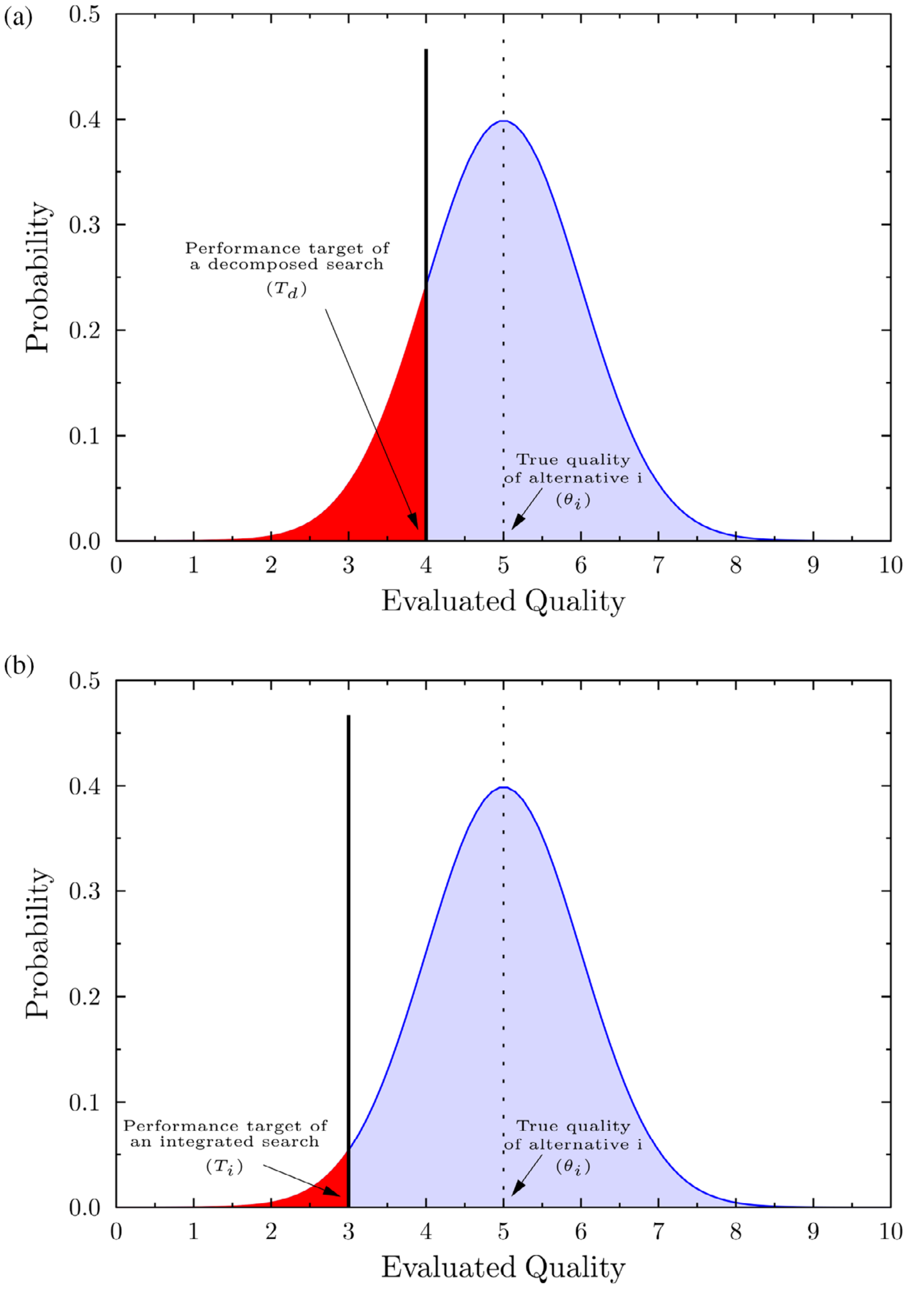

FIGURE 1 Decomposed search versus integrated search in performance target and omission errors after first evaluation. The true quality of alternative i is 5, and the evaluated performance of an alternative is a random draw from a normal distribution ($N(5, 1)$). The dark-colored (red-colored) area represents the omission errors made in giving second evaluation chances to an alternative

their first release, as an exemplary case in which Sony missed out on talented artists after an initial failure. The group initially signed with Chess Records (a subsidiary of Sony Music Entertainment) and debuted in 2009 with the single "Mumford & Sons." As executives at Chess

TABLE 1 Cost of producing a release in the music industry

Item	Cost
Cash advance	$50,000–350,000
Recording	$150,000–500,000
Video production	$50,000–300,000
Tour support	$50,000–150,000
Marketing and promotion	$200,000–700,000
Total	$500,000–$2,000,000

Note: Source: International Federation of the Phonographic Industry report, 2014.

Records were disappointed by the commercial outcome of the group's first single, the company did not extend the contract with Mumford & Sons. The group had to leave, but, luckily, they were given a second chance with another company, Island Records, a subsidiary of Universal Music Group. At Island Records, Mumford & Sons made popular songs like "I will wait," and they won a Grammy award in 2014. This case is considered one of Sony Music's biggest mistakes in the 2000s.

3.2 | Singles versus albums

A release is a broad term that covers two different forms: singles or albums. Music firms commonly classify a release with a small number of songs as a single and a release with a large number of songs as an album (which has, on average, 12 songs in my sample). If a music firm produces some of its work as a single (i.e., a decomposed search) instead of an album (i.e., an integrated search), the production and marketing cost is smaller. In addition, another key informant from Sony Music Entertainment states that producing albums requires a greater cost and commitment than producing singles: "Albums are much more expensive. More studio time, more writing, more production hours, more involvement of producers, more people's input [are] needed on an album versus a single. [Albums] also require far more hours in the recording and mixing studios, more hours of mastering. It comes out to [albums being] … more expensive than singles in terms of music production costs."

Many new artists debuted with singles.[3] Elvis Presley made five singles with Sun Records. Another example is the discography of Aqua, a Danish-Norwegian dance-pop band. This band debuted with a single and made singles until they had an international breakthrough with their single, "Barbie Girl," in 1997. More recently, "Cheerleader," a song recorded by Jamaican singer OMI, was released as a single by OUFAH, an independent music firm. The song appeared on the Billboard Hot 100 in the United States in May 2015 and ranked first on 26 countries' music charts.

[3]A new artist usually debuts with a release, which is not a part of an album consisting of different artists' singles. As Musicians' Union (2022) notes, a typical record deal contract with a music firm has a clause ensuring that the artist's work will see the light of day and committing the music firm to distributing and marketing at least one release consisting of a signed artist's music. Due to this so-called "release commitment" clause, it is difficult to find a case in which singles (the first releases of different individual artists) were collected together into a CD or an LP that was then sold on the market as the different artists' first album.

How do music firms and artists choose between singles versus albums? Passman (2014) notes that artists usually have little say on this part, and the company usually decides the format of music releases (i.e., a single or an album). Indeed, as emphasized by Passman (2014, p. 64), "this is not only true for new artists, but also for mid-level and even superstars." Music firms tend to have a high level of bargaining power over artists because music firms play a critical role in producing and commercializing music (Caves, 2000; Passman, 2014). Coyle (2004, pp. 32-33) vividly describes this situation as follows: "Yet what they[artists] lack as individual artists is the enormous marketing muscle it takes [to] turn a great song into a hit." Because of the essential role of music firms and the perennial over-supply of would-be artists,[4] "record deals are traditionally structured with the company having the smallest obligation that it can negotiate, while keeping the option to get as much product as possible" (Passman, 2014, p. 64). For a regular record deal, a company usually commits to record one release (either a single or an album)[5] of an artist and has the option to produce an additional four or five releases, each of which is at the company's election.

The artistic and commercial importance of the single (as compared to the album) has varied over time and across countries. Britt (1989) notes that "the single enjoyed its peak in the 1960s [during] the rise of musical phenomena like the British Invasion, Motown, and R&B." However, starting from the mid-sixties, the album became a greater focus as artists created albums of coherent, themed songs. Bob Dylan's first album, *Bob Dylan*, is an exemplary case. As a result, singles generally received increasingly less attention in the United States, Japan, and South Korea compared to albums. However, in other countries like the United Kingdom, the Netherlands, and Australia, singles survived as a different form of music; singles continued to be produced and sold, and they maintained their popularity in these countries.

In this study, I compare two types of firms: (a) firms producing albums only (i.e., firms implementing an integrated search only) and (b) firms producing singles (i.e., firms implementing a decomposed search; 68.5% of these firms produce albums as well as singles; the other 31.5% firms produce singles only). For all countries, before digitization, albums were the main format of releases. Table 2 summarizes the link between the hypotheses and the empirical setting.

3.3 | Entry of iTunes music store

Firms' decision-making between two different forms (singles vs. albums) was greatly affected by digitization. In particular, digitization shook the music industry in the late 1990s with the MP3 format, introduced in 1993. Many people illegally downloaded songs through file-sharing websites like Napster. Apple opened the iTunes Music Store (hereafter "iTunes"), the first online music store, in 2003 as a way to solve the piracy problem. Steve Jobs succeeded in convincing the five major labels to offer their content through iTunes, which provided a market for songs as well as albums. The impact of iTunes was great, as indicated by the fact that iTunes accounted for 88% of the U.S. online music market share in the late 2000s. The popularity of

[4]For a new-to-the-world artist, the chance of getting signed with a music firm is low. A recent survey done by ReverbNation and Digital Music News (2016) revealed that more than 75% of (unsigned) artists want to get signed with music firm(s), but in reality, most artists do not have such fortune (ReverbNation & Digital Music News, 2016). Because competition for getting signed with music firms is fierce, the bargaining power of music firms usually dominates the bargaining power of new artists unless they have some popularity before the signed deal.

[5]A standard record deal (i.e., contract) was a typical record deal before the digital revolution; the contract was based on the number of artists' albums that music firms own the copyright. A standard record deal is no more standard after the digital revolution; single deals, which are based on the number of singles, became standard in the industry.

TABLE 2 Link between theoretical constructs and empirical context

Theoretical construct	Implementing a *decomposed search*	Implementing only an *integrated search*
Empirical definition	Music firms producing singles and album(s)	Music firms producing only album(s)
Sample proportion	39.3% of the sample firm-years	60.7% of the sample firm-years
Variation generation	Producing and commercializing the first **single** or first **album** of each artist	Producing and commercializing the first **album** of each artist
Selection and retention	Giving a second chance (production and commercialization) to an artist after evaluating the commercial outcomes of the first release	Giving a second chance (production and commercialization) to an artist after evaluating the commercial outcomes of the first release
H1-dependent variable: Number of new artists	Prediction: Experimenting with **more** new artists due to the low cost of experimentation	Prediction: Experimenting with **fewer** new artists due to the high cost of experimentation
H2-dependent variable: Number of talented artists who were missed after producing and commercializing their first release	Prediction: Missing out on a **larger** number of the top 20% talented artist(s) if their song popularity is below the top 10% popularity score	Prediction: Missing out on a **smaller** number of the top 20% talented artist(s) if their song popularity is below the top 10% popularity score

singles increased after the introduction of iTunes. This change brought about by iTunes increased music firms' incentive to produce singles. In 2004, only 19% of music firms produced a single(s) in the United States, but this proportion increased to 33% in 2011.

Beginning in 2004, iTunes became available in many countries other than the United States. Online Appendix B summarizes the history of iTunes' market entry into foreign countries. The timing of iTunes' introduction varies across different countries. Apple attained great success in the world music market. On the October 10, 2012, the iTunes Store was reported to have a 64% share of the global online music market. For example, the entry of iTunes into Japan in August 2005 was successful. The popularity of singles increased significantly after the introduction of iTunes in Japan. The proportion of single-producing firms in Japan increased from 35% in 2004 to 74% in 2011. I use iTunes' staggered entries into 29 countries as an instrumental variable to mitigate a potential concern regarding endogeneity between single production and the talent level of the artists. I further explain this issue in the following methodology section.

4 | EMPIRICAL STRATEGY

4.1 | Sample

The sample consists of all music production firms reported on the MusicBrainz database from 1995 to 2015. The sample includes only music production firms because other types of music firms lack A&R executives or teams, who search for and recruit new artists. I choose 29 countries that have more than 200 unique music production firms in the MusicBrainz database.

I exclude firm-years in which firm i does not release any song at year t. The final sample consists of 29,317 firm-years associated with 9,667 firms; the panel is unbalanced.

4.2 | Variables

4.2.1 | Independent variables

When I test the first and second hypotheses, the unit of analysis is the firm-year observation. The independent variable is a dummy, $Dummy\_Firm\_Single_{it}$, that is equal to 1 when at least one release of firm i is released as a single in year t and is otherwise 0.[6] Instead of a continuous variable, I employ a dummy variable as the main variable. This is because the expected quality of the most promising outside options (i.e., the expected talent level of the most talented artist among new-to-the-world artists that firms may experiment with) critically depends on whether firm i produces at least one single (i.e., implements decomposed search). To check the robustness of the results, I use two alternative, continuous measures of this variable, namely, the ratio of singles to all releases of firm i in year t and the average number of songs per release of firm i in year t, in the additional analyses.

4.2.2 | Dependent variables

The first dependent variable measures the number of new artists (i.e., new-to-the-world artists, $Number\_New\_Artists_{it}$) in music firm i at year t. Second, I measure the case of missing out on talented artists after the failure of their first releases with the variable, $Miss\_Talented\_Artist_{it}$, which is the number of new artists (who were given the chance of producing an initial release by firm i in year t) who rank in the top 20% in terms of lifetime popularity but experienced failure with their first release (which was not included in the top 10% of popular songs) and then moved to another firm to produce their subsequent release(s). The cutoffs (i.e., top 20% lifetime popularity and top 10% song popularity) are based on my interview with a former EMI producer, who notes that only 10% of releases break even and that these songs are made mostly by top 20% artists. I test the robustness of the results to different cutoffs and find that the results are qualitatively identical. I drop nine artists who were let go after their first release and came back to the same firm for later releases (i.e., their third or later releases). I use lifetime popularity scores from the Spotify Echo Nest API and song popularity scores from the Spotify Web API. I use unique international standard recording code ids, song names, and artists' names for songs to match the Spotify Web API and the MusicBrainz data. As shown in Figure 2, both lifetime popularity and song popularity have skewed distributions.

4.2.3 | Control variables

I control for (a) genre complexity of firm i's main genre (by following Piazzai & Wijnberg, 2019; the details are in Online Appendix C); (b) the number of songs (lag 1 year) as a firm size proxy;

[6]Occasionally, music firms make compilation albums by bundling various artists' previously released popular songs. Thus, I drop such compilation albums from the sample.

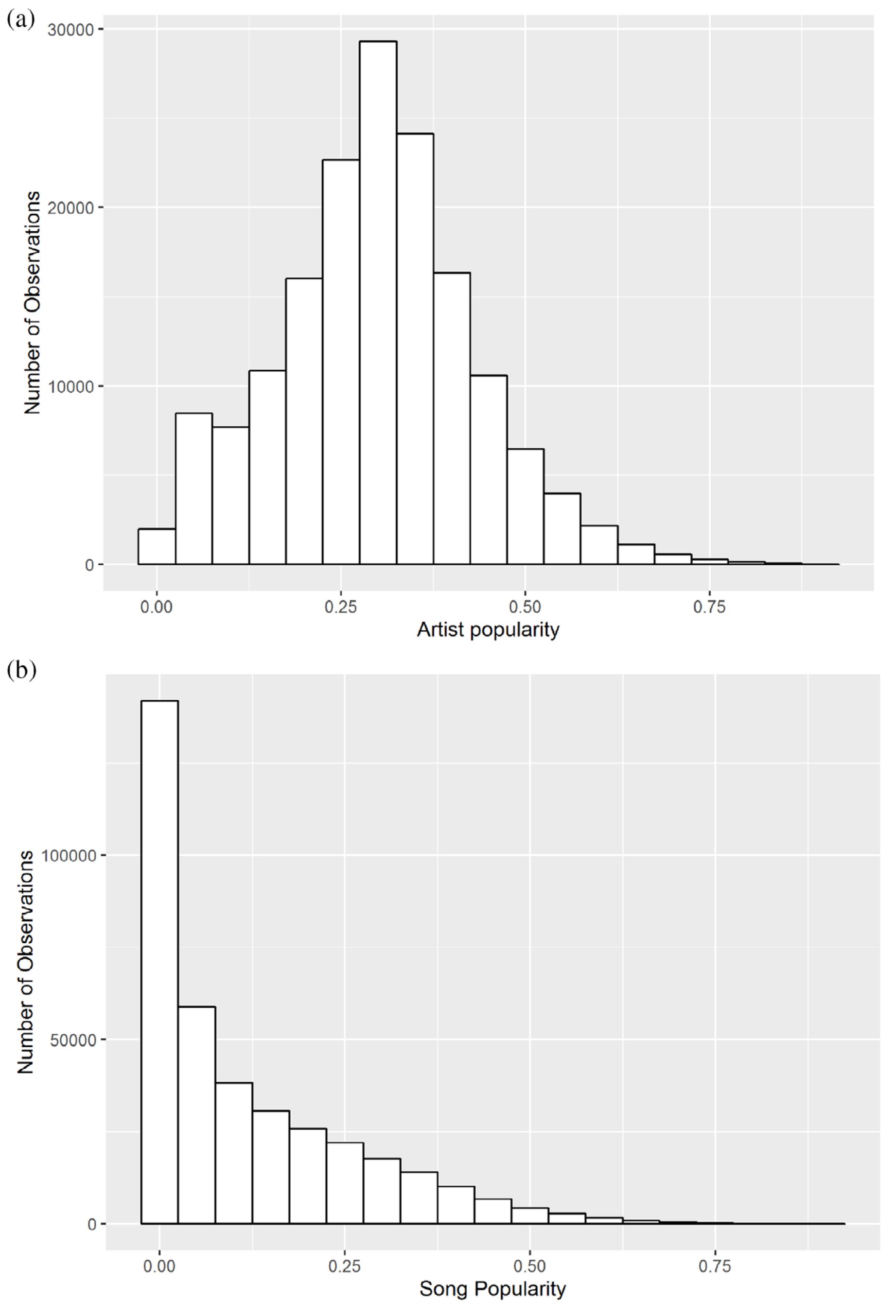

FIGURE 2 Popularity distributions. I excluded observations with popularity equal to 0 from both distributions. The figure shows that the popularity distributions are highly skewed. Additionally, it demonstrates that the song popularity distribution in Panel (b) is more skewed than the artist lifetime popularity distribution in Panel (a)

and (c) the mean number artists' prior releases (lag one year) as a firm status proxy. I also include (d) a dummy that takes the value of one if firm i produced at least one top-5% song in the previous year; (e) the Herfindahl index for music genres in firm i; (f) a dummy for entrepreneurial firms (firm age $\leq$5); (g) year dummies; (h) genre dummies; and (i) country dummies.

4.3 | Empirical specification

4.3.1 | Baseline OLS models and endogeneity issues

I use OLS regressions as the baseline tests. I add a vector of control variables that might influence music firms' decisions on producing singles. Thus, the initial specification is

$$Number\_Artists_{it} = \beta_0 + \beta_1 Dummy\_Firm\_Single_{it} + \beta_2 X_{it} + C_i + G_{it} + T_t + F_i + e_{it},$$

$$Miss\_Talented\_Artists_{it} = \beta_0 + \beta_1 Dummy\_Firm\_Single_{it} + \beta_2 X_{it} + C_i + G_{it} + T_t + F_i + e_{it},$$

where i is the indexes firms, t is the indexes calendar year, X_{it} is a set of observable characteristics of the firm as described above in control variables, C_i is the country fixed effect, G_{it} is the genre-fixed effect, T_t is the year-fixed effect, and F_i is the firm-fixed effect. *SE*s are clustered at the firm level.

Whereas the above equations control for the correlation between producing singles and the control variables, concerns may still arise about selection based on omitted variables (Angrist & Pischke, 2008; Chang, Kogut, & Yang, 2016; Hamilton & Nickerson, 2003; Semadeni, Withers, & Trevis Certo, 2014; Wooldridge, 2013). In an ideal experimental design, I would randomly assign single production status and measure the ex post difference in the dependent variables. In practice, I observe changes in both the production of singles and the dependent variables.

4.3.2 | Two-stage least squares estimator (instrumental variable estimators)

I attempt to address this endogeneity and omitted variable issue by employing two-stage least squares estimators (2SLS) (Angrist & Pischke, 2008; Wooldridge, 2013). To do this, I utilize two instrumental variables: (a) the staggered introduction of iTunes and (b) the country-level proportion of albums to all releases in the previous year. In the first stage regression, I estimate the following equation: $Dummy\_Firm\_Single_{it} = \beta_{IV} Z_{it} + \mu_{it}$, where Z_{it} is a set of firm characteristics, the other fixed effects, and instrumental variables, and μ_{it} is an error term. Then, I estimate the following second-stage OLS regression model.[7]

$$\begin{aligned} Number\_Artists_{it} = {} & \beta_0 + \beta_1 Dummy\_F\hat{i}rm\_Single_{it} + \beta_2 X_{it} + C_i + G_{it} + T_t + F_i \\ & + \left[\eta_{it} + \beta_1 \left(Dummy\_Firm\_Single_{it} - Dummy\_F\hat{i}rm\_Single_{it}\right)\right] \end{aligned}$$

$$\begin{aligned} Miss\_Talented\_Artists_{it} = {} & \beta_0 + \beta_1 Dummy\_F\hat{i}rm\_Single_{it} + \beta_2 X_{it} + C_i + G_{it} + T_t + F_i \\ & + \left[\eta_{it} + \beta_1 \left(Dummy\_Firm\_Single_{it} - Dummy\_F\hat{i}rm\_Single_{it}\right)\right] \end{aligned}$$

[7]One approach to estimating these two-stage equations is manually estimating the first-stage *SE*s and then plugging their fitted values into the second-stage regression model. However, as Angrist and Pischke (2008) note, the OLS *SE*s produced through this manual approach are incorrect because the OLS *SE*s are the *SD* of $\eta_{it} + \beta_1 (Dummy\_Firm\_Single_{it} - Dummy\_F\hat{i}rm\_Single_{it})$ while the correct 2SLS *SE* is the *SD* of η_{it} only. To prevent this mistake, I use the *ivregress 2sls* and *xtivereg* routines in Stata because this approach correctly estimates the standard errors of the second-stage regression (Angrist & Pischke, 2008).

Regarding the instrumental variables, the first instrumental variable is a dummy variable that takes a value of one if iTunes was introduced in year *t* in country *c* and 0 otherwise. The staggered market entry of iTunes into 29 countries offers an exogenous variation. The introduction of iTunes increases the commercial importance of the single significantly because music is sold in the form of individual songs that were previously only or primarily sold as parts of albums. As the introduction timing of iTunes and other digital services is mainly determined by the difference in intellectual property regimes between the United States and local countries, rather than due to differences in countries' talent discoveries, this variable is less correlated with factors in the error term that influence music firms' decisions on experimenting with new artists.

The second instrumental variable is the country-level proportion of albums to all releases in the previous year. As I noted earlier, in some countries, singles have survived as a different music release format, even in the 1990s. For example, in 1995, 47% of U.K. music releases were produced as singles. In contrast, at that time, only 22% of U.S. releases were singles. Moreover, South Korea is an extreme example; no music in South Korea was produced as a single in 1995. In countries (e.g., United Kingdom) where singles have survived as a different music release format, music firms were more likely to produce singles than music firms in other countries where the presence of single releases was weak. For example, firms in countries such as the United Kingdom are more likely to produce singles than firms in other countries such as the United States; this difference is less correlated with factors in the error term that influence music firms' decisions on experimenting with new artists. Likewise, this cross-national difference in the presence of single releases offers another variation for identification.

An ideal instrumental variable would generate firm-level variation in the incentive to produce singles. For example, A&R managers' preferences on producing singles (which could be measured based on whether they discovered talented artists before by producing singles) could be a candidate for a firm-level instrumental variable. Due to data limitations, however, I could not access a reliable database that summarizes which A&R managers participated in music production. Moreover, all other available firm-level variables (such as firm size, firm status, whether firms produced top 5% popular songs in the previous year, the dummy for entrepreneurial firms, etc.) could be correlated with both production mode (i.e., singles vs. albums) and talent search strategy (i.e., new artists vs. experienced artists). For example, entrepreneurial firms are more likely to produce singles because they have less financial resources. Moreover, entrepreneurial firms are more likely to experiment with new artists than incumbent firms are.

Because I do not have a firm-level instrumental variable, my identification strategy could be vulnerable to omitted variables that are correlated with both my country-level instruments and firm-level change in the discovery of new talent. However, I expect any resulting bias to be small because my specification controls for a number of time-varying observables at the firm level.

4.3.3 | Propensity score matching

To complement the 2SLS models, I use a matching estimator: propensity score matching. Propensity matching estimators control for selection bias by creating a matched sample of treatment and control observations that are similar to the observable characteristics (De Figueiredo, Meyer-Doyle, & Rawley, 2013; Rosenbaum & Rubin, 1983; Villalonga, 2004). To implement propensity score matching, I estimate a probit model of the firm's decision to produce singles and use fitted values from that model as estimates of the propensity score.

I calculate the propensity scores $p(X_{it})$ of the firms in the sample and match firms with propensity scores within a radius caliper of 0.05. The results are robust to the use of different radius caliper values. The propensity score matching estimator for the average treatment effect on the treated firms is the mean difference in the number of artists at the firm level and the chance of missing out on talented artists: $\delta_{Number\_New\_Artists} = E[E[Number\_New\_Artists_{it} | Dummy\_Firm\_Single_{it} = 1,\ p(X_{it})] - E[Number\_New\_Artists_{it} | Dummy\_Firm\_Single_{it} = 0,\ p(X_{it})]]$, and $\delta_{Miss\_Talented\_Artists} = E[E[Miss\_Talented\_Artists_{it} | Dummy\_Firm\_Single_{it} = 1,\ p(X_{it})] - E[Number\_New\_Artists_{it} | Dummy\_Firm\_Single_{it} = 0,\ p(X_{it})]]$. For this analysis, I use the *psmatch2* routine in Stata. There are 16,980 matched samples with common support. I trim firm-year observations off the common support of the propensity score distribution to obtain the matched sample; I trim 12,337 unmatched samples. I use the matched samples to test all the hypotheses and mechanisms. The matched sample is consistent throughout the paper. The kernel density distributions from before and after matching are visualized in Online Appendix D. Panel (a) shows that before matching, the distributions of the propensity scores of single-producing firms and album-only-producing firms are different. Panel (b) demonstrates that after matching, there is a tighter fit between the single-producing firms and the album-only-producing firms. [Correction made on 20 March 2023 after first online publication: part of the equation in section 4.3.3, "d_{miss}_talented_artists" has been updated to "$d_{miss\_talented\_artists}$" in this version.]

4.4 | Sample statistics

Table 3 reports the descriptive statistics on all the variables at the firm-year level. First, the descriptive statistics for the independent variables show that the proportion of firm-year observations that produce at least one single is 39.3%.[8] Second, the average number of new artists is 1.178, and the average number of top 20% talented artists whom firms missed out on after their first release is 0.036.[9] In addition, I report the descriptive statistics of the two instrumental variables. First, the proportion of firm-year observations corresponding to the post-iTunes introduction period is 0.587; 58.7% of the firm-year observations are from after the introduction of iTunes, and the other 41.3% observations are from before the introduction of iTunes. Second, the average of the second instrumental variable, namely, the country-level proportion of albums to all releases in the previous year, is 0.736. Finally, the correlations among the variables are provided in Online Appendix E.

5 | RESULTS

5.1 | Does producing singles increase the number of new artists in the firm?

I test whether producing singles increases the number of new artists in a music firm. I compare single-producing firms and album-only-producing firms. Table 4 shows the results from the tests on the impact of producing singles on the number of new artists in the firm. I estimate three different versions of the same equation: OLS, a propensity score weighted regression, and

[8]The proportion of artists whose first release was a single is 71.7%.

[9]15.8% of artists had a second production chance in the single-producing firms. 21.7% of artists had a second production chance in the album-only-producing firms.

TABLE 3 Summary statistics

Variable name	Level of variation	Mean	*SD*	Min.	Max.
Independent variable					
(Dummy) one if the firm produced at least one single	Firm	0.393	0.488	0	1
Dependent variables					
Number of new artists	Firm	1.178	2.001	0	52
Number of top 20% talented artists whom the firm missed out on after their first release	Firm	0.036	0.314	0	11
Other variables					
(Dummy) one if iTunes was introduced in country *c*	Country	0.587	0.492	0	1
County-level proportion of albums to all releases (year *t*-1)	Country	0.736	0.141	0.357	1
Complexity of the firm's main genre	Genre	33.740	1.143	26.277	39.585
log (number of songs)	Firm	2.534	1.498	0	7.517
log (mean number of artists' prior releases)	Firm	1.059	1.044	0	6.174
(Dummy) one if the firm produced at least one top 5% song (year *t*-1)	Firm	0.039	0.194	0	1
Herfindahl index for genres in the firm	Firm	0.893	0.206	0.174	1
(Dummy) one if the firm was an entrepreneurial firm	Firm	0.493	0.500	0	1
Other statistics					
Number of songs	Firm	35.010	59.582	1	1838
Number of releases (albums + singles)	Firm	3.905	6.099	1	237
Number of singles	Firm	1.184	3.151	0	142
Proportion of singles to releases	Firm	0.264	0.382	0	1
Year	Firm	2005.102	5.570	1995	2015
Number of firm-year observations	29,317				
Number of unique firms	9,667				
Number of unique artists	42,422				
Number of unique releases	114,488				
Number of unique songs	1,026,390				

an instrumental variables analysis (2SLS). Column 1 reports the estimates of a simple OLS specification. I find a strong correlation between producing singles and the number of new artists. The number of new artists in the firm increases by 0.4147 in firms that produce some of their work as a single(s) compared to those that produce their work only as albums. The T statistic of the coefficient is 13.16, which means the p-value is close to 0.

Column 2 presents estimates from the same model after matching to control for observable differences between single-producing firms and album-only-producing firms. The coefficient

TABLE 4 (Variation generation stage) Does producing singles facilitate experimenting with more new artists?

	DV: Number of new artists		
	(1) OLS	(2) Propensity matching OLS	(3) 2SLS
(Dummy) one if the firm produced at least one single	0.4147 (0.0315) (p = .000)	0.4761 (0.0378) (p = .000)	1.4955 (0.4788) (p = .002)
Complexity of the firm's main genre	−0.0082 (0.0100)	−0.0048 (0.0184)	−0.0086 (0.0096)
log (number of songs) (1 year lag)	0.3625 (0.0233)	0.1407 (0.0236)	0.2163 (0.0145)
log (mean number of artists' prior releases) (1 year lag)	−0.1932 (0.0180)	−0.0010 (0.0247)	−0.1162 (0.0162)
(Dummy) one if the firm produced at least one top 5% song	0.7149 (0.1881)	0.2528 (0.0880)	0.1745 (0.1248)
Herfindahl index for genres in the firm	−1.1286 (0.1112)	−0.8580 (0.0945)	−0.6841 (0.1022)
(Dummy) one if the firm was an entrepreneurial firm	0.1410 (0.0277)	0.1017 (0.0684)	0.0718 (0.0237)
Constant	1.5270 (0.3993)	1.5563 (0.7177)	1.6503 (0.3908)
Year effect	*Yes*	*Yes*	*Yes*
Genre effect	*Yes*	*Yes*	*Yes*
Country effect	*Yes*	*Omitted*	*Omitted*
Firm effect	*No*	*Yes*	*Yes*
2SLS first-stage summary statistics			
Coefficient: (Dummy) one if iTunes was introduced in country *c*			0.0308
T-statistic: (Dummy) one if iTunes was introduced in country *c*			2.05
Coefficient: Country-level proportion of albums to all releases in the previous year			−0.5400
T-statistic: Country-level proportion of albums to all releases in the previous year			−11.97
Adjusted R^2	.1975	.0507	n.a.
N	29,317	16,980	29,317

Note: *SE*s are clustered at the firm level. The Sargan's *J*-statistic ($\chi^2(1)$) is 1.332 (p = .2484), alleviating concerns about an overidentification problem.

from this matching model is 0.4761, and its T statistic is 12.58. In Column 3, I present estimates from the 2SLS model, which controls for the potential endogeneity of producing singles using the two instrumental variables. The first-stage relationship between the introduction of iTunes

TABLE 5 (Selection and retention stages) Does producing singles increase the number of talented artists who were missed after their initial release?

	DV: Number of top 20% talented artists whom the firm missed out on after their first release		
	(1) OLS	(2) Propensity matching OLS	(3) 2SLS
(Dummy) one if the firm produced at least one single	0.0212 (0.0089) (p = .017)	0.0261 (0.0111) (p = .019)	0.3793 (0.1099) (p = .001)
Complexity of the firm's main genre	−0.0028 (0.0054)	−0.0140 (0.0079)	−0.0089 (0.0038)
log (number of songs) (1 year lag)	0.0177 (0.0044)	0.0259 (0.0058)	0.0192 (0.0046)
log (mean number of artists' prior releases) (1 year lag)	−0.0019 (0.0048)	−0.0050 (0.0062)	−0.0193 (0.0075)
(Dummy) one if the firm produced at least one top 5% song	0.0559 (0.0289)	0.0541 (0.0294)	−0.0653 (0.0462)
Herfindahl index for genres in the firm	−0.0888 (0.0220)	−0.1002 (0.0279)	−0.0086 (0.0352)
(Dummy) one if the firm was an entrepreneurial firm	0.0171 (0.0105)	0.0227 (0.0141)	0.0162 (0.0111)
Constant	0.3427 (0.2003)	0.0000 (.)	31.1467 (2.5280)
Year effect	*Yes*	*Yes*	*Yes*
Genre effect	*Yes*	*Yes*	*Yes*
Country effect	*Yes*	*Omitted*	*Omitted*
Firm effect	*No*	*Yes*	*Yes*
2SLS first-stage summary statistics			
Coefficient: (Dummy) one if iTunes was introduced in country c			0.0277
T-statistic: (Dummy) one if iTunes was introduced in country c			1.92
Coefficient: Country-level proportion of albums to all releases in the previous year			−0.7720
T-statistic: Country-level proportion of albums to all releases in the previous year			−11.31
Adjusted R^2	.0493	.0580	n.a.
N	16,721	10,435	16,721

Note: *SE*s are clustered at the firm level. The Sargan's J-statistic ($\chi^2(1)$) is 3.120 (p = .0773), alleviating concerns about an overidentification problem.

and producing singles by the firm is positive (T statistic: 2.05), and the first-stage relationship between country-level firms' proportion of albums to all releases in the previous year and the production of singles by the firm is strongly negative: the T statistic on this instrumental variable is −11.97. Overall, the first-stage T statistics indicate powerful instruments, alleviating the concern regarding weak instruments (see, e.g., Semadeni et al., 2014 for summaries of this issue). Because I have more instrument variables than endogenous variables, I conduct a test of overidentifying restrictions using Sargan's J statistic. The overidentification test does not reject the null hypothesis that both instrument variables are valid ($\chi^2(1) = 1.332$; $p = .2484$), alleviating concerns about an overidentification problem. In the second stage, the estimated changes in the talent level of new artists are positive. The coefficient is 1.4955 (p-value: .002). The 2SLS estimate in Column 3 is noisier than the matching estimate in Column 2, and the Z statistic of the difference between the coefficient in Column 2 (0.4761) and the coefficient in Column 3 (1.4955) is 2.13. Collectively, when firms produce singles, they experiment with more talented artists than when they produce artists' work only as albums.

5.2 | Does producing singles increase the number of talented new artists who were missed out on after their initial release?

I turn now to the second hypothesis, which tests the impact of producing singles on missing out on talented new artists after the failure of their initial release. Here, the sample firms are those that experimented with at least one new artist in year t. Table 5 shows the results from the tests on the effect of single production on omission errors in giving a second chance to new artists. Column 1 reports the estimates from a simple OLS model. I find a positive relationship between producing singles and omission errors. Specifically, the estimate in Column 1, namely, 0.0212, suggests that omission errors are associated with an increase of 58.89% when firms experiment with a new artist by producing a single.[10] Column 2 presents the estimates of the matching model. The coefficient has a similar value: 0.0261. Finally, in Column 3, I present the estimates of the 2SLS model with the same two instrumental variables. The first-stage coefficients (T statistics) of the relationship between the instrumental variables and producing singles are 0.0277 (1.92) and −0.7720 (−11.31). These coefficients and T statistics indicate powerful instruments. In the second stage, the estimated changes in the omission error are positive (0.3793) with a p-value of .001.

To determine whether producing singles for new artists drives my results, I run additional regressions in which the dependent variable is the number of missed top 20% popular artists whose first release was a single (that was not included in the top 10% of popular songs) and who then moved to another firm to produce their subsequent releases. Online Appendix F presents the results. The results mainly show that the missed top 20% popular artists whose first release was a single drive the results in Table 5.

5.3 | Does producing singles increase the performance target for selection and retention?

I test the mechanism for the second hypothesis. I propose that the increased chance of missing out on talented artists may come from an increased performance target of the single production.

[10]Moreover, in Online Appendix G, I run the same OLS regression with the subsample of firms that discovered top 20% popular artists. The estimate is 0.0782, and the effect size is an increase of 14.91% (= 0.0782/0.5116).

TABLE 6 (Selection and retention stages) Does producing singles increase the performance target of new artists' first releases for selection and retention?

	DV: Performance target for selection and retention (popularity of the most popular song among the releases of new artists who were not given second chances from the same firm)		
	(1) **OLS**	**(2)** **Propensity matching OLS**	**(3)** **2SLS**
(Dummy) one if the firm produced at least one single (β_a, (SE_a))	0.9719 (0.0932) (p = .000)	0.6296 (0.1283) (p = .000)	1.6038 (0.7356) (p = .029)
Complexity of the firm's main genre	−0.0668 (0.0374)	−0.1837 (0.1245)	−0.0026 (0.0295)
log (number of songs) (1 year lag)	−0.0038 (0.0386)	−0.1210 (0.0968)	0.0011 (0.0387)
log (mean number of artists' prior releases) (1 year lag)	0.0961 (0.0671)	0.2643 (0.1492)	0.0618 (0.0742)
(Dummy) one if the firm produced at least one top 5% song	4.6381 (0.9388)	−0.1510 (0.6071)	4.4215 (0.9877)
Herfindahl index for genres in the firm	−1.5732 (0.3537)	−0.4332 (0.4265)	−1.4021 (0.4019)
(Dummy) one if the firm was an entrepreneurial firm	−0.0039 (0.0967)	0.1947 (0.2965)	0.0031 (0.0985)
Constant	3.2275 (1.4186)	7.6240 (5.5473)	−58.9912 (19.1399)
Year effect	*Yes*	*Yes*	*Yes*
Genre effect	*Yes*	*Yes*	*Yes*
Country effect	*Yes*	*Omitted*	*Omitted*
Firm effect	*No*	*Yes*	*Yes*
2SLS first-stage summary statistics			
Coefficient: (Dummy) one if iTunes was introduced in country *c*			0.0341
T-statistic: (Dummy) one if iTunes was introduced in country *c*			2.50
Coefficient: Country-level proportion of albums to all releases in the previous year			−1.0191
T-statistic: Country-level proportion of albums to all releases in the previous year			−16.55
Adjusted R^2	.0758	.0107	n.a.
N	16,721	10,435	16,721

Note: *SE*s are clustered at the firm level. The Sargan's *J*-statistic ($\chi^2(1)$) is 3.510 (p = .0610), alleviating concerns about an overidentification problem.

TABLE 7 Sobel test for the mediation through the performance target

Panel (a). Testing H2 with the mediator and the independent variable	**DV: Number of top 20% talented artists whom firm missed out on after their first release**	
	(1) **OLS**	**(2)** **Propensity matching OLS**
Performance target for selection and retention (β_b, (SE_b))	0.0039 (0.0016) (p = .017)	0.0040 (0.0016) (p = .014)
(Dummy) one if the firm produced at least one single	0.0174 (0.0090) (p = .053)	0.0220 (0.0111) (p = .048)
Percentage explained by the mediation through an increase in the performance target	**17.92**% $\left(=1-\frac{0.0174}{0.0212}\right)$	**15.71**% $\left(=1-\frac{0.0220}{0.0261}\right)$
Control variables	*Yes*	*Yes*
Year, genre, and country effects	*Yes*	*Yes*
Firm effect	*No*	*Yes*
Adjusted R^2	.0508	.0603
N	29,317	16,980

Panel (b). Sobel test statistics	**(1)** **OLS**	**(2)** **Propensity matching OLS**
Sobel test statistics $\left((\beta_a \times \beta_b)/\sqrt{\left(\beta_b^2 \times SE_a^2 + \beta_a^2 \times SE_b^2\right)}\right)$	2.3735 (0.0016) (p = .018)	2.2276 (0.0011) (p = .026)

Note: *SE*s are clustered at the firm level.

To study the performance target, I use another dependent variable, the popularity of the most popular song in the first release (i.e., single or album) of the new artists who were not given second chances from the same firm. Columns 1–3 in Table 6 demonstrate a strong relationship between producing singles and the performance target. The coefficients (0.9719, 0.6296, and 1.6038) are positive: the *p*-values of these three estimates are .000, .000, and .029. As 5.2095 is the average popularity score of the most popular song of the first release produced by the new artists who did not receive a second chance in the same firm, single production is associated with a 12.50% (= 0.6296/5.0337)–30.79% (= 1.6038/5.2095) increase in performance target for selection and retention.[11]

In Table 7, I formally test whether and how much the performance target mediates the relationship between single production (i.e., independent variable) and omission errors in giving a second chance to a top 20% popular artist (i.e., dependent variable). Sobel (1982) formulated a significance test for the indirect impact of the independent variable on the dependent variable

[11] I run additional regressions in which I control for the total number of new artists of firm i in year t. I include these results in Online Appendix H. The results are qualitatively identical to the main findings in Table 6.

through the mediator. The subsequent literature has christened it the "Sobel test" (e.g., Baron & Kenny, 1986). The coefficient of the path from the independent variable to the mediator is denoted as β_a, and its SE is SE_a; β_a and SE_a were estimated in Table 6. The statistics in Columns 1–2 show that the mediation path explains 17.92 and 15.71% of the relationship between single production and the omission errors in giving second chances to top 20% popular artists. The coefficient of the path from the mediator to the dependent variable is denoted as β_b, and its SE is SE_b; β_b and SE_b are estimated in Table 7, Panel (a). In the first two regression models in Tables 5 and 6,[12] the Sobel test statistics $(\beta_a \times \beta_b)/\sqrt{\beta_b^2 \times SE_a^2 + \beta_a^2 \times SE_b^2}$, (2.3735, 2.2276) and their p-values (.018, .026) are estimated and presented in Table 7, Panel (b). Overall, the statistics show that the performance target mediates the relationship between single production and the omission errors in giving a second chance to a top 20% popular artist at least p-value = .026.

5.4 | Boundary conditions and robustness checks

Boundary conditions for Hypothesis (H2)

I explore the boundary conditions under which single production increases the number of omission errors in giving second chances to talented artists. I test two boundary conditions: (a) established firms versus entrepreneurial firms and (b) pop music genres (i.e., pop, hip-hop, rock, and funksoul) versus other niche genres.

First, established firms have more alternative options because would-be artists are more interested in getting signed with established firms. This is mainly because established firms have more financial and relational resources than entrepreneurial firms (Passman, 2014). Thus, I can predict that the talent level of the most promising alternative option (the popularity level of the most popular artists that the firm may discover) of an established firm may increase more if the firm produces single(s) than it would if an entrepreneurial firm produces a single(s). Established firms may have higher performance targets and experience more omission errors than entrepreneurial firms. Table 8 Panel (a) supports these predictions. The coefficients (0.0363, 1.4338) for the established firms are positive and larger than the coefficients (0.0119, 0.6780) for the entrepreneurial firms.

Second, there are more would-be artists for pop music genres (pop, hip-hop, rock, and funksoul) (ReverbNation & Digital Music News, 2016). Firms whose main genre is one of the pop genres will encounter more outside options, leading to a higher performance target. Therefore, they will experience more omission errors than firms whose main genre is not one of the pop genres (e.g., alternative, jazz, reggae, folk, etc.). Table 8 Panel (b) supports these predictions. The coefficients (0.0362, 1.3721) for the established firms are positive and larger than the coefficients (0.0229, 1.0108) for the entrepreneurial firms.

Difference in the quality of experimented alternatives

When firms produce singles, firms may experiment with different types of talent whose potential may be higher than when they produce albums. Because of the high uncertainty in predicting the talent of an artist before production and commercialization in the music industry, the term "nobody knows principle" has been coined by industry experts (Caves, 2000). Therefore, it is unlikely that the single production itself may bring more talented artists than

[12]The Sobel test for the instrumental variable estimators (2SLS) has yet to be developed.

TABLE 8 Boundary conditions for Hypothesis (H2)

Panel (a). Established firms vs. entrepreneurial firms

	DV: number of omission errors (number of top 20% talented artists whom firm missed out after their first release)		DV: Performance target (popularity of the most popular song among the releases of new artists who were not given second chances from the same firm)	
	Subsample: Established firms (1) Propensity matching OLS	Subsample: Entrepreneurial firms (2) Propensity matching OLS	Subsample: Established firms (3) Propensity matching OLS	Subsample: Entrepreneurial firms (4) Propensity matching OLS
(Dummy) one if the firm produced at least one single	0.0363 (0.0124) (p = .003)	0.0119 (0.0191) (p = .533)	1.4338 (0.1570) (p = 0.000)	0.6780 (0.0975) (p = .000)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Year, genre, and country effects	*Yes*	*Yes*	*Yes*	*Yes*
Firm effect	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R^2	.0890	.0443	.0880	.0331
N	5,443	4,992	5,443	4,992

Panel (b). Pop genres (pop, hip-hop, rock, funksoul) vs. non-pop genres

	DV: Number of omission errors (number of top 20% Talented artists whom Firm missed out after Their first release)		DV: Performance target (popularity of the most popular Song among the releases Of new artists who were Not given second chances From the same firm)	
	Subsample: Pop Genres (1) Propensity matching OLS	Subsample: Non-pop Genres (2) Propensity matching OLS	Subsample: Pop Genres (3) Propensity matching OLS	Subsample: Non-pop Genres (4) Propensity matching OLS
(Dummy) one if the firm produced at least one single	0.0362 (0.0191) (p = .059)	0.0229 (0.0140) (p = .102)	1.3721 (0.1844) (p = .000)	1.0108 (0.1242) (p = .000)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Year, genre, and country effects	*Yes*	*Yes*	*Yes*	*Yes*
Firm effect	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R^2	.0719	.0582	.0672	.0924
N	3,443	6,992	3,443	6,992

Note: *SE*s are clustered at the firm level.

TABLE 9 Difference between singles and albums in the average talent level of artists

	Sample: Firm-level		Sample: Artist-level	
	DV: Average talent level of new artists		DV: Talent level of artist *j*	
	(1) Propensity matching OLS	(2) 2SLS	(3) Propensity matching OLS	(4) 2SLS
(Dummy) one if the firm produced at least one single	0.0905 (0.2480) (p = .715)	2.5758 (1.7558) (p = .142)		
(Dummy) one if the first release of artist *j* was produced as a single			−0.0133 (0.0619) (p = .831)	1.4064 (3.3042) (p = .670)
Complexity of the firm's main genre	−0.1997 (0.1337)	−0.1306 (0.0593)	−0.0259 (0.0322)	−0.3071 (0.0716)
log (number of songs) (1 year lag)	−0.2695 (0.1139)	0.1607 (0.0467)	0.0368 (0.0177)	−0.1776 (0.1021)
log (mean number of artists' prior releases) (1 year lag)	0.2028 (0.1190)	−0.3727 (0.0787)	−0.0853 (0.0317)	−0.1450 (0.1082)
(Dummy) one if the firm produced at least one top 5% song	0.8245 (0.4289)	0.4996 (0.6035)	0.2166 (0.0828)	0.3283 (0.3355)
Herfindahl index for genres in the firm	−1.2511 (0.4811)	−1.2085 (0.5029)	−0.0904 (0.1029)	−1.4681 (0.3457)
Dummy) one if the firm was an entrepreneurial firm	−0.0049 (0.3391)	0.2372 (0.1324)	0.0376 (0.0568)	0.7410 (0.2521)
Constant	21.2401 (6.0759)	11.1143 (2.6811)	0.0239 (1.1022)	1,220.1770 (62.8332)
Year effect	*Yes*	*Yes*	*Yes*	*Yes*
Genre effect	*Yes*	*Yes*	*Yes*	*Yes*
Country effect	*Yes*	*Omitted*	*Yes*	*Omitted*
Firm effect	*No*	*Yes*	*No*	*Yes*
Adjusted R^2	.1175	n.a.	.2972	n.a.
N	16,980	29,317	11,751	42,422

Note: *SE*s are clustered at the firm level.

album production. One way to rule out this concern is by comparing the talent levels of new artists between single-producing firms and album-only-producing firms. I analyze two different samples: firm-level sample and artist-level sample.

I do not find a strong relationship between producing singles and the average talent level of new artists. Columns 1 and 2 in Table 9 report estimates from the firm-level analysis. Although the coefficients (0.0905 and 2.5758) are positive, the *p*-values of these two estimates are .715 and .142. Columns 3 and 4 report estimates from the artist-level analysis. The results are similar. The coefficient (−0.0133) in Column 1 is negative, but the *p*-value for this estimate is .831. Although the coefficient in Column 4 (2SLS) is positive (1.4064), the *p*-value of the coefficient is

TABLE 10 Does producing singles increase commission errors in the selection and retention stages (giving second chances to unpromising options)?

	DV: Number of commission errors: Number of bottom 80% artists who were given second chances from the same firm		
	(1) OLS	(2) Propensity matching OLS	(3) 2SLS
(Dummy) one if the firm produced at least one single	−0.1161 (0.0073) (p = .000)	−0.1025 (0.0093) (p = .000)	−0.4216 (0.0780) (p = .000)
Complexity of the firm's main genre	0.0012 (0.0036)	0.0093 (0.0053)	0.0045 (0.0027)
log (number of songs) (1 year lag)	0.0389 (0.0031)	0.0454 (0.0036)	0.0324 (0.0031)
log (mean number of artists' prior releases) (1 year lag)	−0.0176 (0.0039)	−0.0186 (0.0045)	−0.0010 (0.0054)
(Dummy) one if the firm produced at least one top 5% song	0.0200 (0.0183)	−0.0042 (0.0187)	0.1101 (0.0294)
Herfindahl index for genres in the firm	−0.0962 (0.0167)	−0.0872 (0.0185)	−0.1498 (0.0240)
(Dummy) one if the firm was an entrepreneurial firm	0.0225 (0.0079)	0.0086 (0.0093)	0.0270 (0.0085)
Constant	0.3601 (0.1847)	0.0000 (.)	24.9305 (1.6316)
Year effect	*Yes*	*Yes*	*Yes*
Genre effect	*Yes*	*Yes*	*Yes*
Country effect	*Yes*	*Omitted*	*Omitted*
Firm effect	*No*	*Yes*	*Yes*
2SLS first-stage summary statistics			
Coefficient: (Dummy) one if iTunes was introduced in country *c*			0.0341
T-statistic: (Dummy) one if iTunes was introduced in country *c*			2.50
Coefficient: Country-level proportion of albums to all releases in the previous year			−1.0191
T-statistic: Country-level proportion of albums to all releases in the previous year			−16.55
Adjusted R^2	.0884	.0961	n.a.
N	16,721	10,435	16,721

Note: *SE*s are clustered at the firm level. The Sargan's *J*-statistic ($\chi^2(1)$) is 3.510 (p = .0610), alleviating concerns about an overidentification problem.

TABLE 11 Commission errors by person (solo) versus group

Panel (a). Subsample—Person (solo)			
	Sample: Artist-level DV: Commission error (dummy) one if a bottom 80% artist was given a second chance from the same firm		
	(1) IPW[a] logit	**(2) Propensity matching + IPW logit**	**(3) 2SLS**
(Dummy) one if the first release of artist j is produced as a single	−0.0209 (0.0048) (p = .000)	−0.0244 (0.0066) (p = .000)	−0.0569 (0.0125) (p = .000)
Control variables	*Yes*	*Yes*	*Yes*
Year, genre, and country effects	*Yes*	*Yes*	*Yes*
Firm effect	*No*	*Yes*	*Yes*
2SLS first-stage summary statistics			
Coefficient: (Dummy) one if iTunes was introduced in country c			0.0140
T-statistic: (Dummy) one if iTunes was introduced in country c			7.28
Coefficient: Country-level proportion of albums to all releases in the previous year			−0.8852
T-statistic: Country-level proportion of albums to all releases in the previous year			−39.69
Log likelihood/Adjusted R^2	n.a.	n.a.	n.a.
N	18,510	7,703	18,510
Panel (b). Subsample—Group (>1 person)			
	Sample: Artist-level DV: Commission error (dummy) one if a bottom 80% artist was given a second chance from the same firm		
	(1) IPW[a] logit	**(2) Propensity matching + IPW logit**	**(3) 2SLS**
(Dummy) one if the first release of artist j is produced as a single	−0.0284 (0.0056) (p = .000)	−0.1019 (0.0121) (p = .000)	−0.0585 (0.0000) (p = .000)
Control variables	*Yes*	*Yes*	*Yes*
Year, genre, and country effects	*Yes*	*Yes*	*Yes*
Firm effect	*No*	*Yes*	*Yes*
2SLS first-stage summary statistics			
Coefficient: (Dummy) one if iTunes was introduced in country c			0.0105

TABLE 11 (Continued)

Panel (b). Subsample—Group (>1 person)			
	Sample: Artist-level DV: Commission error (dummy) one if a bottom 80% artist was given a second chance from the same firm		
	(1) IPW[a] logit	**(2) Propensity matching + IPW logit**	**(3) 2SLS**
T-statistic: (Dummy) one if iTunes was introduced in country *c*			4.70
Coefficient: Country-level proportion of albums to all releases in the previous year			−0.9721
T-statistic: Country-level proportion of albums to all releases in the previous year			−35.99
Log likelihood/Adjusted R^2	n.a.	n.a.	n.a.
N	12,913	8,514	12,913

Note: *SE*s are clustered at the firm level.

Abbreviation: IPW, inverse probability weighting.

[a]I estimate the average treatment effect by using an IPW. An inverse probability weighting involves two steps. First, for each t, I estimate a logit of s_{it} (i.e., single production) on X_{it}. Let p_{it} be the fitted probabilities. In the second step, the objective function of (i, t) is weighted by $1/p_{it}$ (Angrist & Pischke, 2008). For this analysis, I use the *teffects ipw* routine in Stata.

.670. In summary, I find no evidence for a difference in the average quality of new artists with whom firms experimented through single production.

Noisier quality signal from single production

The increase in the omission errors may come from a nosier quality signal of the single production. In reality, even though music firms allow an artist to produce an album, the firms focus on one title song in the commercialization process. Thus, albums also produce a similarly noisy signal on the talent of new artists. One way to rule out this concern is by considering commission errors in giving second chances to untalented artists. If single production generates a noisier signal than album production, we would see that single-producing firms make more commission errors in giving a second chance to new artists (as well as omission errors in giving second chances). In the presence of a noisier signal (from single production), new artists will be more likely to face lucky draws as well as unlucky draws. If the suggested mechanism of this article works (i.e., the single production is associated with a higher performance target); however, we will see fewer commission errors because of the increased performance target for selection and retention.

Table 10 shows that the patterns regarding commission errors are more consistent with this article's suggested theoretical mechanism than the alternative story (i.e., the noisier-signal story). The results suggest that single production decreases the chance of making commission errors because single production increases the performance target for selection and retention. Columns 1–3 report estimates from the models where the dependent variable is the number of bottom 80% artists who were given a second chance in firm *i*. The coefficients (−0.1161, −0.1025, and −0.4216) are negative; the *p*-values for these three estimates are .000.

Escalation of commitment

Another alternative explanation of Hypothesis (H2) could be the escalation of commitment in sequential investment, a type of limitation in information processing (e.g., Brockner, 1992; Staw, 1976; Wong & Kwong, 2018). The escalation of commitment is a behavioral bias in which an individual or a firm facing negative outcomes from an investment nevertheless continues the behavior instead of terminating investment (e.g., Eggers, 2012; Guler, 2007; McNamara, Moon, & Bromiley, 2002). Thus, when firms produce albums (which requires more resource commitment), they are more likely to continue their commitment (i.e., fewer omission errors in giving a second chance) than when they produce singles.

One way to rule out this concern is by examining commission errors across different commitment levels. I examine the different commitment levels by comparing solo artists and group artists. Experimenting with a group (>1 person) usually requires more financial commitment than experimenting with a solo artist (Passman, 2014). For example, the amount of cash advance increases as the number of people in the group increases. If the escalation of commitment explains the observed pattern, when a firm experiments with a group, the firm will be more likely to make a commission error in giving a second chance (e.g., giving a second chance to a bottom 80% popular artist) than when the firm experiments with a solo artist.

For solo artists, the chance of making commission errors is 47.80%; for group artists, the chance of making commission errors is 46.66%. The probability of making commission errors for solo artists is as high as that of making commission errors for groups. The patterns in Table 11 are more consistent with this article's suggested theoretical mechanism than the escalation of commitment story. Panels (a) and (b) show the results regarding the subsamples of solo artists and groups, respectively. Columns 1–3 report estimates of the impact of single production on making commission errors, and the corresponding variable is equal to one if the same firm gives a second chance to artists who rank in the bottom 80%. The coefficients (−0.0209, −0.0244, and −0.0569) in Panel (a) are not smaller than the coefficients (−0.0284, −0.1019, −0.0585) in Panel (b), suggesting that firms do not make more commission errors when they produce singles for groups than when they do the same for solo artists.

Other robustness checks

This study's sample has three categories: (a) single-only-producing firms, (b) single-and-album-producing firms (i.e., firms that produce both singles and albums), and (c) album-only-producing firms. For the independent variable of the main analysis (i.e., the dummy for a decomposed search), I treat the first two types (i.e., single-only-producing firms and single-and-album-producing firms) as firms that implement a decomposed search. I test the main findings' robustness to two different operationalizations of the independent variable. In the first robustness test (Online Appendix I), I treat single-only-producing firms as firms that implement a decomposed search (i.e., the baseline firms are single-and-album producing firms and album-only-producing firms). In the second robustness test (Online Appendix J), I use the two independent variables, (a) the dummy for single-only-producing firms and (b) the dummy for single-and-album-producing firms (i.e., the baseline firms are album-only-producing firms). This study's main findings are robust to these two alternative ways of operationalizing the independent variable.

Also, this study's main findings are robust to the use of alternative measures of the independent variable: the average number of songs per release (Online Appendix K) and the proportion of singles to all releases in firm i (Online Appendix L Panel A). The results are qualitatively identical to those of the baseline models, alleviating concerns about the measurement of the independent variable. Finally, the main findings are robust to the use of different cutoff levels to measure the chance of missing out on talented artists. In Online Appendix L Panel B, it is clear that the results are robust to the different cutoff levels used to identify top talented artists: top 20%, top 15%, top 10%, and top 5%.

Finally, for some missed artists, the period between the first release (in the first firm) and the second release (in the second firm) could be too long. It is possible that during this period, some artists (who were not top 20% artists) may develop sufficient talent to be considered top 20% artists. As the gap between the first and second firms increases, this possibility could increase.[13] To mitigate this concern, I conduct additional robustness tests by dropping any artists whose gap between the first and second firms was too long. The average gap between the first and second firms was about 2.2 years. I test with the following thresholds: the gap should be within (a) 2 years (which is shorter than the average gap) and (b) 4 years (which is longer than the average gap). For 61.2% of the top 20% artists (who were missed), the gap is within 2 years. For 79.7% of the top 20% (who were missed), the gap is within 4 years. The results are presented in Appendices M and N (Panel A for the first threshold [≤2 years] and Panel B for the second threshold [≤4 years]). The results are qualitatively identical to the main findings of this study.

6 | DISCUSSION AND CONCLUSIONS

I explore the two opposite effects of a decomposed search. To do this, I divide the discovery process into the (a) the variation generation stage and (b) selection and retention stages. I predict that a decomposed search generates more variations, some of which turn out to be promising options. However, a decomposed search may lead to worse selection and retention for two reasons. First, in the presence of noise, as firms experiment with more alternatives, more alternatives will face an unlucky draw in their initial evaluation. Promising alternatives are not exceptions to this tendency; some of them will also face an unlucky draw and be evaluated as unpromising despite their underlying quality. Second, I argue that a decomposed search may increase performance targets because implementing a decomposed search increases the number of outside options that firms can experiment with, resulting in a higher expected quality of the best option among these outside options.

My findings demonstrate that music firms that produce some of their products as singles tend to experiment with more new artists. However, they are more likely to miss out on talented artists who experienced failures in their first releases. In sum, a decomposed search generates a trade-off between variation (i.e., experimenting with more options) and selection and retention (i.e., missing out on promising options after decomposed experimentations). Specifically, approximately 80% of the increase in neglecting top-tier artists came from the increases in the number of new artists experimented (due to single production), and the other 20% of the increase came from a higher performance target.

[13] Also, an anonymous reviewer raised an important concern. It is possible that even if a signed artist is removed from a contract after the artist's first release (either an album or a single), the artist could become successful in the online world with self-releases and then return to another music firm for a record deal by leveraging their bargaining power. Because the performance of self-releases in the online world cannot be observed with my data, I could not rule out this possibility. I note this as a study limitation in the discussion and conclusions section.

One of the general approaches for search effectiveness is to decompose the overall problem into subproblems (Simon, 1962). Prior theoretical work has explored the performance implications of partitioning a system into subsystems by focusing on whether a decomposed or integrated search is superior (e.g., Levinthal & Warglien, 1999), how to solve coordination problems between modules under high complexity (e.g., Rivkin & Siggelkow, 2003), and how granular each module should be to solve a complex problem (e.g., Ethiraj & Levinthal, 2004). This stream of work has utilized simulation methodology. It has been based on two common assumptions, namely, that (a) a decomposed search facilitates experimentation and that (b) managers do not change their performance targets regardless of whether their search mode is a decomposed search or an integrated search. In this study, I explore whether these two assumptions represent search behavior in the real world. By exploring these assumptions, I attempt to enhance our understanding of this topic.

First, I provide evidence that is consistent with the first assumption that a decomposed search facilitates the creation of more variations. Starting with the work of Nelson (1961), strategy scholars have examined the role of experimentation in the discovery of new solutions (e.g., Eggers, 2012; Ethiraj & Levinthal, 2004; Posen et al., 2013). This study highlights that decomposability could be an important antecedent of heterogeneous experimentation. Specifically, this study speaks to the burgeoning body of empirical literature on the role of decomposability and complexity in search (e.g., Chang, Eggers, & Keum, 2022; Jacobides & Tae, 2015; Natividad & Rawley, 2016; Piazzai & Wijnberg, 2019; Zhou, 2011). As Baumann et al. (2019) note, to date, this theoretical work has been only incidentally complemented by empirical research, and the theoretical and empirical studies remain rather disconnected. I attempt to tighten the link between theoretical and empirical work by analyzing an unusual setting to measure decomposability and its role in discovering new promising alternatives.

More importantly, regarding the second assumption, this study speaks to the literature on the performance target and aspiration level (e.g., Bromiley, 1991; Cyert & March, 1963; Greve, 2003; Keum & Eggers, 2018; Lant et al., 1992). Changes in search behavior in response to performance below the performance target have been an active research topic in organizational learning (Greve & Gaba, 2017). While there have been studies on the ramifications of financial performance aspirations (e.g., ROE, ROS, and ROA) on subsequent firm behaviors (e.g., Audia & Greve, 2006; Chen & Miller, 2007), little attention has been given to how organizational performance targets are determined (Bascle & Jung, 2022; Greve & Teh, 2018). As Shinkle (2012) notes, "the literature lacks robust empirical evidence on the antecedents of aspirations[performance targets]. Most studies rely on the formal theoretical model of behavioral theory to infer aspiration levels[performance targets]." This study provides empirical evidence as well as a theoretical argument that decomposability plays an important role in shaping performance targets. This article's findings highlight that the performance target plays an essential role in search, especially under imperfect evaluation. With these findings, this study bridges two core tenets of the behavioral theory of the firm: the tenet of the architecture on complexity (e.g., Ethiraj & Levinthal, 2004; Fang & Kim, 2018; Simon, 1962) and the tenet of the performance target and aspiration level (e.g., Cyert & March, 1963; Greve, 2003).

Finally, this study speaks to the literature on the role of noise in performance evaluation (e.g., Adner & Helfat, 2003; Cyert & March, 1963; Denrell, Fang, & Liu, 2014). Prior studies on imperfect evaluation have examined the bias and performance implications of the heterogeneity in forecasting ability (e.g., Denrell & Fang, 2010; Makadok & Walker, 2000) and organization structure (Csaszar, 2012; Knudsen & Levinthal, 2007; Sah & Stiglitz, 1986). I consider a decomposed search as a heuristic to complement forecasting abilities or organization structure. I highlight a hidden drawback of decomposed search.

This study has several limitations. First, this article's empirical setting is complex in the sense that it concerns many elements (i.e., many songs) with a low level of interdependence among them (i.e., a low level of interdependence between songs). Therefore, from an *NK* model perspective (in which *N* stands for the number of elements and *K* stands for the level of interdependence among the elements (Kauffman, 1996)), this article's setting has a high *N* with a low *K*. When interdependence is more substantial (e.g., in a setting like designing state-of-the-art semiconductor chips (Chang, Lee, & Song, 2022, Ethiraj & Levinthal, 2004)), the benefits of decomposed search could be limited. Second, this study has little to say about the origins of heterogeneous qualities of alternatives. I treat the quality of an alternative as an exogenous endowment, akin to a gift to an artist. Extending on the theoretical framework to endogenize the quality of alternatives, including matching between firms and artists, skill, style, or knowledge gained as the outcome of a learning process in the firm, would be interesting avenues of exploration. However, they are beyond the scope of this work. Third, I cannot observe pre-commercialization experimentation or the performance of online self-releases due to data limitations. Future research could build comparable data on pre-commercialization experimentation and the performance of online self-releases. Finally, in uncertain situations (i.e., when nobody knows), social factors such as the strength of ties might play a critical role in shaping resource allocation decisions. Artists who produce albums as their first releases may be more likely to develop strong ties with firms and receive second production chances. I believe exploring such social factors could be an important topic for future research.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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