Essays on Organization, Creativity, and Globalization

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ABSTRACT

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This dissertation examines an underexplored type of innovation - the discovery of new resources. Schumpeter distinguishes among five types of innovation: new products, new processes, new organizations, new markets, and new resources. Most prior work has focused on the first three types of innovation. This study focuses on the last type of innovation, the discovery of new resources, in creative industries where talent is the most important resource of creativity and profit. This dissertation is comprised of three chapters. Each of the chapters examines a strategy or an environmental change such as unbundling, digitalization, and cross-border acquisition which may facilitate or weaken the discovery of new talent and experiment with new artists. In the first chapter, I explore the impact of unbundling on the discovery of new talent. The results highlight the trade-off between breadth-oriented experimentation (experimenting with more new alternatives by producing unbundled products) and depth-oriented experimentation (collecting more accurate information on fewer alternatives by producing bundled products) and suggest that unbundling may facilitate firms' breadth-oriented experimentation and the discovery of new talent. In the second chapter, I investigate whether digitalization (digital market) facilitated the discovery of new talent by entrepreneurial firms. Digitalization offers diverse niche opportunities from a long-tail market and decreases the cost of experimenting with new artists. However, the findings from this chapter suggest that entrepreneurial firms did not benefit from such opportunities; iTunes and YouTube did not

facilitate entrepreneurial firms' discovery of new talent and experimentation with new artists (compared to incumbent firms). In the third chapter, I turn to look at the impact of foreign ownership or capital on the discovery of new domestic talent. The "liability of foreignness" argument suggests that foreign ownership may weaken the discovery of new talent from the host country because foreign owners may lack a good understanding of the host country culture. This study analyzes the case of Sony's acquisition of CBS Records (a US major label) in 1988, which is the first merger by a Japanese firm with a firm of a distant culture. The results suggest that Sony did not undermine CBS Records' discovery of domestic new talent but instead increased the popularity of new domestic artists in CBS Records and its subsidiaries.

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Dedicated to my late parents, Sook-hee Park and Hae-geun Chang

Introduction

This dissertation examines an underexplored type of innovation - the discovery of new resources. Schumpeter (1934) distinguishes among five types of innovation: new products, new processes, new organizations, new markets, and new resources. Most prior work has focused on the first three types of innovation. This study focuses on the last type of innovation, the discovery of new resources, in creative industries where talent is the most important resource of creativity and profit. This dissertation is comprised of three chapters. Each of the chapters examines a strategy or an environmental change such as unbundling, digitalization, and cross-border acquisition which may facilitate or weaken the discovery of new talent and experiment with new artists.

In the first chapter, I explore the impact of unbundling on the discovery of new talent. Digitalization has engendered a fundamental unbundling of creative goods. In the music industry, for instance, digitalization has enabled music to be purchased as both individual songs (i.e., a single) and a bundle of songs (i.e., an album). I explore whether unbundling facilitates firms' experimentation and the discovery of new artists. For this purpose, I study a model of unbundling and the discovery of new talent and test its empirical implications in the music industry. To identify a causal effect of unbundling on the discovery of new talent, I utilize iTunes' staggered market entries into 29 countries based on a novel dataset from multiple large-scale music databases, including Spotify APIs. Consistent with the theoretical predictions, I find that as unbundling lowers the cost of experimenting with new artists, single-producing firms have a higher proportion of new artists than album-only-producing firms. In contrast, as information on artist talent from one-shot unbundled experimentation is less accurate than that from albums, single-producing firms make more omission errors. Overall, the results suggest that the positive effect of the decreased cost of experimentation outweighs the negative effect of the loss of information quality on talent. Thus, single-producing firms discover more popular artists and artists who create new markets (genres) than album-only-producing firms. These results highlight the trade-off between breadth-oriented experimentation (experimenting with more new alternatives) and depth-oriented experimentation (collecting more accurate information on fewer alternatives) and suggest that unbundling may facilitate firms' breadth-oriented experimentation and the discovery of new talent.

In the second chapter, I investigate whether digitalization (digital market) facilitated the discovery of new talent by entrepreneurial firms. One theoretical argument suggests that entrepreneurial firms may benefit from digitalization because it offers diverse niche opportunities from a long-tail market and decreases the cost of experimenting with new artists. Another theoretical argument challenges this simple positive relationship by arguing that an adverse impact may result from the fact that would-be artists can demonstrate their talent through many services, such as YouTube or social media, in the digital age. As incumbent firms also observe these would-be artists who have obvious talent, the advantage of entrepreneurial firms' discovery of new talent may be undermined. By utilizing iTunes' and YouTube's staggered market entries into 29 countries, this study produces results from a difference-in-difference-in-differences (DDD) specification. The findings suggest that iTunes and YouTube did not facilitate entrepreneurial firms' discovery of new talent but decreased the average and maximum popularity of new artists in entrepreneurial firms. In contrast, entrepreneurial firms increase their reliance on incumbent artists. In short, the average popularity of new artists in entrepreneurial labels decreased and reached a level similar to the average popularity of new artists in incumbent labels. Considering that entrepreneurial firms have relied more on the discovery of new talent (their proportion of new artists is higher than that in incumbent labels), the discovery performance of entrepreneurial labels was lower than that of incumbent labels.

Finally, in the third chapter, I examine whether foreign ownership or capital undermine the discovery of new domestic talent in the cultural industry. One theoretical argument suggests that foreign ownership may weaken the discovery of new talent from the host country because foreign owners may lack a good understanding of the host country culture ("liability of foreignness"). Another theoretical argument challenges this simple negative relationship by arguing that foreign ownership may have an offsetting advantage that can be transferred from the home country to a foreign subsidiary at a cost that outweighs the liability of foreignness. This study focuses on the case of Sony's acquisition of CBS Records (a US major label) in 1988, which is the first merger by a Japanese firm with a firm of a distant culture. The estimates from a difference-in-differences (DD) specification suggest that Sony did not undermine CBS Records' discovery of domestic new talent but rather increased the popularity of new domestic artists in CBS Records and its sublabels. In contrast, Sony's acquisition decreased CBS Records' reliance on incumbent artists and foreign (outside the US) artists. Finally, I also conduct the same analysis with nine other major mergers and compare the results with the results from Sony's acquisition of CBS Records. The results are consistent with the results from Sony's acquisition of CBS Records.

Chapter 1

Does Unbundling Facilitate Experimentation and the Discovery of New Talent?

1.1 Abstract

This study examines an underexplored type of innovation - the discovery of new resources - in creative industries of the digitalization era. Digitalization has engendered a fundamental unbundling of creative goods. In the music industry, for instance, digitalization has enabled music to be purchased as both individual songs (i.e., a single) and a bundle of songs (i.e., an album). I explore whether unbundling facilitates firms' experimentation and the discovery of new artists. For this purpose, I study a model of unbundling and the discovery of new talent and test its empirical implications in the music industry. To identify a causal effect of unbundling on the discovery of new talent, I utilize iTunes' staggered market entries into 29 countries based on a novel dataset from multiple large-scale music databases, including Spotify APIs. Consistent with the theoretical predictions, I find that as unbundling lowers the cost of experimenting with new artists, single-producing firms have 27.25% higher proportion of new artists than album-only-producing firms. In contrast, as information on artist talent from a one-shot unbundled experimentation is less accurate than that from albums, single-producing firms make 29.75% more omission

errors. Overall, the results suggest that the positive effect from the decreased cost of experimentation outweighs the negative effect from the loss of information quality on talent. Thus, single-producing firms discover more popular artists and artists who create new markets (genres) than album-only-producing firms. These results highlight the trade-off between breadth-oriented experimentation (experimenting with more new alternatives) and depth-oriented experimentation (collecting more accurate information on fewer alternatives) and suggest that digitalization may facilitate firms' breadth-oriented experimentation and the discovery of new talent.

1.2 Introduction

Schumpeter (1934) distinguishes among five types of innovation: new products, new processes, new organizations, new markets, and new resources. Most prior work has focused on the first three types of innovation (e.g., Abernathy and Utterback 1978, Nelson and Winter 1982, Cohen and Levinthal, 1990, Kogut and Zander 1992, Tripsas and Gavetti 2000, Adner and Kapoor 2010, Leiponen and Helfat 2010, Casadesus-Masanell and Zhu 2013). This study focuses on the last type of innovation, the discovery of new resources, in creative industries where artist talent - a type of resource - is the most important source of creativity and profit. The discovery of new talent has become increasingly important in creative industries as creative industries have transformed into a "super-star" or "winner-take-all" market in which a few talented artists dominate with respect to industry sales and profit (Bakos and Brynjolfsson, 1999). In particular, experimenting with new talent is fundamental in the discovery of new talent because the attributes required for an artist to be a successful can hardly be known in advance or deduced from some of set of principles (e.g., Caves 2000, Benner and Waldfogel 2016).

This study explores the impact of digitalization, a radical technological change, on experimentation and the discovery of new talent. Digitalization has spurred a fundamental unbundling of creative industries. As transaction costs are lower in online channels, digitalization enables firms to offer single products that were previously sold only or primarily as a part of bundles (Elberse 2010). While prior work has mainly focused on the impact of unbundling on industry- and product-level sales (e.g., Bakos and Brynjolfsson 1999, Elberse 2010, Liebowitz 2016) or the impact of online piracy - another phenomenon of digitalization - on industry- or product-level sales (e.g., Oberholzer-Gee and Strumpf 2007, Rob and Waldfogel 2007), this study focuses on the impact of unbundling on firm-level experimentation behavior and its ramifications for the discovery of new artists. Quantitatively assessing experimentation and the discovery of new talent is more challenging than documenting a reduction or increase in sales. Indeed, determining whether the impact of unbundling on experimentation is positive or negative is far from straightforward, as unbundling affects both the costs and benefits of experimenting with new artists.

I develop a model describing how unbundling influences the discovery of new talent and test its empirical implications in the music industry where single products (i.e., "singles": a release of a song) and bundled products (i.e., "albums": a release with multiple songs) have coexisted since the 19th century. As albums have been the main format of music production, many firms have produced only albums, while some firms have produced both albums and singles. My model proposes that unbundling has two competing effects on the discovery of new talent. First, as unbundling lowers the cost of experimenting with new artists, it may have a positive effect on the discovery of new talent by allowing firms to experiment with more new artists. This is consistent with the experimentation literature (e.g., Kulkhani and Simon 1988), which argues that firms are less likely to stick to their existing options when they faced with a low cost of experimenting with new alternatives.

However, unbundling may have a negative impact on the discovery of new talent because in the presence of high noise in the commercial outcomes of creative work (e.g., Caves 2000, Salganik, Dodds, Watts 2006), it will be challenging for firms to infer an artist's true talent from a one-shot unbundled experimentation result of success or failure. For example, when an artist has the opportunity to produce an album with ten songs, a firm will gain more information than when an artist produces a single. As the information about a new artist's talent from singles is noisier than the information from albums, single-producing firms may be more vulnerable to both commission errors (giving future production opportunities to untalented artists) and omission errors (giving no future production opportunities to talented artists) than album-only-producing firms. Omission errors are more problematic in this situation, as talented artists that face an unlucky failure from their single may mistakenly be considered untalented by firms and lose future production opportunities.

Given these competing effects, I argue that the positive effect of unbundling on the discovery of new talent may outweigh its negative effect in the music industry. First, in the music industry, most firms face high costs when experimenting with a new artist (more than one million dollars) (IFPI 2014, Benner and Waldfogel, 2016) and are entrepreneurial firms (usually called "independent labels") that are under financial constraints. These firms incur a higher opportunity cost of experimentation when they produce albums only, as album production costs are at least 2-4 times higher than single production costs. As shown in the labor economics literature (e.g., Tervio 2009, Pallais 2014), the high cost of experimenting with a new artist (from an album-producing firm) may be the main reason why they experiment with too few artists and rarely discover talent. Second, the marginal benefit that a firm can receive from additional experimentation with one artist decreases rapidly as the number of experimentations increases. Thus, the number of songs in an album may be more than sufficient to evaluate the talent of the artist. The benefits from increased experimentation owing to the decreased cost of experimentation may thus outweigh the loss of information quality regarding each artist's talent level from a one-shot unbundled experimentation.

To identify the causal effect of unbundling on the discovery of new talent, I utilize staggered market entries of iTunes Music Store (hereafter "iTunes") into 29 countries as an exogenous shock. The introduction of iTunes has significantly increased the commercial importance of singles because music is sold in the form of individual songs that were previously only or primarily sold as part of albums. As iTunes increased its market share, music firms had a larger incentive to produce their work through singles. This offers a natural experimental setting because different entry timing into many countries generated an exogenous shock that increased firms' incentives to produce singles; however, it was not related to each firm's unobserved attributes and their intention to hire new artists. I build a novel dataset collected and matched from multiple large-scale datasets, including the Spotify APIs and Musicbrainz. The sample covers 165,464 artists, 2,349,776 songs, and 22,157 music firms in 29 countries for the period from 1950 to 2015.

The results support the proposed theory on the impact of unbundling on experimentation and the discovery of new talent. First, a positive effect of unbundling is observed: single-producing firms experiment with more new artists than album-only-producing firms. Specifically, the proportion of new artists to all artists is 27.25% (a 4.62% point) higher in single-producing firms than in album-only-producing firms. Second, single-producing firms make more omission and commission errors. Third, single-producing firms discover artists with greater talent and produce more popular songs; that is, the most popular artist and song in single-producing firms are more popular than those in album-only-producing. Finally, single-producing firms are more likely to discover artists who created at least one new genre, suggesting that unbundling facilitates the creation of new markets.

In addition, I conduct contingency analyses on whether the proposed mechanism that firms under financial resource constraints may benefit more from producing singles. As noted previously, firms that are under financial resource constraints may benefit more from unbundling because they can experiment with more new artists when they produce singles. In contrast, the negative impact of unbundling from high noise commonly applies for all firms. Even firms with sufficient financial resources cannot avoid this noise. Thus, for firms that are under financial resource constraints, the positive impact of unbundling may outweigh its negative impact. The results indeed show that small firms, which are more likely to be under financial resource constraints, benefit more from unbundling than large firms.

This study contributes to two streams of strategy research. First, it contributes to the literature on innovation and experimentation (e.g., Thomke 1998). This study focuses on the most underexplored type of innovation - the discovery of new resources. In particular, this study shows that concerning human resources, experimenting with more new workers (breadth-oriented search) is more beneficial than collecting more precise information on each worker (depth-oriented search). Thus, the findings contribute to the literature on parallel search (i.e., a type of breath-oriented search) (Nelson 1961, Posen and Levinthal 2012, Eggers and Green 2012) by providing empirical support for the benefits of breadth-oriented search in human resource discovery.

Second, this study contributes to the strategic factor market literature. As Makadok and Barney (2001) and Ahuja and Katila (2004) note, few studies have explored how new valuable resources can be discovered through effective information acquisition. This study fills this gap. In particular, this study highlights the impact of the cost of experimentation on information acquisition by shedding theoretical light on the trade-off between the benefits of experimenting with more new artists and the benefits of producing bundled works to gain more reliable information.

Third, this study speaks to the economics of digitalization literature by demonstrating the impact of unbundling on supply-side issues. The impact of digitalization, a technological change, has begun to garner attention from strategy scholars (e.g., Benner and Waldfogel 2016). By providing evidence on the impact of digitalization on an important supply-side issue (i.e., experimentation), this study complements prior work on the role of digitalization on the demand side (e.g., piracy, sales, or long tail) (Rob and Waldfogel 2006, Zentner 2006, Oberholzer-gee and Strumpf 2007, Elberse 2010, Zhang 2014).

1.3 Related Literature and Model

Digitalization, unbundling, and their implications for strategic management

Digitalization has brought forth a trend toward unbundling in many creative industries. As transaction costs are lower in online channels, the Internet enables firms to offer individual products that were previously only (or primarily) sold as a part of bundles (Elberse 2010). For instance, with the advent of online music stores such as iTunes, music is now sold in the form of individual songs instead of albums with a dozen or so songs. Through online stores, consumers can watch one episode of a television show at a time rather than pay for an entire season on DVD. Furthermore, newspapers such as The Economist have unbundled their online content by selling individual articles to users for a small fee, and publishers such as McGraw-Hill have unbundled their online content by selling access to the chapters of certain books.

Unbundling (or bundling) is one of the most important topics in the literature on industrial organization, marketing, and information systems. Most research on unbundling has examined the impact of bundling on consumer surplus and industry sales (or profits) (e.g., Bakos and Brynjolfsson 1999, Varian 2001, Elberse 2010, Liebowitz 2016). However, the impact of unbundling on supply-side issues, such as firm-level experimentation and creativity (i.e., experimenting with new artists and discovering popular and creative artists in creative industries), has yet to be explored. While firms experimentation and creativity are fundamental topics in the strategic management and innovation literature (e.g., March

1991, Thomke, von Hippel, and Franke 1998, Kogut and Kulatilaka 2001, West and Iansiti 2003), as Waldfogel (2012) notes, quantitatively assessing quality or creativity is more challenging than documenting increases or reductions in sales. Indeed, whether the impact of unbundling on experimentation is positive or negative is far from straightforward, as unbundling affects both the costs and benefits of experimenting with new alternatives. I discuss the impact of unbundling on the benefits and costs of experimentation in the following subsections.

In creative industries, the cost of experimentation is high because most creative goods such as music are experience goods that consumers generally cannot determine whether they like until they have used them (e.g., listened to a song or an album) repeatedly. This creates a challenge for firms that want to predict whether new artists have the potential to be popular (Benner and Waldfogel 2016). Industry experts refer to this feature as the "nobody knows property." Caves (2000) notes such difficulty in predicting the commercial success of creative work as follows:

> "A creative product is an "experience good", but the buyer's satisfaction will be a subjective reaction. The producer's intimate knowledge of the good's production process still leaves him in the dark about whether customers will like it: nobody knows. ... Research and pretesting are largely ineffective, because a creative product's success is seldom explained even ex post by the satisfaction of some pre-existing need (Caves 2002)."

Thus, in creative industries, organizing effective experimentation is important for firms to gain and sustain a competitive advantage over other firms. As digitalization affects the cost of experimenting with new artists, exploring the impact of unbundling will offer implications for strategic management.

In addition, more broadly, radical technological change and its impact on firms' adaptation has been an important topic in the strategic management and innovation literature (e.g., Tushman and Anderson 1986, Henderson and Clark 1990, Christensen 1997, Tripsas and Gavetti 2000). As digitalization, an era marked by a shift from analog to digital technology, is itself a radical technological change, examining digitalization and its impact on firms' adaptation will yield important implications for strategy and innovation scholars (Benner and Waldfogel 2016). Although economists have recently begun to study digitalization and its impact on creative industries, the prior literature has not examined this at the firm level, nor has it provided strategy implications for firms facing digitalization, a technological change. Thus, this study attempts to contribute to the literature by exploring the impact of digitalization on firms' adaptation strategy in creative industries.

The positive effect of unbundling on creativity: Breadth-oriented search

I review the related literature on experimentation and discuss it in the context of information and creative industries. In these industries, winner-take-all or superstar effects are prominent; only a small number of products or workers (in creative industries, "artists") dominate industry sales and profits. As creativity and popularity significantly depend on artists' talent, discovering new talent is critical for firms to sustain and gain competitive advantages. Thus, to discover new creative or popular artists, firms must experiment with new artists. In the strategy literature, experimentation is considered a trial-and-error problem-solving activity (Thomke, von Hippel, and Franke 1998). It begins with the selection of one or more possible alternatives. Thus, through experimentation firms can reveal information on new alternatives; if one or more new alternatives outperform existing options, the new ones will replace the old. Therefore, the benefits of experimentation arise from information on whether new alternatives have upside potential.

Such experimentation can be considered exploration in the search literature; although firms have a tendency to stick with existing options, exploring new alternatives with upside potential is critical for organization learning and search (e.g. March 1991, Levinthal and March 1993, Levinthal 1997). The problem that arises with the discovery of new alternatives has been well understood by management scholars at least since Kulkarni and Simon (1988, 1990) and March (1991). In particular, the problem is considered a trade-off between exploration and exploitation (i.e., the trade-off between experimenting with the new and using the old instead). Theoretically, the optimal solution to experimentation problems draws on the "bandit" literature (e.g., Denrell and March 2001, Posen and Levinthal 2012, Lee and Puranam 2016), which shows how firms can account for the trade-off between immediate output now and information that can help increase output in the future. The real option literature has also explored the value of revealing information about new alternatives (e.g., Kogut and Kulatilaka 1994). In creative industries popular, styles often change unexpectedly. According to the real option logic, on top of the benefit from the upside potential that firms can obtain from experimentation, investing in new alternatives offers an additional option value for firms, particularly when firms encounter turbulent environments.

However, to experiment with new alternatives (in my setting, new artists), firms incur both production and opportunity costs. The production cost is high because the quality of new artists can only be revealed on the job. Furthermore, creative goods are experience goods; therefore, without the introduction of creative work made by the new artists to the market, their talent cannot be tested. The second type of cost is opportunity cost. When a firm experiments to a greater extent with new artists, it sacrifices sales and profits from existing options. If firms are more likely to be under more financial constraints, opportunity costs compose a larger part of the cost of experimentation. This increased cost of experimentation may then generate a tendency for firms to stick with existing options or, in other words, to become stuck with the local peak options (March 1991, Levinthal 1997, Rivkin 2000).

When firms experiment with new artists through unbundled products instead of bundled goods, the cost of experimenting with a new artist can be decreased. For example, in the music industry, the cost of producing a song is much lower than the cost of producing an album, as firms need to hire more composers, lyricists, and music engineers and Artists and Repertoire (A&R) executives need to spend more time on the artist when they produce an album. Thus, when the information that a firm obtains from experimenting with unbundled products remains unchanged or at least does not decrease significantly, the relative benefit (i.e., information on new alternatives) over the cost of experimenting with a new artist increases. The decreased benefit from experimenting engendered by unbundling will be discussed in the next subsection. Thus, under a low cost of experimentation, the relative benefit over the cost of experimenting with incumbent artists compared with new artists does not significantly increase. This leads to the conclusion that new artists will require a larger proportion of resources in firms that produce unbundled works.[1] This logic is mathematically formulated and proven in the Model section.

Under the assumption that an artist's talent is a random draw from any distribution, a firm will be more likely to select better new artists when it experiments with more new artists through unbundled products, some of which are created by artists will have high talent. This conclusion is consistent with the real option perspective that investing in new alternatives may offer option values for firms under uncertainty (Kogut and Kulatilaka 2001). Furthermore, this increased proportion of new artists in firms can be considered to result from breadth-first search or breadth-oriented search. Breadth-oriented search has been explored by prior work on parallel search, which is defined as the simultaneous pursuit of two or more distinct alternatives. Parallel search is contrasted with a sequential strategy, where firms fully commit to the best apparent approach and explore other possibilities only if the first proves unsuccessful (Nelson 1961, Abernathy and Rosenbloom 1969, Loch, Terwiesch, and Thomke 2001).

In particular, Nelson (1961, p. 353) emphasizes that in the parallel search strategy, firms can benefit from information acquired by engaging in multiple alternatives simultaneously, rather than sequentially. As alternatives constitute different approaches to solving the same problem, and to answering the same need, the cost of experimenting with new alternatives is an important factor that determines the optimal number of alternatives that a firm would search for simultaneously. For example, two different bomb designs developed concurrently in the Manhattan Project were used in the bombs dropped in Hiroshima and Nagasaki in 1945. More recently, in the strategy field, Loch, Terwiesch,

[1]Ewens, Nanda, and Rhodes-Kropf (2015) also build a model and test this relationship in the context of the venture capital industry. Their findings suggest that a low cost of experimentation induces firms to invest more in new options. They call this approach a "spray and pray" strategy.

and Thomke (2001) and Posen, Matignoni, and Levinthal (2012) have theoretically explored the benefits and costs of parallel search, and Leiponen and Helfat (2010), Eggers (2012), and Eggers and Green (2012) have explored them empirically. The logic of the theoretical benefits from parallel search is the same as the theoretical prediction in this study. The cost of experimenting with multiple new alternatives is explored by Eggers (2012) and Eggers and Green (2012) and is discussed in the next subsection.

The negative effect of unbundling on creativity: Decreased information quality

In view of the quality of information perspective, unbundling has a negative impact on the discovery of new talent. The uncertainty of creative works' commercial success generates noise when firms experiment with new artists, and noise makes it difficult for firms to infer new artists' talent solely from commercial success or failure. In particular, the fact that most information and creative goods are network goods makes it more difficult for firms to predict the success of creative work (Arthur 1989, Varian 2001, Farrell and Klemperer 2007). When consumers buy network goods, consumers' choices are affected by other consumers' choices. Arthur (1989) argues that under the presence of network effects, insignificant events may give one product an advantage over others. Consequently, unpredictability is amplified during product diffusion among consumers. Salganik, Dodds, Watts (2006) offer evidence on Arthur's theoretical argument by creating an artificial cultural market and conducting experiments on this market. Their findings suggest that increasing the strength of social influence increases inequality and the unpredictability of success.[2] To sum up, the commercial success of creative work is only partly determined by quality.

The fact that the commercial success of creative work is only partly determined by quality makes it difficult for firms to infer talent from new artists' success or failure. Solving the problem of choosing among alternatives to a given objective is difficult (Nelson 1961), and it is very easy to make choices which, ex post, turn out to be the wrong ones in the presence of noise (Simon 1969, Thomke, von Hippel, Franke 1998, Denrell and March 2001). One feature that distinguishes the behavioral theory of choice from conventional models of choice in economics is that the evaluation of searched alternatives is likely to be imperfect (e.g., Knudsen and Levinthal, 2007, Csaszar 2012, 2013, Fang, Kim, Miliken 2014). There are two types of imperfections: firms may erroneously accept an inferior alternative (i.e., commission error or type II error) or falsely reject a superior alternative (i.e., omission error or type I error). Scholars have examined factors that increase or decrease commission errors and omission errors, and both omission and commission errors decrease the benefit of bundling with respect to search performance.

As unbundling decreases opportunities offered to a new artist, the new artist will have fewer opportunities to show their talent. For example, in the music industry, creative work (i.e., a song or an album) is usually made by one singer or group. Whereas singers has one opportunity to demonstrate their talent when producing a song, they have multiple chances to demonstrate their talent when producing multiple songs for an album. The combination of fewer chances for new artists and the considerable noise in commercial

[2]This is one reason why information and creative industries are described as "superstar" or "winner-take-all" markets where blockbuster products or artists dominate sales.

success decreases the reliability of information that firms acquire from experimentation. Firms that produce through unbundled work may be more vulnerable to both omission errors (giving no future production opportunities to talented artists) and commission errors (giving future production opportunities to untalented artists) than bundle-producing firms. As for omission errors, talented artists that experience an unlucky failure in their unbundled product may mistakenly be considered untalented by firms and lose future production opportunities. In contrast, if music firms experiment with new artists through bundled products, those artists are given more opportunities to show their true talent by creating and testing multiple products in bundled products. Commission errors occur when bad alternatives may receive a lucky draw and are erroneously considered high-performing alternatives and receive future production opportunities. Tervio (2009) argues that there are too many mediocre incumbent artists whose talent is not sufficiently high to justify the crowding out of novice artists with lower expected talent but with more upside potential. This type of commission error in the allocation of future opportunities may be one more reason for the large number of mediocre incumbent artists.

A model of unbundling and the discovery of talent

In this section, my goal is to provide a model of unbundling that can highlight how lower costs of experimentation can alter the composition of artists and how unbundling can affect the discovery of new artists. The basic setup is a multi-armed bandit problem.[3] For

[3]There has been a considerable amount of work modeling innovation and experimentation that has used a multi-armed bandit machine. From the classic work of Nelson (1961), Evenson and Kislev (1976), Denrell and March (2001), Tervio (2009), and Posen and Levinthal (2012), I build on Evenson and Kislev (1976) and Tervio (2009) by altering features of the problem to explore the effect of unbundling on experimentation and the discovery of new talent.

simplicity, I assume that the only parameter is the number of new artists in a firm and that net income is in direct proportion to the top artist's talent.[4]

I describe firms' search process as a sequence of experiments. Talent is drawn from a distribution with a continuous and strictly increasing cumulative distribution function. Incumbent artists have released their songs in the past, and their talent is known to everyone. In contrast, new artists have never released their songs, and the talent of a new artist is unknown to everyone, including herself/himself. At any period t, a firm decides the number of new artists to maximize its expected returns. m_t is the maximum talent among all artists in the firm, n_t is the number of experiments (i.e., new artists) in the firm, which is the main choice parameter, $c(n_t)$ is the cost of experimentation and is increasing at an increasing rate, x_i is the talent quality of new artist i and is a random draw from a distribution with positive support $[x_{min}, x_{max}]$, $f(x)$ is a probability density function of x_i, $F(x)$ is the cumulative probability density function of x_i, y is the largest value in a sample of the random draws $X = \{x_1, x_2, ..., x_n\}$, and γ is the discount factor. For each experimentation, any firm can combine one artist with other inputs. Each experimentation produces an observation on the quality of a new artist's talent. The outcome of experimentations is the most talented artist in their sample.[5]

I assume that the matching of individuals and firms is inconsequential. In each time period, a firm experiments with n new artists (i.e., it makes n draws from a random distribution). The result of each experimentation is an observation x_i, and the talent level

[4]The talent is skewed, and the success of a label depends on the discovery of extremely popular new artists. For example, in the music industry, only 5% of albums or singles produced by EMI, a major music company, broke even in 2014 (EMI, 2015).

[5]The statistical process of choosing the largest value from a set of samples is called the theory of extreme values in the subject of order statistics (Gumbel 1958, Epstein 1960, Evenson and Kislev 1976).

associated with the tested artist i. If the talent of the new artist is higher than m_t, the highest talent level in the firm at time t, the new artist is selected to produce songs, and the maximum talent quality in the firm at time $t+1$ (m_{t+1}) increases. The cumulative distribution of m, the most talented artist's talent, is $F^n(y) = Pr(y = max\{x_1, x_2, ..., x_n\})$.

The expected value of the talent increment with n experimentations is

$$E_n(\Delta m) = \int_m^\infty (1 - F^n(y))dy.$$

This function has a positive value, as $F^n(y) \leq 1$ and the first-order difference $\Delta E_n(\Delta m_t) = \int_m^\infty F^{n-1}(y)(1 - F(y))dy$ is positive and decreases with n, since $F^{n-1}(y)$ decreases in n. Hence, the contribution of an additional experiment decreases. As this is a one-period model, there is no trade-off between the upside potential of experimenting with new artists and the upfront investment.

Now, I check whether this relationship is robust to the case when firms are potentially infinitely lived and maximize average per-period profits. More formally, a firm's search for creativity advances over time by discovering higher talent whenever possible. The net present value of the firm's profit is

$$V(m_0) = E\left\{\sum_{t=0}^{\infty} \gamma^t [m_t - c(n_t)]\right\}.$$

Firms will choose the number of new artists n_t at each time period that maximizes $V(m_0)$. I consider the steady state. In the steady state, all firm-level variables are constant over time, although individual firms' fortunes vary over time. Let $V^*(m_0)$ denote the net present value of the firm profit in the steady state (i.e., firms choose the optimal experimentation policy). The optimized net present value can be written as a Bellman equation as

$$
\begin{aligned}
V^*(m) &= \max_n \left[m - c(n_t) + \gamma E \left\{ \sum_{t=0}^{\infty} \gamma^t [m_t - c(n_t)] \right\} \right] \\
&= \max_n \left[m - c(n_t) + \gamma \int_m^{\infty} V^*(y) F^n(y) dy + \gamma V^*(m) F^n(m) \right]
\end{aligned}
$$

where $m = m_0$. The first two terms, $m - c(n_t)$, are the profit in the current period, and the last two terms, , are the expected benefits $E(B(m,n))(= b(m,n))$ from n experimentations in the current period. The term $\gamma \int_m^{\infty} V^*(y) F^n(y) dy$ is the additional expected benefit from a more talented artist that a firm discovers from experimentations in the current period, and the term $\gamma V^*(m) F^n(m)$ is the expected value from the most talented artist in the current period. By taking the first derivative of these two terms and the number of new artists, I derive the following lemma, whose proof is given in Appendix 1. The essence of this lemma is summarized in Figure 1.

> *Lemma 1. (Under no noise in talent discovery) The benefit from experimenting with an additional new artist is positive and decreases with the number of new artists.*
> *Proof. See Appendix 1.*

I assume that the cost function $c(n)$ is an increasing function at a non-decreasing rate with n. As Lemma 1 shows that the additional benefit of an experimentation $\Delta E(B(m,n))$ decreases in n, there exists a unique optimal experimentation policy n^* such that $b(m, n-1) - c(n-1) \leq b(m, n^*) - c(n^*)$ and $b(m, n+1) - c(n+1) \leq b(m, n^*) - c(n^*)$. The only corner solution is when n^* is 0 when $\Delta b(m, 1) =$

$\gamma \int_m^\infty \frac{\partial V^*(y)}{\partial y}(2F^{n-1} - F^n - F^{n-2})dy < \Delta c(1)$.

I now turn to the impact of unbundling on the cost of experimentation. Let $\Delta b_u(m,n)$ and $\Delta b_b(m,n)$ denote the benefit function under the unbundling and bundling strategy, respectively. Furthermore, let $\Delta c_u(n)$ and $\Delta c_b(n)$ denote the cost function under the unbundling and bundling strategy, respectively. If a firm adopts an unbundling strategy, it can reveal a new artist's talent with a small amount of cost. Using *Lemma 1* and the assumption that the cost function increases at non-decreasing rate with n, it is straight forward that there exists a unique optimal solution n^*. Given that there exists no noise in talent discovery, while unbundling does not change the benefit function (i.e., no change in the marginal benefit $\Delta b(m,n) = \Delta b_u(m,n) = \Delta_b(m,n)$), it moves the marginal cost function downwards ($\Delta c_b(n) > \Delta c_u(n)$). Hence, unbundling increases the optimal number of new artists $n*$. As the number of incumbent artist is 1, the increased number of new artists increases the proportion of new artists ($\frac{n^*}{n^*+1}$) in firms that produce unbundled work. As the number of new artists with whom firms experiment increase, firms will discover more talent artists, meaning that $m^*|_{t=\infty}$ has a higher value under the optimal experimentation policy n^*. This logic leads to the following lemma:

> *Lemma 2. (Under no noise in talent discovery) Firms that adopt an unbundling strategy will increase the proportion of new artists and discover more talented artists.*

The above model does not incorporate the role of noise in talent discovery when a new artist demonstrates talent. As I cover in the literature review section, there is considerable noise when firms experiment with new artists. Here, I build an extended model with noise in talent discovery. In the presence of noise, it will be more challenging for firms to infer the quality of an artist's talent from her/his commercial outcome. Therefore, noise decreases the benefit from experimentation. More formally, let e denote the noise. When a firm experiments with a new artist through unbundled work, the noise will increase the occurrence of omission errors. A talented artist i whose talent x_i is higher than m_t may have a large negative noise term e_i such that $x_i + e_i < m_t$, and the firm would not produce artist i's work in the subsequent periods. Also the noise will increase commission errors; an untalented artist j whose talent x_j is lower than m_t may encounter a large positive noise term e_j such that $x_j + e_j > m_t$, and the firm produce artist j's work in the subsequent period(s). Thus, $H(x, e)$ decreases with the size of e at a decreasing rate, $\lim_{e \to 0} H(x, e) = F(x)$ and $\lim_{e \to \infty} H(x, e) = \frac{x - x_{min}}{x_{max} - x_{min}}$ if $x_{min} \leq x \leq x_{max}$. Let the noise under the unbundling strategy be e_u and the size of the noise under the bundling strategy be e_b and assume that $e_u > e_b \geq 0$. As the noise e decreases the benefit of additional experimentation, it does not change the cost of additional experimentation. Hence, the optimal experimentation policy n^* decreases as the noise increases. This logic leads to the following lemma:

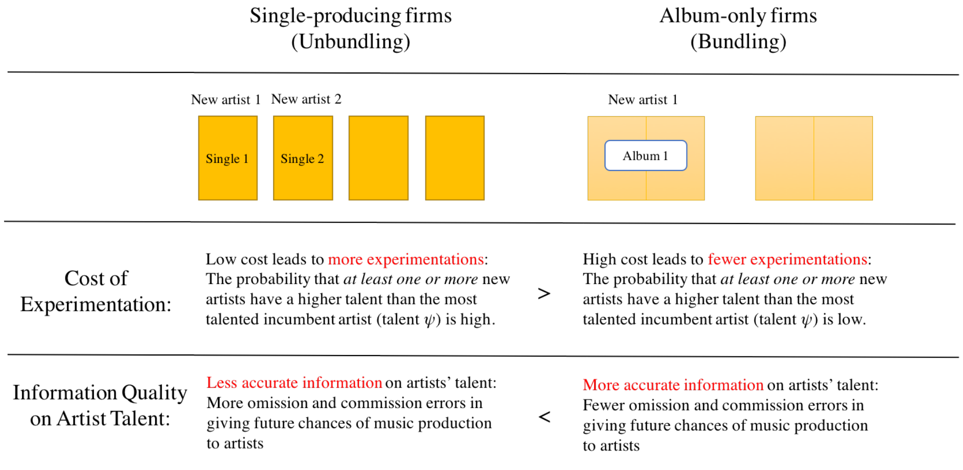
Lemma 3. Ceteris paribus, as the noise of talent discovery increases, firms will decrease the proportion of new artists and discover less talented artists.

I analyze the impact of noise on bundling choices. It will be more challenging for firms to infer an artist's true talent from a one-shot unbundled experimentation result of success or failure. For example, when an artist has the opportunity to produce an album with ten songs, a firm will gain more information than when an artist produces a single. As the information about a new artist's talent from singles is noisier than the information from albums, single-producing firms may be more vulnerable to both commission errors (giving future production opportunities to untalented artists) and omission errors (giving no future production opportunities to talented artists) than album-only-producing firms. By combing Lemmas, Result 1 summarizes the characteristics of the optimal experimentation policy in the steady state.

> *Result 1. In the equilibrium, the impact of unbundling on experimentation and the discovery of talent depends on the amount of noise in inferring new artists' talent from commercial outcomes.*
>
> *(i) The unbundling strategy will lead to a smaller proportion of new artists and the discovery of less talented artists when the noise is larger than a threshold* ψ^* *such that* $\int_m^\infty \frac{\partial V^*}{\partial y}(H^{n-1}(y,\psi^*) - H^n(y,\psi^*)) < \Delta c_u(n_b^*)$*, where* n_b^* *is the optimal number of experimentations under the bundling strategy.*
>
> *(ii) The unbundling strategy will lead to a larger proportion of new artists and the discovery of more talented artists otherwise.*

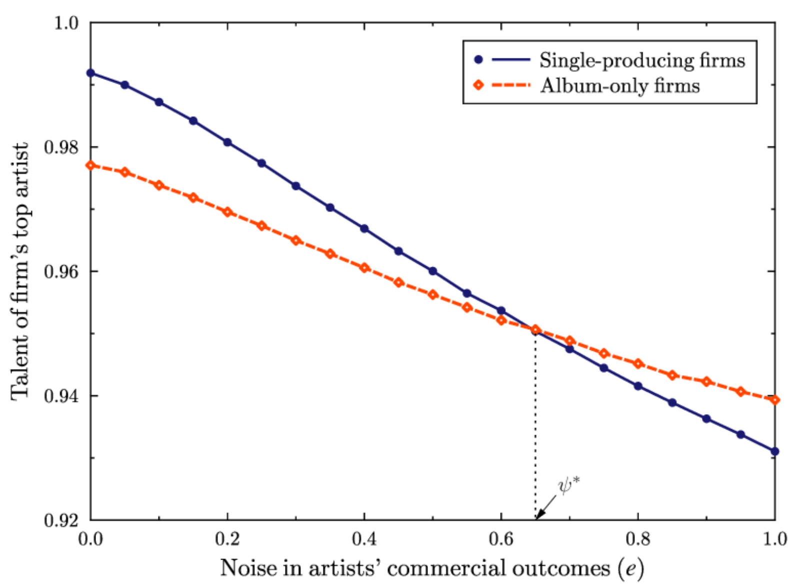
Hence, the relationship between unbundling and experimenting with new artists is far from straightforward. I summarize the impacts of unbundling on the discovery of new talent in Figure 1.1 and visualize Result 1 with a numerical example in Figure 1.2. One might believe that the lower cost of experimentation (from unbundling) may obviously lead to a higher proportion of new artists. However, if there exists high noise from a new artist's commercial success, unbundling may lead to a decreased proportion of new artists. The boundary condition is described in Result 1. The condition in the music industry should be examined to determine whether unbundling may lead to a higher proportion of new artists. Another interpretation of this result is that if firms face high noise in evaluating new artists' talent, unbundling may decrease firms' experimentation and may be detrimental to new artists.

Figure 1.1: Intuition of the theoretical model on the impact of unbundling on the discovery of new talent



Note: I assume that an album has twice more songs than a single does. Talent is drawn from any distribution with a continuous and strictly increasing cumulative distribution function, F, with positive support $[\theta_{min}, \theta_{max}]$.

Figure 1.2: A numerical example of the theoretical model



Note: The talent of an artist i ((x_i)) is a random draw from $U(0, 1)$. The noise parameter e determines the range of a uniform distribution (i.e., $U(-0.5 \times e, 0.5 \times e)$). Thus, the actual noise, e_i is a random draw from this uniform distribution. The lines show talent of firm's top artist under the optimal experimentation policy (n^*). Each point is the average of 20,000 simulations. Other functions and parameters of this numerical example are specified in Appendix A.

1.4 Empirical Context and Hypotheses

Empirical context: The music industry and the advent of iTunes

The music industry and the discovery of new artists

Music firms are called record labels or labels. In this study, I focus on music production firms that coordinate production, distribution, and marketing processes. These music production firms also scout talent and develop new artists, which is called "artists and repertoire (A&R)," and maintain contracts with recording artists or bands. The International Federation of the Phonographic Industry (IFPI 2012, p. 9) describes music as "an investment-intensive business," as the first major activity that music production firms have traditionally undertaken is the discovery of new artists. Indeed, music firms' investment in A&R and marketing in 2014 totaled more than US $4.3 billion, which accounts for more than 10% of global music sales (IFPI 2014). According to the IFPI, at least US $500,000 is required to experiment with a new artist. Common features of contracts signed with emerging artists include the payment of advances, recording costs, tour support, video production and marketing and promotion costs, as shown in Table 1.1. In comparison with music production firms, online music providers such as Spotify, iTunes, Google, or SoundCloud spent no money on upfront investment for talent discovery. Thus, music production firms remain the largest upfront investors in artists' careers.

Many would-be artists seek to make their music available to consumers, for example, by submitting "demo tapes" to music production firms. These potential music products differ substantially in both their ex ante promise (how broadly appealing the artist would

Table 1.1: Cost of producing a release in the music industry

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

Source: International Federation of the Phonographic Industry report, 2014

be if their work was produced) and their ex post success (how successful they turn out to be) (Benner and Waldfogel 2016). Even artists themselves do not know their own talent (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." Elvis himself did not know his own 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 at Sun Records, the CEO Sam Phillips and his secretary wrote down his name and added her own commentary: "Good ballad singer. Hold." Sun Records is currently referred as the music firm where rock and roll was born. This example shows how difficult it is for firms to evaluate artists' talent ex ante.

Singles vs albums: Decline of singles in the late 20th century

A release is a broad term that covers the two different forms: singles and albums. Music firms commonly classify a release with a small number of songs as singles and a release with a large number of songs as albums. If a music firm produces some of its work by a single instead of an album, the cost of production or opportunity cost of a single is smaller than that of an album. In addition, one of my key informants from Sony Music Entertainment confirms that producing albums requires 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 needed on an album vs. a single. It also requires far more hours in the recording and mixing studios, more hours of mastering. It comes out to 12-15 times more expensive than singles in terms of music production costs."

Many new artists have debuted with singles. Elvis Presley recorded five singles at Sun Records. The discography of Aqua, a Danish-Norwegian dance-pop band, is also a good example, as the band debuted with a single and made singles until they made an international breakthrough with their single "Barbie Girl" in 1997. A more recent example is the song "Cheerleader" by the Jamaican singer OMI, which was released as a single by the independent label Oufah. The song first debuted on the Billboard Hot 100 in the United States in early May 2014, as the song peaked in the UK.

The commercial and artistic importance of the single (as compared with the album) has varied over time, throughout technological development, and according to the audience of particular artists and genres. The golden age of the single was in the 1950s to early 1960s, in the early years of rock music. Starting in the mid-1960a, albums became a greater focus and more important as artists created albums of uniformly high quality and coherent themes, a trend that reached its apex in the development of the concept album. Over the 1990s and early 2000s, the single generally received less attention in the United States than albums. On the one hand, the production cost of a new medium, the compact disc (CD), gave greater incentive to labels to produce their works by albums, because CDs required virtually identical production and distribution costs as singles but could be sold at a higher price.

The advent of iTunes

Before the iTunes Store, most songs were downloaded through illegal file-sharing websites, such as Napster. Steve Jobs expressed concern that people were illegally obtaining music, as it was the only option they had. In 2002, Steve Jobs made an agreement with the five major labels to offer their content through iTunes and, in 2003, introduced iTunes, which provided a market for songs and albums. This was an unexpected shock to the music industry. In response to the change that iTunes brought, music labels started to produce their songs as not only albums but also singles. The iTunes music store affected the music industry hence significantly; indeed, iTunes held approximately 90% of the online market share in the late 2000s. For instance, on September 12, 2006, Steve Jobs announced in his "It's Showtime" keynote that Apple had 88% of the legal US music download market, and on February 26, 2008, iTunes surpassed Best Buy to become the second-largest music vendor in the US behind Walmart. It then became number one on April 3, 2008.

Since 2004, the service has become available in a number of countries other than the US. Table 1.2 summarizes the history of the iTunes' market entry into foreign countries and shows the various timing of iTunes' introduction across different countries. Apple has attained considerable success in the global music market. For example, the entry of Apple's iTunes into Japan in August 2005 received a considerable amount of attention. On October 10, 2012, the iTunes Store was reported to have a 64% share of the global online music market.

Table 1.2: History of staggered entries of iTunes into 29 sample countries

	Country	Entry time	Ranking by no. of unique labels	No. of unique labels in Musicbrainz	No. of label-year observations	Proportion of label-year observations
1	United States	28-Apr-03	1	16,916	25,238	29.64%
2	United Kingdom	15-Jun-04	2	8,914	15,977	18.76%
3	France	15-Jun-04	5	2,974	5,552	6.52%
4	Germany	15-Jun-04	3	5,398	9,890	11.61%
5	Austria	26-Oct-04	23	355	631	0.74%
6	Belgium	26-Oct-04	14	729	1,394	1.64%
7	Finland	26-Oct-04	10	1,329	2,198	2.58%
8	Greece	26-Oct-04	21	366	753	0.88%
9	Italy	26-Oct-04	6	1,919	3,187	3.74%
10	Netherlands	26-Oct-04	9	1,490	2,406	2.83%
11	Portugal	26-Oct-04	26	258	208	0.24%
12	Spain	26-Oct-04	11	1,249	1,621	1.90%
13	Canada	3-Dec-04	8	1,638	2,196	2.58%
14	Ireland	6-Jan-05	28	234	274	0.32%
15	Sweden	10-May-05	7	1,660	2,261	2.65%
16	Norway	10-May-05	16	546	901	1.06%
17	Switzerland	10-May-05	17	528	687	0.81%
18	Denmark	10-May-05	19	443	631	0.74%
19	Japan	4-Aug-05	4	3,676	3,145	3.69%
20	Australia	25-Oct-05	12	1,152	1,767	2.07%
21	New Zealand	6-Dec-05	24	307	428	0.50%
22	Mexico	4-Aug-09	29	217	240	0.28%
23	Czech Republic	29-Sep-11	25	288	469	0.55%
24	Estonia	29-Sep-11	22	359	193	0.23%
25	Poland	29-Sep-11	15	573	764	0.90%
26	Argentina	13-Dec-11	27	235	244	0.29%
27	Brazil	13-Dec-11	18	467	573	0.67%
28	Russia	4-Dec-12	13	817	1,018	1.20%
29	Turkey	4-Dec-12	20	375	316	0.37%
	Total	-	-	55,412	85,162	100%

Note: I exclude countries which have fewer than 200 unique music production firms in the Musicbrainz database. The final sample consists of 85,162 firm-years associated with 22,067 firms.

Hypotheses

As shown in the literature review and theory section, there are competing effects of unbundling on firms' experimentation. First, the decreased cost of experimentation will lead to more experimentation with new artists (i.e., an increase in proportion of new artists in firms). Second, the noise in the commercial success or failure of new artists will increase omission and commission errors in giving future production opportunities to artists. I initially test these predictions.

> *Hypothesis 1: Single-producing firms will have a larger proportion of new artists than album-only-producing firms.*

> *Hypothesis 2: Single-producing firms will make more omission and commission errors in talent discovery than album-only-producing firms.*

I now turn to my main hypothesis: the relationship between unbundling and the discovery of new talent. First, the negative effect of unbundling from high noise commonly applies for all firms. Even firms that have sufficient financial resources cannot avoid this noise. However, the positive effect of unbundling depends on a firm-level variable: financial resource constraint. The cost of experimentation comprises actual production costs and opportunity costs. If album-producing firms are under financial resource constraints, the opportunity cost of experimenting with new artists will be higher than that in single-producing firms, and the high cost of experimenting with a new artist (from album-producing) may be the main reason why they experiment with too few artists and rarely discover talent. Thus, for firms that are under financial resource constraints, the positive impact of unbundling may outweigh the negative impact of unbundling. In fact, most music production companies are small: the average number of releases a firm produces per year is 2.778, and the average number of songs per year is approximately 25. As most music firms that are under financial resource constraints are small and entrepreneurial firms, the positive impact of unbundling on the proportion of new artists may outweigh the negative impact. Based on this logic, I predict that unbundling may increase, on average, the proportion of new artists (among all artists in labels). As shown in the mathematical model, the proportion of new artists is a profit-maximizing experimentation policy of a firm. If a firm experiments with more new artists, the chance of discovering extremely popular artists and artists who can create new-to-the-world genres (the chance of discovering an extreme value) will increase. Thus, this logic leads to following hypotheses:

> *Hypothesis 3a: Single-producing firms will discover more popular artists than album-only-producing firms. (The popularity score of the most popular artist will be higher in single-producing firms than in album-only-producing firms.)*

> *Hypothesis 3b: Single-producing firms will be more likely to discover artists who create at least one new-to-the-world genre than album-only-producing firms.*

1.5 Empirical Strategy

Sample

The sample comprises all music production record labels reported on the Musicbrainz database for the period from 1947 to 2015. The sample includes only music production labels because other labels lack A&R executives or teams, which play a role in searching for and recruiting new artists. I choose 29 countries that have more than 200 unique labels in the Musicbrainz database, and I exclude label-years in which firm i does not release any song in year t. The final sample consists of 85,162 label-years associated with 22,197 labels; the panel is unbalanced.

Variables

Independent variables

My research question is whether labels that produce some of their works in singles are more likely to try out and discover new talent. The first independent variable, $Dummy\_Label\_Single_{it}$, is a dummy, which is equal to 1 when at least one release of label i is released as a single in year t and 0 otherwise. An alternative measure for this variable, the proportion of singles to all releases, is also used to check the robustness of the results in Appendix 5. When I test the second hypothesis, the unit of analysis is an artist. I n this test, I use a dummy variable $Dummy\_Artist\_Single_i$ which takes one if the first release of artist i is produced by a single, otherwise 0.

Dependent variables

The first key dependent variable is the proportion of new artists in a label, measured as the ratio of new artists to all artists of label i in year t. A new artist is a singer or band who did not release a song before year t. By using the Musicbrainz database, I count the numbers of new artists in proportion to all artists of each label.

The next set of dependent variables measures the popularity of artists and songs for each label-year. First, I calculate the maximum popularity of all artists for label-years. I obtain the popularity score of artists from the Spotify Echonest API. The Spotify Echonest API offers a platform, which is called the Rosetta Stone, to match Spotify Echonest IDs and Musicbrainz IDs. I use this platform to calculate firm-level maximum popularity of artists. The range of individual artist popularity is between 0 to 1. Second, I calculate the maximum popularity of all songs for label-years. I obtain the popularity score of artists from the Spotify Web API, which is a distinct API from Spotify Echonest API. I explain differences between these two APIs in Appendix 2. I use unique the international standard recording code (ISRC) IDs for songs to match Spotify Web API and Musicbrainz data. The range of song popularity is between 0 and 100, and I normalize the score to (0, 1) by dividing by 100.

The next dependent variable measures creativity. The Spotify Echonest API offers genre tags for all artists. Overall, 1,347 unique genre tags exist, and each artist has more than or equal to one genre tag(s). I code a dummy that is equal to one if label i discovers a new artist who has a "new to the world" genre tag. For example, as shown in Table 1.3, Jimi Hendrix has five genre tags: blues-rock, classic rock, psychedelic rock, rock, and classic funk rock. He is the first artist who has a genre tag, classic funk rock. Track Records, an independent label in the United Kingdom, signed with him and produced his first single Hey Joe in 1966. The dummy variable for Track Records in 1966 is coded as one.

Also, the dummy variable for an omission error takes one if a music firm did not give no second production opportunities to top 20% talented artists, and these artists left the firm and produced their releases in other firms. The dummy variable for an commission error takes one if a music firm gave more production opportunities to bottom 20% talented artists.

Table 1.3: The 20 most popular artists who created at least one new genre

	Genre	Artist	Popularity	All genre tags that the artist is related
1	Classic funk rock	Jimi Hendrix	0.844746	blues-rock|classic rock|psychedelic rock|rock|classic funk rock
2	Rap rock	Three Days Grace	0.72003	post-grunge|alternative metal|rap rock|canadian metal|rap metal|alternative rock|pop rock|nu metal|funk metal
3	Modern classical	Philip Glass	0.718992	minimal|fourth world|modern classical||drone
4	Canadian country	Shania Twain	0.708148	country|country dawn|canadian country|contemporary country|pop rock
5	Operatic pop	Andrea Bocelli	0.690948	operatic pop|opera|italian pop|pop christmas
6	Progressive electro house	Steve Angello	0.68801	house|edm|electro house|big room|progressive house
7	Chillwave	James Blake	0.674761	indie r&b|bass music|chillwave||progressive electro house|tech house
8	P funk	Bootsy Collins	0.653654	classic funk rock|p funk|funk rock|funk|soul christmas|soul
9	Metropopolis	Grimes	0.649263	indie r&b|grave wave|chillwave|metropopolis|indietronica|nu gaze
10	Indie folk	Jenny Lewis	0.645795	indie folk|stomp and holler|indie pop
11	Alternative rock	Bob Mould	0.638338	alternative pop|power pop|permanent wave|jangle pop|alternative rock
12	Girl group	The Shangri-Las	0.637551	brill building pop|girl group|
13	Blues-rock	Ten Years After	0.630591	blues-rock|british blues|classic rock|psychedelic rock|modern blues|texas blues|blues|chicago blues|rock|electric blues|album rock|southern rock
14	Roots reggae	Toots and The Maytals	0.627068	reggae|world christmas|roots reggae|ska|
15	Britpop	Jarvis Cocker	0.625673	britpop|madchester|chamber pop
16	Juggalo	Geto Boys	0.625638	gangster rap|juggalo|dirty south rap|rap|old school hip hop|crunk|southern hip hop|hardcore hip hop|g funk|hip hop
17	Hardstyle	Showtek	0.618621	hardstyle
18	Acid house	The Future Sound of London	0.617926	electronic|illbient|big beattrip hop|ambient|acid house| breakbeat|downtempo|intelligent dance music chill-out|abstract
19	Yé-yé	Françoise Hardy	0.61561	chanson|yé-yé|cabaret

Note: This table shows information about the 20 most popular artists who created at least one genre. In this table, a genre tag is considered as a genre. Overall, 992 artists created 1,425 genres. The artists who created a genre are not necessarily popular artists. The popularity and genre data are collected from the Spotify Echnonest API.

Control variables

I control for (1) the number of songs (lag 1 year) as a firm size proxy, (2) the mean number of artists' prior releases (lag 1 year) as a firm status proxy, (3) a dummy for the label's founding year, (4) a dummy that takes the value of one if label i produced at least one top 5% song in the previous year, (5) country dummies, (6) genre dummies, and (7) decade dummies. I also use these variables to match similar firms before running the main stage regressions.

Instrumental variables

I address the potential endogeneity of producing singles by using two 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 otherwise 0. The introduction of iTunes increases firms' incentive to produce singles exogenously. The second instrumental variable is the country-level proportion of CDs to all releases. The CD was the main medium of music releases in the 1980-90s. After the introduction of iTunes, CDs have been replaced by digital downloads. The second instrumental variable captures the continuous change in the medium, complementing the dummy variable for iTunes' staggered market entries. A high proportion of CDs means that the share of digital music market is small, resulting in a smaller incentive for firms to produce singles. Thus, the proportion of CDs has a negative influence on the production of singles. As the introduction of iTunes and other digital services was determined by the difference in intellectual property regimes between US and local countries rather than differences in local countries' talent discovery, these variables should be uncorrelated with factors in the error term that influence music labels' decision to experiment with new artists.

Figure 1.3 previews why the staggered introduction of iTunes can be a valid instrumental variable. Panel A shows that the decreasing production of singles rather than albums changed to an increasing extent after the introduction of iTunes. Panel B demonstrates that proportions of single-producing labels in the seven representative countries increased after the introduction of iTunes. The seven countries are randomly selected by choosing one country from each entry year (US from 2003, France from early 2004, Italy from late 2004, the Netherlands from late 2004, Switzerland from early 2005, Japan from late 2005, and Poland from 2011). First, the suggestive pattern in Figure 1.3 supports the notion that the introduction of iTunes increased music firms' incentive to produce singles and that the proportion of single-producing music firms increased accordingly (inclusion restriction). This is tested with multiple statistics in the results section; the test statistics support the pattern in this figure. Second, this introduction of iTunes is not correlated with their preference for new talent over incumbent artists (exclusion restriction).

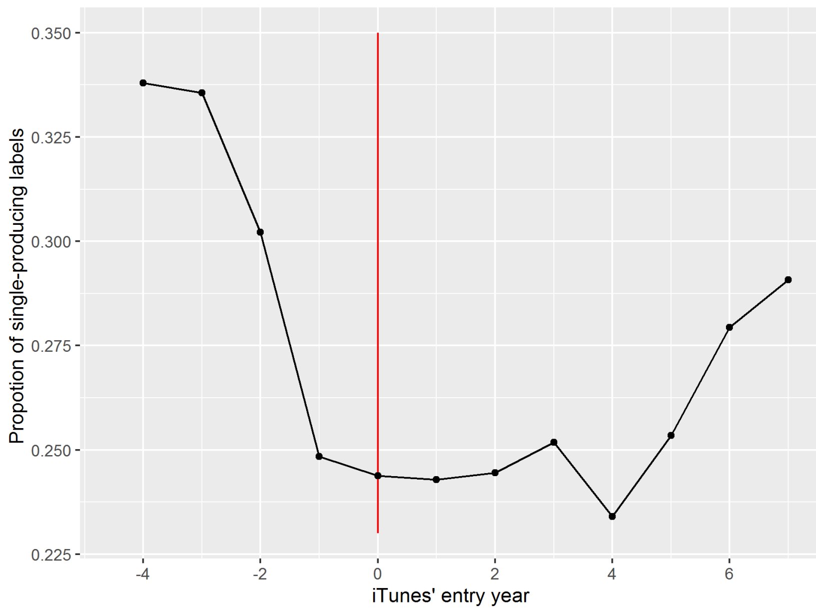
Empirical specification

Baseline OLS models and endogeneity issues

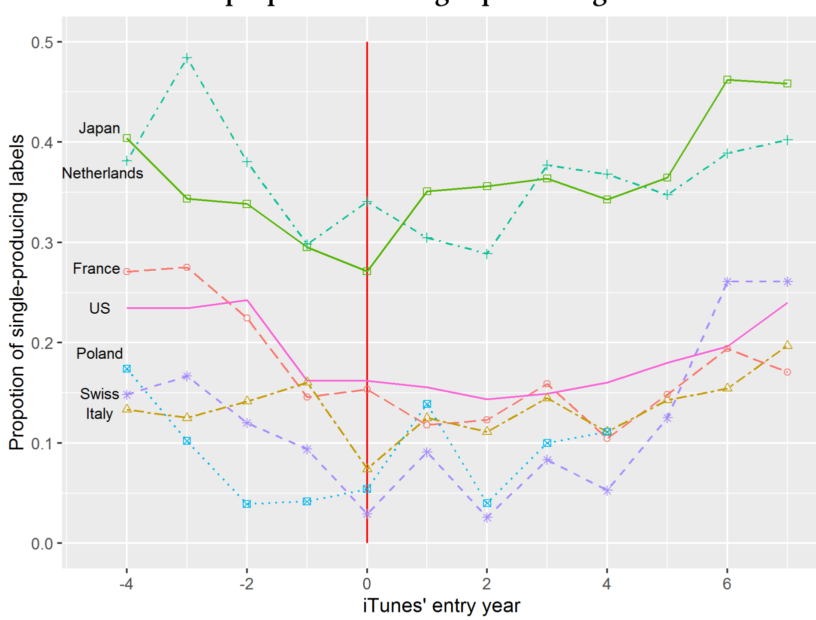
I use OLS regressions as the baseline tests for my hypotheses to validate the impact of whether label i produces some of its works as singles in year t with respect to the proportion of new artists and popularity of artists and their songs in label i at time t. I add a vector of control variables that might influence labels' decision to produce singles. Thus,

Figure 1.3: Introduction of iTunes and single-producing labels

Panel A. Proportion of single-producing labels around event time



Panel B. Seven countries' proportion of single-producing labels around event time



Note: Figure 1.3 previews why iTunes' staggered entries into many countries can be a valid instrumental variable. Panel A shows that after the introduction of iTunes, the decreasing trend in producing singles changed to an increasing trend. Panel B demonstrates that proportions of single-producing labels in the seven representative countries increased after the introduction of iTunes. The seven countries are randomly chosen from each entry cohort (US from 2003, France from early 2004, Italy from late 2004, Netherlands from late 2004, Swiss from early 2005, Japan from late 2005, and Poland from 2011). This shows that the introduction of iTunes might have increased label's incentive to produce singles and the proportion of single-producing labels increased (*inclusion restriction*). This is tested with multiple statistics in the results section; the test statistics support the pattern in this figure.

my initial specification is

$$\begin{aligned}
Dependent_Variable_{it} &= \beta_0 + \beta_1 Dummy_Label_Single_{it} + \beta_2 X_{it} + C_i + G_{it} \\
&+ T_t + e_{it}, \\
Dependent_Variable_{i} &= \beta_0 + \beta_1 Dummy_Artist_Single_{i} + \beta_2 X_{it} + C_i + G_{it} \\
&+ T_t + e_{it},
\end{aligned}$$

where i indexes firms, t indicates the calendar time, X_{it} is a set of observable characteristics of the firm described above as control variables, C_i is country fixed effects, G_{it} is genre fixed effects, and T_t is the year fixed effect. Standard errors are clustered at the label level.

Whereas equation (1) controls for correlation between producing singles and control variables, one may still be concerned about selection based on omitted variables (Hamilton and Nickerson, 2003). In an ideal experimental design, I would randomly assign single production status and measure ex post the difference in proportion of new artists and popularity of artists and their songs. In practice, we observe changes in both the practice of producing singles and the proportion of new artists and popularity of artists and their songs. In this setting, one important potential omitted variable will be a firm's intention to discover new talent. If a music firm desires to discover new talent more than other music firms, it may be more likely to produce singles and to simultaneously experiment with more new talent and subsequently discover more new talent.

Instrumental variable estimators (2SLS)

I address this endogeneity issue by utilizing the aforementioned instrumental variables: staggered introduction of iTunes and country-level proportion of CDs to all releases. In iTunes, a firm must sell its products as songs as well as albums, which induces an increase in single production. iTunes was introduced by Apple in different countries at different times, where the entry timing for each country was exogenous to the music industry. By exploiting this different entry timing, I measure the impact of the introduction of an unbundled market on the adoption of singles production. This approach also solves the endogeneity issue partly by using an exogenous variable, which increases the incentive to adopt singles production but does not necessarily affect a music firm's intention to try out new artists. In the first-stage regression, I estimate the following equation: $Dummy\_Label\_Single_{it} = \beta_{IV} Z_{it} + \mu_{it}$, where Z_{it} is a set of firm characteristics and instrumental variables and μ_{it} is an error term. Then, I estimate the second-stage OLS regression model:

$$\begin{aligned}
Dependent_Variable_{it} &= \beta_0 + \beta_1 Dummy_L\hat{a}bel_Single_{it} + \beta_2 X_{it} + C_i + G_{it} + T_t \\
&\quad + [\eta_{it} + \beta_2 (Dummy_Label_Single_{it} \\
&\quad - Dummy_L\hat{a}bel_Single_{it}]. \\
Dependent_Variable_{it} &= \beta_0 + \beta_1 Dummy_A\hat{r}tist_Single_i + \beta_2 X_{it} + C_i + G_{it} + T_t \\
&\quad + [\eta_{it} + \beta_2 (Dummy_Artist_Single_i \\
&\quad - Dummy_A\hat{r}tist_Single_i].
\end{aligned}$$

An ideal instrumental variable would generate firm-level variation in the incentives to produce singles, thereby allowing me to control for market-specific trends in the discovery of new talent. Unfortunately, I cannot identify any firm-level instruments, so my identification strategy is 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 time-invariant, firm-specific factors and a number of time-varying observables at the firm level.

Matching estimators: Propensity score matching and CEM

To complement the instrumental variables analysis, I use matching estimators: propensity score matching (Rosenbaum and Rubin 1983) and coarsened exact matching (CEM) (Iacus et al., 2011). Matching estimators control for selection bias by creating a matched sample of treatment and control observations that are similar with respect to the observable characteristics (Rosenbaum and Rubin 1983). To implement propensity score matching, I estimate a probit of firms' decision to produce singles and use fitted values from that model as estimates of the propensity score. I then trim extreme values and firm-year observations off the common support of the propensity score distribution to obtain my matched sample.

To implement CEM, continuous variables are 'coarsened' into splines for the purposes of creating 'strata' - or discrete mutually exclusive bundles of control variables. Treatment and control group observations are then matched exactly within each stratum, which eliminates the need to compare the means of the treatment and control groups after matching. I allow for unbalanced matching within each strata, as recommended by Iacus et al. (2011).

Then, I adjust the second-stage regressions by weighting so that the results can be interpreted as average treatment effects.

Sample Statistics

Table 1.4 reports descriptive statistics on all the variables for the sample at the firm-year level. First, the descriptive statistics for the independent variable show that the proportion of firm-years that produce at least one single is 31.3%. Second, I have four firm-level dependent variables: the proportion of new artists to all artists, maximum artist popularity, maximum song popularity, and a dummy variable that takes the value of one if label i experiments with at least one new artist who created a new genre. The average proportion of new artists is 0.428, and the standard deviation is large (0.435). The averages of maximum artist popularity and maximum song popularity are 0.146 and 0.021, respectively. The variances of these variables are also large (0.189 and 0.094, respectively). As shown in Figure 1.4, popularity distributions are highly skewed, and the skewness of the song popularity is larger than that of artist popularity. In addition, I report descriptive statistics on the two instrumental variables. First, the proportion of firm-year observations that iTunes was introduced in country c is 0.450; that is, 45% of firm-year observations are after the introduction of iTunes, and the other 55% are before the introduction of iTunes. Second, the average of the second instrumental variable, the country-level proportion of CDs to all releases, is 0.735.

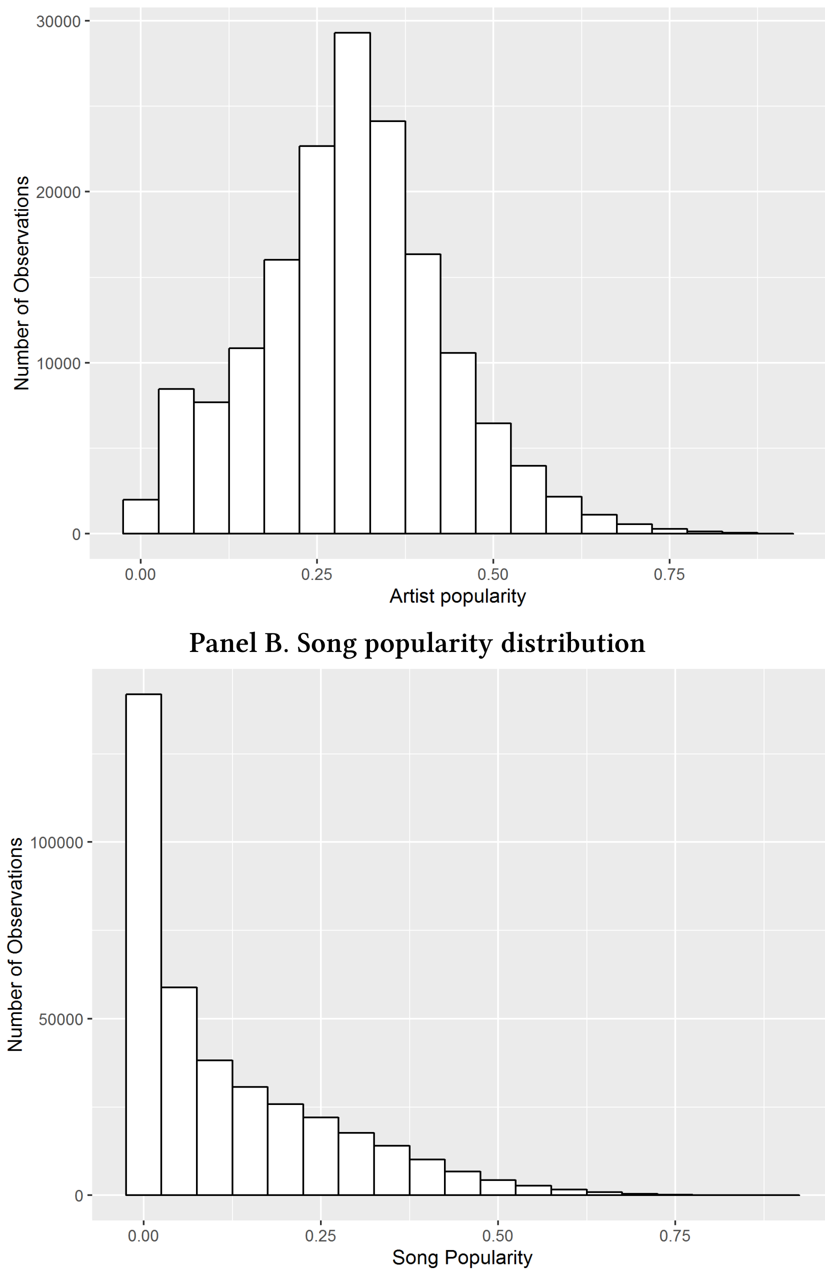
Table 1.4: Summary statistics

Variable name	Level of variation	Mean	Std. Dev.	Min.	Max.
Independent variables:					
(Dummy) one if label produces at least one single	Firm	0.313	0.464	0	1
(Dummy) one if the first release of artist i is produced by a single	Artist	0.199	0.399	0	1
Dependent variables:					
Proportion of new artists to all artists	Firm	0.428	0.435	0	1
Omission error	Artist	0.036	0.187	0	1
Commission error	Artist	0.471	0.499	0	1
Maximum artist popularity	Firm	0.146	0.189	0	0.884
Maximum song popularity	Firm	0.021	0.094	0	0.880
(Dummy) one if at least one new artist created a new genre	Firm	0.003	0.055	0	1
Instrumental variables:					
(Dummy) one if iTunes was introduced in country c	Country	0.450	0.497	0	1
County-level proportion of CDs to all releases in the previous year	Country	0.735	0.057	0	0.792
Control variables:					
log (Number of songs)	Firm	2.15	1.517	0	6.960
log (Mean number of artists' prior releases)	Firm	0.735	0.921	0	6.339
Dummy one if label's founding year	Firm	0.246	0.431	0	1
(Dummy) one if label produced at least one top 5% song in the previous year	Firm	0.246	0.431	0	1
Herfindahl index for genre in label	Firm	0.135	0.312	0	1
Other variables:					
Number of songs	Firm	25.491	46.132	1	1839
Number of releases (albums + singles)	Firm	2.778	4.723	1	238
Number of singles	Firm	0.785	2.409	0	142
Proportion of singles to releases	Firm	0.212	0.372	0	1
Number of unique artists	Firm	2.409	3.665	1	159
Number of new artists	Firm	0.946	1.664	0	57
Number of new foreign artists	Firm	0.202	0.898	0	36
Year	Firm	2000.056	11.455	1950	2015
Number of label-year observations		85,162			
Number of unique labels		22,157			
Number of unique artists		165,464			
Number of unique releases		343,156			
Number of unique songs		2,349,776			

Figure 1.4: Popularity distributions

Panel A. Artist popularity distribution

Panel B. Song popularity distribution



Note: I excluded observations with popularity 0 from both distributions. Figure 1.4 shows that popularity distributions are highly skewed. Also, it demonstrates that the label-level mean artist popularity distribution in Panel B is more skewed than the artist popularity in Panel A.

1.6 Results

Does producing singles increase the proportion of new artists?

I test the hypothesis that producing singles leads to increased experimentation with new artists and increased discovery of more popular artists by releasing more new artists. Table 1.5 shows the results of testing the impact of producing singles on the proportion of new artists in firms. For this purpose, I estimate five different versions of the same equation: OLS, firm fixed effects, propensity score weighted regression, CEM matching regression, and instrumental variables analysis (2SLS). Column 1 reports estimates from a simple OLS specification with control variables. I find a strong partial correlation between producing singles and the proportion of new artists. Specifically, the proportion of new artists increases by 3.71% in firms that produce some of their work as single(s) comparison with those that produce their work only as albums. Column 2 shows the results of the same model after I control for firm fixed effects, which are not substantially different from the OLS specification. Columns 3 and 4 present estimates from the same model after matching to control for observable differences between single-producing firms and non-single-producing firms. Figure 5 shows why and when matching may matter. In Panel A, the distributions of propensity scores of single-producing firms and album-only-producing firms are largely different before matching. Panel B demonstrates the distributions after matching; visually there is a tighter fit between the two groups after matching. Column 3 shows results the from matching and weighting by the propensity score, and Column 4 shows results from the CEM matching model. The coefficients from these matching models, 4.10% and 4.62%, are similar to the results from the OLS and fixed effect models.

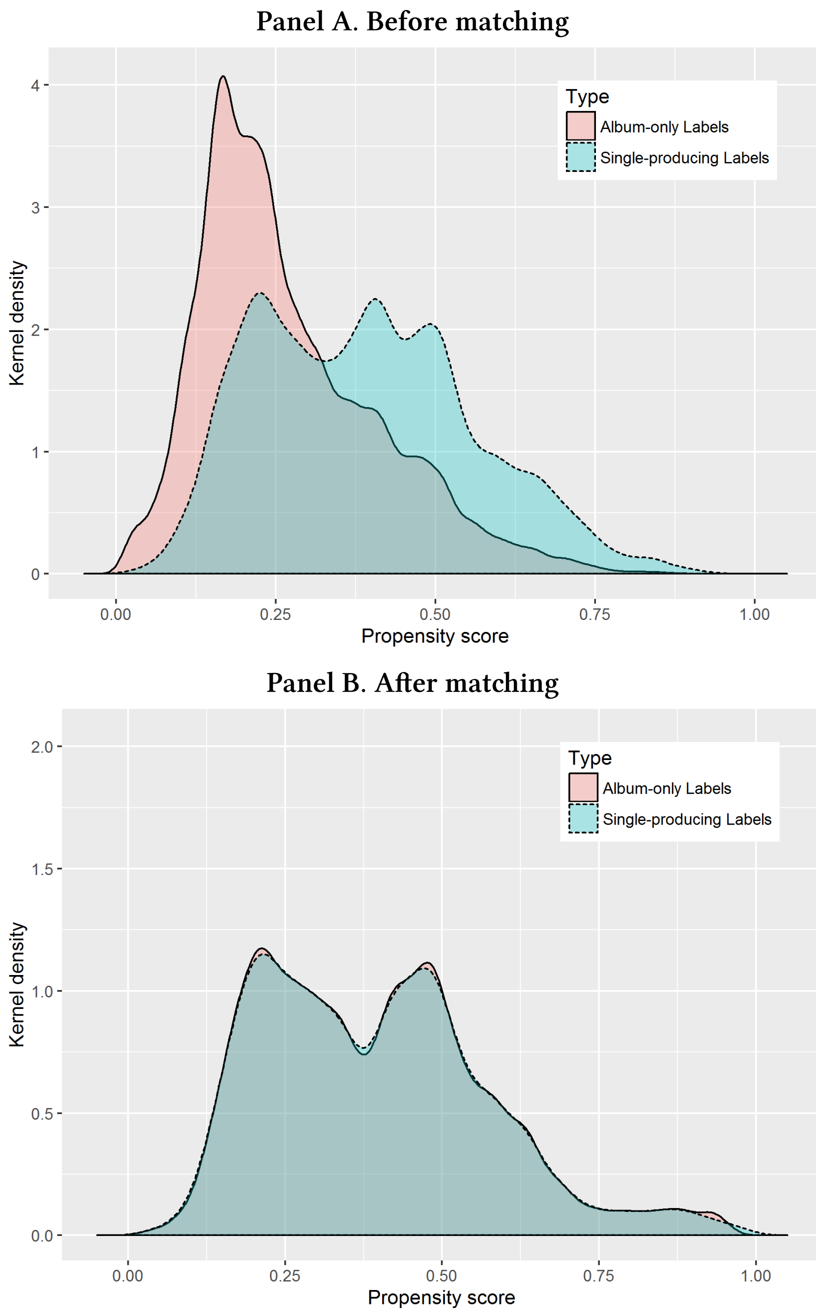
Table 1.5: Does producing singles increase experimenting with new artists?

	DV: Proportion of new artists in label				
	(1)	(2)	(3)	(4)	(5)
	OLS	Fixed Effects	Propensity Matching	CEM	2SLS
(Dummy) one if label produces at least one single	0.0371**	0.0437**	0.0410**	0.0462**	0.2411**
	(0.0038)	(0.0049)	(0.0055)	(0.0060)	(0.0886)
log (No. of songs) (1 year lag)	0.0024	-0.0301**	-0.0293**	-0.0378**	-0.0377**
	(0.0024)	(0.0022)	(0.0025)	(0.0029)	(0.0040)
log (Mean no. of artists' prior releases) (1 year lag)	-0.0643**	0.0493**	0.0330**	0.0783**	0.0498**
	(0.0019)	(0.0022)	(0.0025)	(0.0030)	(0.0020)
(Dummy) one if label's founding year	0.1888**	0.1641**	0.1733**	0.1657**	0.1474**
	(0.0072)	(0.0071)	(0.0093)	(0.0086)	(0.0100)
(Dummy) one if label produced at least one top 5% song in the previous year	-0.0371**	-0.0140	-0.0040	-0.0279*	-0.0305*
	(0.0079)	(0.0085)	(0.0086)	(0.0127)	(0.0135)
Herfindahl index for genre in label	-0.1302**	-0.1053**	-0.0963**	-0.1058**	-0.1107**
	(0.0046)	(0.0053)	(0.0060)	(0.0068)	(0.0062)
Constant	7.7354**	15.2257**	13.4111**	20.8601**	11.8820**
	(0.9055)	(1.1792)	(1.3541)	(1.5949)	(1.8463)
Label fixed effect	*no*	*yes*	*yes*	*yes*	*yes*
Country fixed effect	*yes*	*omitted*	*omitted*	*omitted*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
Period fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
2SLS first-stage summary statistics					
F-statistic					51.94
T-statistic: (Dummy) one if iTunes was introduced in country c					4.70
T-statistic: Country-level proportion of CDs to all releases in the previous year					-12.98
Adjusted R^2					0.0271
Adjusted R^2	0.1196	0.0860	0.0699	0.1111	n.a.
N	85,162	85,162	56,087	63,101	85,162

Note: Standard errors are in parentheses, $^{*}p < 0.05, ^{**}p < 0.01$. Standard errors are robust and clustered at the label level. The Durbin-Wu-Hausman test rejects the null hypothesis that the instruments are not necessary at the 5% level ($\chi^2(1)$ = 5.423 in the 2SLS specification, column (5)). The Sargan's J-statistic ($\chi^2(1)$) is 0.205 (p = 0.6505), alleviating concerns about an over-identification problem.

Because the decision to produce singles is endogenous, the results shown in Columns 1-4 can be interpreted only as correlations. In Column 5, I present estimates from the 2SLS model, which controls for the potential endogeneity of producing singles by using two instrumental variables. The first instrumental variable is a dummy variable that is assigned a value of one if iTunes was introduced in the country in that year, whereas the second instrumental variable is the country-level proportion of CDs to all releases by all firms in the previous year.

Figure 1.5: Kernel density distribution of the probability of producing at least one single



Note: Figure 1.5 shows why matching may matter. In Panel A, the distributions of the propensity scores before matching are quite different from the treatment group and control group ($n = 85,162$). Panel B demonstrates that the distributions of the propensity scores after matching ($n = 56,087$). Visually there exists a tighter fit between the two groups after matching. I trim 29,075 observations which are off the common support of the propensity distribution to get the matched sample.

For the first instrumental variable, the first-stage relationship between the introduction of iTunes and the production of singles by the firm is strongly positive: the t-statistic on this dummy variable is 4.7. The second instrumental variable also shows a strongly negative first-stage relationship between country-level proportion of CDs to all releases in the previous year and the production of singles by the firm: the t-statistic on this instrumental variable is -12.98. Overall, the first-stage F-statistic of 51.94 indicates that the instruments are powerful. In the second stage, the estimated change in the proportion of new artists is positive 24.11%, which is statistically significant at the 1% level. I interpret this result as evidence of a causal relationship between producing singles and greater experimentation with new artists. Whereas the 2SLS point estimate is larger than the matching estimate in Column 4, the difference between two coefficients is not statistically significant (at the 5% level). Collectively, the findings in Table 1.5 suggest that firms experiment with more new artists and decrease the proportion of incumbent artists when they produce unbundled products (singles) instead of bundled products (albums) only.

Does producing singles increase omission and commission errors?

I turn now to the second hypothesis, which tests the impact of producing singles on omission and commission errors. Table 1.6 shows the results of tests on the impact of producing singles on these errors. I estimate three different versions of the same equation: OLS, logistic regression, and instrumental variables analysis (2SLS). Columns 1 and 4 report estimates from a simple OLS specification, Column 2 and 5 report estimates from a logistic regression model. I find a strong partial correlation between producing singles and omission errors and did not find a strong partial correlation between producing singles and commission errors. Specifically, omission errors increase by 29.75% when firms experiment with new artist through a single.

Table 1.6: Does producing singles increase omission and commission errors?

	DV: (Dummy) Omission error			DV: (Dummy) Commission error		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Logit (Odds ratios)	2SLS	OLS OLS	Logit (Odds ratios)	2SLS
(Dummy) one if the first release of artist i is produced by a single	0.0092*	0.2605*	0.1959*	-0.0213	-0.0849	-0.2047
	(0.0046)	(0.1290)	(0.0828)	(0.0136)	(0.0613)	(0.1832)
log (No. of songs) (1 year lag)	-0.0075**	-0.1716**	-0.0073*	0.0595**	0.2708**	0.0050
	(0.0019)	(0.0545)	(0.0033)	(0.0069)	(0.0320)	(0.0073)
log (Mean no. of artists' prior releases) (1 year lag)	-0.0017	0.0085	0.0034	-0.0098	-0.0429	0.0064
	(0.0023)	(0.0743)	(0.0041)	(0.0067)	(0.0297)	(0.0091)
(Dummy) one if label's founding year	-0.0242**	-0.5198**	-0.0272*	0.1403**	0.6409**	0.0527
	(0.0066)	(0.1984)	(0.0131)	(0.0216)	(0.0987)	(0.0290)
(Dummy) one if label produced at least a top 5% song	-0.0210*	-0.6223*	-0.0286*	-0.0913**	-0.4218**	-0.0049
	(0.0096)	(0.2909)	(0.0127)	(0.0285)	(0.1285)	(0.0282)
Herfindahl index for artists' genre in label	0.0509**	1.2957**	0.0362**	-0.1362**	-0.5955**	-0.0998**
	(0.0051)	(0.1284)	(0.0076)	(0.0142)	(0.0637)	(0.0167)
Constant	3.2608*	124.5912**	2.1015	-36.2690**	-159.5302**	-20.3040**
	(1.2812)	(39.0763)	(1.9847)	(3.5947)	(15.8488)	(4.3899)
Label fixed effect	*no*	*no*	*yes*	*no*	*no*	*yes*
Country fixed effect	*yes*	*yes*	*omitted*	*yes*	*yes*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Period fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
2SLS first-stage summary statistics						
F-statistic			38.24			38.24
T-statistic: (Dummy) one if iTunes was introduced in country c			2.16			2.16
T-statistic: Country-level proportion of CDs to all releases in the previous year			-8.59			-8.59
Adjusted R^2			0.0372			0.0372
Adjusted R^2 / Pseudo R^2	0.0420	0.1135	n.a.	0.0978	0.0747	n.a.
N	10,850	10,850	10,850	10,850	10,850	10,850

Note: Standard errors are in parentheses, $^*p < 0.05,^{**}p < 0.01$. Standard errors are robust and clustered at the label level. The Durbin-Wu-Hausman test rejects the null hypothesis that the instruments are not necessary at the 5% level ($\chi^2(1)$ = 4.106 in the 2SLS specification, column 3 and 6). The Sargan's J-statistic ($\chi^2(1)$) is 2.822 (p = 0.093), alleviating concerns about an over-identification problem.

Because the decision to produce singles is endogenous, the results shown in Columns 1-2 and 4-5 can be interpreted only as correlations. In Columns 5 and 10, I present estimates from the 2SLS model, which controls for the potential endogeneity of producing singles by using the aforementioned two instrumental variables. The first-stage relationship between the introduction of iTunes and producing singles by the firm is strongly positive: the t-statistic on this dummy variable is 2.16. The first-stage relationship between country-level proportion of CDs 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 -8.59. Overall, the first-stage F-statistic of 38.24 indicates powerful instruments. In the second stage, the estimated changes in the omission error are positive 0.1959 which is statistically significant at the 5% level. On the other hand, the estimated changes in the commission error are negative -0.2047 which is statistically insignificant at the 5% level. Collectively, the findings in Table 6 suggest that experimenting with a new artist through a single increases omission errors.

Does producing singles increase the popularity of artists and their songs?

I turn now to the third hypothesis, which tests the impact of producing singles on the experimentation performance of a firm. I am particularly interested in the popularity of artists and songs in firms as experimentation performance variables. Table 1.7 shows the results of tests on the impact of producing singles on these performance (or popularity) variables. I estimate five different versions of the same equation: OLS, firm fixed effects, propensity score weighted regression, CEM matching regression, and instrumental variables analysis (2SLS). Columns 1 and 6 report estimates from a simple OLS specification with control variables. I find a strong partial correlation between producing singles and the popularity of artists and songs. The range of artist popularity and song popularity variables is from 0 to 1. Specifically, the maximum popularity of artists increases by 0.0311 in firms that produce some of their work as single(s) in comparison with those that produce their work only as albums. The maximum popularity of songs increases by 0.0263 in firms that produce some of their work as single(s) in comparison with those that produce their work only as albums. Next, Columns 2 and 7 show results of the same model after I control for firm fixed effects, which show that they are not substantially different from the OLS specification. Columns 3, 4, 8, and 9 present estimates from the same model after I match to control for observable differences between single-producing firms and non-single-producing firms. Columns 3 and 8 show the results from matching and weighting by the propensity score, and Column 4 shows results from the CEM matching model. The coefficients from these matching models, 0.0147, 0.0138, 0.0161, and 0.0109, are similar to the results from the OLS and fixed effect models.

Because the decision to produce singles is endogenous, the results shown in Columns 1-4 and 5-9 can be interpreted only as correlations. In Columns 5 and 10, I present estimates from the 2SLS model, which controls for the potential endogeneity of producing singles by using the aforementioned two instrumental variables. The first-stage relationship between the introduction of iTunes and producing singles by the firm is strongly positive: the t-statistic on this dummy variable is 3.26. The first-stage relationship between country-level proportion of CDs 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 -6.47. Overall, the first-stage F-statistic of 18.97 indicates powerful instruments. In the second stage, the estimated changes in the maximum popularity scores are positive 0.1434 for artists and 0.0892 for songs, which are statistically significant at the 5% level. I interpret this result as

Table 1.7: Does producing singles increase maximum popularity of label's artists and songs?

	DV: Maximum **artist** popularity in label					DV: Maximum **song** popularity in label				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Fixed Effects	Propensity Matching	CEM	2SLS	OLS	Fixed Effects	Propensity Matching	CEM	2SLS
(Dummy) one if label produces at least one single	0.0311^{**}	0.0177^{**}	0.0147^{**}	0.0138^{**}	0.1434^{*}	0.0263^{**}	0.0149^{**}	0.0161^{**}	0.0109^{**}	0.0892^{*}
	(0.0018)	(0.0022)	(0.0024)	(0.0024)	(0.0696)	(0.0014)	(0.0015)	(0.0017)	(0.0016)	(0.0405)
log (No. of songs) (1 year lag)	0.0240^{**}	0.0092^{**}	0.0097^{**}	0.0081^{**}	0.0048	0.0137^{**}	0.0054^{**}	0.0062^{**}	0.0050^{**}	0.0028
	(0.0010)	(0.0010)	(0.0011)	(0.0012)	(0.0025)	(0.0010)	(0.0007)	(0.0009)	(0.0008)	(0.0015)
log (Mean no. of artists' prior releases) (1 year lag)	0.0139^{**}	-0.0010	-0.0014	-0.0030^{**}	-0.0004	0.0057^{**}	0.0001	-0.0003	-0.0002	0.0005
	(0.0010)	(0.0008)	(0.0011)	(0.0011)	(0.0008)	(0.0006)	(0.0005)	(0.0006)	(0.0007)	(0.0005)
(Dummy) one if label's founding year	-0.0336^{**}	0.0107^{**}	0.0126^{**}	0.0067	0.0031	0.0263^{**}	0.0116^{**}	0.0072^{**}	0.0110^{**}	0.0071^{*}
	(0.0036)	(0.0034)	(0.0043)	(0.0041)	(0.0053)	(0.0029)	(0.0021)	(0.0025)	(0.0023)	(0.0031)
(Dummy) one if label produced at least one top 5% song in the previous year	-0.0003	0.0060	0.0066	0.0102	-0.0035	0.2162^{**}	0.0153	0.0104	0.0008	0.0096^{*}
	(0.0064)	(0.0053)	(0.0054)	(0.0067)	(0.0070)	(0.0123)	(0.0084)	(0.0085)	(0.0109)	(0.0041)
Herfindahl index for genre in label	0.0714^{**}	-0.0020	0.0007	-0.0030	-0.0037	0.0072^{**}	0.0041^{**}	0.0033	0.0040^{*}	0.0032^{*}
	(0.0027)	(0.0024)	(0.0028)	(0.0029)	(0.0023)	(0.0015)	(0.0014)	(0.0017)	(0.0017)	(0.0013)
Constant	13.3172^{**}	10.0241^{**}	9.9696^{**}	10.9483^{**}	8.6239^{**}	-1.0665^{**}	-2.6660^{**}	-3.6089^{**}	-3.4863^{**}	-3.4961^{**}
	(0.4465)	(0.5535)	(0.7159)	(0.7176)	(0.9284)	(0.2098)	(0.3680)	(0.5230)	(0.4825)	(0.5407)
Label fixed effect	*no*	*yes*	*yes*	*yes*	*yes*	*no*	*yes*	*yes*	*yes*	*yes*
Country fixed effect	*yes*	*omitted*	*omitted*	*omitted*	*omitted*	*yes*	*omitted*	*omitted*	*omitted*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
2SLS first-stage summary statistics										
F-statistic					18.97					18.97
T-statistic: (Dummy) one if iTunes was introduced in country c					3.26					3.26
T-statistic: Country-level proportion of CDs to all releases in the previous year					-6.47					-6.47
Adjusted R^2					0.0145					0.0145
Adjusted R^2	0.3597	0.2011	0.2135	0.1989	n.a.	0.2331	0.0183	0.0202	0.0152	n.a.
N	76,158	76,158	48,656	56,972	76,158	76,158	76,158	48,656	56,972	76,158

Note: Standard errors are in parentheses, $^{*}p < 0.05,^{**} p < 0.01$. Standard errors are robust and clustered at the label level. The Durbin-Wu-Hausman test rejects the null hypothesis that the instruments are not necessary at the 1% level (χ^2 = 11.623 and χ^2 = 13.531 in the 2SLS specification, column (5) and (10)). The Sargan's J-statistics ($\chi^2(1)$) are 0.782 (p = 0.3765) and 0.166 (p = 0.6834), alleviating concerns about an over-identification problem.

evidence of a causal relationship between producing singles and discovering more popular artists. Although my 2SLS estimates in Columns 5 and 10 have greater noise than the matching estimates in Columns 4 and 8, the differences in coefficients are not statistically significant (at the 5% confidence level). Collectively, the findings in Table 1.7 suggest that when firms produce singles, they discover more popular artists and songs than when they produce their work only as albums.

New artists vs. incumbent artists: Who is the source of increased popularity?

Who is the main source of increased popularity in single-producing firms: new artists or incumbent artists? My model predicts that the benefit of producing singles that arises from higher popularity is mainly driven by trying out more new artists rather than incumbent artists. Table 1.8 presents tests of this hypothesis. Here, I use two dependent variables: (1) the maximum popularity of new artists (both artist popularity and song popularity) and (2) the maximum popularity of incumbent artists (both artist popularity and song popularity). I use the 2SLS model to estimate the causal relationship between producing singles and these two dependent variables. Column 1 and 2 show that producing singles has a positive influence on the maximum popularity of new artists and their songs, with positive effects of 0.3256 for artist popularity and 0.0645 for song popularity. In contrast, Columns 3 and 4 demonstrate that producing singles has no statistically significant impact on the maximum popularity of incumbent artists and their songs. In sum, these results suggest that the benefits of single production come from new artists.

Table 1.8: Do new artists benefit more than incumbent artists from producing singles?

	DV: Maximum **artist** popularity of **new** artists in label (1) 2 SLS	DV: Maximum **song** popularity of **new** artists in label (2) 2SLS	DV: Maximum **artist** popularity of **incumbent** artists in label (3) 2SLS	DV: Maximum **song** popularity of **incumbent** artists in label (4) 2SLS
(Dummy) one if label produces at least one single	0.3256**	0.0645**	-0.1295	0.0599
	(0.0705)	(0.0244)	(0.0669)	(0.0354)
log (No. of songs) (1 year lag)	-0.0140**	-0.0010	0.0185**	0.0033*
	(0.0026)	(0.0009)	(0.0024)	(0.0013)
log (Mean no. of artists' prior releases) (1 year lag)	0.0044**	0.0005	-0.0050**	0.0001
	(0.0008)	(0.0003)	(0.0008)	(0.0004)
(Dummy) one if label's founding year	-0.0197**	0.0006	0.0113*	0.0101**
	(0.0058)	(0.0020)	(0.0055)	(0.0029)
(Dummy) one if label produced at least one top 5% song in the previous year	-0.0248**	0.0054*	0.0155*	0.0210**
	(0.0071)	(0.0025)	(0.0067)	(0.0036)
Herfindahl index for genre in label	0.0366**	-0.0021*	0.1869**	0.0032*
	(0.0029)	(0.0010)	(0.0028)	(0.0015)
Constant	6.7250**	-1.6400**	4.8529**	-3.0905**
	(0.9370)	(0.3242)	(0.8893)	(0.4699)
Label fixed effect	*yes*	*yes*	*yes*	*yes*
Country fixed effect	*omitted*	*omitted*	*omitted*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*
Period fixed effect	*yes*	*yes*	*yes*	*yes*
2SLS first-stage summary statistics				
F-statistic	18.97	18.97	18.97	18.97
T-statistic: (Dummy) one if iTunes was introduced in country c	3.26	3.26	3.26	3.26
T-statistic: Country-level proportion of CDs to all releases in the previous year	-6.47	-6.47	-6.47	-6.47
Adjusted R^2	0.0145	0.0145	0.0145	0.0145
Adjusted R^2	n.a	n.a.	n.a	n.a
N	76,158	76,158	76,158	76,158

Note: Standard errors are in parentheses, $^{*}p < 0.05,^{**} p < 0.01$. Standard errors are robust and clustered at the label level. 2SLS test statistics are the same with the statistics in Table 5 and 7.

Do small firms benefit more from producing singles?

The cost of experimentation comprises actual production costs and opportunity costs. Firms under financial constraints have a higher opportunity cost of trying out new artists when they produce only albums. Therefore, as small firms are more likely to be under financial constraints, my model predicts that small firms may benefit more from producing singles by increasing the number of experimentation with new artists. Thus, in this analysis, I am particularly interested in the coefficient on the interaction between producing singles and firm size. A negative coefficient on this interaction term would provide evidence of larger benefits (higher popularity) for small firms, whereas a positive coefficient would point toward larger benefits for large firms.

Table 1.9 shows the 2SLS results, where firm size is measured using the number of songs produced by firm i in year t. Column 1 first shows the impact of the interaction between producing singles and firm size on the proportion of new artists. The main effect of producing singles continues to be large, positive, and strongly statistically significant with a point estimate of 0.2818. The point estimate on the interaction term is large and negative, -0.0387, and statistically significant at the 1% confidence level. Thus, I find that small firms, which are more likely to be under financial constraints, are more likely to experiment with new artists if they produce singles.

Columns 2 and 3 demonstrate the impact of interaction between producing singles and firm size on the popularity of artists and their songs. The main effects of producing singles continue to be large, positive, and strongly statistically significant with point estimates of 0.1683 for artist popularity and 0.2919 for song popularity. Furthermore, the point estimates on the interaction term are large and negative, -0.0115 for artist popularity and -0.0272 for song popularity, the latter of which is statistically significant at the 1% level. To sum up, the results suggest that small firms gain more experimentation benefits from producing singles than large firms do. This effect is visualized in Figure 1.6.

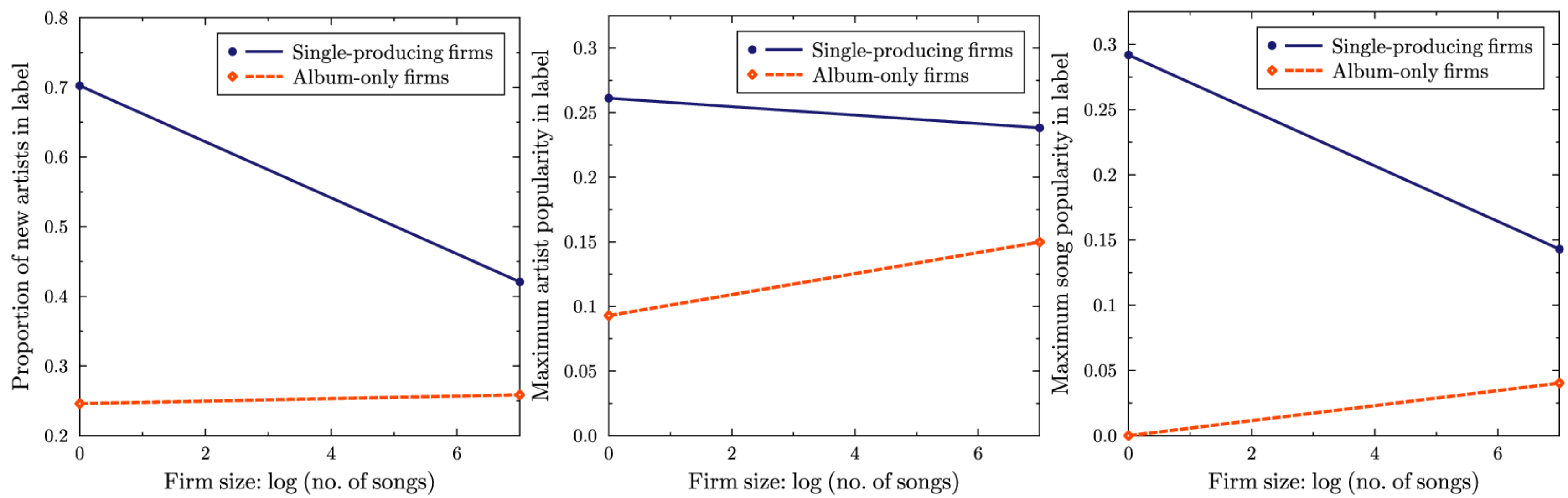
Table 1.9: Do small firms benefit more from producing singles?

	DV: Proportion of new artists in label (1) 2 SLS	DV: Maximum **artist** popularity in label (2) 2SLS	DV: Maximum **song** popularity in label (3) 2SLS
(Dummy) one if label produces at least one single × *log* (No. of songs) (1 year lag)	-0.0387*	-0.0115	-0.0272**
	(0.0193)	(0.0135)	(0.0100)
(Dummy) one if label produces at least one single	0.2818**	0.1683*	0.2919**
	(0.0775)	(0.0681)	(0.0502)
log (No. of songs) (1 year lag)	-0.0251**	0.0082	0.0058
	(0.0080)	(0.0046)	(0.0034)
log (Mean no. of artists' prior releases) (1 year lag)	0.0505**	-0.0002	0.0017**
	(0.0020)	(0.0009)	(0.0006)
(Dummy) one if label's founding year	0.1536**	0.0033	-0.0010
	(0.0099)	(0.0050)	(0.0037)
(Dummy) one if label produced at least one top 5% song in the previous year	-0.0099	0.0010	0.0094
	(0.0168)	(0.0085)	(0.0063)
Herfindahl index for genre in label	0.0001	-0.0026	0.0038*
	(0.0059)	(0.0026)	(0.0019)
Constant	12.9131**	8.7393**	-4.8376**
	(1.0606)	(0.8682)	(0.6406)
Label fixed effect	*yes*	*yes*	*yes*
Country fixed effect	*omitted*	*omitted*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*
Period fixed effect	*yes*	*yes*	*yes*
2SLS first-stage summary statistics			
F-statistic	51.94	18.97	18.97
T-statistic: (Dummy) one if iTunes was introduced in country c	4.70	3.26	3.26
T-statistic: Country-level proportion of CDs to all releases in the previous year	-12.98	-6.47	-6.47
Adjusted R^2	0.0271	0.0145	0.0145
Adjusted R^2 / Pseudo R^2	n.a.	n.a	n.a
N	85,162	76,158	76,158

Note: Standard errors are in parentheses. $^{*}p < 0.05,^{**} p < 0.01$. Standard errors are robust and clustered at the label level. 2SLS test statistics are the same with the statistics in Table 5 and 7.

Figure 1.6: Does small firms benefit more from producing singles?

Panel A. Proportion of new artists **Panel B. Artist popularity** **Panel C. Song popularity**



Note: Figure 6 shows small firms benefit more from producing singles. When firms produce singles, small firms not only experiment with more new artists than large firms do, but they discover more popular artists and songs. I use the coefficients in Table 9. The interaction effect in Panel A and C are statistically significant at 5% level, but the interaction effect in Panel B is not significant at 5% level.

Does producing singles facilitate the discovery of artists who create new genres?

I now turn to the final goal of this paper, that is, to test the relationship between producing singles and creativity. Table 1.10 shows the results of tests on the impact of producing singles on the discovery of artists who created new-to-the-world music genres. I estimate six different versions of the same equation: OLS, logistic regression, firm fixed effects, propensity score weighted regression, CEM matching regression, and instrumental variables analysis (2SLS). Column 1 reports estimates from a simple OLS specification with control variables, and the results suggest a strong partial correlation between producing singles and the discovery of new artists who created at least one new genre. Specifically, the chance of discovering genre-creating artists increases by 0.0013 in firms that produce some of their work as single(s) in comparison with those that produce their work only as albums. Columns 2 and 3 show the results of a logistic regression with the same model, Column 2 presents the results in odd ratios, and Column 3 presents the results in average marginal effects. First, the results are not substantially different from those for the OLS specification. Second, the probability of discovering new genre-creating artists is low (0.3%). The odd ratio results in Column 2 show that single-producing firms are 36.57% more likely to discover new genre-creating artists than album-only-producing firms. Column 4 shows the results from a fixed effect model, which are not substantially different from the results in Column 1-3.

Columns 5 and 6 present estimates from the same model after I match to control for observable differences between single-producing firms and non-single-producing firms.

Column 3 shows the results from matching and weighting by propensity score, and Column 4 shows the results from the CEM matching model. The coefficients from these matching models, 0.0020 and 0.0015, are similar to the results from the OLS and fixed effect models. Column 7 demonstrates the results for the 2SLS specification. The estimated change in the possibility of discovering genre-creating artists is a positive 14.95%, which is statistically significant at the 1% level. I interpret this result as evidence of a causal relationship between producing singles and creativity.

Table 1.10: Does producing singles facilitate the discovery of new artists who created a new genre?

	DV: (Dummy) one if at least one new artist created a new genre						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	Logit (Odds ratios)	Logit (Marginal Effects)	Fixed Effects	Propensity Matching	CEM	2SLS
(Dummy) one if label produces at least one single	0.0013*	0.3657*	0.0012*	0.0024**	0.0020*	0.0015*	0.1459**
	(0.0005)	(0.1708)	(0.0006)	(0.0008)	(0.0010)	(0.0007)	(0.0153)
log (No. of songs) (1 year lag)	0.0011**	0.3277**	0.0011**	0.0003	0.0004	-0.0001	-0.0049**
	(0.0003)	(0.1011)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0007)
log (Mean no. of artists' prior releases) (1 year lag)	-0.0005*	-0.2018	-0.0007	-0.0002	-0.0003	-0.0001	0.0009*
	(0.0002)	(0.1146)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
(Dummy) one if label's founding year	0.0022*	0.4622	0.0015	0.0018	0.0029	0.0018	-0.0083**
	(0.0011)	(0.3357)	(0.0011)	(0.0013)	(0.0020)	(0.0016)	(0.0019)
(Dummy) one if label produced at least a top 5% song in the previous year	-0.0015	-0.3725	-0.0012	-0.0029	-0.0031	-0.0003	-0.0140**
	(0.0024)	(0.4448)	(0.0014)	(0.0035)	(0.0039)	(0.0030)	(0.0024)
Herfindahl index for artists' genre in label	0.0003	0.2956	0.0010	-0.0007	-0.0004	-0.0009	-0.0035**
	(0.0008)	(0.2131)	(0.0007)	(0.0009)	(0.0012)	(0.0011)	(0.0010)
Constant	0.1711*	-2.5099**	0.0035**	0.1154	-0.0029*	-0.0615	0.6653**
	(0.0803)	(0.6063)	(0.0002)	(0.1070)	(0.0014)	(0.1045)	(0.2349)
Label fixed effect	*no*	*no*	*no*	*yes*	*yes*	*yes*	*yes*
Country fixed effect	*yes*	*yes*	*yes*	*omitted*	*omitted*	*omitted*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Period fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
2SLS first-stage summary statistics							
F-statistic							51.94
T-statistic: (Dummy) one if iTunes was introduced in country c							4.70
T-statistic: Country-level proportion of CDs to all releases in the previous year							-12.98
Adjusted R^2							0.0271
Adjusted R^2 */ Pseudo* R^2	0.0297	0.3070	0.3070	0.0117	0.0109	0.0048	n.a.
N	85,162	64,531	64,531	85,162	56,087	63,101	85,162

Note: Standard errors are in parentheses, $^{*}p < 0.05, ^{**}p < 0.01$. Standard errors are robust and clustered at the label level. 2SLS test statistics are the same with the statistics in Table 5 and 7. In Column 3, average marginal effects are reported.

1.7 Discussion and Conclusion

This paper develops and tests a simple formal model that demonstrates how digitalization-induced unbundling can alter firms' experimentation and creativity. While simple, the model represents an important first step toward formalizing the relationship between technological change and firms' experimentation behavior and creativity that lies at the heart of the literature on organizational learning and innovation (e.g., Nelson 1961, Kulkarni and Simon 1988, March 1991, Kogut and Kulatilaka 2001, Posen and Levinthal 2012). I test the model's core prediction using data on the production of unbundled work in music production firms. iTunes created a market for both singles (unbundled work) and albums (bundled work), and I exploit the staggered entries of iTunes into 29 countries that offer a natural experimental setting. I find the causal relationship between producing unbundled work and experimentation behavior and creativity. Specifically, music production firms that produced unbundled work in the form of singles increased their proportion of new artists by 27.25% (a 4.62% point) relative to firms that produced only albums. Furthermore, music production firms that produced unbundled work experienced increased popularity of their artists by 21.3% relative to firms that produced only albums. This result is robust to the inclusion of controls for endogenous decisions on producing unbundled work, suggesting that the technology-induced changes in bundling lead to changes in experimentation and the discovery of new talent (creativity) in a predictable manner.

This paper exploits a unique empirical setting to make a credible causal inference about the impact of unbundling on experimentation and creativity. However, the idiosyncrasies of the music industry should not cloud the general applicability of my conceptual approach to a broad range of firms and industries. Indeed, starting with the seminal work of Nelson (1961), scholars have long examined whether parallel search or experimenting with multiple options facilitates innovation. In my setting, if firms produce unbundled work, they can simultaneously experiment with multiple new artists, suggesting that producing unbundled work leads to parallel search. In particular, my model highlights that the cost of experimentation has been missing from the characterization of heterogeneous experimentation and the discovery of new resources, such as new technologies, assets, or workers. Although I do not claim that my model is universal to all industries, the findings of Eggers (2012), Eggers and Green (2012) and Posen et al. (2012) hint at its broad applicability to settings outside the music industry.

In addition, although I identify conditions under which producing unbundled work leads to increased experimentation with new artists and creativity and show that my particular empirical context fits well with these conditions, I have little to say about the origins of heterogeneous artist talent. I treat each artist's talent as an exogenous endowment, akin to a gift. Extending the model to endogenize artist talent, skill, style, or knowledge gained as the outcome of a learning process would perhaps be an interesting extension of my model, but that is beyond the scope of this work.

Methodologically, this study highlights the opportunities inherent in exploiting staggered iTunes' entry into 29 countries to identify the causal effects of organizational strategies. Empirical research in strategy is increasingly concerned with identification (Hamilton and Nickerson 2003), and localized industries offer tremendous potential for generating empirical tests that control for the endogeneity of organization choices (Rawley and Simcoe 2013).

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1.9 Appendices

Appendix 1. Proof of Lemma 1 and functions and parameters for Figure 2

Proof of Lemma 1. Assume no noise in talent discovery (i.e., the talent of an artist revealed with an experimentation is a true value of the artist), an arbitrary distribution $F(y)$ on artists' talent, the incremental benefit from an additional experimentation can be written as follows.

$$\begin{aligned}
\Delta b(n) &= b(m,n) - b(m,n-1) \\
&= (\gamma \int_m^\infty V^*(y)dF^n(y) + \gamma F^n(y)V^*(m)) \\
&\quad -(\gamma \int_m^\infty V^*(y)dF^{n-1}(y) + \gamma F^{n-1}(y)V^*(m)) \\
&= [\gamma \int_m^\infty V^*(y)\{nf(y)F^{n-1}(y)\}dy + \gamma F^n(y)V^*(m)] \\
&\quad -[\gamma \int_m^\infty V^*(y)\{(n-1)f(y)F^{n-2}(y)\}dy + \gamma F^{n-1}(y)V^*(m)] \\
&= \gamma \int_m^\infty V^*(y)\{nf(y)F^{n-1}(y) - (n-1)f(y)F^{n-2}(y)\} \\
&\quad +\gamma V^*(m)(F^n(m) - F^{n-1}(m))
\end{aligned}$$

Let u denote $F^{n-1}(y) - F^n(y)$ and v denote $V^*(y)$. By integrating by parts, the equation can be rewritten as

$$\begin{aligned}
\Delta b(n) &= \gamma \int_m^\infty v^{'}udy \\
&= \gamma \int_m^\infty \frac{\partial V^*(y)}{\partial y}(F^{n-1}(y) - F^n(y))dz \geq 0,
\end{aligned}$$

because $\partial V^*(y)/\partial y > 0$ and $F^{n-1}(y) - F^n(y)$. Therefore, the benefit of an additional experimentation has a positive value under no noise in talent discovery. Now, I turn to the change in $\Delta b(n)$ with the number of experimentations n.

$$\begin{aligned}
\Delta b(m,n) - \Delta b(m,n-1) &= \gamma \int_m^\infty \frac{\partial V^*(y)}{\partial y}(F^{n-1}(y) - F^n(y))dz \\
&\quad -\gamma \int_m^\infty \frac{\partial V^*(y)}{\partial y}(F^{n-2}(y) - F^{n-1}(y))dz \\
&= \gamma \int_m^\infty \frac{\partial V^*(y)}{\partial y}\{(F^{n-1}(y) - F^n(y)) \\
&\quad -(F^{n-2}(y) - F^n(y)\}dz \leq 0,
\end{aligned}$$

because $0 \leq F(y) \leq 1$ implies $F^{n-1}(y) - F^n(y) \leq F^{n-2}(y) - F^{n-1}(y)$. Therefore, the incremental benefit from an additional experimentation decreases.

Functional forms and parameters in the numerical example of Result 1 in Figure 2. The cost of experimenting with a new artist by a single song is 0.002 and cost of experimenting with a new artist by an album is 0.01. There are 10 songs in an album. To calculate the optimal experimentation policy n^*, I run 20,000 simulations and calculate an average over these simulations. The distribution of talent of artists $F(y)$ is a uniform distribution with the range $[0, 1]$ (a well-known characteristic of the uniform distribution is $F^n = n/(n+1)$.). The noise parameter e determines the range of a uniform distribution (i.e., $e_i \sim U(-0.5 \times e, 0.5 \times e)$). Thus, the actual noise, e_i is a random draw from this uniform distribution. Thus, for each single, a firm observes a performance of an artists which is the sum of true talent of artist i ($x_i \sim U(0, 1)$) and a noise term $e_i \sim U(-0.5 \times e, 0.5 \times e)$. If the observed performance of an artist is larger than the existing top talented artist, the firm will replace the existing top artist with the new artist. When a firm experiments with new artists by albums, the firm observes the average of 10 draws of the sum of the true talent of artist i ($x_i \sim U(0,1)$) and a noise term $e_i \sim U(-0.5 \times e, 0.5 \times e)$; therefore, the observed performance under album-producing is more accurate than that under single-producing. The discount factor γ is 1 (i.e., no time discount).

Appendix 2. Description on Databases

1. Musicbrainz Database

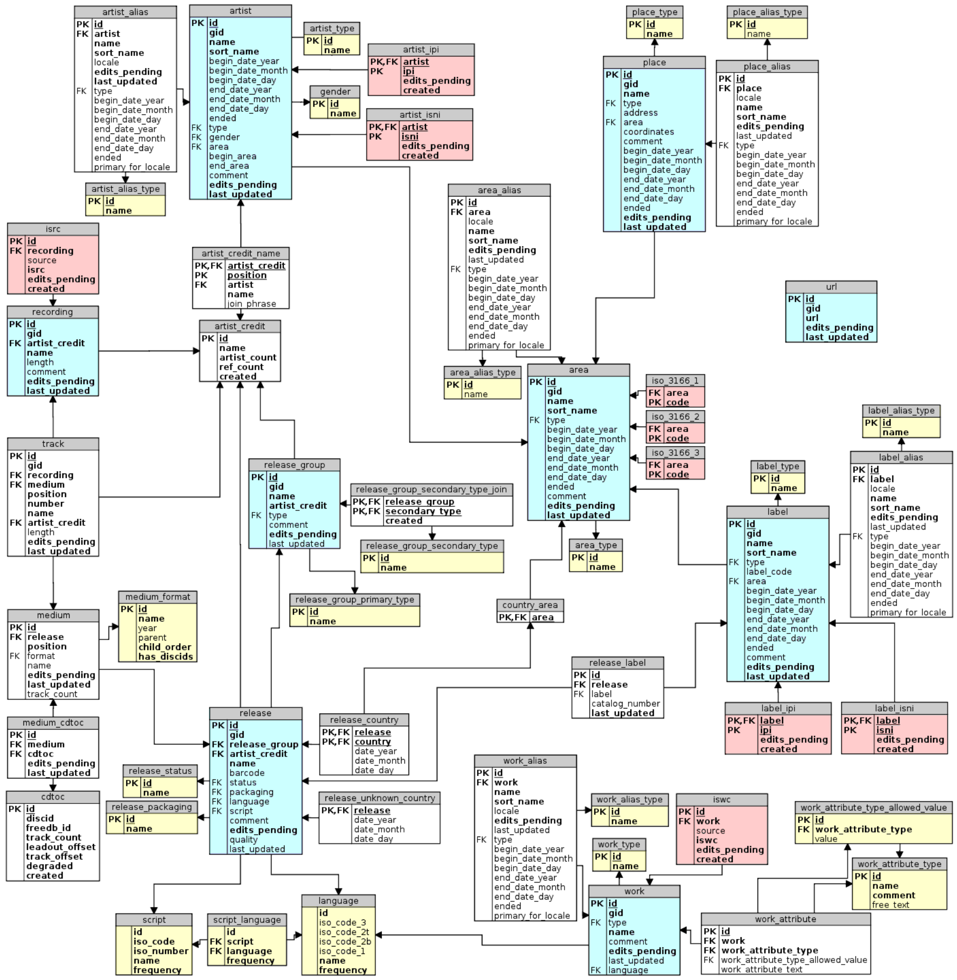
The MusicBrainz Database is developed with the PostgreSQL relational database engine and offers all of MusicBrainz's music metadata. This data includes information about artists, release groups, releases, recordings, works, and labels, as well as the many relationships between them as shown in Figure A2.1. The database also contains a full history of all the changes that the MusicBrainz community has made to the data (Musicbrainz, 2016). The first strength of Musicbrainz database is its large coverage. The second strength is that it has information on labels; Spotify APIs do not offer the label information on their databases (Highfield, 2007).

MusicBrainz is a project that aims to create an open content music database. Originally, MusicBrainz started as a database for software applications to search audio compact disc data on the Internet. MusicBrainz has expanded its scope to offer more data beyond a compact disc metadata storehouse to be an open online database for music (Wikipedia, 2018).

2. Spotify Echo Nest API

The Echo Nest is a music data platform company for software developers and media-related firms. The company is located in Somerville, MA. The Echo Nest started its business as a spin-off company from the MIT Media Lab to analyze the audio and textual content of recorded music (Zax 2011). Its creators intended it to perform music identification, recommendation, playlist creation, audio fingerprinting, and analysis for consumers and

Figure A2.1. Schema of Musicbrainz database



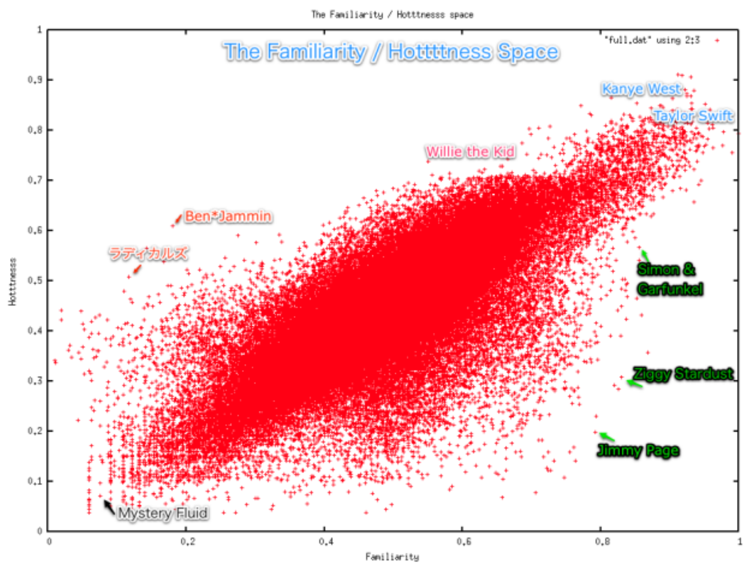
Source: Musicbrainz webpage (https://musicbrainz.org/doc/MusicBrainz_Database/Schema).

developers. On March 6, 2014 Spotify announced that they had acquired The Echo Nest. Spotify shut down the Echo Nest API on May 31, 2016 and developers was encouraged to use the Spotify Echo Nest API which integrate the original Echo Nest API instead.

The Echo Nest offered their automatically-derived database of data about 30 million songs aggregated from web crawling, data mining, and digital signal processing techniques. The strength of the database is that by using multiple sources such as web crawling, data mining, and digital signal processing, they measure popularity of artists. This is derived from many sources, including play counts, mentions on the web, mentions in music blogs, music reviews, Twitter, Facebook, and the catalogue of streaming applications.

The Echo Nest offered two popularity measures: familiarity and hotness. I choose fa-

Figure A2.2. Two popularity measures and their relation

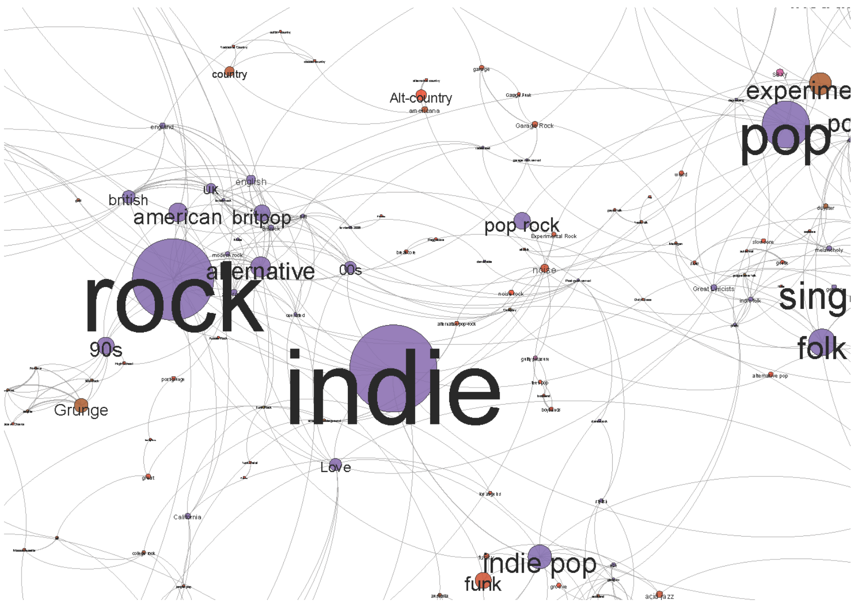


Source: Music Machinery (https://musicmachinery.com/2009/12/09/a-rising-star-or/).

miliarity as my popularity measure because it measures the life-time popularity of artists. Specifically, familiarity measures how well known in an artist is. One can understand familiarity as the likelihood that any person selected at random will have heard of the artist. Beatles have a familiarity close to 1, while a band like 'Hot Rod Shopping Cart' has a familiarity close to zero. On the other hand, hotness corresponds to how much buzz the artist is getting right now. Figure A2.1 shows the results. The x-axis is familiarity, and the y-axis is hotness. Clearly, there is a correlation between hotness and familiarity. Familiar artists are more likely to be hotter than non-familiar artists. At artists at the top right are artists who hit the top list of the Billboard chart such as Taylor Swift, while artists at the bottom left are artists who one has never heard of such as Mystery Fluid. This plot shows artists as well as the popular artists whose popularity has been declining. Outlier artists at the left and above the main diagonal part are the artists on the rise (Music Machinery, 2009).

The Echo Nest also identify artist genre and offer genre tags for all artists in the database. There are 1,347 unique genre tags in the database. Figure A2.3 visualize the relationship among genres. If many artists have two common genres, there a link between these genres.

Figure A2.3. Map of genres - a part of the map



Source: The Echo Nest Lab (http://static.echonest.com/playlist/moms/).

The last strength of the Echo Nest is that it offers an ID matching scheme for many different databases. One of the problems faced by music researchers is the issue of ID translation. The Echo Nest eliminated some of the trouble with mapping IDs with Project Rosetta Stone. Rosetta Stone is to allow a researcher to use any music id from any music API with the Echo Nest web services. I use this matching scheme to merge multiple databases.

3. Spotify Web API

In June 2014, Spotify released a new Web API that allowed third-party developers to integrate Spotify content in their own applications (Spotify, 2014). The Spotify Web API is a web service that can be accessed by programs through the Hypertext Transfer Protocol. It returns data about albums, artists, tracks, playlists and other Spotify resources in JSON format. I use song popularity data. The popularity of a track is calculated with the data on (1) the total number of plays and (2) how recent those plays are (Spotify, 2014). I extract song popularity data with the International Standard Recording Code code and match with Musicbrainz and Echo Nest data.

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Appendix 3. First stage regression results

	DV:(Dummy) one if label produces at least one single		DV:(Dummy) one if the first release of artist i is produced by a single
	(1) Fixed Effects	(2) Fixed Effects	(3) Fixed Effects
(Dummy) one if iTunes was introduced in country c	0.0235**	0.0202**	0.0072*
	(0.0050)	(0.0061)	(0.0033)
Country-level proportion of CDs to all releases in the previous year	-0.4791**	-0.4383**	-0.8098**
	(0.0369)	(0.0682)	(0.0943)
log (No. of songs) (1 year lag)	0.0387**	0.0341**	-0.0154
	(0.0018)	(0.0019)	(0.0046)
log (Mean no. of artists' prior releases) (1 year lag)	-0.0027	-0.0044*	-0.0030
	(0.0017)	(0.0017)	(0.0057)
(Dummy) one if label's founding year	0.0856**	0.0721**	0.0611**
	(0.0056)	(0.0060)	(0.0171)
(Dummy) one if label produced at least a top 5% song in the previous year	0.0829**	0.0758**	-0.0038
	(0.0095)	(0.0102)	(0.0178)
Herfindahl index for artists' genre in label	0.0277**	0.0263**	0.0018
	(0.0048)	(0.0050)	(0.0105)
Constant	13.4295**	12.2003**	3.3929
	(1.1031)	(1.3825)	(3.3541)
Label fixed effect	*yes*	*yes*	*yes*
Country fixed effect	*omitted*	*omitted*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*
Period fixed effect	*yes*	*yes*	*yes*
Adjusted R^2	0.1492	0.0166	0.0348
N	85,162	76,158	13,902

Note: Standard errors are in parentheses, $^{*}p < 0.05,^{**} p < 0.01$. Column 1 shows the results from the first stage regression in Table 5, and Column 2 shows that the results from the first stage regression in Table 7. The reason why the number of observations is smaller in Table 6 is that the observations before 1985 are excluded because there are too many missing values for popularity scores. before 1985. Column 3 shows the results from the first stage regression in Table 6.

Appendix 4. Does producing singles affect the average popularity of artists and songs in a label?

	DV: Average **artist** popularity in label					DV: Average **song** popularity in label				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Fixed Effects	Propensity Matching	CEM	2SLS	OLS	Fixed Effects	Propensity Matching	CEM	2SLS
(Dummy) one if label produces at least one single	-0.0063^{**}	-0.0149^{**}	-0.0191^{**}	-0.0150^{**}	0.1192^{*}	0.0158^{**}	0.0092^{**}	0.0098^{**}	0.0072^{**}	0.0528^{*}
	(0.0013)	(0.0015)	(0.0017)	(0.0017)	(0.0526)	(0.0008)	(0.0010)	(0.0011)	(0.0011)	(0.0260)
log (No. of songs) (1 year lag)	-0.0134^{**}	-0.0042^{**}	-0.0049^{**}	-0.0024^{**}	-0.0088^{**}	0.0058^{**}	0.0023^{**}	0.0026^{**}	0.0023^{**}	0.0008
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0019)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0009)
log (Mean no. of artists' prior releases) (1 year lag)	0.0087^{**}	-0.0025^{**}	-0.0024^{**}	-0.0034^{**}	-0.0019^{**}	0.0035^{**}	0.0001	-0.0002	0.0002	0.0003
	(0.0008)	(0.0006)	(0.0007)	(0.0008)	(0.0006)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0003)
(Dummy) one if label's founding year	-0.0337^{**}	-0.0086^{**}	0.0028	-0.0062^{**}	-0.0183^{**}	0.0132^{**}	0.0068^{**}	0.0032^{*}	0.0072^{**}	0.0036
	(0.0022)	(0.0020)	(0.0028)	(0.0024)	(0.0043)	(0.0012)	(0.0011)	(0.0014)	(0.0013)	(0.0021)
(Dummy) one if label produced at least one top 5% song	-0.0255^{**}	-0.0035	-0.0013	-0.0025	-0.0137^{**}	0.1194^{**}	0.0096	0.0073	0.0019	0.0063^{*}
in the previous year	(0.0046)	(0.0031)	(0.0032)	(0.0040)	(0.0053)	(0.0062)	(0.0054)	(0.0054)	(0.0073)	(0.0026)
Herfindahl index for genre in label	0.1750^{**}	0.1397^{**}	0.1301^{**}	0.1441^{**}	0.1361^{**}	0.0028^{**}	0.0032^{**}	0.0036^{**}	0.0031^{*}	0.0020
	(0.0026)	(0.0023)	(0.0026)	(0.0027)	(0.0022)	(0.0010)	(0.0011)	(0.0014)	(0.0013)	(0.0011)
Constant	9.2226^{**}	6.8598^{**}	6.9103^{**}	8.2754^{**}	5.3549^{**}	-0.6062^{**}	-1.5462^{**}	-2.1180^{**}	-1.9881^{**}	-2.0339^{**}
	(0.3513)	(0.3944)	(0.4963)	(0.5078)	(0.6985)	(0.1345)	(0.2244)	(0.3197)	(0.3053)	(0.3449)
Label fixed effect	*no*	*yes*	*yes*	*yes*	*yes*	*no*	*yes*	*yes*	*yes*	*yes*
Country fixed effect	*yes*	*omitted*	*omitted*	*omitted*	*omitted*	*yes*	*omitted*	*omitted*	*omitted*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
2SLS first-stage summary statistics										
F-statistic					18.97					18.97
T-statistic: (Dummy) one if iTunes was introduced in country c					3.26					3.26
T-statistic: Country-level proportion of CDs to all releases in the previous year					-6.47					-6.47
Adjusted R^2					0.0145					0.0145
Adjusted R^2	0.3597	0.2011	0.2135	0.1989	n.a.	0.2331	0.0183	0.0202	0.0152	n.a.
N	76,158	76,158	48,656	56,972	76,158	76,158	76,158	48,656	56,972	76,158

Note: Standard errors are in parentheses, $^{*}p < 0.05,^{**} p < 0.01$. Standard errors are robust and clustered at the label level. 2SLS test statistics are the same with the statistics in Table 5 and 7.

Appendix 5. Alternative measure for the independent variable: proportion of singles to all releases in label

	DV: Proportion of new artists in label		DV: Maximum **artist** popularity in label		DV: Maximum **song** popularity in label	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
(Dummy) one if label produces at least one single	0.0696**	0.2132**	0.0155**	0.1978*	0.0166**	0.0716
	(0.0046)	(0.0769)	(0.0019)	(0.0788)	(0.0012)	(0.0483)
log (No. of songs) (1 year lag)	0.0060*	-0.0324**	0.0214**	0.0046**	0.0141**	0.0045**
	(0.0024)	(0.0026)	(0.0009)	(0.0017)	(0.0010)	(0.0010)
log (Mean no. of artists' prior releases) (1 year lag)	-0.0643**	0.0499**	0.0133**	-0.0003	0.0064**	0.0006
	(0.0019)	(0.0020)	(0.0009)	(0.0008)	(0.0006)	(0.0005)
(Dummy) one if label's founding year	0.1941**	0.1543**	0.0295**	-0.0018	0.0335**	0.0121**
	(0.0071)	(0.0082)	(0.0025)	(0.0053)	(0.0027)	(0.0032)
(Dummy) one if label produced at least one top 5% song in the previous year	-0.0385**	-0.0211	0.0163**	-0.0036	0.2236**	0.0129**
	(0.0080)	(0.0118)	(0.0050)	(0.0058)	(0.0125)	(0.0035)
Herfindahl index for genre in label	-0.1298**	-0.1031**	0.2453**	0.2197**	0.0028	0.0051**
	(0.0046)	(0.0056)	(0.0026)	(0.0021)	(0.0021)	(0.0013)
Constant	7.2463**	12.6653**	11.5891**	6.6617**	-0.8557**	-3.0922**
	(0.9079)	(1.5965)	(0.4091)	(0.8272)	(0.2109)	(0.5065)
Label fixed effect	*no*	*yes*	*no*	*yes*	*no*	*yes*
Country fixed effect	*yes*	*omitted*	*yes*	*omitted*	*yes*	*omitted*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
2SLS first-stage summary statistics						
F-statistic		51.94		18.97		18.97
T-statistic: (Dummy) one if iTunes was introduced in country c		4.70		3.26		3.26
T-statistic: Country-level proportion of CDs to all releases in the previous year		-12.98		-6.47		-6.47
Adjusted R^2		0.0271		0.0145		0.0145
Adjusted R^2	0.1215	n.a.	0.4759	n.a.	0.2221	n.a.
N	85,162	85,162	76,158	76,158	76,158	76,158

Note: Standard errors are in parentheses, $^*p < 0.05, ^{**}p < 0.01$. Standard errors are robust and clustered at the label level. 2SLS test statistics are the same with the statistics in Table 5 and 7.

Chapter 2

Does Digitalization Facilitate Entrepreneurial firms' Discovery of New Talent? The Impact of iTunes and YouTube on the Recorded Music Industry

2.1 Abstract

Does digitalization facilitate the discovery of new talent by entrepreneurial firms? One theoretical argument suggests that entrepreneurial firms may benefit from digitalization because it offers diverse niche opportunities from a long-tail market and decreases the cost of experimenting with new artists. Another theoretical argument challenges this simple positive relationship by arguing that an adverse impact may result from the fact that would-be artists can demonstrate their talent through many services, such as YouTube or social media, in the digital age. As incumbent firms also observe these would-be artists who have obvious talent, the advantage of entrepreneurial firms' discovery of new talent may be undermined. By utilizing iTunes' and YouTube's staggered market entries into 29 countries, this study produces results from a difference-in-difference-in-differences (DDD) specification. The findings suggest that iTunes and YouTube did not facilitate entrepreneurial firms' discovery of new talent but decreased the average and maximum pop-

ularity of new artists in entrepreneurial firms. In contrast, entrepreneurial firms increase their reliance on incumbent artists. In short, the average popularity of new artists in entrepreneurial labels decreased by at least 26% and reached a level similar to the average popularity of new artists in incumbent labels. Considering that entrepreneurial firms have relied more on the discovery of new talent (their proportion of new artists is approximately 20% higher than that in incumbent labels), the discovery performance of entrepreneurial labels was lower than that of incumbent labels.

2.2 Introduction

The competitive dynamics between entrepreneurial and incumbent firms is a critical topic in Schumpeterian competition literature (Schumpeter 1934). Technological changes shape this competition dynamics, and many studies have examined the role of technological change in shaping the competitive dynamics between entrepreneurial and incumbent firms (e.g., Tripsas and Gavetti 2000, Tushman and Anderson 1986). Digitalization is a radical technological change, and many studies in information systems, marketing, and economics have examined how digitalization has shaped industry environments, such as the long-tail phenomenon and unbundling (e.g., Bakos and Brynjolfsson 1999, Elberse and Oberholzer-Gee 2007). However, relatively little attention has been devoted to the competition between entrepreneurial and incumbent firms in the field of strategy. This study aims to contribute to strategy literature by exploring whether or not digitalization offers a competitive advantage to entrepreneurial firms.

Entrepreneurial firms often generate creative destruction by experimenting with new products, technologies or strategies (Schumpeter 1934). As the empirical setting of this study is the recorded music industry, where discovering new superstars plays an essential role not only in making profits but also in creating industry fashions or norms (Caves 2000), this study will focus on the impact of digitalization on the discovery of new talent in the setting of the music industry.

Does digitalization create a more favorable competitive environment for entrepreneurial firms? The answer is far from straightforward because there exist both positive and negative impacts of digitalization on entrepreneurial firms. More obviously, digitalization has played an essential role in increasing the demand for niche products, in creating a "long tail" in the cultural market (Brynjolfsson, Hu, and Smith 2010a). This long tail may have created new business opportunities for potential entrepreneurs. AlsoIn addition, digitalization has dramatically decreased the cost of experimentation by lowering production, distribution, and promotion costs. Therefore, even though the entrepreneurial firm has fewer resources and a lower reputation than incumbent labels, they may experiment with a risky, distant, and novel forms of cultural product in the presence of the digitized market and supply chain (Benner and Waldfogel 2016). These entrepreneurial firms' experimentations often include experimenting with new artists, which will lead to the discovery of better new talent.

On the other hand, there exists a negative impact on the entrepreneurial firms' discovery of new talent. Prior to digitalization, many would-be artists had more channels, such as YouTube or SoundCloud, to demonstrate their talent even before making a deal with music labels. In addition, the hiring process in the music industry was usually through an offline channel, including submitting a "demo" or arranging an audition with a music producer. Thus, the diffusion of information about the talent of new artists was limited. Today, in the presence of many social media in the digital age, many would-be artists have more channels to demonstrate their talent. However, in the digital age, both entrepreneurial and incumbent firms are exposed to similar information through multiple social media and web-services. In hiring a would-be artist who is already popular, incumbents may have an advantage because they have more useful resources and a reputation. In fact, most YouTube music stars, who had become popular before they signed with music labels, usually make deals with incumbent labels with a better reputation and more plentiful resources than entrepreneurial labels. Therefore, as this liability of newness increases in the digital age, digitalization may have a negative impact on the discovery of new talent by entrepreneurial firms.

The empirical setting of this study is the recorded music industry, which may be one of the most visible examples of industries impacted by digitalization. This study excludes the major labels (Universal, Sony, Warner, and their subsidiaries) because these major labels have a disproportionately large amount of resources and are less likely to rely on the discovery of new talent; their primary business model is hiring popular incumbent artists to utilize their network. In contrast, independent labels play an important role in discovering new talent. Most entrants (entrepreneurial firms) in the 1990s and 2000s are independent labels (Benner and Waldfogel 2016). Therefore, the comparable set of entrepreneurial firms will be independent labels. Some independent labels were reasonably successful in discovering new talent, and these independent labels made a profit by producing more releases with new popular artists or being acquired by the major labels.

This study utilizes the stagger market entries of iTunes and YouTube to estimate the causal impact of digitalization on the discovery of new talent by entrepreneurial labels. The estimates from a difference-in-difference-in-differences (DDD) specification suggest that iTunes and YouTube did not facilitate entrepreneurial firms' discovery of new talent but decreased the average and maximum popularity of new artists in entrepreneurial firms. In contrast, entrepreneurial firms increase their reliance on incumbent artists. In sum, the average popularity of new artists in entrepreneurial labels decreased by at least 26%, and it reached a level similar to the average popularity of new artists in incumbent labels. Considering that entrepreneurial firms have relied on the discovery of new talent regarding the proportion of new artists (their proportion of new artists is approximately 20% higher than that of incumbent labels), the discovery performance of entrepreneurial labels became lower than that of incumbent labels.

In addition, iTunes and YouTube have increased the popularity of incumbent artists in entrepreneurial labels; thus, the gap between entrepreneurial and incumbent labels has narrowed, but the popularity of incumbent artists in incumbent labels is still 54.29% higher than that of entrepreneurial labels. This finding suggests that digitalization weakened the relative performance of entrepreneurial labels compared to incumbent labels.

This study offers two main contributions to strategy literature. First, it provides the first empirical evidence linking digitalization and the competitive dynamics between entrepreneurial and incumbent firms. This study shows that digitalization differentially impacts the discovery strategy of entrepreneurial firms versus incumbent firms, suggesting that digitalization weakened the competitive advantages of entrepreneurial firms. Second, this study also makes a significant methodological contribution. Many studies on how incumbent firms respond to technological changes have depended on case studies of only a few organizations (Tripsas and Gavetti 2000, Benner 2010, Henderson and Clark 1990). While these studies provide rich, in-depth insights into the dynamics of incumbent firms faced with technological change, their research produced little causal evidence (Benner and Waldfogel 2016). Methodologically, this study used a large-scale sample with a causally identified relationship between technological change and firm strategy/performance to make a significant empirical contribution to strategy research.

2.3 Setting and Related Literature

Is digitalization good or bad for entrepreneurial firms? As there exist two competing effects of digitalization on entrepreneurial firms' discovery of new talent, it is difficult to conclude whether digitalization is good or bad. First, the positive impact arises from the fact that digitalization creates a long-tail market where more diverse products can be consumed compared to the market prior to digitalization, and the fact that the cost of experimentation (music production cost, distribution cost) is lower than before digitalization. Second, the negative impact arises from the fact that talented artists who are yet to be discovered are in a more advantageous position than prior to digitalization, as talented artists have more channels through which to let many labels know about their talent before they are discovered, or even to commercialize their songs themselves. When entrepreneurial labels and incumbent labels compete against each other over new artists with obvious talent or popularity, incumbent labels have an advantage over entrepreneurial labels because of their reputation and resources. In the following subsections, I review the theoretical arguments and empirical findings that support these two competing effects of digitalization on entrepreneurial firms' relative advantage in discovering new talent.

Positive impact of digitalization on entrepreneurial firms

Digitalization has also enabled the distribution of products available to customers. Even before the expression "The Long Tail" was coined by Anderson (2006), many Internet companies had successfully implemented digital strategies based on the long-tail concept (Brynjolfsson et al. 2010a). For example, whereas Walmart only carries a small number of music releases (top 3,000) with a broad appeal, due to limited shelf space and local demand, online music providers such as iTunes can profitably carry niche singles and albums with limited appeal since the cost of listing an additional single or album is close to zero, and online music providers can aggregate demand by finding niche audiences across the country (Zhang, 2016). The long-tail argument suggests that a new niche content, such as remote genres, and music from new artists, can find an audience and earn similar profits close to a "hit" single or album (Anderson 2006). The long-tail effect of digitalization has been documented in other products such as book sales (Brynjolfsson et al. 2010a, Brynjolfsson, Hu and Smith 2010b, Brynjolfsson, Hu and Simester 2011), home video sales (Elberse and Oberholzer-Gee 2007), and music consumption (Bhattacharjee et al. 2007, Dewan and Ramaprasad 2012). Missing from the debate, however, is the link between the firms' responses to digitalization.

Moreover, the cost of experimenting with a new artist has declined because digitalization has lowered the cost of searching for new artists and producing, promoting, and distributing their releases. Aguiar and Waldfogel (2016) noted that these cost reductions are substantial enough to have enabled growth in the number of new products, and the number of new music products released each year has increased since 1990 and more rapidly since 2000 (Oberholzer-Gee and Strumpf 2010, Handke 2012, Waldfogel 2013). This decline in the cost of experimentation may facilitate projects that labels can take on in terms of what has traditionally been the costly and risky "discovery" of "new-to-the-world" artists, instead of hiring incumbent artists to produce one more release (Benner and Waldfogel 2016). Chang (2017) shows that music labels decrease the cost of experimentation by producing their releases by singles, which requires fewer resources, and these single-producing music labels tend to increase the proportion of new artists. Entrepreneurial firms tend to be under financial constraints; thus, entrepreneurial firms may benefit from the low cost of experimentation by facilitating their experimentation and discovery of new talent.

Negative impact of digitalization on entrepreneurial firms

Vogel (2007) noted that unless an artist is a superstar, he or she has no bargaining power in making deals with music labels. Digitalization has given more power to new artists by enabling them to advertise themselves even before they sign with music labels. Some of them upload their demo to YouTube or SoundCloud, become popular and are dubbed YouTube Stars or YouTube Millionaires (McAlone, 2017). This phenomenon is not limited to YouTube or SoundCloud, as social media are also useful tools for unsigned artists to advertise and commercialize their work (Next Big Sound, 2013). Even though there exist many channels through which to make money, unsigned artists want deals with music labels (Resnikoff, 2014).

Entrepreneurial firms tend to have the liability of newness because they lack resources and reputation. When talented unsigned artists can signal talent through YouTube or social media, entrepreneurial firms may find it difficult to make deals with these talented new artists because incumbent labels with more resources and a better reputation can also offer deals to these talented new artists. For example, unsigned artists who become popular through YouTube or a similar channel tend to sign with incumbent labels (either independent labels or major labels) that can offer more favorable terms than those of entrepreneurial firms. It is well known that Justin Bieber was discovered on YouTube (Benner and Waldfogel 2016, Widdicombe, 2012).

2.4 Empirical Strategy

Sample

The sample comprises all record labels reported on the MusicBrainz database for the period between 1996 and 2015. The sample includes only record labels before and after iTunes and YouTube were introduced in its country.

The criteria are the same as in the first chapter except for the sample period. I choose 29 countries that have more than 200 unique labels because the treatment in this study is a country-level shock. This study excludes major labels from our sample by using the same criteria as Thomson (2009) and Benner and Waldfogel (2016). In addition, the sample includes only record production labels since other label types lack A&R (Artists and

Repertoire) staffs that play an important role in searching and recruiting new artists. The above selection criteria resulted in 64,471 label-year observations associated with 22,265 record labels.

Variables

Independent variables

The research question is whether entrepreneurial firms are more likely to rely on the discovery of new talent as opposed to incumbent artists. The first explanatory variable is an interaction between the two variables; the first dummy variable is $NEWFIRM_{it}$, which captures whether a firm began its business in year t, and the second variable is $ITUNES_{tc}$, which captures whether iTunes was in service in year t in country c. The second explanatory variable is an interaction between the two variables; the first dummy variable is $NEWFIRM_{it}$, and the second variable is $YOUTUBE_{tc}$, which captures whether YouTube was in service in year t in country c.

Dependent variables

The first set of dependent variables measures the popularity of artists and songs form each label-year: $POPNEW_{it}$ and $POPINCUM_{it}$. The next set of dependent variables measures the popularity of artists for each label-year. First, I calculate the average and maximum popularity of new artists and incumbent artists respectively for label-years. I obtain the popularity score (familiarity score) of artists from the Spotify Echonest API. The Spotify Echonest API offers a platform, called Rosetta Stone, to match Spotify Echonest IDs and MusicBrainz IDs. I use this platform to calculate the firm-level maximum popularity of artists. The range of individual artist popularity is between 0 and 1.

The next set of dependent variables measures each label's experimentations. I use (1) number of artists, (2) number of releases, and (3) proportion of new artists who had never before released a song.

Control variables

I control for variables: (1) the dummy equals 1 if label i produces at least one single release(s) in year t, (2) the number of songs as a firm size proxy, (3) the mean number of artists' prior releases as a firm status proxy, (4) the Herfindahl index for genre in label in year t, (5) country dummies, (6) genre dummies, and (7) year dummies.

Empirical specification

This study estimates the change in the popularity of new artists and incumbent artists in new firms after the introduction of iTunes and YouTube. As I utilize staggered entering of iTunes and YouTube into 29 countries, this study uses difference-in-difference-in-differences estimators by including two dependent variables (new artists popularity $POPNEW_{it}$, incumbent artists popularity $POPINC_{it}$), control variables X_{it}, firm fixed effect F_i, country fixed effects C_c, genre fixed effects G_{it}, and year fixed effect Y_t along with the explanatory variables $NEWFIRM_{it} \times ITUNES_{tc}$ and $NEWFIRM_{it} \times YOUTUBE_{tc}$, as in

$$POPNEW_{it} = \alpha + \beta_x X_{it} + \beta_{NI}(NEWFIRM_{it} \times ITUNES_{ct})$$

$$
\begin{aligned}
& +\beta_{NY}(NEWFIRM_{it} \times YOUTUBE_{ct}) + \beta_N NEWFIRM_{it} \\
& +\beta_I ITUNES_{ct} + \beta_Y YOUTUBE_{ct} + F_i + C_c + G_{it} + Y_t + e_{it}, \\
POPINC_{it} \quad = \quad & \alpha + \beta_x X_{it} + \beta_{NI}(NEWFIRM_{it} \times ITUNES_{ct}) \\
& +\beta_{NY}(NEWFIRM_{it} \times YOUTUBE_{ct}) + \beta_N NEWFIRM_{it} \\
& +\beta_I ITUNES_{ct} + \beta_Y YOUTUBE_{ct} + F_i + C_c + G_{it} + Y_t + e_{it}.
\end{aligned}
$$

The total effect of iTunes on entrepreneurial firms is as $\beta_{NI} + \beta_I$, and the total effect of the iTunes on incumbent firms as β_I. The coefficient β_{NI} measures how the effect varies with label type. The coefficient β_N measures the direct effect of being an entrepreneurial firm. In the case where the dependent variable is the popularity of the new, the conjecture is that entrepreneurial labels rely less on new artists, implying that the coefficient β_{NI} in the equation should be negative.

In the case where the dependent variable is the popularity of artists, the first difference compares the popularity of new artists (and incumbent artists) that labels hire before and after the introduction of iTunes and YouTube separately for entrepreneurial labels (treatment group) and incumbent labels (control group). This yields two differences, one for the control group and one for the treatment groups. The second difference takes the difference between these two differences. The result is an estimate of the effect of iTunes on the popularity of artists in entrepreneurial labels and incumbent labels. The interaction terms in equations (1) and (2), $NEWFIRM_{it} \times ITUNES_{tc}$ and $NEWFIRM_{it} \times YOUTUBE_{tc}$, estimate third differences, namely, whether the iTunes effect (or the YouTube effect) is different for entrepreneurial labels and incumbent labels. Importantly, the staggered market entries of iTunes (or YouTube) into 29 countries implies that the control group is not restricted to labels in countries where iTunes has never been introduced. The control group includes all labels in countries where iTunes (or YouTube) was not in service by time t. Thus, it includes labels in countries where iTunes (or YouTube) has never been introduced, as well as labels in countries where iTunes (or YouTube) was introduced after time t.

Sample statistics

Table 2.1 reports descriptive statistics on all the variables for the sample at the firm-year level. First, the descriptive statistics for the independent variable show that the proportion of firm-years when iTunes was in service is 60.4%, and the proportion of firm-years when YouTube was in service is 44.2%. In addition, the proportion of firm-years that were new (entrepreneurial) labels is 22.8%, and the proportion of firm-years that produced pop genre music is 6.3%.

Second, I have seven firm-level dependent variables. The first set of variables is about the firm-level popularity of new and incumbent artists; there are four variables: the average popularity of new artists, maximum popularity of new artists, average popularity of incumbent artists, and maximum popularity of incumbent artists. The averages of firm-level average and maximum popularity of new artists are 0.023 and 0.03, respectively; they have large standard deviations that are about three times larger than average values. The averages of firm-level average and maximum popularity of incumbent artists are higher than those of new artists; they are 0.023 and 0.03, respectively; they have large standard deviations that are approximately 1.5 times larger than average values. Additionally, pop-

Table 2.1: Summary statistics

Variable name	Level of variation	Mean	Std. Dev.	Min.	Max.
Independent variables:					
Dummy one if iTunes was in service	Country	0.604	0.489	0	1
Dummy one if YouTube was in service in country c	Country	0.442	0.497	0	1
Dummy one if label was a new firm in country c	Firm	0.228	0.42	0	1
Dummy one if label produced pop genre music in year t	Firm	0.063	0.243	0	1
Dependent variables:					
Average popularity of new artists	Firm	0.023	0.081	0	0.841
Maximum popularity of new artists	Firm	0.03	0.099	0	0.841
Average popularity of incumbent artists	Firm	0.081	0.136	0	0.880
Maximum popularity of incumbent artists	Firm	0.115	0.177	0	0.880
Number of artists	Firm	2.349	3.463	1	159
Number of releases (singles + albums)	Firm	2.686	4.501	1	238
Proportion of new artists to all artists	Firm	0.406	0.432	0	1
Control variables:					
Number of tracks that label produced in year t	Firm	25.386	45.277	1	1839
Average # of prior releases that label's artists produced	Firm	5.582	17.544	0	664
Herfindahl index for genre in label in year t	Firm	0.129	0.305	0	1
Dummy on if label produced at least one single in year t	Firm	0.28	0.449	0	1
Other variables:					
Year	Firm	2005.383	5.111	1996	2015
Number of label-year observations		64,471			
Number of unique labels		22,265			
Number of unique artists		151,441			
Number of unique releases		173,181			
Number of unique songs		1,636,682			

ularity distributions are highly skewed. The average number of artists per year is 2.349, and the average number of releases per year is 2.686, which is slightly larger than the average number of artists per year. These two variables show that the average size of the music label is quite small. The average proportion of new artists is 40.6% (0.406), and the standard deviation is large and has a similar size (0.432).

Third, there are four control variables. The first control variable is the number of tracks produced per firm-year, and the average value is 25.386. The second control variable is the average number of prior releases that each label's artists produced. The average value is 5.582. Considering that 40% of artists are new, incumbent artists had ten prior releases on average; this shows that the industry comprises new artists with the potential to be popular and incumbent artists with proven records; most new artists do not have a second chance in the music industry.

2.5 Results

Did iTunes and YouTube facilitate the discovery of new talent?

I test the hypothesis that iTunes and YouTube facilitated entrepreneurial labels' discovery of new talent. Table 2.2 shows the results of testing the impact of iTunes and YouTube on entrepreneurial firms' relative reliance on the discovery of new talent compared to incumbent artists.

I estimate two different versions of the popularity of new artists: the average and maximum popularities. Columns 1 and 2 report the estimates from DD specifications with the two dependent variables: the average popularity of new artists and the maximum popularity of new artists. Columns 1 and 2 show the average effect of the introduction of iTunes and YouTube on the average and maximum popularities of new artists across all labels.

The coefficients on the iTunes dummy are -0.0027 and -0.0032; although the coefficients have negative values, these coefficients are not significant at the 5% level. The coefficients on the YouTube dummy are -0.0044 and -0.0053, implying that YouTube decreases the popularity of new artists on average. Given that the average and maximum popularity of new artists in labels are 0.023 and 0.03, respectively, the change from YouTube implies decreases in average popularity of 19.13% and maximum popularity of 17.66%. Overall, although iTunes' impact was not significant, the negative values of the four coefficients suggest that music labels are less likely to rely on the discovery of new talent.

The coefficients of the dummy for new (entrepreneurial) labels in Columns 1 and 2 are positive and significant at the 1% level (0.0091 and 0.0052 respectively), suggesting that entrepreneurial labels are more likely to rely on the discovery of new talent. In addition, the coefficients of the dummy for pop producing labels in Columns 1 and 2 (0.0220 and 0.0325 respectively) show that pop labels' new artists are much more popular than other genre labels.

Next, I estimate two different versions of the popularity for incumbent artists: the average and maximum popularities. Columns 3 and 4 report the estimates from DD specifications with the two dependent variables: the average and maximum popularities of incumbent artists. Columns 1 and 2 show the average effect of the introduction of iTunes and YouTube on the average and maximum popularities of incumbent artists across all labels. All four coefficients for the dummy for iTunes and the dummy for YouTube are not significant at the 5% level. The impacts of iTunes and YouTube on the average popularity of incumbent artists in Column 3 are negative, but the impacts of iTunes and YouTube on the maximum popularity of incumbent artists in Column 4 are negative. Overall, there is no clear impact of iTunes and YouTube on labels' reliance on incumbent artists.

The coefficients of the dummy for new (entrepreneurial) labels in Columns 1 and 2 are positive and significant at the 1% level (-0.0192 and -0.0249 respectively), suggesting that entrepreneurial labels are less likely to rely on the discovery of new talent. Moreover, the coefficients of the dummy for pop producing labels in Columns 3 and 4 (0.0581 and 0.0915 respectively) show that pop labels' new artists are much more popular than other genre labels; this result is consistent with the findings in Columns 1 and 2.

Table 2.2: Did iTunes and YouTube facilitate music labels' discovery of new talent?

	(1) Average popularity of new artists OLS D-in-D	(2) Maximum popularity of new artists OLS D-in-D	(3) Average popularity of incumbent artists OLS D-in-D	(4) Maximum popularity of incumbent artists OLS D-in-D
Dummy one if iTunes was in service	-0.0027	-0.0032	-0.0017	0.0002
	(0.0023)	(0.0028)	(0.0031)	(0.0036)
Dummy one if YouTube was in service	-0.0044**	-0.0053**	-0.0006	0.0008
	(0.0015)	(0.0019)	(0.0025)	(0.0030)
Dummy one if label was a new firm in year t	0.0091**	0.0052**	-0.0192**	-0.0249**
	(0.0012)	(0.0014)	(0.0015)	(0.0017)
Dummy one if label produced pop genre music in year t	0.0220**	0.0325**	0.0581**	0.0915**
	(0.0029)	(0.0037)	(0.0033)	(0.0039)
Number of tracks that label produced in year t	-0.0000**	0.0001**	-0.0002**	0.0005**
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Average # of prior releases that label's artists produced	-0.0002**	-0.0002**	0.0003**	0.0004**
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Herfindahl index for genre in label in year t	0.0268**	0.0297**	0.1244**	0.1683**
	(0.0023)	(0.0028)	(0.0027)	(0.0031)
Constant	0.0587**	0.0797**	0.0578**	0.0555**
	(0.0032)	(0.0040)	(0.0034)	(0.0043)
Firm fixed effects	*yes*	*yes*	*yes*	*yes*
Genre fixed effects	*yes*	*yes*	*yes*	*yes*
Country fixed effects	*yes*	*yes*	*yes*	*yes*
Year fixed effects	*yes*	*yes*	*yes*	*yes*
Adjusted R^2	0.4111	0.4170	0.6080	0.6759
N	64,471	64,471	64,471	64,471

Note: Standard errors are in parentheses. $^{+}p < 0.1, ^{*} p < 0.05, ^{**} p < 0.01$. Standard errors are robust and clustered at the label level.

Did iTunes and YouTube facilitate the discovery of new talent by entrepreneurial firms?

I turn now to the impact of iTunes and YouTube on entrepreneurial firms' discovery performance. Here, I test the hypothesis with a DDD specification. Table 2.3 estimates the impacts of iTunes and YouTube and their interactions with the dummy for entrepreneurial firms.

Columns 1 and 2 report the results of whether the impact of iTunes and YouTube on the popularity of new artists is different for entrepreneurial and incumbent labels. First, the interaction term between the dummy for entrepreneurial firms and the dummy for iTunes has coefficients of -0.0115 for average popularity, which is significant at the 0.01 level, and -0.0079 for the maximum popularity, which is significant at the 0.01 level, implying that the decrease in the popularity of new artists came from entrepreneurial labels. The entrepreneurial labels are less likely to discover more popular new artists after the introduction of iTunes. For the magnitude of the effect, the decreases in the average and maximum popularity of new artists in entrepreneurial firms are substantial; they are 50% and 26.33% of the average values, respectively. Figure 2.1 shows the dynamic effect of iTunes on the discovery of new talent by entrepreneurial firms compared to incumbent firms.

Second, the interaction term between the dummy for entrepreneurial firms and the dummy for YouTube has coefficients of -0.0030 for average popularity, which is significant at the 0.1 level, and 0.0003 for maximum popularity, which is not significant. Entrepreneurial labels are less likely to discover more popular new artists after the intro-

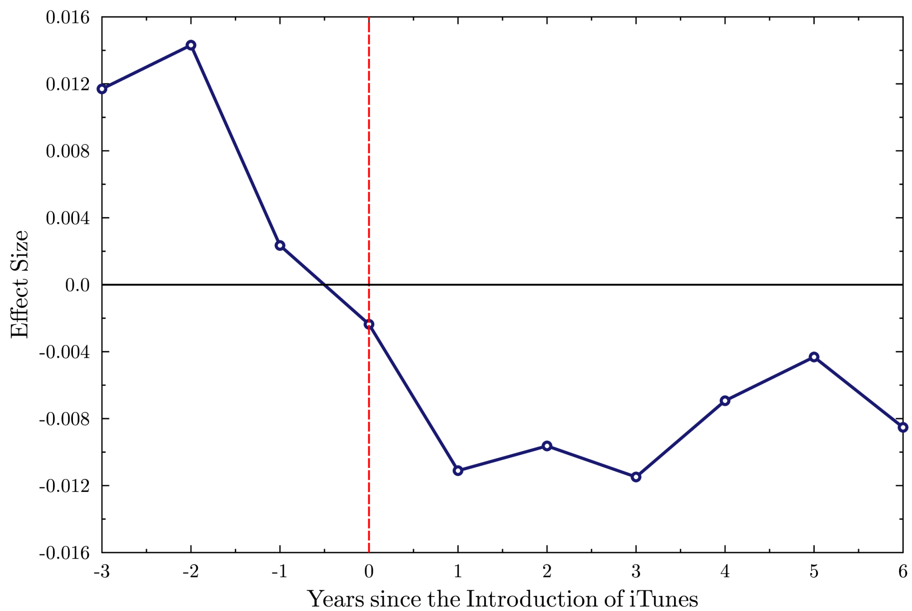
Table 2.3: Did iTunes and YouTube facilitate entrepreneurial music labels' discovery of new talent?

	(1) Average popularity of new artists OLS D-in-D-in-D	(2) Maximum popularity of new artists OLS D-in-D-in-D	(3) Average popularity of incumbent artists OLS D-in-D-in-D	(4) Maximum popularity of incumbent artists OLS D-in-D-in-D
Dummy one if label was a new firm	-0.0115^{**}	-0.0079^{**}	0.0099^{**}	0.0113^{**}
$\times$ Dummy one if iTunes was in service	(0.0026)	(0.0030)	(0.0034)	(0.0038)
Dummy one if label was a new firm	-0.0030+	0.0003	0.0184^{**}	0.0169^{**}
$\times$ Dummy one if YouTube was in service	(0.0018)	(0.0021)	(0.0031)	(0.0035)
Dummy one if iTunes was in service	-0.0013	-0.0023	-0.0030	-0.0012
	(0.0024)	(0.0029)	(0.0032)	(0.0037)
Dummy one if YouTube was in service	-0.0043^{**}	-0.0054^{**}	-0.0021	-0.0006
	(0.0015)	(0.0019)	(0.0025)	(0.0031)
Dummy one if label was a new firm	0.0151^{**}	0.0087^{**}	-0.0285^{**}	-0.0345^{**}
	(0.0021)	(0.0024)	(0.0023)	(0.0026)
Dummy one if label produced pop genre music in year t	0.0221^{**}	0.0325^{**}	0.0579^{**}	0.0914^{**}
	(0.0029)	(0.0037)	(0.0033)	(0.0039)
Number of tracks that label produced in year t	-0.0000^{**}	0.0001^{**}	-0.0002^{**}	0.0005^{**}
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Average # of prior releases that label's artists produced	-0.0002^{**}	-0.0002^{**}	0.0003^{**}	0.0004^{**}
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Herfindahl index for genre in label in year t	0.0268^{**}	0.0296^{**}	0.1244^{**}	0.1684^{**}
	(0.0023)	(0.0028)	(0.0027)	(0.0031)
Constant	0.0572^{**}	0.0788^{**}	0.0600^{**}	0.0577^{**}
	(0.0032)	(0.0040)	(0.0034)	(0.0043)
Firm fixed effects	*yes*	*yes*	*yes*	*yes*
Genre fixed effects	*yes*	*yes*	*yes*	*yes*
Country fixed effects	*yes*	*yes*	*yes*	*yes*
Year fixed effects	*yes*	*yes*	*yes*	*yes*
Adjusted R^2	0.4116	0.4171	0.6086	0.6763
N	64,471	64,471	64,471	64,471

Note: Standard errors are in parentheses. $^{+}p < 0.1, ^{*} p < 0.05, ^{**} p < 0.01$. Standard errors are robust and clustered at the label level.

duction of YouTube in terms of the average popularity of new artists. For the magnitude of the effect, the decreases in the average and maximum popularity of new artists in entrepreneurial firms are smaller than the decrease resulting from iTunes; they are 13.04% of average values. Figure 2.2 shows the dynamic effect of YouTube on the discovery of new talent by entrepreneurial firms compared to incumbent firms. In sum, the results in Columns 1 and 2 suggest that iTunes and YouTube weakened entrepreneurial labels' discovery of new artists compared to incumbent labels.

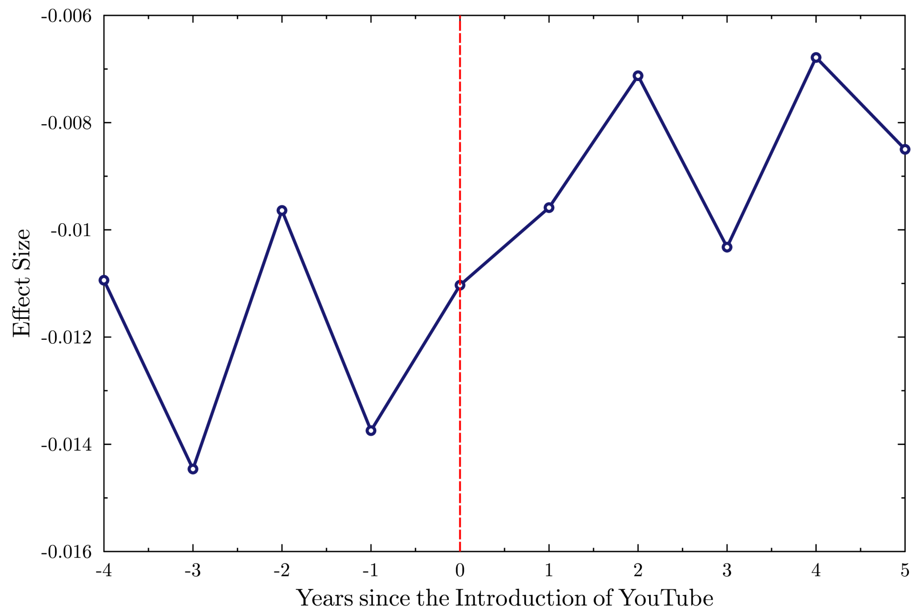
Figure 2.1: Dynamic Impact of iTunes on the Discovery of New Talent by Entrepreneurial Firms



Note: Figure 2.1 plots estimated year by year pre- and post-iTunes in the discovery of new talent from OLS regressions with fixed effects and controls. Each point represents the estimated difference between the treated group (entrepreneurial firms after the introduction of iTunes) and control group (incumbent firms after the introduction of iTunes) in each year.

Columns 3 and 4 report the results of whether the impact of iTunes and YouTube on the popularity of incumbent artists is different for entrepreneurial and incumbent labels.

Figure 2.2: Dynamic Impact of YouTube on the Discovery of New Talent by Entrepreneurial Firms



Note: Figure 2.2 plots estimated year by year pre- and post-YouTube in the discovery of new talent from OLS regressions with fixed effects and controls. Each point represents the estimated difference between the treated group (entrepreneurial firms after the introduction of YouTube) and control group (incumbent firms after the introduction of YouTube) in each year.

First, the interaction term between the dummy for entrepreneurial firms and the dummy for iTunes has coefficients of 0.0099 for average popularity, which is significant at the 0.01 level, and 0.0113 for the maximum popularity, which is also significant at the 0.01 level. Considering that the impact of iTunes on overall labels' incumbent popularity was not significant, the relative increase in the popularity of incumbent artists in entrepreneurial labels means a relative decrease in the popularity of incumbent artists in incumbent labels. Entrepreneurial labels are more likely to rely on more popular incumbent artists after the introduction of iTunes. For the magnitude of the effect, the decreases in the average and maximum popularity of new artists in entrepreneurial firms are substantial; they are 12.23% and 9.83% of average values, respectively.

Second, the interaction term between the dummy for entrepreneurial firms and the dummy for YouTube has coefficients of 0.0184 for average popularity, which is significant at the 0.01 level, and 0.0169 for maximum popularity, which is significant at 0.01. Entrepreneurial labels are more likely to rely on more popular incumbent artists after the introduction of YouTube in terms of the average and maximum popularity of incumbent artists. For the magnitude of the effect, the increases in the average and maximum popularity of incumbent artists in entrepreneurial firms are more substantial than the decrease resulting from iTunes; they are 22.71% and 14.70% of average values, respectively. In sum, the results in Columns 3 and 4 suggest that iTunes and YouTube make entrepreneurial labels rely more on incumbent artists than on incumbent labels.

Are all entrepreneurial firms and genres equally affected?

Table 2.4 explores whether the negative impact on entrepreneurial labels differs based on genre. I test the previous results across different genres: the pop genre vs. non-pop genres. Columns 1 to 4 report results on a subsample of pop-genre music producing labels, while Columns 5 to 8 report results on the other subsample of non-pop-genre music producing labels.

In a subsample of pop-genre music producing labels in Columns 1 and 2, the previously negative and significant coefficients for the iTunes and YouTube dummies turn non-significant. In Columns 3 and 4, the previously positive and significant coefficients of the iTunes dummy turn non-significant, but the previously positive and significant coefficients of the YouTube dummy become larger. This suggests that pop-genre music

Table 2.4: Contingent effects based on genre: pop-song labels vs non pop-song labels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample: Pop-song-producing labels				Sample: Non-pop-song-producing labels			
	Average popularity of new artists OLS D-in-D-in-D	Maximum popularity of new artists OLS D-in-D-in-D	Average popularity of incumbent artists OLS D-in-D-in-D	Maximum popularity of incumbent artists OLS D-in-D-in-D	Average popularity of new artists OLS D-in-D-in-D	Maximum popularity of new artists OLS D-in-D-in-D	Average popularity of incumbent artists OLS D-in-D-in-D	Maximum popularity of incumbent artists OLS D-in-D-in-D
Dummy one if label was a new firm	-0.0530	-0.0493	0.0163	0.0478	-0.0129**	-0.0106**	0.0101**	0.0105**
× Dummy one if iTunes was in service	(0.0436)	(0.0521)	(0.0470)	(0.0487)	(0.0025)	(0.0028)	(0.0034)	(0.0038)
Dummy one if label was a new firm	-0.0503	-0.0525	0.1696**	0.1290**	-0.0034*	-0.0013	0.0167**	0.0165**
× Dummy one if YouTube was in service	(0.0383)	(0.0473)	(0.0485)	(0.0455)	(0.0017)	(0.0020)	(0.0031)	(0.0035)
Dummy one if iTunes was in service	-0.0184	-0.0240	0.0000	0.0090	0.0006	0.0000	-0.0039	-0.0022
	(0.0165)	(0.0220)	(0.0149)	(0.0162)	(0.0023)	(0.0028)	(0.0032)	(0.0038)
Dummy one if YouTube was in service	-0.0166	-0.0280+	-0.0103	-0.0055	-0.0028+	-0.0028	-0.0022	-0.0016
	(0.0108)	(0.0163)	(0.0133)	(0.0134)	(0.0015)	(0.0018)	(0.0026)	(0.0032)
Dummy one if label was a new firm	0.1055**	0.1018**	-0.1310**	-0.1598**	0.0165**	0.0123**	-0.0272**	-0.0327**
	(0.0210)	(0.0235)	(0.0220)	(0.0224)	(0.0021)	(0.0023)	(0.0023)	(0.0026)
Number of tracks that label produced in year t	-0.0001*	0.0001	-0.0003**	0.0001*	0.0000	0.0002**	-0.0002**	0.0007**
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Average # of prior releases that label's artists produced	-0.0006+	-0.0011*	0.0004	0.0007*	-0.0001**	-0.0002**	0.0003**	0.0004**
	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Herfindahl index for genre in label in year t	-0.0408*	-0.0573*	-0.0594**	-0.1355**	0.0324**	0.0387**	0.1273**	0.1746**
	(0.0175)	(0.0229)	(0.0163)	(0.0192)	(0.0027)	(0.0034)	(0.0032)	(0.0038)
Constant	0.1914**	0.2788**	0.2753**	0.4260**	0.0462**	0.0626**	0.0597**	0.0552**
	(0.0199)	(0.0263)	(0.0170)	(0.0213)	(0.0032)	(0.0040)	(0.0036)	(0.0048)
Firm fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Genre fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Country fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adjusted R^2 (Pseudo R^2)	0.6683	0.6613	0.7524	0.7672	0.4171	0.4096	0.5930	0.6401
N	4,073	4,073	4,073	4,073	60,398	60,398	60,398	60,398

Note: Standard errors are in parentheses. $^{+}p < 0.1, ^{*} p < 0.05, ^{**} p < 0.01$. Standard errors are robust and clustered at the label level.

producing labels are much more likely to rely on incumbent artists after the introduction of YouTube. In the other subsample of non-pop-genre music producing labels in Columns 5 to 8, the results are very similar to the previous results, but the magnitude of the negative impact of iTunes and YouTube on entrepreneurial labels' discovery of new artists becomes larger and the coefficients become more significant. The magnitude of entrepreneurial labels' popularity of incumbent artists is almost identical to previous results. This suggests that the previous negative results of entrepreneurial labels' discovery of new artists mainly come from non-pop-genre music labels.

Are all entrepreneurial firms and genres equally affected?

We consider the decrease in the popularity of new artists in entrepreneurial labels as a decrease in their discovery of new artists. Can the decrease in the popularity of new artists in entrepreneurial labels be a decrease in discovery performance or smaller investment in new artists?

An alternative explanation would be that iTunes and YouTube facilitated the founding of more entrepreneurial labels (which are more open to new artists), or entrepreneurial labels lowered their bar for new artists and experimented with more new artists. The lower popularity for new artists may have come from this increased experimentation. If this is true, more new entrepreneurial firms would be founded or experimentations would be facilitated. Table 2.5 explores whether iTunes and YouTube facilitated firm founding and experimentations. Columns 1 and 2 show that iTunes and YouTube did not facilitate firm founding. Column 1 shows the results from an OLS model, and Column 2 shows the results from a logistic regression model. Here, the dependent variable is the dummy if label i is a new firm in year t. The coefficients of the dummies for iTunes are 0.0084 and 0.0375, but none of these coefficients are significant. The coefficients of the dummies for YouTube are 0.0004 and 0.0106, but none of these coefficients are significant.

Columns 3 to 5 explore whether iTunes and YouTube facilitated experimentations in the music industry. Each column has a different measure for experimentation: number of artists, number of releases, and proportion of new artists. In Columns 3 to 5, the coefficients of the dummy for iTunes are negative but not significant, and the coefficients of the dummy for YouTube are also negative but not significant. In Column 5, the coefficient of the dummy for new firms is 0.1901, which is significant at the 1% level, implying that entrepreneurial labels were more open to new artists.

Columns 6 to 8 examine whether iTunes and YouTube facilitated entrepreneurial labels' experimentations. The coefficients of the dummies for iTunes and YouTube remain negative and non-significant. However, the coefficients of the interaction between the dummy for new labels and the dummy for YouTube are -0.2488 and -0.2984, which are negative and significant at the 1% level, implying that YouTube decreased entrepreneurial firms' experimentations in terms of the number of artists and releases. However, the proportion of new artists in entrepreneurial labels did not change after the introduction of iTunes and YouTube compared to that in incumbent labels.

In sum, the results in Table 2.5 offer evidence that refutes the alternative explanation that the decrease in the popularity of new artists in entrepreneurial labels may stem from increased experimentations with new artists (with a lower bar for new artists).

Table 2.5: Did iTunes and YouTube facilitate label founding and experimentations?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dummy one if label was a new firm		Number of artists	Number of releases	Proportion of new artists	Number of artists	Number of releases	Proportion of new artists
	OLS D-in-D	Logit D-in-D	OLS D-in-D-in-D	OLS D-in-D-in-D	OLS D-in-D-in-D	OLS D-in-D-in-D	OLS D-in-D-in-D	OLS D-in-D-in-D
Dummy one if label was a new firm						0.1158	0.0776	-0.0056
× Dummy one if iTunes was in service						(0.0766)	(0.0641)	(0.0152)
Dummy one if label was a new firm						-0.2488**	-0.2984**	-0.0265
× Dummy one if YouTube was in service						(0.0860)	(0.0675)	(0.0166)
Dummy one if iTunes was in service	0.0084	0.0375	-0.0817	-0.0220	-0.0015	-0.0926	-0.0281	-0.0006
	(0.0100)	(0.0561)	(0.0596)	(0.0764)	(0.0113)	(0.0601)	(0.0780)	(0.0114)
Dummy one if YouTube was in service	0.0004	0.0106	-0.0810	-0.1046	0.0005	-0.0569	-0.0764	0.0028
	(0.0081)	(0.0474)	(0.0602)	(0.0855)	(0.0092)	(0.0504)	(0.0876)	(0.0094)
Dummy one if label was a new firm			-0.2156**	-0.2548**	0.1901**	-0.2009**	-0.2096**	0.1997**
			(0.0225)	(0.0297)	(0.0060)	(0.0408)	(0.0400)	(0.0083)
Dummy one if label produced pop genre music in year t			1.0748**	1.3629**	-0.0293**	1.0761**	1.3646**	-0.0291**
			(0.0980)	(0.1341)	(0.0070)	(0.0477)	(0.1341)	(0.0070)
Number of tracks that label produced in year t					0.0002**			0.0002**
					(0.0000)			(0.0000)
Average # of prior releases that label's artists produced			-0.0031**	-0.0018	-0.0048**	-0.0031**	-0.0018+	-0.0048**
			(0.0007)	(0.0010)	(0.0003)	(0.0007)	(0.0010)	(0.0003)
Herfindahl index for genre in label in year t			0.0091	-0.0824	-0.1059**	0.0086	-0.0831	-0.1060**
			(0.0679)	(0.0908)	(0.0064)	(0.0401)	(0.0908)	(0.0064)
Dummy on if label produced at least one single in year t			0.9918**	1.5530**	0.0348**	0.9917**	1.5529**	0.0348**
			(0.0372)	(0.0458)	(0.0058)	(0.0321)	(0.0458)	(0.0058)
Constant	0.2906**	-0.8962**	2.0681**	1.8542**	0.4894**	1.7505**	1.8445**	0.4765**
	(0.0307)	(0.1912)	(0.0773)	(0.1000)	(0.0108)	(0.0588)	(0.1015)	(0.0110)
Firm fixed effects	*no*	*no*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Country fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adjusted R^2 (Pseudo R^2)	0.0365	0.0393	0.7355	0.7197	0.4923	0.7355	0.7198	0.4924
N	64,471	64,471	64,471	64,471	64,471	64,471	64,471	64,471

2.6 Discussion and Conclusion

The empirical findings thus far illustrate that the introduction of iTunes and YouTube changed entrepreneurial labels' discovery strategies and performance as opposed to those of incumbent labels. How does digitalization affect the discovery of new talent by entrepreneurial firms? Theoretical research challenges the intuitive positive relationship; the negative impact from the increased advantage of would-be artists with visible talent may outweigh the positive impact from a long-tail market and decreased cost of experimentation.

The results confirm that the negative impact of digitalization would overshadow the positive impact of digitalization. The estimates from a difference-in-difference-in-differences specification suggest that iTunes and YouTube did not facilitate entrepreneurial firms' discovery of new talent but decreased the average and maximum popularity of new artists in entrepreneurial firms. In contrast, entrepreneurial firms increase their reliance on incumbent artists. In sum, the average popularity of new artists in entrepreneurial labels decreased by at least 26% and reached a similar level of the average popularity of new artists in incumbent labels. Considering that entrepreneurial firms have relied on the discovery of new talent in terms of the proportion of new artists (their proportion of new artists is approximately 20% higher than that in incumbent labels), the discovery performance of entrepreneurial labels became lower than incumbent labels.

In addition, iTunes and YouTube increased the popularity of incumbent artists in entrepreneurial labels; thus, the gap between entrepreneurial and incumbent labels has narrowed, but the popularity of incumbent artists in incumbent labels is 54.29% higher than that of entrepreneurial labels. This suggests that digitalization weakened the relative performance of entrepreneurial labels compared to incumbent labels.

I note an important limitation to these findings. This study does not use sales and cost data. Thus, using popularity data only, we cannot confirm that the change in the discovery of new talent in entrepreneurial firms increased sales or profits. Therefore, future work may analyze the impact of digitalization on entrepreneurial firms' sales by merging another dataset, such as the Nielsen Soundscan database.

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2.8 Appendices

Appendix 2.1 Did iTunes facilitate music entrepreneurial firms' discovery of new talent over time?

	(1) Average popularity of new artists OLS D-in-D-in-D	(2) Maximum popularity of new artists OLS D-in-D-in-D	(3) Average popularity of incumbent artists OLS D-in-D-in-D	(4) Maximum popularity of incumbent artists OLS D-in-D-in-D
Dummy one if label was a new firm	-0.0058+	-0.0023	-0.0039	-0.0036
× Dummy one if iTunes started its service in the same year (year 0)	(0.0033)	(0.0039)	(0.0049)	(0.0056)
Dummy one if label was a new firm	-0.0066*	0.0000	0.0028	0.0041
× Dummy one if iTunes started its service in the previous year (year 1)	(0.0032)	(0.0038)	(0.0048)	(0.0056)
Dummy one if label was a new firm	-0.0066*	0.0023	0.0081+	0.0060
× Dummy one if iTunes started its service two year ago (year 2)	(0.0032)	(0.0038)	(0.0047)	(0.0055)
Dummy one if label was a new firm	-0.0059+	0.0039	0.0147**	0.0144**
× Dummy one if iTunes started its service three year ago (year 3)	(0.0031)	(0.0037)	(0.0046)	(0.0053)
Dummy one if label was a new firm	-0.0076*	0.0017	0.0154**	0.0192**
× Dummy one if iTunes started its service four year ago (year 4)	(0.0031)	(0.0037)	(0.0047)	(0.0054)
Dummy one if label was a new firm	-0.0076*	0.0023	0.0227**	0.0273**
× Dummy one if iTunes started its service five year ago (year 5)	(0.0033)	(0.0040)	(0.0050)	(0.0057)
Dummy one if label was a new firm	-0.0071*	0.0026	0.0214**	0.0259**
× Dummy one if iTunes started its service six year ago (year 6)	(0.0036)	(0.0042)	(0.0053)	(0.0062)
Dummy one if label was a new firm	0.0106**	0.0044**	-0.0384**	-0.0562**
	(0.0013)	(0.0015)	(0.0019)	(0.0022)
Dummy one if iTunes started its service in the same year (year 0)	0.0031	0.0017	-0.0009	-0.0010
	(0.0026)	(0.0031)	(0.0039)	(0.0045)
Dummy one if iTunes started its service in the previous year (year 1)	0.0022	0.0017	0.0019	0.0025
	(0.0035)	(0.0042)	(0.0053)	(0.0061)
Dummy one if iTunes started its service two year ago (year 2)	-0.0007	-0.0020	0.0051	0.0097
	(0.0043)	(0.0051)	(0.0064)	(0.0074)
Dummy one if iTunes started its service three year ago (year 3)	-0.0036	-0.0054	0.0024	0.0058
	(0.0050)	(0.0059)	(0.0074)	(0.0085)
Dummy one if iTunes started its service four year ago (year 4)	-0.0051	-0.0065	0.0003	0.0018
	(0.0055)	(0.0066)	(0.0082)	(0.0095)
Dummy one if iTunes started its service five year ago (year 5)	-0.0089	-0.0113	0.0002	0.0011
	(0.0061)	(0.0072)	(0.0090)	(0.0105)
Dummy one if iTunes started its service six year ago (year 6)	-0.0140*	-0.0167*	0.0050	0.0075
	(0.0067)	(0.0079)	(0.0099)	(0.0115)
Control variables:				
Dummy on if label produced at least one single	0.0089**	0.0160**	0.0000	0.0235**
	(0.0009)	(0.0010)	(0.0013)	(0.0015)
Number of tracks that label produced in the same year	-0.0000	0.0002**	-0.0003**	0.0007**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Average # of prior releases that label's artists produced	-0.0003**	-0.0003**	0.0004**	0.0005**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Herfindahl index for genre in label in the same year	0.0380**	0.0415**	0.1670**	0.2124**
	(0.0013)	(0.0015)	(0.0019)	(0.0022)
Constant	0.0378**	0.0501**	0.0543**	0.0396*
	(0.0094)	(0.0111)	(0.0139)	(0.0161)
Genre fixed effect	*yes*	*yes*	*yes*	*yes*
Country fixed effect	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*
Adjusted R^2	0.1420	0.1766	0.2967	0.4355
N	47,117	47,117	47,117	47,117

Note: Standard errors are in parentheses. $^{+}p < 0.1, ^{*} p < 0.05, ^{**} p < 0.01$. Standard errors are robust and clustered at the label level.

Appendix 2.2
Did YouTube facilitate music entrepreneurial firms' discovery of new talent over time?

	(1) Average popularity of new artists OLS D-in-D-in-D	(2) Maximum popularity of new artists OLS D-in-D-in-D	(3) Average popularity of incumbent artists OLS D-in-D-in-D	(4) Maximum popularity of incumbent artists OLS D-in-D-in-D
Dummy one if label was a new firm	-0.0002	0.0056+	0.0112*	0.0075
× Dummy one if YouTube started its service in the same year (year 0)	(0.0025)	(0.0030)	(0.0044)	(0.0051)
Dummy one if label was a new firm	0.0014	0.0066*	0.0087+	0.0107*
× Dummy one if YouTube started its service in the previous year (year 1)	(0.0026)	(0.0031)	(0.0045)	(0.0052)
Dummy one if label was a new firm	0.0002	0.0060+	0.0126**	0.0171**
× Dummy one if YouTube started its service two year ago (year 2)	(0.0026)	(0.0031)	(0.0045)	(0.0052)
Dummy one if label was a new firm	-0.0012	0.0049	0.0216**	0.0255**
× Dummy one if YouTube started its service three year ago (year 3)	(0.0028)	(0.0033)	(0.0048)	(0.0056)
Dummy one if label was a new firm	0.0009	0.0077*	0.0198**	0.0247**
× Dummy one if YouTube started its service four year ago (year 4)	(0.0032)	(0.0038)	(0.0055)	(0.0065)
Dummy one if label was a new firm	-0.0010	0.0050	0.0177**	0.0200**
× Dummy one if YouTube started its service five year ago (year 5)	(0.0033)	(0.0039)	(0.0058)	(0.0067)
Dummy one if label was a new firm	-0.0005	0.0060	0.0199**	0.0252**
× Dummy one if YouTube started its service six year ago (year 6)	(0.0039)	(0.0046)	(0.0068)	(0.0079)
Dummy one if label was a new firm	0.0021*	-0.0018	-0.0331**	-0.0499**
	(0.0010)	(0.0012)	(0.0017)	(0.0020)
Dummy one if YouTube started its service in the same year (year 0)	-0.0060**	-0.0085**	-0.0009	0.0016
	(0.0020)	(0.0024)	(0.0035)	(0.0041)
Dummy one if YouTube started its service in the previous year (year 1)	-0.0064**	-0.0087**	-0.0018	-0.0026
	(0.0022)	(0.0026)	(0.0038)	(0.0044)
Dummy one if YouTube started its service two year ago (year 2)	-0.0088**	-0.0115**	-0.0046	-0.0057
	(0.0027)	(0.0032)	(0.0047)	(0.0055)
Dummy one if YouTube started its service three year ago (year 3)	-0.0117**	-0.0152**	-0.0023	-0.0032
	(0.0030)	(0.0035)	(0.0052)	(0.0060)
Dummy one if YouTube started its service four year ago (year 4)	-0.0152**	-0.0189**	-0.0054	-0.0050
	(0.0034)	(0.0041)	(0.0060)	(0.0069)
Dummy one if YouTube started its service five year ago (year 5)	-0.0177**	-0.0213**	0.0024	0.0051
	(0.0038)	(0.0045)	(0.0066)	(0.0076)
Dummy one if YouTube started its service six year ago (year 6)	-0.0214**	-0.0261**	-0.0048	-0.0039
	(0.0043)	(0.0051)	(0.0075)	(0.0087)
Dummy on if label produced at least one single	0.0035**	0.0069**	-0.0037**	0.0199**
	(0.0007)	(0.0008)	(0.0012)	(0.0014)
Number of tracks that label produced in the same year	-0.0000	0.0001**	-0.0003**	0.0006**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Average # of prior releases that label's artists produced	-0.0002**	-0.0002**	0.0005**	0.0006**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Herfindahl index for genre in label in the same year	0.0258**	0.0273**	0.1779**	0.2321**
	(0.0011)	(0.0013)	(0.0020)	(0.0023)
Constant	0.0441**	0.0571**	0.0491**	0.0323**
	(0.0062)	(0.0073)	(0.0107)	(0.0125)
Genre fixed effect	*yes*	*yes*	*yes*	*yes*
Country fixed effect	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*
Adjusted R^2	0.1315	0.1610	0.3199	0.4641
N	46,200	46,200	46,200	46,200

Note: Standard errors are in parentheses. $^+p < 0.1, ^* p < 0.05, ^{**} p < 0.01$. Standard errors are robust and clustered at the label level.

Chapter 3

Does Foreign Ownership Weaken the Discovery of New Talent from the Host Country? Evidence from Sony's Acquisition of CBS Records

3.1 Abstract

Does foreign ownership or capital undermine the discovery of new domestic talent in the cultural industry? One theoretical argument suggests that foreign ownership may weaken the discovery of new talent from the host country because foreign owners may lack a good understanding of the host country culture ("liability of foreignness"). Another theoretical argument challenges this simple negative relationship by arguing that foreign ownership may have an offsetting advantage that can be transferred from the home country to a foreign subsidiary at a cost that outweighs the liability of foreignness. This study focuses on the case of Sony's acquisition of CBS Records (a US major label) in 1988, which is the first merger by a Japanese firm with a firm of a distant culture. The estimates from a difference-in-differences (DD) specification suggest that Sony did not undermine CBS Records' discovery of domestic new talent but rather increased the popularity of new domestic artists in CBS Records and its sublabels by 44.48%. In contrast, Sony's acquisition

decreased CBS Records' reliance on incumbent artists and foreign (outside the US) artists. Finally, I also conduct the same analysis with nine other major mergers and compare the results with the results from Sony's acquisition of CBS Records. The results are consistent with the results from Sony's acquisition of CBS Records.

3.2 Introduction

Does foreign ownership or capital weaken the discovery of new domestic talent? As foreign owners' culture and language are different from the domestic ones, many practitioners express concern about foreign owners' acquisitions of cultural companies. For example, in the 1980s, the Japanese economy was growing, and Japanese companies often performed better than did US companies. In the 1980s, many Japanese companies started to acquire US companies in the cultural industry. One of the most successful Japanese firms in the 1980s, Sony, acquired CBS Records, one of the major music labels in the United States. Sony's acquisition of CBS Records was one of the most visible examples in this trend. Industry experts worried about the invasion of Japanese capital into American culture as follows.

> "With the announcement of Sony's purchase of CBS Records, some in the record industry lamented the selling of a part of American culture to the Japanese. "We're obviously very disappointed that a great American record company with a very strong history in the business has been sold to a foreign company," a Warner's executive told The Wall Street Journal. One columnist wrote of the Japanese, "They make good cars, TV sets, tractors. But will they, or the executives they hire, know another Duke Ellington when they hear one?" '' (New York Times, 18 Sep 1988)

Can foreign owners of firms understand overseas countries' culture and improve the discovery of new talent from the host country? The answer is far from clear because there exist both positive and negative impacts of foreign ownership on the discovery of new talent from the host country. This is related to the standard economic reasoning for foreign direct investment, which relies on two factors that were well-documented by Stephen Hymer 50 years ago (Hymer 1960, Chang, Kogut, and Yang 2016). The first factor is that a firm, when it ventures outside its national market, faces a disadvantage that subsequent literature has coined as the "liability of foreignness" (Zaheer, 1995). Thus, foreign owners may struggle with the liability of foreignness. In the setting of the music industry, it is plausible that foreign owners and the executives they hire may miss artists who would become stars because the foreign owners may not be able to understand the culture of the host country to the fullest.

On the other hand, a positive impact of foreign ownership may result from the fact that the firm must have an offsetting advantage that can be transferred from the home country to the foreign subsidiaries at a cost that does not overshadow the benefits of the competitive advantage (Chang et al. 2016). There is considerable empirical research that supports the existence of offsetting competitive advantages (e.g., Caves 1971, Caves 1996, Morck and Yeung 1991, Zaheer and Mosakowski 1997). In emerging economies' cross-border M&As , the acquiring firms tend to have access to more capital and better management. This advantage may not only offset the liability of foreignness but also overshadow the negative impact of the liability of foreignness. In this setting, the acquiring companies often have better financial resources and management systems; Sony was one of the most innovative and successful firms in the 1980s.

The empirical setting of this study is the music record industry, which is perhaps the most visible example of industries impacted by cross-border mergers. This research focuses on the case of Sony's acquisition of CBS Records in 1988, which was the first merger by a Japanese firm with a firm of a distant culture . Sony's acquisition of CBS Records offers a novel setting to measure the impact of Sony's purchase on the discovery of new talent in CBS Records and its sublabels. The estimates from a difference-in-differences (DD) specification suggest that Sony did not weaken CBS Records' discovery of new talent but rather increased the popularity of new artists in CBS Records and its sublabels by 84.19%. In contrast, Sony's acquisition decreased CBS Records' reliance on incumbent artists; the popularity of incumbent artists CBS Records had hired decreased by 49.78%. Additionally, there is no evidence that Sony reduced the popularity of domestic artists and the proportion of domestic artists in CBS Records. The additional analyses show that the increase in the popularity of new artists in CBS Records resulted from the spike in the popularity of domestic new artists in CBS Records. The results from the release level analysis are consistent with these findings.

Finally, I also conduct the same analysis with nine other merger cases and compare the results with the results from Sony's acquisition of CBS Records. The results from these mergers seem to be consistent with the results from Sony's acquisition of CBS Records.

This study offers two main contributions to strategy literature. First, this study provides the first empirical evidence on the relation between cross-border merger and performance in the cultural industry, which tends to be of a local nature. This research shows that although there are concerns about the negative impact of foreign ownership on the discovery of new talent from the host country, the acquiring company can overcome the liability of foreignness by bringing its own competitive advantage. Second, this study also makes a significant methodological contribution. Much of the work on how cultural firms respond to ownership change has depended on case studies of a few organizations. While these studies provide rich, in-depth insights into the performance of companies acquired by foreign owners, their research produces little causal evidence. Methodologically, this study analyzes a large-scale sample with a causally identified relationship between foreign ownership and firms' discovery performance in the cultural industry, making a significant empirical contribution to strategy research.

The rest of this paper proceeds as follows. The next section provides an overview of the relevant literature. Section 4 provides the empirical strategy, data, and sample statistics. Section 5 presents the results, and Section 6 presents concluding remarks.

3.3 Literature Review

The persistent performance differences across firms within industries is pervasive, and searching for sources of such performance differences is one of the fundamental issues in strategy. One salient example of the performance differences is that multinational subsidiaries face a competitive disadvantage compared with local firms. Although the most prevalent form of multinational entry mode is acquisition (89 percent of foreign direct investment in developed countries was through acquisitions – Barba Navaretti and Venables 2006), rather than through greenfield investment, prior research has focused on greenfield investment (Guadalupe, Kuzmina, and Thomas 2012). This study focuses on foreign direct investment through acquisition. Little research has examined whether the relative performance of firms acquired by multinational corporations over local firms increases or decreases and the extent to which newly acquired subsidiaries increase or decrease their discovery performance in a culturally embedded industry – the music industry.

Theoretical arguments suggest that foreign ownership can have both positive and negative effects on the discovery of new talent from the host country. The argument predicting a negative impact of foreign ownership relies upon the liability of foreignness.

Liability of Foreignness

The purpose of this chapter is to explore the question, ‘is there a liability of foreignness in the discovery of new talent in the music industry?’ Scholars in global strategy have long theorized that multinational corporations doing business in foreign countries encounter costs coming from the unfamiliarity of the environment, among other factors (Zaheer 1995, Song 2014). Hymer (1960) was the first to explore why foreign firms are likely to encounter a cost, a liability of foreignness, relative to host country firms. Hymer argues that host country firms (domestic firms) have the general advantage of better information about their country and its economy, language, laws, and politics. Zaheer (1995) argues that this liability of foreignness has been the fundamental assumption driving theories of the multinational corporation (e.g., Buckley and Casson 1976, Caves 1971, Dunning 1977, Kostova 1999, Kostova and Zaheer 1999). Based on this assumption, some scholars have tested whether manufacturing or professional services firms have experienced the liability of foreignness (e.g., Zaheer and Mosakowski 1997, Mata and Portugal 2002, Miller and Parkhe 2002, Rugman and Verbeke 2007, Barkema and Vermeulen 1998).

Zaheer (1995) classifies the sources of the liability of foreignness into four categories:

(1) firm-specific costs related to unfamiliarity with a local environment or lack of information networks, (2) costs arising from spatial distance such as travel, transportation, and coordination across time zones, (3) costs associated with the lack of legitimacy of foreign firms, and (4) costs resulting from the home country environment. Among these factors, Zaheer and Mosakowski (1997) suggest that the liability of foreignness arises mainly from the foreign firm not being sufficiently embedded in the information networks in the host country.

Additionally, Miller and Parkhe (2002) point out that unfamiliarity also arises from the host country's perspective. They argue that one of the significant issues for multinational subsidiaries is nationalistic or discriminatory behavior on the part of host country consumers, firms, and institutions. For instance, in the mid-2010s, US subsidiaries experienced Chinese customers' discriminatory behavior towards US products, including Apple iPhones, because the political and economic relationship between China and US became more competitive than before.

Finally, barriers to international operation may arise from discrimination by the government (Miller and Parkhe 2002). Hymer (1960) notes that the general treatment that affects both domestic and foreign firms is not essential. What is important is the fact that in certain countries, foreign firms and domestic firms may receive very different treatment. A notable example is the acquisition of Fox Television Network by News Corporation, an Australian company controlled by Rupert Murdoch. To ensure that News Corporations' acquisition of Fox Television Network met FCC guidelines, Murdoch became a U.S. citizen, but he had to continue to defend Fox Television Network's ownership (Larson 1995, Zaheer and Mosakowski 1997).

This study focuses on the liability of foreignness arising from cultural differences. First, to coordinate (or integrate) between the parent enterprise and foreign subsidiaries, the parent enterprise is more likely to send home country executives and employees to foreign subsidiaries. The change in ownership affects the style and culture of the acquired companies. This change may result in hiring a different people and discovering less popular artists (in the host country). Second, the foreign ownership may directly affect the host country consumers' behavior; they might become more reluctant to purchase products or services from foreign-owned companies. As the empirical setting of this study is the music industry, both effects will decrease the discovery of new local talent in the host country.

Overcoming the Liability of Foreignness

The positive effect of foreign ownership on the discovery of new talent in the host country mainly results from an advantage of the multinational corporation that can compensate for the liability of foreignness. As reviewed above, the existence of a liability of foreignness underlies the theory of international business (Hymer, 1960; Caves, 1971; Hennart, 1982; Zaheer 1995; Chang et al. 2016). Most of the subsequent theoretical and empirical work has focused on how multinational corporations might overcome or compensate for this liability (e.g., Zaheer and Mosakowski 1997; Miller and Parkhe 2002).

Scholars have highlighted potential advantages of the multinational corporation, such as economies of scale or scope, superior technology, risk diversification, and operating flexibility (Kogut and Kulatilaka 1994, Zaheer and Mosakowski 1997, Kogut and Kulatilaka

2001, Chang et al. 2016). There are also compelling reasons and research that point to the superior performance due to the synergy between the parent enterprise in the home country and foreign subsidiaries. This value has its roots in the internalization theory of synergy, proposed by Caves (1971). According to this view, the parent enterprise can contribute to (or increase) foreign subsidiaries' superior performance in the presence of substantial intangible assets, marketing skills, and management quality (Morck and Yeung, 1991a, 1991b). Chang et al. find that this approach also encompasses the transfer of intangible assets, such as tacit or explicit knowledge, and management capabilities that have been the main topic of recent studies (Kogut and Zander 1992, Zander and Kogut 1995, Almeida, Song, and Grant 2002, Mezias 2007, Song and Shin 2007).

This line of theoretical and empirical research assumes that the business of foreign subsidiaries is similar to the business of the parent enterprise; thus, it is rather easy to predict the benefit from exploiting the tangible or intangible advantage of the parent enterprise. This line of reasoning can extend to the synergy between different businesses such as the synergy between computer hardware and software or the synergy between television networks and contents. This study focuses on the synergy between hardware manufacturing companies and content providers. The synergy between these two distinct businesses was the vision of Sony, which was the most profitable electronics company in the 1980s. This study explores whether the synergy between Sony's tangible and intangible assets offset the liability of foreignness in discovering new talent from the host country, the US.

3.4 Empirical Strategy

Sample

The sample of the treatment group comprises CBS Records and its music sublabels located in the US, and the sample of the control group consists of all other US labels. We collect the data for the labels above from the MusicBrainz database for the period between 1977 and 1998, which covers the period from ten years before to ten years after Sony's acquisition of CBS Records. Artists and repertoire (A&R) is the division of a record label that is responsible for talent discovery and overseeing the development and management of artists. Thus, the sample includes only record production labels that have an A&R division. The unit of analysis for the empirical tests is the firm-year. The above selection criteria leave us with 7,263 label-year observations associated with 2,624 record labels.

Variables

Independent variables

Our main explanatory variable is a dichotomous time-varying variable $SONY_{it}$, which captures whether Sony's acquisition affects the discovery of domestic and new talent in CBS Records. $SONY_{it} = ACQUISITION_t \times CBS_i$, where $ACQUISITION_t$ is equal to one in all periods following Sony's acquisition of CBS Records and zero before the acquisition, and CBS_i is equal to one if label i belongs to CBS Records.

Dependent variables

A set of dependent variables measures the popularity of artists for each label-year. The first set of dependent variables captures the popularity of artists and songs from each label-year: the popularity of new artists in firm i, $POPNEW_{it}$; the popularity of the most popular incumbent artists in firm i, $POPINCUM_{it}$; and the popularity of all artists POP_{it}. First, to calculate the average and maximum popularity of new artists and incumbent artists for the label-years, I collect the popularity score (familiarity score) of artists from the Spotify Echonest API. The Spotify Echonest API offers a platform, which is called the Rosetta Stone, to match Spotify Echonest IDs and MusicBrainz IDs. I use this platform to calculate the popularity of the most popular artists and the average popularity of artists for each firm. The range of individual artist popularity is from 0 to 1.

The second key dependent variable is the proportion of new artists $PROPNEW_{it}$, measured as the ratio of new artists to all artists of label i in year t. A new artist is a singer or band who did not release a song before year t. By using the MusicBrainz database, I count the numbers of new artists in proportion to all artists of each label.

Control variables

I control for variables: (1) a dummy that equals 1 if label i produces at least one single release in year t, (2) the number of songs as a firm size proxy, (3) the mean number of artists' prior releases as a firm status proxy, (4) the Herfindahl index for genres in the label in year t, (5) firm dummies, (6) country dummies, (7) genre dummies, and (8) year dummies.

Empirical specification

This study estimates the change in the popularity of artists and the proportion of new and domestic artists in CBS Records and its sublabels after Sony's acquisition of CBS Records. Sony's acquisition in 1988 is an exogenous shock to CBS Records. Thus, the treatment group is the set of labels belonging to CBS Records. The control group is all other labels.

This study uses differences-in-differences estimators by including control variables X_{it}, firm fixed effects F_i, country fixed effects C_c, genre fixed effects G_{it}, and year fixed effects Y_t along with the explanatory variables $SONY_{it}$, as in

$$POPNEW_{it} = \alpha + \beta_x X_{it} + \beta_N SONY_{it} + F_i + C_c + G_{it} + Y_t + e_{it},$$

$$POPINCUM_{it} = \alpha + \beta_x X_{it} + \beta_N SONY_{it} + F_i + C_c + G_{it} + Y_t + e_{it}.$$

The total effect of Sony's acquisition of CBS Records can be computed as β_N. In the case of (1) where the dependent variable is the popularity of new artists, the first difference compares the popularity of new artists of CBS Records hired before and after Sony's acquisition (treatment group) and that of other labels hired before and after Sony's acquisition (control group). This yields two differences, one for the control group and one for the treatment groups. The second difference takes the difference between these two differences. The result is an estimate of the effect of Sony's acquisition on the popularity of artists in CBS Records.

Sample statistics

Table 3.1 reports descriptive statistics on all the variables for the sample at the firm-year level. First, the descriptive statistics for the independent variable show that the proportion of the treatment group's firm-year observations (sublabels belonging to CBS Records during the sample period) is 0.5%. Moreover, the proportion of firm-year observations after Sony's acquisition is 87.6%.

Second, this study uses the four firm-level dependent variables. The first set of variables concerns the firm-level popularity of new and incumbent artists, and there are three variables: the average popularity of new artists, average popularity of new artists, and average popularity of all artists. The average of the firm-level average popularity of new artists is 0.031; it has a large standard deviation, which is three times larger than the average value. The average of the firm-level average popularity of incumbent artists is higher than that of new artists, at 0.084; it has a large standard deviation, which is approximately 1.5 times larger than the average value. Next, the average proportion of new artists is 42.7% (0.427), and the standard deviation has a similar size (0.435).

Third, this study uses four control variables. The first control variable is the dummy for single-producing labels, and 31.2% of the labels produced at least one single. The second control variable is the number of tracks produced per firm-year, and the average value is 25.504. The third control variable is the average number of prior releases that each label's artists produced. The average value is 5.133. Forty percent of artists are new artists who have the potential to be famous but have no proven records. Incumbent artists have ten prior releases on average. The fourth control variable is the Herfindahl index for the genre, and the average value is 0.142.

Table 3.1: Summary statistics

Variable name	Level of variation	Mean	Std. Dev.	Min.	Max.
Independent variables:					
Dummy one if label i belongs to CBS Records	Firm	0.005	0.071	0	1
Dummy one if after Sony's acquisition	Year	0.876	0.329	0	1
Dependent variables:					
Average popularity of new artists	Firm	0.031	0.093	0	0.88
Average popularity of incumbent artists	Firm	0.084	0.138	0	0.88
Average popularity of all artists	Firm	0.094	0.138	0	0.845
Average popularity of domestic artists	Firm	0.111	0.145	0	0.824
Average popularity of foreign artists	Firm	0.027	0.086	0	0.717
Proportion of new artists to all artists	Firm	0.427	0.435	0	1
Control variables:					
Dummy one if label produced at least one single in year t	Firm	0.312	0.463	0	1
Number of tracks that label produced in year t	Firm	25.504	46.242	0	1839
Average # of prior releases that label's artists produced	Firm	5.133	15.826	0	664
Herfindahl index for genre in label in year t	Firm	0.142	0.316	0	1
Other variables:					
Year	Firm	1990.974	6.172084	1977	1998
Number of label-year observations		7,263			
Number of unique labels		2,624			
Number of unique artists		20,028			
Number of unique releases		22,559			
Number of unique songs		218,304			

3.5 Results

Did Sony weaken the discovery of new talent by CBS Records?

I test whether Sony's acquisition undermined CBS Records' discovery of new talent. Table 3.2 shows the results of testing the impact of Sony on the popularity of artists hired by CBS Records. I estimate the three different versions of the popularity of artists and the proportion of new artists.

First, Columns 1 and 2 report the estimates from the DD specifications with the dependent variable, the average popularity of new artists. Column 1 reports the results from a pooled OLS model, and Column 2 reports the results from a firm fixed effects model. Columns 1 and 2 show the average effect of Sony's acquisition on the average popularity of new artists in CBS Records by comparing the popularity before and after Sony's acquisition. The coefficients on the interaction between the dummy for CBS Records and the dummy for Sony's acquisition are 0.0384 and 0.0261; both coefficients have positive values and are significant at the 1% level. These coefficients imply that Sony did not weaken CBS Records' discovery of new talent but rather improved it. Given that the average popularity of new artists in the labels is 0.031, Sony increased the popularity of new artists of CBS Records by at least 84.19%.

Next, I explore the impact of Sony on the popularity of incumbent artists in CBS Records. In Columns 3 and 4, the coefficients of the interaction between the dummy for CBS Records and the dummy for Sony's acquisition are -0.0048 and -0.0468, respectively; these coefficients are negative, and the coefficient in the fixed effects model (Column 2) is significant at the 5% level. This result suggests that CBS Records became less reliant on in-

Table 3.2: (Label-level analysis) Did Sony weaken the discovery of new talent by CBS record?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DV: Average popularity of new artists		Average popularity of incumbent artists		Average popularity of all artists		Proportion of new artists	
	OLS D-in-D	Firm FE D-in-D	OLS D-in-D	Firm FE D-in-D	OLS D-in-D	Firm FE D-in-D	OLS D-in-D	Firm FE D-in-D
Dummy if label belonged to CBS Record	0.0384*	0.0261*	-0.0048	-0.0468*	0.0307+	0.0110	0.0755	0.1157
× Dummy if after Sony's acquisition	(0.0153)	(0.0131)	(0.0208)	(0.0197)	(0.0183)	(0.0159)	(0.0507)	(0.0729)
Dummy if label belonged to CBS Record	-0.0588**		0.0209		-0.0101		-0.1195**	
	(0.0113)		(0.0157)		(0.0142)		(0.0379)	
Dummy if after Sony's acquisition	-0.0057	-0.0289+	0.0018	0.0274+	-0.0003	-0.0030	-0.0196	-0.2015**
	(0.0124)	(0.0170)	(0.0116)	(0.0162)	(0.0120)	(0.0162)	(0.0371)	(0.0430)
Control variables:								
Dummy one if label produced at least one single	0.0057+	0.0015	-0.0190**	-0.0148*	-0.0242**	-0.0211**	0.0648**	0.0328+
	(0.0031)	(0.0054)	(0.0033)	(0.0059)	(0.0032)	(0.0057)	(0.0103)	(0.0181)
Number of tracks that label produced in the same year	-0.0000	0.0002**	-0.0003**	-0.0002**	-0.0006**	-0.0003**	-0.0003**	0.0003*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Average # of prior releases that label's artists produced	-0.0014**	-0.0008**	0.0010**	0.0003	-0.0001	-0.0001	-0.0146**	-0.0089**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0030)	(0.0028)
Herfindahl index for genre in label in the same year	0.0800**	0.0631**	0.1326**	0.1020**	0.1636**	0.1230**	-0.1065**	-0.0469**
	(0.0054)	(0.0063)	(0.0055)	(0.0071)	(0.0044)	(0.0063)	(0.0131)	(0.0155)
Constant	0.0513**	0.0760**	0.0658**	0.0516**	0.1058**	0.1087**	0.5538**	0.7359**
	(0.0118)	(0.0153)	(0.0107)	(0.0135)	(0.0113)	(0.0140)	(0.0364)	(0.0352)
Firm fixed effect	*no*	*yes*	*no*	*yes*	*no*	*yes*	*no*	*yes*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adjusted R^2	0.1237	0.0826	0.1954	0.1461	0.2611	0.2066	0.1435	0.0957
N	7,263	7,263	7,263	7,263	7,263	7,263	7,263	7,263

Note: Standard errors are in parentheses. $^+p < 0.1, ^* p < 0.05, ^{**} p < 0.01$. Standard errors are robust and clustered at the label level.

cumbent artists after Sony's acquisition. Given that the average popularity of incumbent artists in labels is 0.094, the change due to Sony's acquisition decreased the popularity of incumbent artists of CBS Records by at least 49.78%.

Third, I estimate the impact of Sony on the popularity of all artists in CBS Records. Columns 5 and 6 report the coefficients of the interaction between the dummy for CBS Records and the dummy for Sony's acquisition (0.0307 and 0.0110); these coefficients are positive but are not significant at the 5% level.

Finally, I estimate the impact of Sony on the proportion of new artists in CBS Records. Columns 5 and 6 report the coefficients of the interaction between the dummy for CBS Records and the dummy for Sony's acquisition (0.0755 and 0.1157, respectively); although these coefficients are positive, they are not significant at the 5% level. These coefficients imply that Sony's acquisition did not lead to an increase in the proportion of new artists but that it led to an increase in the discovery performance. Sony may have invested more money in discovering more talented artists. All in all, the results in Table 2 suggest that CBS Records became less reliant on incumbent artists after Sony's acquisition.

Did Sony weaken CBS Records' discovery of domestic (US) new talent?

I turn now to the impact of Sony's acquisition on the balance between domestic (American) new artists and foreign new artists. In Table 3, using DD specifications, I test the hypothesis that Sony's acquisition weakened CBS Records' discovery of domestic (American) talent. Table 3 shows the results of testing the impact of Sony's acquisition on the popularity of artists hired by CBS Records. I estimate the impact of Sony's acquisition on the popularity of domestic new artists, the popularity of foreign new artists, and the proportion of new artists.

First, Columns 1 and 2 report the estimates from DD specifications with the dependent variables, the average popularity of domestic artists. Column 1 reports the results from a pooled OLS model, and Column 2 reports the results from a firm fixed effects model. The coefficients on the interaction between the dummy for CBS Records and the dummy for Sony's acquisition are 0.0257 and 0.0106, respectively; both coefficients have positive values, and the second coefficient is significant at the 5% level. These coefficients imply that Sony's acquisition at least did not weaken CBS Records' discovery of domestic talent.

Next, I explore the impact of Sony's acquisition on the popularity of foreign artists hired by CBS Records. In Columns 3 and 4, the coefficients of the interaction between the dummy for CBS Records and the dummy for Sony's acquisition are -0.0143 and -0.0273, respectively; these coefficients are negative, and the second coefficient is significant at the 5% level. These results suggest that CBS Records became less reliant on foreign artists after Sony's acquisition. Given that the average popularity of incumbent artists in the labels is 0.084, Sony's acquisition led the popularity of new artists of CBS Records to decrease by at least 32.5%.

Finally, I estimate the impact of Sony's acquisition on the proportion of foreign new artists in CBS Records. Columns 5 and 6 report the coefficients of the interaction between the dummy for CBS Records and the dummy for Sony's acquisition (-0.0960 and -0.0200, respectively); the first coefficient is significant at the 5% level. This coefficient implies that Sony's acquisition did not lead to an increase in the proportion of foreign new artists. Sony may have invested more money in discovering better talented domestic artists. All

Table 3.3: (Label-level analysis) Did Sony weaken the discovery of domestic talent by CBS record?

	(1)	(2)	(3)	(4)	(3)	(4)
	DV: Average popularity of domestic artists		Average popularity of foreign artists		Proportion of foreign artists	
	OLS D-in-D	Firm FE D-in-D	OLS D-in-D	Firm FE D-in-D	OLS D-in-D	Firm FE D-in-D
Dummy if label belonged to CBS Record × Dummy if after Sony's acquisition	0.0257	0.0106	-0.0143	-0.0273*	-0.0960*	-0.0200
	(0.0188)	(0.0149)	(0.0137)	(0.0130)	(0.0483)	(0.0617)
Dummy if label belonged to CBS Record	-0.0106		-0.0066		0.0825*	
	(0.0156)		(0.0092)		(0.0403)	
Dummy if after Sony's acquisition	-0.0040	0.0019	0.0174**	0.0075	0.0533*	0.0185
	(0.0120)	(0.0165)	(0.0052)	(0.0092)	(0.0242)	(0.0285)
Control variables:						
Number of tracks that label produced in the same year	-0.0006**	-0.0003**	0.0001**	0.0001	0.0008**	-0.0003**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Dummy one if label produced at least one single	-0.0234**	-0.0181**	0.0057*	0.0059	0.0026	0.0077
	(0.0032)	(0.0057)	(0.0022)	(0.0046)	(0.0078)	(0.0123)
Average # of prior releases that label's artists produced	-0.0003*	-0.0002	0.0003*	0.0001	0.0044**	0.0026**
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0006)	(0.0004)
Herfindahl index for genre in label in the same year	0.1303**	0.1019**	0.0320**	0.0316**	0.0143	0.0015
	(0.0050)	(0.0069)	(0.0048)	(0.0065)	(0.0109)	(0.0121)
Constant	0.1012**	0.0976**	-0.0063	0.0017	0.0435+	0.1331**
	(0.0112)	(0.0140)	(0.0043)	(0.0078)	(0.0225)	(0.0235)
Firm fixed effect	*no*	*yes*	*no*	*yes*	*no*	*yes*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adjusted R^2	0.2389	0.1834	0.0888	0.0532	0.0496	0.0191
N	7,263	7,263	7,263	7,263	7,263	7,263

Note: Standard errors are in parentheses. $^{+}p < 0.1,^{*} p < 0.05,^{**} p < 0.01$. Standard errors are robust and clustered at the label level.

in all, the results in Table 3 suggest that CBS Records became more reliant on domestic new artists after Sony's acquisition (and less reliant on foreign artists).

Subgroup analysis: (1) New vs. Incumbent artists and (2) Domestic vs. Foreign artists

In Table 3.4, I divide artists into four categories: domestic new artists, domestic incumbent artists, foreign new artists, and foreign incumbent artists. I calculate the average popularity scores for these four groups and use them as dependent variables. Every two columns show the results for each dependent variable.

First, in Columns 1 and 2, the coefficients for the interaction term between the dummy for CBS Records and the dummy for Sony's acquisition are 0.0402 and 0.0258, respectively. The first coefficient is significant at the 5% level, and the second coefficient is significant at the 10% level. These coefficients imply that Sony's acquisition improved the discovery of domestic new talent.

Second, Columns 3 and 4 show that the coefficients of the interaction term are -0.0039 and -0.0370, respectively, and both coefficients are not significant at the 5% level. These coefficients imply that Sony's acquisition did not change the discovery of incumbent domestic talent.

Third, Columns 5 and 6 show that the coefficients of the interaction term are -0.0061 and -0.0013, respectively, and both coefficients are not significant at the 5% level. These coefficients imply that Sony's acquisition did not change the discovery of foreign new talent.

Table 3.4: (Label-level analysis) Subgroup analysis: (1) New vs. Incumbent artists and (2) Domestic vs. Foreign artists

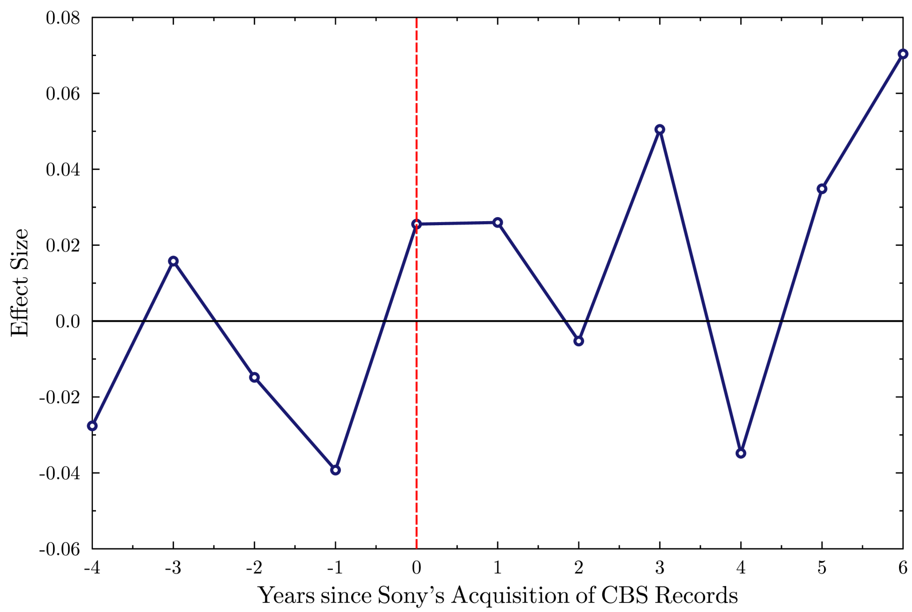
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DV: Average popularity of domestic new artists		Average popularity of domestic incumbent artists		Average popularity of foreign new artists		Average popularity of foreign incumbent artists	
	OLS D-in-D	Firm FE D-in-D	OLS D-in-D	Firm FE D-in-D	OLS D-in-D	Firm FE D-in-D	OLS D-in-D	Firm FE D-in-D
Dummy if label belonged to CBS Record	0.0402^{*}	0.0258+	-0.0039	-0.0370	-0.0061	-0.0013	-0.0199	-0.0358^{*}
× Dummy if after Sony's acquisition	(0.0158)	(0.0147)	(0.0220)	(0.0244)	(0.0090)	(0.0141)	(0.0147)	(0.0140)
Dummy if label belonged to CBS Record	-0.0546^{**}		0.0157		0.0002		-0.0026	
	(0.0114)		(0.0176)		(0.0057)		(0.0098)	
Dummy if after Sony's acquisition	-0.0051	-0.0259	-0.0070	0.0201	-0.0062	-0.0107	0.0173^{**}	0.0105
	(0.0122)	(0.0170)	(0.0117)	(0.0164)	(0.0055)	(0.0086)	(0.0044)	(0.0088)
Control variables:								
Dummy one if label produced at least one single	0.0024	-0.0008	-0.0162^{**}	-0.0108+	0.0066^{**}	0.0052+	0.0029	0.0044
	(0.0030)	(0.0051)	(0.0033)	(0.0056)	(0.0015)	(0.0028)	(0.0021)	(0.0043)
Number of tracks that label produced in the same year	-0.0001	0.0001^{*}	-0.0003^{**}	-0.0001^{*}	0.0001^{**}	0.0001	0.0002^{**}	0.0001+
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Average # of prior releases that label's artists produced	-0.0013^{**}	-0.0007^{**}	0.0008^{**}	0.0001	-0.0001^{**}	-0.0001	0.0004^{**}	0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Herfindahl index for genre in label in the same year	0.0660^{**}	0.0538^{**}	0.0996^{**}	0.0765^{**}	0.0016	0.0015	0.0278^{**}	0.0281^{**}
	(0.0056)	(0.0064)	(0.0059)	(0.0077)	(0.0028)	(0.0035)	(0.0046)	(0.0063)
Constant	0.0477^{**}	0.0700^{**}	0.0666^{**}	0.0495^{**}	0.0065	0.0161^{*}	-0.0103^{**}	-0.0061
	(0.0116)	(0.0152)	(0.0109)	(0.0136)	(0.0052)	(0.0078)	(0.0035)	(0.0072)
Firm fixed effect	*no*	*yes*	*no*	*yes*	*no*	*yes*	*no*	*yes*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adjusted R^2	0.1205	0.0792	0.1783	0.1309	0.0655	0.0217	0.1021	0.0579
N	7,263	7,263	7,263	7,263	7,263	7,263	7,263	7,263

Note: Standard errors are in parentheses. $^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01$. Standard errors are robust and clustered at the label level.

Fourth, Columns 7 and 8 show that the coefficients of the interaction term are -0.0199 and -0.0358, respectively, and the second coefficient is significant at the 5% level. These coefficients imply that after Sony's acquisition, CBS Records became less reliant on incumbent foreign talent.

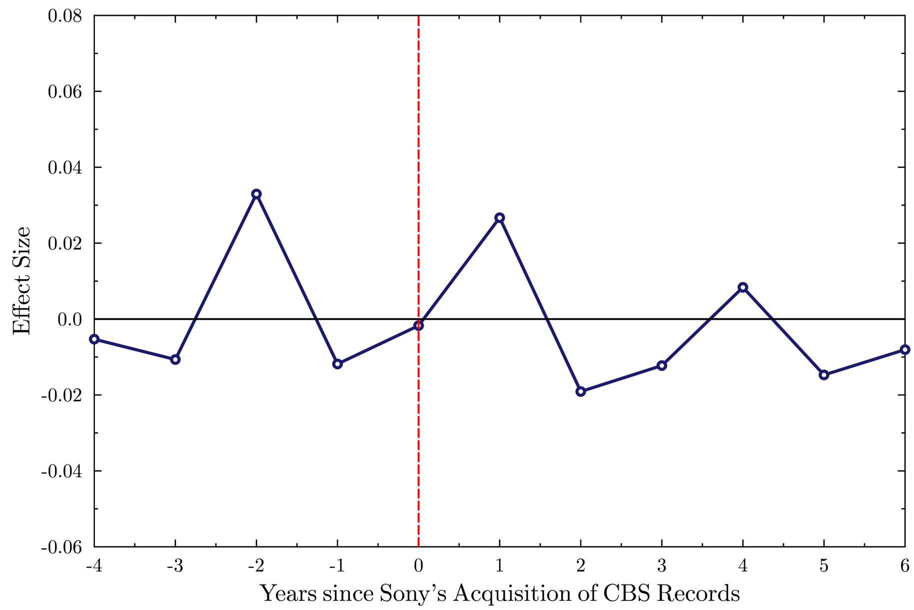
Finally, Figure 3.1 shows the dynamic effect of Sony's acquisition of CBS Records on the discovery of US new talent. It suggests that CBS records' discovery of US new talent increased after Sony's acquisition. Also, Figure 3.2 shows the dynamic effect of Sony's acquisition of CBS Records on the discovery of US new talent. It suggests that CBS Records' discovery of foreign new talent did not increase after Sony's acquisition.

Figure 3.1: Dynamic impact of Sony's Acquisition of CBS Records on the Discovery of US New Talent



Note: Figure 3.1 plots estimated year by year pre- and post-Sony's acqusition of CBS Records in the discovery of US new talent from OLS regressions with fixed effects and controls. Each point represents the estimated difference between the treated group (labels of CBS Records) and control group (other labels) in each year.

Figure 3.2: Dynamic Impact of Sony's Acquisition of CBS Records on the Discovery of Foreign New Talent



Note: Figure 3.2 plots estimated year by year pre- and post-Sony's acqusition of CBS Records in the discovery of foreign new talent from OLS regressions with fixed effects and controls. Each point represents the estimated difference between the treated group (labels of CBS Records) and control group (other labels) in each year.

Release level analysis

Table 5 shows the results at the release level. The unit of analysis is the release, and the model controls firm-level attributes. The classification is the same as that in the former subsection. There are four subsamples: releases by domestic new artists, releases by domestic incumbent artists, releases by foreign new artists, and releases by foreign incumbent artists. Additionally, for robustness, I use two dependent variables: the popularity of the release (from Spotify API) in Columns 1-4 and a dummy for the top 30% of the popular releases in Columns 5-8. The results suggest that the popularity scores for the first three groups (domestic new artists, domestic incumbent artists, and foreign new artists) in CBS Records increased after Sony's acquisition.

Table 3.5: (Release level subgroup analysis) Did Sony weaken the discovery of domestic new talent by CBS record?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DV: Popularity of Release				Dummy one if popularity of release is in top 30%			
	Group 1 Domestic new artists	Group 2 Domestic incumbent artists	Group 3 Foreign new artists	Group 4 Foreign incumbent artists	Group 1 Domestic new artists	Group 2 Domestic incumbent artists	Group 3 Foreign new artists	Group 4 Foreign incumbent artists
	Firm FE D-in-D				Firm FE D-in-D			
Dummy if label belonged to CBS Record	3.4761**	1.9638+	3.0002**	0.2891	0.1166**	0.0575*	0.0777*	-0.0047
× Dummy if after Sony's acquisition	(1.2220)	(1.1455)	(1.1110)	(1.0122)	(0.0291)	(0.0278)	(0.0374)	(0.0293)
Dummy if label belonged to CBS Record	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*	*omitted*
Dummy if after Sony's acquisition	0.2863	2.8151**	0.2862	0.7226	0.0168	0.0593**	-0.0034	0.0490
	(0.8944)	(0.6825)	(1.1080)	(2.1275)	(0.0198)	(0.0183)	(0.0298)	(0.0567)
Control variables:								
Number of tracks that label produced in the same year	-0.0017	-0.0001	-0.0019	-0.0022	-0.0001*	0.0000	-0.0001*	-0.0000
	(0.0018)	(0.0017)	(0.0023)	(0.0023)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
dummy_single_release	1.1978**	-0.1890	0.5171	-0.0744	0.0502**	-0.0074	0.0610**	-0.0007
	(0.2456)	(0.2841)	(0.5825)	(0.4995)	(0.0083)	(0.0075)	(0.0167)	(0.0152)
Average # of prior releases that label's artists produced	-0.0128	0.0292**	0.0271**	-0.0000	-0.0002	0.0008**	0.0012**	-0.0003+
	(0.0091)	(0.0104)	(0.0086)	(0.0065)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Herfindahl index for genre in label in the same year	-0.1794	0.1461	0.9188*	-0.7985+	-0.0066	0.0006	0.0052	-0.0180
	(0.2382)	(0.3086)	(0.4541)	(0.4494)	(0.0061)	(0.0075)	(0.0126)	(0.0134)
Constant	0.7070	0.5542	0.1251	3.5079+	0.0019	0.0224	-0.0153	0.0799
	(0.8366)	(0.5537)	(0.8594)	(2.0510)	(0.0171)	(0.0153)	(0.0252)	(0.0538)
Firm fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Genre fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Adjusted R^2	0.1852	0.1521	0.3163	0.1463	0.1996	0.1426	0.3356	0.1400
N	7,263	7,263	7,263	7,263	7,263	7,263	7,263	7,263

Note: Standard errors are in parentheses. $^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01$. Standard errors are robust and clustered at the label level.

Comparison with other foreign acquisitions during the period 1980–2015

I run the same regression models used in the previous four subsections to analyze other major acquisition deals among the major labels in the music industry. Table 6 lists all acquisition deals (10 deals) among major labels. Table 6 reports all the coefficients for the interaction term between the dummy for CBS Records and the dummy for Sony's acquisition. Column 1 reports the results from the model with the dependent variable, the average popularity of all artists in the acquired label. None of the coefficients are negative and significant, but four coefficients are positive and significant at the 5% level. This result offers suggestive evidence that foreign acquisition was helpful in improving the overall popularity of the artists in the acquired labels.

Columns 2-4 report the results from the model with the three dependent variables: the average popularity of new artists, the average popularity of incumbent artists, and the proportion of new artists. First, four coefficients in Column 2 are positive and significant at the 5% level, but no coefficients are negative and significant. Second, two coefficients in Column 3 are negative and significant at the 5% level, but one coefficient is positive and significant. Third, five coefficients in Column 4 are positive and significant at the 10% level, but no coefficients are negative and significant. In sum, the results in Columns 2-4 offer suggestive evidence that the discovery of new talent and experimenting with new artists improved after the acquisitions.

Columns 5-7 report the results from the model with the three dependent variables: the average popularity of new artists, the average popularity of incumbent artists, and the proportion of new artists. First, four coefficients in Column 5 are positive and significant at the 5% level, but only one coefficient is negative and significant. Second, two coefficients in Column 6 are negative and significant at the 5% level, but no coefficient is positive and significant. Third, three coefficients in Column 7 are positive and significant at the 5% level, but only one coefficient is negative and significant. In sum, the results in Columns 5-6 offer suggestive evidence that acquired labels improve the discovery of domestic talent and experimenting with new artists after the acquisition. The results in Column 7 are inconclusive; the direction is opposite to the results from Sony's acquisition of CBS Records.

Columns 8-11 reports the results from the model with the three dependent variables: the average popularity of domestic new artists, the average popularity of domestic incumbent artists, the popularity of foreign new artists, and the popularity of foreign new artists. First, four coefficients in Column 8 are positive and significant at the 10% level, but only one coefficient is negative and significant. Second, two coefficients in Column 9 are negative and significant at the 5% level, and two coefficients are positive and significant at the 5% level. Third, three coefficients in Column 10 are positive and significant at the 5% level, and three coefficients are negative and significant at the 5% level. Finally, three coefficients in Column 11 are positive and significant at the 10% level, and two coefficients are negative and significant at the 5% level. In sum, the results in Columns 8-11 offer suggestive evidence that acquired labels improve the discovery of domestic new talent after the acquisition. The results in Columns 9-11 are inconclusive; the direction is opposite to the results from Sony's acquisition of CBS Records.

Table 3.6: (Label level analysis - Coefficients and SEs only) Did acquisitions among major labels weaken the discovery of domestic new talent by acquired labels?

	(1) DV: Average popularity of all artists	(2) Average popularity of new artists	(3) Average popularity of incumbent artists	(4) Proportion of new artists	(5) Average popularity of domestic artists	(6) Average popularity of foreign artists	(7) Proportion of foreign artists	(8) Average popularity of domestic new artists	(9) Average popularity of domestic incumbent artists	(10) Average popularity of foreign new artists	(11) Average popularity of foreign incumbent artists
						Firm FE D-in-D					
(1) Dummy if label belonged to CBS Records × Dummy if after Sony's acquisition in 1987	0.0110 (0.0159)	0.0261* (0.0131)	-0.0468* (0.0197)	0.1157 (0.0729)	0.0106 (0.0149)	-0.0273* (0.0130)	-0.0200 (0.0617)	0.0258+ (0.0147)	-0.0370 (0.0244)	-0.0013 (0.0141)	-0.0358* (0.0140)
(2) Dummy if label belonged to MCA Records × Dummy if after Matsushita's acquisition	-0.0005 (0.0084)	0.0014 (0.0341)	-0.0464** (0.0152)	0.1298+ (0.0770)	-0.0218* (0.0094)	0.0150 (0.0262)	0.0019 (0.0185)	-0.0013 (0.0278)	-0.0725** (0.0267)	-0.0154* (0.0073)	0.0160 (0.0390)
(3) Dummy if label belonged to Universal Records × Dummy if after Vivendi's acquisition	0.0373** (0.0084)	0.0420** (0.0138)	0.0035 (0.0399)	0.1158** (0.0232)	0.0326** (0.0108)	0.0026 (0.0473)	-0.0718* (0.0286)	0.0237** (0.0081)	0.0143 (0.0225)	0.0085 (0.0161)	-0.0212 (0.0566)
(4) Dummy if label belonged to PolyGram × Dummy if after Vivendi(Seagram)'s acquisition	-0.0532 (0.0333)	0.0477** (0.0118)	-0.0597 (0.0374)	0.1973** (0.0677)	-0.0022 (0.0220)	0.0139 (0.0320)	-0.0083 (0.0808)	0.0429** (0.0091)	-0.0244 (0.0210)	0.0247* (0.0110)	0.0179 (0.0353)
(5) Dummy if label belonged to Arista Records × Dummy if after BMG's acquisition	-0.0127 (0.0369)	-0.0094 (0.0175)	-0.0138 (0.0450)	-0.1476 (0.1908)	-0.0003 (0.0372)	-0.0363** (0.0127)	0.0230 (0.0223)	-0.0073 (0.0112)	-0.0042 (0.0428)	-0.0428** (0.0146)	-0.0526** (0.0176)
(6) Dummy if label belonged to RCA Records × Dummy if after BMG's acquisition	0.0562** (0.0208)	-0.0050 (0.0129)	0.0292 (0.0233)	0.0867 (0.0844)	0.0426** (0.0130)	-0.0269 (0.0240)	0.0236 (0.0199)	0.0047 (0.0121)	0.0366** (0.0136)	-0.0585** (0.0128)	-0.0278 (0.0236)
(7) Dummy if label belonged to BMG × Dummy if after Sony's acquisition (starting from JV)	0.0711** (0.0243)	0.0401** (0.0143)	0.0742** (0.0212)	0.0835 (0.0839)	0.0644** (0.0137)	0.0463 (0.0300)	-0.0310 (0.0650)	0.0500** (0.0106)	0.0536** (0.0143)	-0.0139 (0.0168)	0.0508+ (0.0309)
(8) Dummy if label belonged to Vivendi Universal 0.0325** × Dummy if after GE(NBC)'s acquisition	0.0411* (0.0120)	0.0183 (0.0174)	0.0075 (0.0368)	0.0200** (0.0800)	0.0363+ (0.0073)	-0.0111 (0.0192)	0.0447** (0.0659)	-0.0050 (0.0103)	-0.0080 (0.0076)	0.0347 (0.0198)	(0.0221)
(9) Dummy if label belonged to EMI (EMI, Virgin, Capitol) × Dummy if after Universal's acquisition	0.0103 (0.0118)	-0.0161 (0.0105)	-0.0060 (0.0127)	0.1331** (0.0313)	-0.0069 (0.0138)	-0.0004 (0.0137)	0.1111** (0.0271)	-0.0285** (0.0097)	-0.0263+ (0.0157)	0.0116* (0.0057)	0.0280* (0.0139)
(10) Dummy if label belonged to EMI Parlophone Universal × Dummy if after Warner's acquisition	-0.0294 (0.0275)	-0.0029 (0.0174)	0.0001 (0.0166)	0.0934* (0.0467)	-0.0298 (0.0200)	0.0132 (0.0201)	0.1225** (0.0357)	-0.0121 (0.0188)	0.0103 (0.0311)	0.0123+ (0.0073)	0.0410+ (0.0226)

Note: Standard errors are in parentheses. $^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01$. Standard errors are robust and clustered at the label level.

3.6 Discussion and Conclusion

The empirical findings thus suggest that Sony's acquisition did not decrease CBS Records' discovery performance as compared to the performance of other US labels that were not acquired by foreign owners. How does foreign ownership affect the discovery of host country new talent by acquired firms? Theoretical research challenges the negative effect of the liability of foreignness. The positive impact of the access to Sony's tangible and intangible assets and the synergy between the hardware and content business may outweigh the negative impact of the liability of foreignness and enhance the discovery performance of CBS Records.

The results suggest that the positive effect of Sony's acquisition would overshadow the negative impact of the liability of foreignness. The estimates from the difference-in-differences (DD) specifications suggest that Sony's acquisition did not decrease CBS Records' discovery of new talent from the host country (the US) but that it increased the average popularity of releases by American new artists hired by CBS Records. Additionally, the reliance of CBS Records on American new artists did not decrease; the proportion of American new artists hired by CBS Records even after Sony's acquisition did not decrease. In sum, the average popularity of new artists in CBS Records increased by at least 110%.

Additionally, this study tests whether the findings from Sony's acquisition of CBS Records can be generalized to other music acquisition deals. I collect data from the other nine major acquisition deals in the music industry after the mid-1980s. I compare the coefficients from the same regression analyses on the ten acquisition deals including Sony's acquisition of CBS Records. The impact of foreign ownership (foreign acquisition) on the discovery performance in the host country (the popularity scores of the host country new artists) tends to be positive; except for one case (Matsushita's acquisition of MCA Records), the coefficients are negative and significant. In four cases, the coefficients are positive and significant at the 10% level, suggesting that the impact of foreign ownership tends to be positive.

I note a limitation to these findings. This study shares the same limitations as the other two chapters of the dissertation. This study does not use music sales or cost data. Thus, the increase in the popularity score from Spotify may not imply an increase in the financial performance of CBS Records. Thus, the results may also reflect the fact that Sony invested a great deal of money into the music business. Future work may be able to collect the sales and cost data from the music companies and analyze the impact of foreign ownership on the discovery of new talent from the host country more precisely.

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