Play it Again, Sam?
The Impact of Innovation on Success in the Music Industry

Abhishek Deshmane • Victor Martínez-de-Albéniz

IESE Business School, University of Navarra, Av. Pearson 21, 08034 Barcelona, Spain

adeshmane@iese.edu • *valbeniz@iese.edu*

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Abstract

Newly released music by a certain artist is never assessed in isolation by the audiences, who tend to compare it with the previous musical catalogue of the corresponding artist. Through a repeated interaction with the artist's music, the audiences build their own expectations about the future releases which affect the overall market reception. In this paper, we provide a general framework that incorporates the dynamics of these references towards addressing the classical dilemma of incremental versus radical innovation. We develop a theory rooted in classical behavioral economics of reference-building, and consider preference structures of habit formation and satiation. We then empirically measure the response of audiences to different degrees of innovation in successive musical album releases, by using a multi-attribute musical description of songs, together with their corresponding radio plays and critics' reviews. We find that a median deviation of the musical attributes of the newly released album from the reference levels of the audiences reduces the plays of the newly released albums by 23.1%, while that of the past albums increase by 13.8%, supporting the evidence for the existence of habit formation over radio stations. On the other hand, critics display the effect of satiation with a median deviation from the reference levels resulting in an average increase of 14.9% in their ratings. Our counterfactual analyses demonstrate how these findings can be utilized to adopt appropriate innovation rates to tailor-make products that cater to the preference structures of target consumers.

Keywords: New Product Development, Incremental Vs. Radical Innovation, Reference Effects, Habit Formation, Satiation, Music, Cultural Operations.

1 Introduction

Metallica, the heavy metal band formed in 1981 in Los Angeles, has gone on to become the staple of thrash metal music, with their aggressive musicianship earning them fans from all over the world and making them one of the most successful bands of all time. Despite the more than 40-year long career that the group have had, Metallica has remained true to its roots, emerging as the pioneers of the hard rock genre. Madonna, on the other hand, over an equally long and illustrious music career, has reinvented her style of music many times over. Growing out of the initial disco-pop music that she released in her first three albums, Madonna has very deftly weaved her way through many varied genres such as R&B, Electronica, EDM and Latin pop during her career. The chameleonic nature of her music is so impactful that the word 'reinvention' has become synonymous to her identity, with a host of contemporary artists like Miley Cyrus, Katy Perry, Taylor Swift and Rihanna drawing inspiration from her and reinventing themselves at some point in time in their own careers (Russell 2019, Hunt 2019). Interestingly, the stable career trajectory of Metallica and the innovative one of Madonna can be observed through the musical characteristics of their respective careers: Figure 1 illustrates the evolution of their albums in the dimensions of *Danceability* and *Energy* (see §4.1.1 for a description of these variables).

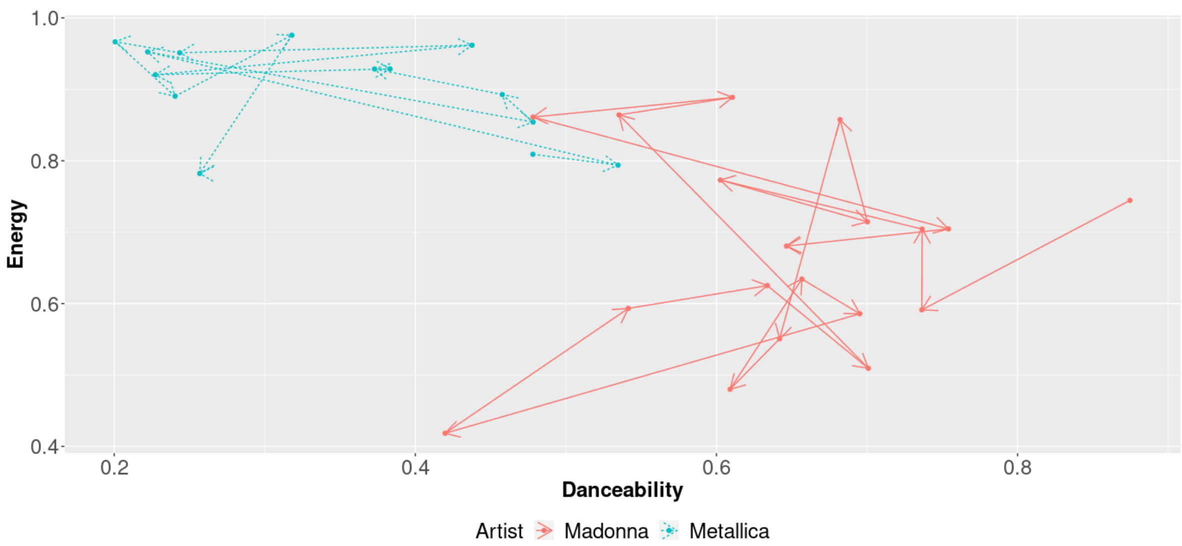


Figure 1: Musical career trajectories of Metallica and Madonna. Each dot corresponds to one album of these artists, and the arrows depict the order in which they were released.

As shown in these two examples, music artists can differ significantly in their creative strategies. From the artist's perspective, it is not clear which is the right one, and why. In the context of cultural markets, the 'product' is inherently related to the hedonic experience that it generates for the audience. The value of the experience is known to be heavily influenced by adaptation (Das Gupta et al. 2016). This gives rise to inter-temporal associations, whereby the perceived magnitude and effect of a stimulus on consumers at a given time becomes dependent on the magnitude and effect of the preceding stimulus (Helson 1964). Translating this process into the consumption of music, by consuming the previously released products by an artist, the audiences internalize the typical artistic features associated with her works and consequently form their own expectations about the upcoming releases. As a result, one would expect artists to conform to these expectations by building similar products to the ones created in the past. At the same time, the same theories (Baucells and Sarin 2012) suggest that audiences might also get bored and prefer some novelty, possibly leading artists to produce creations to surprise their listeners. This generates a dilemma for an artist: innovating in an incremental fashion, to conform to expectations, versus in a more radical way, to subvert preconceptions about the artist. Such choice not only applies to music. Cultural products such as architectural projects, books, paintings or sculptures also require the artist to decide how close or how different she may want to be from her previous creations. A similar tension exists in consumable products, where consumers may associate a style to the maker of the product, e.g., cars, electronics, fashion (Çil and Pangburn 2017).

This brings us to the central question tackled in this paper. How do different innovation choices affect the reactions of an audience, and the resulting success of a product? More specifically, we are interested in better understanding the drivers of this relationship, so we can provide guidance for innovation decisions that characterize how product design choices affect the metrics that the artist may want to focus on. While our goal is to develop a novel and general framework to study these questions, our insights are extracted from the music industry, and should be applicable to other artistic endeavors. In contrast, the application to consumer products, which include important functional aspects, would require replicating a similar analysis in those settings.

To study the impact of creative choices, we build a theoretical framework grounded on sociological theory, which is then applied via a high-dimensional quantitative characterization of the products. The starting point is that a product with a cultural dimension provides an inherently subjective experience to the consumer, with interpretations differing from person to person (Lankford 2002, Tavin 2007, Jones and Maoret 2018) that stem from the interactions between the art and prior individual knowledge, values and beliefs (Hein 1995). The creative decisions made by artists are thus contingent on this elusive nature of the interactions between their works and the audiences: the creation of new products is driven by tendencies to innovate incrementally to stay true to oneself, and to innovate radically to remain original.

This is a classical dilemma that we address here with the notion of reference effects, from classical behavioral economics (Kahneman and Tversky 1979, Kahneman et al. 1993). Specifically, we build a structural, utility-based modelling framework that includes these references in the utility derived from a cultural product. The novelty of our approach is that the references are related to each artist and associated with the multi-dimensional characteristics of their past creations, where utility provided to a consumer is affected by the distance between a new product and the reference that the consumers assign to the producer. Furthermore, we recognize the heterogeneity of preference structures of different factions of the audiences, juxtaposing two contrasting behavioral constructs of *habit formation* and *satiation* against each other, to hypothesize the effect of innovation on audience reactions. This approach allows us (1) to establish a classification of agents according to their preference structure, measured through their reactions towards innovation; and (2) to simulate the impact of different creative strategies and choose the one that best aligns with the producer's goals.

To validate our theory, we focus on the music industry and combine the following three unique datasets that help us isolate the desired effect of innovation: (a) An exhaustive dataset on audio attributes, which allows us to give 'addresses' to musical products, in the form of albums, the unit of musical creation reaching the market; (b) A log of plays on radio stations across 26 European countries, which allows us to measure commercial success of albums; and (c) Ratings given by top music reviewers from across the world, which allows us to measure their critical success. With this, we first use our framework to build the references developed by the audiences and then fit our structural models to establish a relationship between the innovation observed and the corresponding audience reactions. This structural formulation and the corresponding robustness checks provide a causal relation between these two elements.

We can thus separate audiences into two types: radio stations and critics, which may have different appetite for innovation. Our results show that choosing a median deviation, in comparison with no deviation at all, reduces the number of plays of the focal album by 28.1% but increases the plays of the previous works of the artist by 13.8%, suggesting an aversion to artistic innovation. This provides evidence that radio stations exhibit habituation to an artist's style and prefer less innovation to more. On the other hand, the median deviation, in comparison with none, increases the ratings given by critics by 14.9%, implying that they exhibit satiation and prefer more innovation to less.

In addition to these main findings, our analysis also sheds light on temporal factors impacting audience reactions. We specifically consider the role of artist career age, as well as the time lags between subsequent album releases. We find that, on average, radio stations respond less negatively to innovative songs if they are released by artists who have been in the music industry longer. The time lag between releases, however, does not moderate this relationship.

Finally, our model can be applied at the individual agent level too. This allows us to establish a taxonomy that classifies the agents according to their preference structures towards innovation in music. Through the counterfactual analysis, we can estimate the impact of different creative decisions, e.g., how much to innovate and in which direction, on each agent's reactions. This demonstrates how our model can be useful to artists to design their new albums so as to satisfy their desired audience targets, despite the risk of generally less innovative music in the long term (Thompson 2014).

Our work contributes to the literature in three ways. First, we focus on the functional characteristics of an artistic product which have not been explored in the past because of the abstractness typically associated with products with complex cultural dimensions (Lamont and Molnár 2002). This opens up the possibility of applying quantitative techniques to domains that have traditionally been studied with qualitative perspectives. Second, we provide a novel theoretical approach for new product search by incorporating reference effects which link past producer-level positions and future product-level design decisions, and linking them to behavioral economic principles. This is useful to the New Product Development (NPD) community, as well as to Decision Sciences and Operations Management. And finally, we apply our theory in the domain of music uncovering several new insights. Namely, we show that the commercial agents (radios) and the cultural gatekeepers (critics) have distinct preference structures towards innovation, which extends our understanding of the dynamics of culture and contributes to Sociology with a data-driven perspective.

The rest of the paper is organized as follows. §2 provides a review of the relevant literature followed by the development of theory and hypotheses in §3. §4 explains the context and elaborates on the data and methodology used with the results given in §5. Finally, we present managerial implications in §6 and conclude in §7.

2 Literature Review

Our paper primarily contributes towards the literature on NPD, in Operations Management. For this, we use the constructs from behavioral economics to provide a novel way of approaching the classical NPD problem of incremental versus radical innovation in the context of cultural markets.

Innovation strategies have been studied extensively, see Shane and Ulrich (2004) and Kavadias and Ulrich (2020). While not explicitly, Porter (1989) alludes to innovative disruptors by emphasizing the relevance of 'New Entrants' for the level of industry rivalry and gaining competitive advantage. Christensen (1997) highlights the dilemma of disruptive innovation within the context of technological change. While he focuses on innovation that is driven by the external factors, in our work we study musical innovation as a function of the artist's musical past. Hence, our analysis tracks the performance of innovation decisions of the incumbent over time. This is a distinctive factor. It contrasts with most of the innovation management literature, which typically provides a static, cross-sectional view of innovation projects (Tatikonda and Montoya-Weiss 2001, Laursen and Salter 2006, Singh and Fleming 2010). There are also some works that study the dynamic nature of innovation management, which have usually employed an analytical approach, e.g., Sommer and Loch (2004), Krishnan and Ramachandran (2011) or Marshall and Parra (2020). Empirical works have been limited and typically have focused on providing a sales forecast for new products based on similarities with past products (Gallien et al. 2015, Baardman et al. 2017). In comparison, we focus on studying how similarity to past works drives success of music.

The dilemma between incremental and radical innovation has also been extensively discussed. Ettlie et al. (1984) proposes that a firm with high concentration of technical experts and an aggressive technology policy is more likely to display radical innovation. On the other hand, incremental innovation is more common among firms that are structurally formal, complex and decentralized. Ali et al. (1993) provide a game theoretical solution to this dilemma while Dewar and Dutton (1986) empirically look at this phenomenon within the context of footwear companies, respectively. Chao and Kavadias (2008) propose strategic buckets as a way to protect radical innovation.

Closer to our empirical context, there is a substantial body of work that studies NPD in the artistic space. Collaboration dynamics in the process of NPD have been studied by Ramachandran et al. (2017) and Deshmane and Martínez-de Albéniz (2020) within the context of game production and music industry, respectively. Management-related decisions such as content programming have also been explored (Martínez-de Albéniz and Valdivia 2019, Caro and Martínez-de Albéniz 2020), as well as consumer adoption decisions (Deshmane and Barriola 2021). Berger and Packard (2018) and Askin and Mauskapf (2020) have empirically shown the benefits of producing music that is moderately innovative compared to contemporary competitors. While these works study the aggregate effect of music differentiation, Mauskapf and Cho (2019) carry out an artist-level analysis to test the effect of innovation on an aggregate audience. Our work goes a step further by disaggregating both the producer and consumer side, allowing for repeated interactions between the two parties through the construct of reference effects in a structural form that helps us make causal claims.

The construct of reference effects, first introduced by Helson (1964) and later explored by Kahneman and Tversky (1979) and Tversky and Kahneman (1981, 1991), has been a cornerstone for behavioral economics. Both Marketing and Operations Management literatures have significant number of works that ground their theoretical claims on this framework. Lattin and Bucklin (1989), Kalwani et al. (1990) and Hardie et al. (1993) empirically show how reference effects affect customer brand choice. Similarly, the effects of references on housing decisions (Genesove and Mayer 2001), insurance purchase decisions (Barseghyan et al. 2011), and competitive golfing tactics (Pope and Schweitzer 2011) have been well documented. Within the Operations Management literature, Popescu and Wu (2007) and Nasiry and Popescu (2011) analytically prescribe pricing strategies for customers influenced by their references while Aflaki and Popescu (2014) provide insights into customer defection decisions. More relevant to our approach are Das Gupta et al. (2016) and Tereyağoğlu et al. (2018), works that use the construct of references to prescribe optimal sequential experiences like music concerts and pricing strategies for opera houses, respectively. By using the well-established framework of reference effects, we juxtapose the opposing behavioral constructs of habit formation, studied by Becker and Murphy (1988) and Acland and Levy (2015), and satiation, developed by Baucells and Sarin (2007, 2013), to develop our theory on audience reaction to their favorite artists' musical innovation. In addition to this, we provide an empirical validation of Hsee and Abelson (1991)'s 'Velocity' and Hsee et al. (1994)'s 'Quasi-acceleration' relations, in our moderation analysis.

3 Theory for Cultural Innovation

3.1 Agents of the Cultural Industries

Cultural industries hold a unique position in the society - both shaping it and being shaped by it at the same time (Peterson and Anand 2004). Here, we focus on how the perception of the audiences about the newly introduced cultural products is influenced by the previous catalogue of the corresponding producers. Hence, our level of analysis is at the product level and we study the connection between production decisions, with consumption outcomes from the audiences, with the objective of allowing producers to be more strategic in the design of their future production (Jones and Maoret 2018). Table 1 illustrates the prominent agents within different cultural industries, that we describe in more detail next.

Cultural Industry	Producers	Intermediaries
Music	Music artists	Radio stations, music TV channels, critics, awards, charts, etc.
Movie	Production teams	TV channels, movie theatres, critics, awards, etc.
Books	Writers	Publishers, critics, etc.
Artwork	Artists	Museums, exhibitions, critics, etc.

Table 1: Agents of cultural industries.

Consumers - Intermediaries, Critics and General Audiences. The consumers of the products of the cultural industries together have a decisive say in which new product becomes successful. The social structures of the cultural markets, however, results in the emergence of intermediaries like radio stations, TV channels, newspapers, who control the diffusion of these products by providing them with more visibility (Hirsch 1972, Shrum 1991, Moe and Fader 2001). In this sense, intermediaries are prescribers of content to the final consumers, but above all they are representatives of these consumers so that they carry the content with the most commercial interest (Desai and Basuroy 2005, Musgrave 2017).

In addition, critics have especially been identified to have a significant role in the workings of cultural industries and play an indispensable role in the marketing strategies of cultural products (Litman 1983, Wyatt and Badger 1984, Eliashberg and Shugan 1997). Critics, who are cast by Bourdieu (1986) as cultural gatekeepers, consequently grant a cultural capital by conferring legitimacy which contributes towards having an economical impact on the products' performance in the markets (Shrum 1991, Zuckerman 1999, Musgrave 2017). The process of attribution of legitimacy, granted by these entities, is culturally driven, socially constituted and economically realized.

Diffusion channels and critics are thus highly influential members of the consumer side, and their response to newly released products describes the different sentiments that they generate within the general audience.

Producers - Artists. Content producers use their skills and talents to put together new artistic products that go on the market and in turn generate revenues that transcend the economic definitions (Lena and Pachucki 2013). They face a constant struggle of consistently and strategically releasing quality products that earn them the currency for sustenance in the hierarchies of the cultural industries (Faulkner 1983, Bourdieu 1998, Zuckerman 1999). At the heart of these product design decisions are the two following motivations.

First, an artist may create for an audience, and hence consider catering to their expectations as the primary purpose of her work. Indeed, being the purest form of human expression, art is a very intimate representation of the personality of the artist which eventually becomes associated with her identity. In his sociological conceptualization of cultural products, Bourdieu formally theorizes that this identity is built on a combined consideration of economic, social and cultural capitals that an artist earns through her released products (Bourdieu 1986). By creating art, the artist channels authenticity through her work which has been shown to be an important factor for the success of an artwork (Armstrong 2004). Here, 'keeping it real' provides the artists with the necessary legitimacy for their sustenance in the cultural space that transcends the short-term economic factors that determine success. In other words, producing art that does not reflect one's own internal values should result in negative audience reactions because of the lack of artistic consistency and a misalignment with the expectations formed from the previous works by the artist.

In contrast, an artist may also create to respond to an inner call for novelty. Besemer and Treffinger (1981) state that artistic pursuit is inherently linked to the search of novelty that is germinal (provides value to the future creative products), original (how unusual the product is) and transformational (the extent to which it forces a shift in the perception of reality of its consumers). In other words, the inherent artistic curiosity may drive artists to venture into cultural spaces previously unexplored. While the costs associated with idea generation in new spaces can be high (Sinha and Cusumano 1991), producing innovative goods that can reach a wider set of audiences than her regular consumers remains to be an effective way of increasing the 'base market' (Negus 1992). Furthermore, innovation also contributes towards increasing the overall social welfare with the audiences being exposed to newer experiences (Lancaster et al. 1974).

In summary, producers can opt for different creative strategies to prioritize the pursuit of legitimacy, versus the search of new ventures.

3.2 Product Positioning and the Position Relation

Audiences assess the cultural products based on a wide range of information signals which include producer and product characteristics (Peterson 2013, Uzzi and Spiro 2005), peer preferences (Mark 1998, Lizardo 2006, Deshmane and Barriola 2021), and various elements in the institutional environment (Hirsch 1972). Together, this multidimensional representation of a cultural product contributes towards its distinctive identity (Salganik et al. 2006, Goldberg et al. 2016). For example, Leonardo da Vinci's Mona Lisa is a Renaissance period portrait which is an oil on poplar painting owned by the French Republic and insured at $850 million. All these factors play a role in the popularity it commands among the audiences.

Rather than existing in a vacuum, cultural products are perceived in relation to one another in the feature space (Becker and Murphy 1988). Hence, the assessment of a cultural product is contingent on the position it occupies within this feature-continuum of relative space defined by its contemporaries. To formalize the idea of product positioning, given a producer i, we denote the different products released by $j = 1, \ldots$, and let $X_{ij} \in [x_{ij}^1, x_{ij}^2, ..., x_{ij}^n]$, the vector of n artistic attributes that describe the position occupied by product j in a multi-dimensional artistic space.

For a consumer k, we first build a *naive* structural form for the utility of consuming j, as follows.

$$U_{ij}^k = \beta^k X_{ij} + \epsilon_{ij}^k. \tag{1}$$

Here, β^k is a consumer-dependent vector of the coefficients corresponding to the vector of artistic attributes expressed through X_{ij}. Indeed, the interpretative knowledge is constructed as a function of the underlying characteristics of the art and the uncontrolled experiences of the interpreter, which suggests that each consumer k may react differently to different product positions. ϵ_{ij}^k is the random shock experienced by k across all the options ij. Hsee and Abelson (1991) term Equation (1) as the position relation.

3.3 Product Innovation and the Displacement Relation

Bleich (1975) states that the notion of objective evaluation of the arts is 'ludicrous.' Instead, one should understand the process of subjective assessment (Hein 1995). We propose here to factor in the past experiences of the consumer, to account for her subjectivity.

Hedonic adaptation is central to experience associated with a cultural product. The subjective and entity-specific preferences result in inter-temporal associations of products released by the same artist. Specifically, the past experiences result in the formation of expectations, which thereby influence the experienced utility associated with consuming the newly released products (Das Gupta et al. 2016). With the passage of time, the audience not only gets used to the nature of this newly released product, but also assimilates the product-specific attributes to update their expectations about the future products corresponding artist would potentially release (Baucells and Sarin 2007, Hsee and Tsai 2008, Caro and Martínez-de Albéniz 2012, Candia et al. 2019, Baucells and Zhao 2019). This behavior among the audiences may be triggered by psychophysical adaptation or by 'ordinization' (Wilson et al. 2003). This repeated interaction between the artist, with the release of a structurally innovative new product, and the audience, with their assessment, acclimation and the eventual satiation, gives rise to the formation of expectations among the audience about the future releases of the artist. As Jauss and De Man (1982) put it, "A cultural object is received by a reviewer with a particular 'horizon of expectations' about the kind of object it represents."

To better understand how these expectations can be modelled, consider the Latin pop artist Shakira, who released her first album 'Magia' with Sony Music in 1991, at age 13. This was followed by 'Peligro', 'Pies Descalzos' and 'Donde Estan los Ladrones?' in 1993, 1995 and 1998, respectively. Each of these albums had songs which were primarily of Pop and Pop rock genres. As a result of these sequential and artistically proximate albums, Shakira got labelled as a Latin pop artist by the audiences, earning her the corresponding cultural capital and legitimacy (DiMaggio 1987, Desan 2013, Deshmane and Martínez-de Albéniz 2020). Because her albums followed a certain musical trend, the audiences formed their own expectations about the placement of her next album in the musical sphere. Instead of releasing the musically proximal 'Laundry Service' album, had she released an album which primarily featured Folk music, the reaction of the audience would have been affected tremendously as a result of this drastic departure from their expectations. In the case of music, all the previous albums released by the artist remain easily available to the audiences to build their expectations or reference levels associated with the musical attributes (Tereyağoğlu et al. 2018). As a consequence, the deviation in the musical attributes of the newly released album from the musical attributes of its preceding albums captures the overall innovation observed in the portfolio of songs with respect to the previous portfolio in the artist's career. This is in line with the Adaptation Level Theory which explains how individuals adapt to states but react to changes (Helson 1964, Hsee and Tsai 2008, Das Gupta et al. 2016).

Accordingly, we define the reference levels associated with an artist i, at the time of the release of a product j, as follows:

$$R_{ij} = \theta R_{ij-1} + (1-\theta) X_{ij-1}.$$

In this formulation, $\theta \in [0, 1]$ is a factor of memory decay as considered in Lattin and Bucklin (1989), Tereyağoğlu et al. (2018) or Candia et al. (2019), which allows us to capture possible recency effects of the audience (Loewenstein and Prelec 1993, Haugtvedt et al. 2018). We also use alternate considerations for the estimation of reference effects which are given in §5.3.

Finally, we get a standardized measure of deviation from the reference level aggregated to the product-level, namely cosine similarity (most past studies of music use this metric, e.g., Askin and Mauskapf 2020, Askin et al. 2019 and Marshall and Parra 2020), as follows:

$$\Delta X_{ij} = |X_{ij} - R_{ij}| = 1 - \frac{< X_{ij}\ ,\ R_{ij} >}{||X_{ij}|| \times ||R_{ij}||}.$$

Note that one can also choose other deviation metrics. For instance, we replicated our models with ΔX_{ij} being the Euclidean distance between X_{ij} and R_{ij} and obtained similar results.

The experienced utility of entity k for the album j by artist i can thus be defined as

$$U_{ij}^k = \beta^k X_{ij} + f(\Delta X_{ij}) + \epsilon_{ij}^k. \tag{2}$$

Hsee and Abelson (1991) call this the displacement relation. In our case, $\Delta X_{ij} = |X_{ij} - R_{ij}|$ is a representation of the innovation observed on the new product of the focal artist. While we are interested in studying the relationship between this innovation and U_{ij}^k, it is important to control for the actual observed values through X_{ij}, to avoid under or overestimating the role of the innovation observed in the utility derived from consuming a newly released product, termed as impact bias (Schkade and Kahneman 1998, Gilbert et al. 2002).

Note that Equation (2) deviates from standard Prospect Theory (Kahneman and Tversky 1979). Indeed, the experience associated with cultural products is inherently subjective, and it is not possible to categorize a positive (negative) deviation of the observed value from the reference level to be a gain (loss). This is due to the distinctive horizontal nature of the categorization of the musical sphere (Deshmane and Martínez-de Albéniz 2020). Hence, we make a conscious decision to track the innovation as a deviation construct without imposing the directional complexity. However, it is possible to extend the model to consider directional variations when we consider vertically-differentiated attributes, e.g., with car engine power in automotive products.

3.4 Habit Formation Vs. Satiation

Given the highly subjective nature of the interpretability of cultural products, works such as Mark (1998) and Datta et al. (2018) have documented the high variability reflected in the cultural tastes of the audiences. In our view, we explore how tastes are related to the innovation rates rather than the actual underlying features of the product released (although, we control for the latter). Some audiences may prefer the same kind of products while some others may derive more utility when their favorite artists dabble in unexplored ventures. Habit formation and satiation are thus the fundamental behavioral constructs that inform this conjecture and we next elaborate on how they influence the utility of the audience.

Habit Formation. A consistent exposure to a certain kind of stimulus creates a higher preference and inevitably a proclivity towards it (Acland and Levy 2015). As a result of this, the audience reacts much more positively when the deviation from the products previously encountered is minimal, under the framework of habit formation as developed by Ryder and Heal (1973), and Becker and Murphy (1988). In this scenario, the utility of consuming the new product by an artist increases when it is similar to her previous products which is called adjacent complementarity (Becker and Murphy 1988). A slightly different look at this effect is the framework of habituation, where the audience may experience diminishing utility from consuming a similar kind of product. However, due to the underlying 'rational addiction' developed towards it, the audience would experience severe disutility when they are denied a similar kind of cultural experience (Becker and Murphy 1988).

This framework is further reinforced by the notion of the artist earning legitimacy by releasing the same kind of music and consequently being granted the expertise for it, which elevates the experienced utility of consuming the new product (Bourdieu 1986, DiMaggio 1987, Askin and Mauskapf 2020). Moreover, as Negus (1992) puts it, by releasing artistically consistent works, the artist can guarantee a favorable response to her new album from her 'base market', who are her regular consumers.

Consequently, the 'base market', upon coming across a very drastically innovative product, will fail to relate with it due to their artist-specific reference levels and develop a craving for the 'old stuff' from the artist (Wathieu 2004). Under this consideration, a radically innovative cultural product will not fare well with the audience and would prompt them to go back to the artist's previous catalogue of products. For example, in the case of music, failing to relate to the highly innovative newly released focal album, audiences will revert back to listening to the albums released in the past by the corresponding artist. Hence we develop the following hypotheses.

Hypothesis 1A *An increase in the innovation rate of the focal cultural product has a negative effect on its performance metrics.*

Hypothesis 2A *An increase in the innovation rate of the focal cultural product has a positive effect on the performance metrics of the products released in the past by the same artist.*

Satiation. In contrast, satiation outlines a behavioral pattern that has an exact opposite effect on the utilities of the audiences in comparison with habit formation. Here, being exposed to a certain kind of cultural product of the previous release of an artist creates a lingering effect on the consumption of the newly released product. Specifically, if an artist releases a new product which is artistically similar to her previous release, the audience will experience a diminished utility on account of being satiated and bored with having to consume the same kind of product (Baucells and Sarin 2007, 2013). For example, Kanye West's ninth album titled 'Jesus is King', which was released in 2019 was labelled as highly repetitive and hence failed to reach the same heights as that of his previous releases.

As a result of this, audiences become variety-seeking, as shown in Datta et al. (2018) in their econometric study on music consumption patterns. Audiences derive higher utility from a radically innovative new product which subverts expectations and presents new experience which deviates from the reference levels developed for all the artistic attributes. In this scenario, the newly released product receives ample attention, thereby negatively affecting the performance of the products released by the artist in the past. Hence, we build the following hypotheses.

Hypothesis 1B *An increase in the innovation rate of the focal cultural product has a positive effect on its performance metrics.*

Hypothesis 2B *An increase in the innovation rate of the focal cultural product has a negative effect on the performance metrics of the products released in the past by the same artist.*

3.5 Moderating Effect of Time

The displacement relation accounts for one important audience cognition bias. However, not only the deviation from expectations matters, but also the role time plays in the perception of these deviations. Here, we study the impact of time-related moderators, in the form of career age, to account for the memory that audiences may have about an artist, and the lag between the release of subsequent albums, to account for the recency of past stimuli.

We hypothesize that artists in the early stages of their career, with only a few cultural products out in the market, will, by definition, have less of their past work for the audiences to build their expectations on. During this time, an artist would not have established a niche area for herself, which is achieved only by repetitive reinforcements (Bourdieu 1986, DiMaggio 1987). In such a scenario, the audiences will be more tolerant of the radical changes that the new artist makes in her eventual release and not respond as harshly as they would for a similar erratic behavior by a well established one. Hence, we consider $Career\_Age_{ij}$ of artist i at the time of the release of product j as an important moderator affecting the relation between the innovation rate and the audience perception.

Furthermore, the speed at which an artist deviates from expectations should also have a significant impact over how the audiences perceive the new product (Carver and Scheier 1998). Consider two artists who release equally deviant products from their respective profiles, with Artist A releasing it m months after his previous product while Artist B releases it $m' > m$ months after her previous product. Because of the shorter time lapse between the subsequent release by Artist A, the audience will perceive his innovation more radical than Artist B's. A massive change in the type of the product within a short period of time may result into a product which the 'base market' of the artist fails to relate to, is considered to be ahead of its time and receives an overall negative response (Chao and Kavadias 2008, Uzzi et al. 2013). To account for this, we consider the effect of the time elapsed between the two subsequent releases of an artist ($TimeLag_{ij} = RelDate_{ij} - RelDate_{ij-1}$) that captures the dynamic nature of these deviations (Chang et al. 2009). Through this moderator, we map the preference structures of the audiences based on what Carver and Scheier (1990) and Hsee and Abelson (1991) call the velocity relation.

We can also consider how past rates of innovation affect the relationship between the rate of innovation for the focal album and the audience reaction to its release. This has been called the quasi-acceleration relation by Hsee et al. (1994). By being exposed to a certain artist's style of music-making, the audiences become aware of the general trend followed by the artist in her rate of innovation as well. If an artist has consistently released albums with minimal innovation in the past, the audiences expect the new album to be the result of a similar trend and hence be musically proximal to her previous profile. This is evident in the case of the rock band Nickelback, who have enjoyed a fair amount of success by producing a similar kind of music throughout their career. Here, the audiences have become accustomed to a minimal change in the rate of innovation in their successive albums thereby building a loyal base market that appreciates this consistency in their music production (Negus 1992). On the other side of this spectrum, the rock band Velvet Underground from the 1960s was known for their highly innovative music, to the point that every new album essentially reinvented the identity of the band. Over their career, the audiences assimilated the consistency in the rate of innovation and expected increasingly eccentric music from them. We expect this dynamic rate of change of innovation in the past to have a significant impact on the way the innovation of the current album is perceived by the audiences. To study this effect, we use an aggregated measure of the rate of innovation registered by artist i on albums released prior to the focal album j as follows:

$$Past\Delta X_{ij} = \frac{\sum_{j'=1}^{j-1} \Delta X_{ij'}}{j-1}$$

In summary, we test the moderating roles of these time-relevant factors by adopting Equation 2 to the following form.

$$U_{ij}^k = \beta^k X_{ij} + f(\Delta X_{ij}) + g(M_{ij}) + h(M_{ij} \times \Delta X_{ij}) + \epsilon_{ij}^k. \tag{3}$$

where $M_{ij} \in [Career\_Age_{ij}, TimeLag_{ij}, Past\Delta X_{ij}]$.

4 Context, Data and Methodology

4.1 Context and Data

To study the question of innovation management within the cultural markets, we carry out our analyses within the domain of the music industry given its important, paradigmatic position within the cultural space, and the economic, social and cultural influence it has over the society (Negus

1992). While there are various positions within the structure of the music production process that contribute towards the finished product, viz. technicians, writers, engineers, etc., music artists are central to the process. We focus on the music artists and their role in the structure of the music industry as done in Uzzi and Spiro (2005), Askin and Mauskapf (2020) or Mauskapf et al. (2018). Our aim is to track the innovation trajectories of these artists through the albums that they release in their careers and analyze its effect on the audience reactions. Hence, our analysis is at the album level which represents the actual unit of creation, with distinctive underlying artistic characteristics. Indeed, even if an album is made of a collection of songs, these are all released simultaneously, despite, after the release of an album, music labels promoting single songs sequentially, one after the other.

To study this context, we use three main data sources.

4.1.1 Spotify

For identifying the underlying musical characteristics associated with the albums, we consciously decide to not use the construct of genres because of the volatility and ambiguity of such classification which is subject to audience heterogeneity (Lamont and Molnár 2002). Instead, we use the Spotify/Echo Nest data source that provides a more detailed understanding of the position of each album in the artistic space.

The Spotify API provides song-level music attributes which are highly informative about the underlying sonic features. Through machine learning algorithms, every song is given a numeric value for 12 technical and non-technical attributes that help us objectively track the position of the focal song in the musical sphere (Askin and Mauskapf 2020, Mauskapf et al. 2018). We get this data for 959,080 songs of 4,255 artists across 62,724 distinct albums. Since our analysis is at the album level, we aggregate the music attributes to the album level and use it in conjunction with the other album level details provided by Spotify to control for potential confounders. Appendix A elaborates on the factors that we consider to track the album features (1 to 12: Song level technical and non-technical music attributes; 13 to 16: Album level factors.). By tracking the characteristics of chronologically-ordered albums, we can thus map the innovation trajectories of the artists. To avoid any unbalanced influence of one particular attribute in estimating the position of an album within the musical sphere, we normalize these measures to a scale of 0 to 1 as in Askin and Mauskapf (2020). Figure 5 shows how they correlate with each other.

An important aspect, in conjunction with the audio features in Appendix A, that sways the opinion of the audience on way or another about a newly released album is the diversity of the songs on offer. Here, the artist can either opt to provide a widely diverse combination of songs to appeal to a wider market or she may focus on producing songs that occupy a very narrow space within the musical feature continuum of the industry (Negus 1992, Kim et al. 2002, Goldberg et al. 2016). As a result of these varied music assortment strategies, radios with specialized programming may favor albums that are less diverse and more homogeneous, while others may be tempted to play a wider subset of the given assortment because of the high variety on offer. We thus add a measure of album diversity as shown in Appendix A.3.

4.1.2 BMAT

To track the response of the audiences to the newly released music, we first use the metric of number of plays received by the new album on radio stations. For this, we use the data compiled by BMAT, a music identification service that scans radio frequencies and employs its song identification techniques, as our fundamental data source. This data set spans from January 2011 to September 2020 and provides a log of plays registered over 108 radio stations across 26 countries in Europe. Accordingly, 46 million observations are available, an example of which is given in Appendix B. We aggregate these plays to the artist-week level and consider only the 90th percentile in our analysis to focus our attention on the commercial players in the music industry. Accordingly, we analyze careers of 9,440 artists with 125,040 songs, who account for 92% of the total plays registered on the radio stations during this time.

Here, we use the performance of the newly released album during the initial 52 weeks since its release (Peterson 1976, Coase 1979, Musgrave 2017, Deshmane and Martínez-de Albéniz 2020). It provides the most tangible commercial recognition for the song and is in line with the standard metrics used for assessing the product performance in the NPD literature (Lang and Lang 1988, Cohen et al. 2000, Hendricks and Sorensen 2009). Concretely, the cumulative number of plays garnered by the songs on a newly released album j by artist i in the 52 weeks since its release on the radio station k, where j identifies the chronological position of the album in the artist's career, is given by $Plays^k_{ij}$, which becomes our dependent variable. This variable is normalized to adjust for average time-varying effects, with the procedure described in Deshmane and Martínez-de Albéniz (2020).

4.1.3 Album of the Year

Album of the Year (`https://www.albumoftheyear.org/`) provides a detailed overview of the response garnered by the newly released albums from the relevant critic reviewers. Ratings from reputed outlets such as Rolling Stone, Billboard and Entertainment Weekly are compiled together and provided on a scale of 0-100 for each album on the website. We build web-scrapers to collect this data for 16,900 albums by 8,052 artists released from the year 1991 to November 2020 that are reviewed by 75 music-reviewing outlets.

Critics are a vocal community of individual entities who are the self-proclaimed 'experts' tasked with providing reviews of the newly released content. They have especially been identified to have a significant role in the workings of cultural industries and play an indispensable role in the marketing strategies of movies, books, music and other related cultural products (Litman 1983, Wyatt and Badger 1984). In light of the relevance of these agents, we make a separate consideration of these ratings as our dependent variable such that for a newly released album j by artist i $Rating^k_{ij}$ is the score given by critic k.

We build the final dataset by combining these three distinct datasets. We make use of both Levenshtein distances (Levenshtein 1966) and Jaro distances (Boytsov 2011) to robustly match the data across these different sources yielding a sample of 39,241 albums that span the entire careers of 3,959 artists.

4.2 Model

To test our hypotheses, we construct a stylized structural model similar to Lattin and Bucklin (1989) or Tereyağoğlu et al. (2018). The main model is built on the utility-driven framework developed in §3.3, and adapts Equation (2) as follows.

$$Z^k_{ij} = \alpha^k Z^k_{ij-1} + \beta^k X_{ij} + \gamma^k \Delta X_{ij} + \nu^k C_{ij} + \Omega_i + \mu_t + \epsilon^k_{ij}. \tag{4}$$

In Equation (4), the dependent variable can take different forms $Z^k_{ij} \in [Focal\_Plays^k_{ij}, Past\_Plays^k_{ij'}, Ratings^k_{ij}]$, where:

(a) $Focal\_Plays^k_{ij}$ is the number of plays garnered by artist i's album j on radio station k in the first year of its release;

(b) $Past\_Plays^k_{ij'}$ is the number of plays garnered by artist i's albums released prior to the focal album j, that is, albums $j' = 1, \ldots, j-1$, on radio station k in the first year following album j's release; and

(c) $Ratings^k_{ij}$ is the score given by reviewer k to artist i's album j upon its release.

Our main independent variable of interest is the deviation of the newly released music from the reference levels of the audiences which is constructed as explained in §3.3 with the resultant ΔX_{ij} as the measure of musical innovation.

Note that in this specification, we use artist fixed effects Ω_i, to account for artist channel- and time-independent popularity, and time fixed effects μ_t at year level, to account for varying levels of competition (albums on the market at t). We control for the actual observed values of the album audio features in order to disentangle the two which is represented through the vector X_{ij} (Lattin and Bucklin 1989). We further control for the radio station/reviewer k's predisposition towards favoring the content by artist i through more plays or higher ratings by controlling for the corresponding lag variables. Hence, for $Focal\_Plays^k_{ij}$, we use $Focal\_Plays^k_{ij-1}$, which tracks the number of plays artist i's album $j-1$ garnered over radio station k in its first year of release. Accordingly, $Past\_Plays^k_{ij'-1}$ and $Ratings^k_{ij-1}$ help us track the 'loyalty' of entity k towards artist i as in Guadagni and Little (1983). While analyzing the effect of the newly released album on the plays of the albums released in the past (for the dependent variable $Past\_Plays^k_{ij'}$), it is necessary to consider the initial performance of the corresponding past albums. Just as the opening weekend performance of movies is a significant predictor of the eventual ticket sales at the box office, albums that perform well in the first year of their release are more likely to have a larger number of plays when the new album by the same artist is released (Eliashberg et al. 2000, Hendricks and Sorensen 2009, Hu et al. 2019). Hence, we employ an additional control for this scenario with $FirstYr\_Plays^k_{ij'}$ which is the number of plays garnered by artist i's album j during its first year of release on radio station k.

Moreover, we introduce additional controls C_{ij} to account for album-level features. Specifically, we account for the marketing effort of the record labels to promote the music by their artists and use a binary variable with value 1 if the focal album j is released by one of the Big 5 labels (Sony, Warner, BMG, Universal, EMI) in Big_Label_{ij} (Graham et al. 2004, Bishop 2004). We also control for the chronological number of the album j in the career of artist i with $Album\_Num_{ij}$. Since our analysis focuses on the effect of references on the performance of the newly released albums, we do not include $j = 1$ to allow the artist enough exposure to establish a space for herself within the musical sphere.

Finally, to analyze the moderating effect of the time dependent factors ($M_{ij} \in [Career\_Age_{ij}$, $Time\_Lag_{ij}$, $Past\Delta X_{ij}]$) on the relationship between the observed innovation of the focal album and the corresponding radio plays-related dependent variables, we consider a second specification, adapted from Equation (3), as follows.

$$Z_{ij}^k = \alpha^k Z_{ij-1}^k + \beta^k X_{ij} + \gamma_1^k \Delta X_{ij} + \eta^k M_{ij} + \gamma_2^k M_{ij} \times \Delta X_{ij} + \nu^k C_{ij} + \Omega_i + \mu_t + \epsilon_{ij}^k. \quad (5)$$

5 Results

We use Maximum Likelihood Estimation (MLE) to estimate Equations (4) and (5), with Negative Binomial Distribution for the dependent variables constructed as plays and Gaussian Distribution for ratings. Note that in this model θ (the memory decay factor) is a parameter that also requires estimation and interacts recursively with the rest of the variables. We thus use grid search, with increments of 0.05, to estimate the value of θ that results in the highest likelihood. We find that setting the memory decay factor $\theta = 0.9$ gives the best fit for our model with $Focal\_Plays_{ij}^k$ as the dependent variable. Similarly, we use θ with values of 0.1 and 0.8 for $Past\_Plays_{ij}^k$ and $Ratings_{ij}^k$, respectively. This suggests that audiences have a long memory when comparing new releases to the past, given that the metrics associated with the performance of those new releases put emphasis on the earlier works ($\theta = 0.9$ and 0.8). In other words, first impressions in music leave a lasting mark on both radios and critics.

5.1 The Effect of Innovation

The results of the estimation of Equation (4) are shown in Table 2. Our main models are Models (2), (4) and (6), and we provide specifications without the innovation variable in Models (1), (3) and (5) for comparison.

Firstly, we observe in Model (2) that the coefficient of ΔX_{ij} is negative and significant, with a coefficient of -5.774. In other words, as the rate of innovation of the focal album increases, radios tend to play it less. Given that the median deviation from the reference levels of the audiences is $\overline{\Delta X} = 0.0248$, then applying a median innovation ($\Delta X_{ij} = \overline{\Delta X}$, compared to no innovation at all $\Delta X_{ij} = 0$), reduces the plays of the focal album by 28.1%. This suggests that radios clearly favor incremental music from their favorite artists, so that they conform to the expectations that they build based on the past releases. As in Berger and Packard (2018) and Askin and Mauskapf (2020), we also check for the non-linear relationship between the covariate ΔX_{ij} and the dependent variable by using a squared term, but we do not find this effect to be statistically significant, see Table 8 for more details.

On the other hand, the plays of the albums that are released in the past by the artist significantly increase with the rate of innovation of the focal album. Specifically, from Model (4) we find that a

	$Focal\_Plays^k_{ij}$		$Past\_Plays^k_{ij'}$		$Ratings^k_{ij}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$log(Focal\_Plays^k_{ij-1})$	0.152***	0.154***				
	(0.013)	(0.013)				
$log(Past\_Plays^k_{ij'-1})$			0.123***	0.122***		
			(0.009)	(0.009)		
$log(FirstYr\_Plays^k_{ij'})$			0.711***	0.711***		
			(0.008)	(0.008)		
$Ratings^k_{ij-1}$					0.175***	0.174***
					(0.007)	(0.007)
ΔX_{ij}		-5.774***		1.174***		10.521***
		(1.692)		(0.308)		(3.783)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
$FixedEffects$						
$Artist-level$	Yes	Yes	Yes	Yes	Yes	Yes
$Time-level$	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,918	20,918	110,450	110,450	21,830	21,830
Log-Likelihood	-32,882.88	-32,877.17	-58,744.50	-58,737.26	-86,836.32	-86,832.45
BIC	82,966.48	82,965.02	135,023.61	135,020.74	183,244.05	183,246.31
AIC	69223.77	69214.36	120509.02	120496.53	175,588.64	175,582.91

Notes: Observations are at the Artist-album level. Controls include Big_Label_{ij}, $Album\_Num_{ij}$, and all the audio features represented in X_{ij}. Standard errors are shown in parentheses.
$^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$.

Table 2: Effect of innovation on focal and past album plays, and focal album ratings.

median deviation, compared to none, causes the plays of the albums released in the past to increase by 13.8% (coefficient 1.174). This provides evidence that, when innovation is higher, audiences relatively avoid playing the new album, and seek refuge in past albums, suggesting substitution between the future ahead, and the 'good old days' associated with the artist's past works to which they are 'rationally addicted' (Becker and Murphy 1988). As a result, our Hypotheses 1A and 2A are validated providing evidence for habit formation in radio.

Considering critic reactions, we observe in Model (6) a very strong positive effect of innovation on the ratings given by the reviewers. Table 2 shows that with a median deviation from the reference level of the audiences, compared to none, the score given by the reviewers increases by 14.9% (coefficient 10.521). This validates our Hypothesis 1B for the reviewer ratings which provides evidence for the reviewers displaying satiation behavior. From this, we can surmise that the reviewers, on average, appreciate when music artists venture into unexplored musical territories. While they build references based on the past profiles of the music artists, they tend to be satiated by the similar kind of music showing proclivity to favor music that defies expectations. Consequently, they give higher scores to albums that a new musical dimension to the artists' profiles.

Finally, we also studied additional response variables, such as the Gini Index ($Gini\_Index_{ij}^k$) of play distribution between songs in an album, as in Hendricks and Sorensen (2009) or Abeliuk et al. (2015) who use it specifically in the context of music industry. Table 10 in the Appendix contains the results. The effect of ΔX_{ij} is statistically insignificant implying that it is not a predictor of the variation in the distribution of plays across songs in an album.

5.2 Moderating Effect of Time

In Table 3 (See Tables 8-11 for full results), we show the results about the moderating role of time considerations.

First, we check for the effect of the career age on the perception of the innovation observed by the audiences in the newly released albums. We see that while the radio stations react negatively to the increase in innovation, the career age of the focal artist positively moderates this relationship (coefficient 0.004). This implies the response to innovation from an artist that has been in the industry for long is less negative, compared to that of a new artist. In other words, the radio stations are more tolerant of higher innovation rates if they are associated with albums from artists that have been in the music industry for longer periods of time. In contrast, reviewers are not affected by the career age of the artists.

Next, we empirically test Hsee and Abelson (1991)'s velocity relation by considering both the innovation and time lag between successive album releases. We see that the moderating role of $Time\_Lag_{ij}$ on the relationship between ΔX_{ij} and any of the dependent variables remains insignificant. Hence, we do not find statistical evidence for this factor affecting the radio stations and reviewers on average. We further conduct agent-level analyses to explore the heterogeneity within each of the two sub-classes of audiences, which we discuss in §6.

Finally, we check for the quasi-acceleration relation through the moderation analysis of the past innovation rates in $Past\Delta X_{ij}$. We see that the moderation effect is absent for $Focal\_Plays_{ij}^k$. Hence, it does not have any statistical effect on the relationship between the focal album innovation and the plays it receives. However, the relationship between the focal album innovation rate and the plays registered for the past catalogue of the artist is positively moderated by the past innovation rate by the focal artist. This implies that the radio stations prefer a consistent rate of innovation for the $Past\_Plays_{ij'}^k$. Furthermore, critics appear to take the innovation rates of the previous albums into account as well when they assess the focal album. Past albums innovation negatively moderates the relationship between the focal album innovation and the ratings given to the focal album. This means that the reviewers not only want the artists to defy their positional expectations, but also innovate at different rates in their successive releases. In other words, inconsistency in the rate of

	$Focal\_Plays^k_{ij}$			$Past\_Plays^k_{ij}$			$Ratings^k_{ij}$		
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$log(Focal\_Plays^k_{ij-1})$	0.156***	0.154***	0.180***						
	(0.013)	(0.013)	(0.013)						
$log(Past\_Plays^k_{ij'-1})$				0.125***	0.122***	0.122***			
				(0.009)	(0.009)	(0.009)			
$log(FirstYr\_Plays^k_{ij'})$				0.712***	0.711***	0.711***			
				(0.008)	(0.008)	(0.008)			
$Rating^k_{ij-1}$							0.173***	0.174***	0.165***
							(0.007)	(0.007)	(0.007)
ΔX_{ij}	-11.017***	-6.243***	-5.987**	0.852*	-0.091	-0.720	15.461***	6.820	21.432***
	(2.292)	(2.224)	(2.828)	(0.484)	(0.559)	(0.905)	(5.373)	(5.278)	(6.955)
$Career\_Age_{ij}$	-0.01***			0.003**			-0.006		
	(0.003)			(0.001)			(0.008)		
$Career\_Age_{ij} \times \Delta X_{ij}$	0.004***			0.0001			-0.008		
	(0.001)			(0.0002)			(0.007)		
$Time\_Diff_{ij}$	0.0001	-0.0007	0.0004	0.005***	0.004***	0.005***	0.006	0.001	0.001
	(0.0009)	(0.001)	(0.0010)	(0.0002)	(0.0003)	(0.0002)	(0.007)	(0.008)	(0.007)
$Time\_Diff_{ij} \times \Delta X_{ij}$		0.026			0.006***			0.138	
		(0.023)			(0.002)			(0.138)	
$Past\Delta X_{ij}$			18.17***			-0.1			23.05**
			(6.939)			(3.341)			(9.423)
$Past\Delta X_{ij} \times \Delta X_{ij}$			53.48			25.44**			-224.7**
			(44.62)			(11.55)			(111.4)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$FixedEffects$									
$Artist-level$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Time-level$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,167	20,918	19,724	106,462	110,450	110,450	21,446	21,830	19,727
Log-Likelihood	-32,309.03	-32,876.55	-29,657.92	-57,353.81	-58,733.62	-58,734.67	-85,309.38	-86,831.94	-78,427.81
BIC	81,547.43	82,973.72	74,674.38	131,943.60	135,025.08	135,038.79	180,053.51	183,255.29	165,519.05
AIC	68034.08	69215.10	62421.84	117685.62	120491.26	120495.36	172510.780	175583.900	158607.637

Notes: Observations are at the Artist-album level. Controls include Big_Label_{ij}, $Album\_Num_{ij}$, and all the audio features represented in X_{ij}. Standard errors are shown in parentheses.
$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$.

Table 3: Moderating effect of time on the relationship between innovation and album performance.

innovation adds to the experienced utility of the reviewers. The thrill of not knowing whether a rock artist's new album is going to be Pop or Classical keeps critics on their toes and creates a buzz for the new album. To illustrate this effect, we can refer to Radiohead, a band that, up until the year 2000 with the albums 'Pablo Honey', 'The Bends' and 'OK Computer' was considered to belong to Progressive Rock. But with a dramatically different, Electronica-heavy follow-up in the form of 'Kid A', they surprised audiences for a first time. The next album 'Amnesiac' borrowed plenty from its predecessor, but its successors 'Half to the Thief' and 'In Rainbows' again took their music to previously uncharted territories. This inconsistency in Radiohead's rate of innovation could have been the main reason behind them being the favorites of the critics. Critics thus seem consistent in their satiation behavior: to appease them, artists should release music that is innovative and also show capacity to be flexible in the amount of innovation they employ in their new releases over time.

5.3 Robustness Checks

In addition to using Poisson distribution that renders similar results to that of the NBD models presented above, we provide here several additional robustness checks of our main model, including possible endogeneity of ΔX_{ij} and other structural forms for the reference update process.

As shown in Tereyağoğlu et al. (2018), references developed by the audiences may be endogenous which can potentially give inconsistent estimates and raise doubts over the validity of our interpretations. For example, the success of the last project, both in terms of the number of plays it garners over radios, $Plays_{ij}$, and the ratings it gets from the reviewers, $Ratings_{ij}$, could affect the rate of innovation that the artists choose to inculcate in their new albums. We check for this relation and find that neither of them significantly predict the variation in the innovation rate employed by the artist in the newly released album. As shown in Table 12, only the innovation of the last album, ΔX_{ij-1}, is significant and positively related to ΔX_{ij}, which we already account for while constructing our main variable of interest. This provides evidence for the exogeneity of ΔX_{ij}.

As stated in 3.3, we also consider Euclidean distances (as opposed to cosine similarity) to measure the deviation of the newly released albums by the music artists from their references. The results for which are given in Table 13 and show that they are in line with our main model.

In our main analysis, we allowed ΔX_{ij} to be built as a convex combination with $\theta \in [0, 1]$ as our memory factor. However, anchoring on the first and last observation has been shown to be salient in the literature (Nasiry and Popescu 2011, Aflaki and Popescu 2014, Haugtvedt et al. 2018). Along with these two considerations, we allow the references to be built as merely the arithmetic mean of the observed values (Martínez-de Albéniz et al. 2020). We provide the corresponding results in Tables 14, 15 and 16 which shows results consistent with our estimates in the main model.

Finally, the success levels of the albums may have an effect on what audiences remember. For example, a particularly successful album may be remembered more than the less successful ones contributing more towards the references that anchor based on performance levels. Hence, we allow for references to be built as follows.

$$R_{ij} = (\theta + \theta' Success_{ij-1})R_{ij-1} + (1 - \theta - \theta' Success_{ij-1})X_{ij-1}$$

where, $Success_{ij} = \frac{Plays_{ij-1}}{max\{Plays_{i1}, Plays_{i2}, \ldots, Plays_{ij-1}\}}$ takes values between 0 and 1. θ and θ' can be estimated by grid search again. Table 17 shows the results under this consideration, which are consistent with our main estimates, thereby validating our approach.

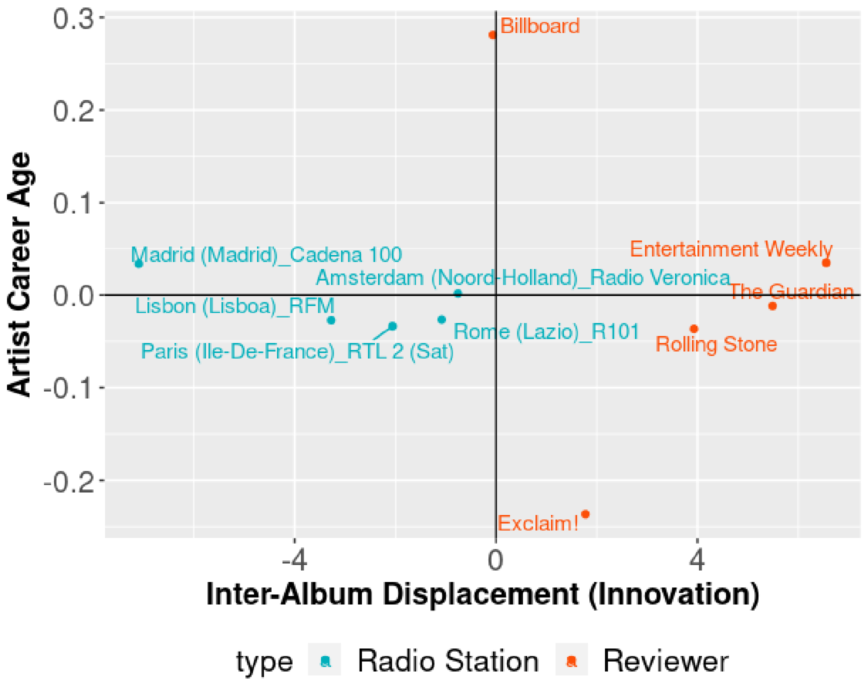


Figure 2: Moderating effect of artist career age.

6 Managerial Implications

The central purpose of this paper is to understand how references built by the audiences have an effect on the way newly released cultural products are perceived by them. This question directly informs the rates of innovation which the corresponding artists can employ in their NPD processes to cater to the expectations of these audiences so that their projects get critical and commercial success. This allows them to manage their artistic portfolio according to their personal objectives.

The findings from §5 are on an aggregate level, generalizing across the population of radio stations and reviewers. In this section, we adopt a more granular approach to track the preferences of the agents in these subclasses separately and to establish a taxonomy that helps in building innovation management strategies tailored to the preference structures of agents across different classifications.

For this, we first run our models for each radio station and reviewer separately and plot the corresponding estimates for $Career\_Age_{ij}$ and ΔX_{ij} in a graph as shown in Figure 2. In the graph, agents on the right side of the figure have positive estimates for increase in innovation, which implies that they react positively to deviations from past works. We classify these agents as Innovative Adopters. In contrast, agents on the left side are classified to be Repetitive Adopters due to their negative response to an increase in innovation. The agents at the top of the figure react positively to music from artists with higher career ages. We call such agents Tenured Adopters. The ones below, however, showcase the exact opposite preference by favoring music from newer artists. Hence, we term them as Rookie Adopters. Taken together, we see that *Entertainment Weekly* is a Tenured Innovative Adopter. Artists who intend to perform well with agents within this quadrant need to be considerably well established in the music industry and showcase high innovation rates in their new projects. In contrast, radio station *Madrid_(Madrid)_Cadena 100* is a Tenured Repetitive Adopter. These agents clearly prefer less innovative music from the superstars of the music industry. Hence, Nickelback would fare well on these radios. Radio station *Rome(Lazio)_R101*, however, is a Rookie Repetitive Adopter. This implies that the new artists can produce less innovative music and yet get positive responses from these agents. And lastly, *Rolling Stone* is a Rookie Innovative Adopter, who expect even the new artists to show high inter-album innovation rates.

Once we understand how individual agents respond to innovation, we illustrate how our framework can be utilized in the form of a counterfactual analysis for artists and record labels to make their NPD decisions. Consider for instance the last album released by the pop artist Rihanna in the year 2016 named 'ANTI'. Through our structural model, we can predict the responses of the radio stations and reviewers for variable ranges of innovation rates she may employ in her upcoming release. Accordingly, the follow-up project by Rihanna could be designed to be very similar to 'ANTI' with an innovation rate closer to 0. Alternatively, she may opt to innovate a lot by adopting higher innovation rates. Thus, we build 10,000 different and random combinations of the underlying 17 musical dimensions that generate 10,000 potential albums for Rihanna. Having identified the control variables, the resulting innovation rates based on her updated references, and setting the release time for the new album to December 2020, we estimate the predicted values of plays across radio stations and scores given by the reviewers for the newly designed album. To illustrate our findings, we plot the expected plays on radio stations and average ratings given by the reviewers in Figure 4. Note that the values are normalized for the ease of interpretation.

We see that Rihanna will, on average, benefit on radios by maintaining low levels of innovation rates, whereby the maximum plays are predicted to be achieved when the innovation rate for the new album is below 0.2 (recall that median innovation in our sample is 0.0248). On the other hand, she will get increasingly better responses from the reviewers for higher innovation rates in her upcoming project. We have carried out a similar analysis for all the artists in our dataset and see a similar trend across all the musical profiles.

To break down this analysis at the dimensional level, we present a heat map for the predicted responses from the radio stations (Figure 4a) and the reviewers (Figure 4b) across *Danceability* and *Energy* audio features of the new album. The heat map provides the predicted number of plays

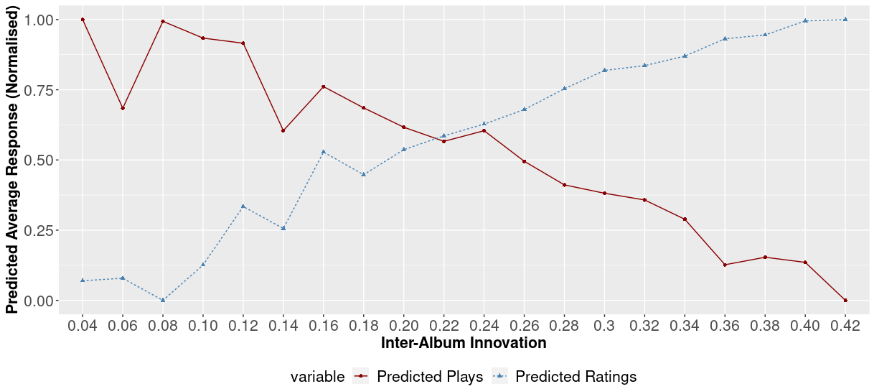
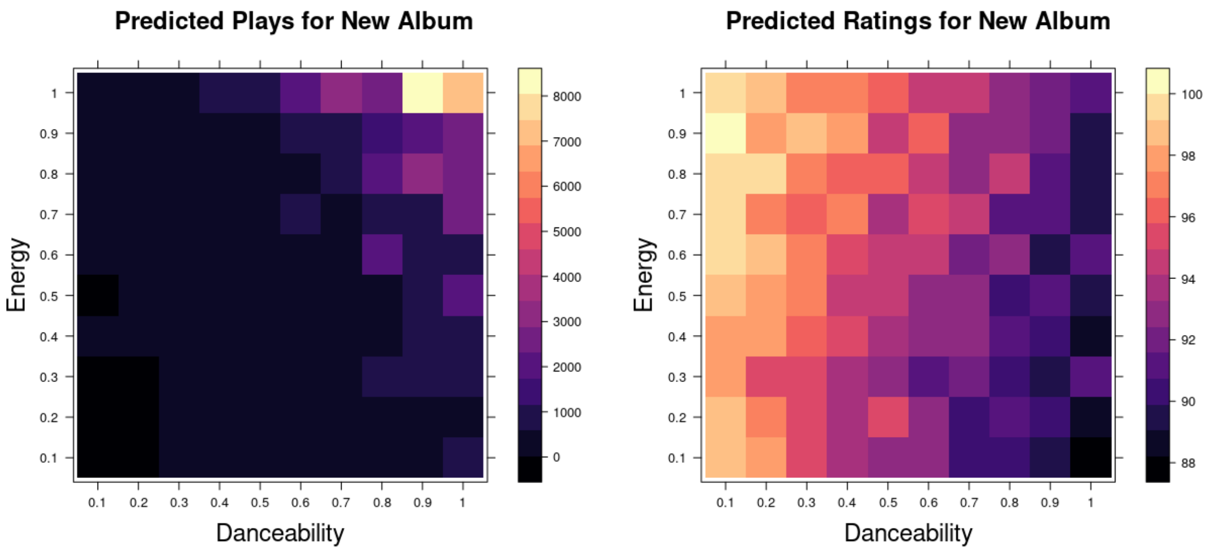


Figure 3: Predicted number of plays and reviewer ratings.

and ratings that the new album may garner for different combinations across these two dimensions. Note that there are 15 other dimensions that need to be considered in conjunction with these values to estimate the given predicted plays, which explains why the Figures do not show a smooth curve.



(a) Expected average plays across radio stations.

(b) Expected average ratings given by reviewers.

Figure 4: Expected response across *Danceability* and *Energy* for Rihanna's next album.

In summary, artists can use our framework to gauge the response from different factions of the audience for their newly released albums. Most importantly, music artists need to understand the implications of the trade-off between incremental and radical innovation on their careers while they make the decisions about their NPD projects. The differential in the preference structures of the different subclasses of the audiences shows that not everyone can be pleased with their new releases. Consequently, the music artists need to identify the faction of the audience they intend to target and accordingly tailor their new album to cater to their preferences. Hence, music artists can use the methodology introduced in this paper to manage their artistic portfolios while the record labels can base their album-designing decisions on these considerations.

7 Conclusion

Cultural products are highly experiential, and consumption patterns of the audiences depend on past experiences with similar products and in particular with the producer's past outputs. In our paper, we describe how hedonic adaptation can lead audiences to form expectations based on the previously consumed cultural products, which influences their interactions with new products released in the future. We develop a theoretical framework inspired by Kahneman and Tversky (1979)'s framework of reference effects, which contains the two fundamental behavioral constructs of habit formation (Becker and Murphy 1988) and satiation Baucells and Sarin (2007). We apply the model to study how audiences react to musical innovation of artists in comparison with past works, by combining three unique datasets that provide a granular representation of innovation employed in the music industry and the corresponding responses of the radio stations and reviewers.

We find that a median deviation of the musical attributes of the newly released album from the references that the audiences build for the corresponding artist causes the focal album's plays over radio stations to drop by 23.1% while the plays of the albums from the past rise by 13.8%; in contrast, reviewer scores for the new album increase by 14.9%. This provides evidence that radio stations behave according to habit formation: they become habituated to a certain kind of music from an artist and prefer consistency with past artistic positions, especially for new artists. However, critics display satiation and show appreciation for when the artists are innovative and venture into musical avenues formerly unexplored, especially if they have not been very innovative in the past.

Our model can also be applied at the agent level, which allows us to measure the response of individual radio stations and reviewers to innovation. We can thus establish a taxonomy to help formulate effective NPD strategies across the different classifications of these cultural intermediaries (Bourdieu 1986). The counterfactual analysis demonstrates the applicability of our framework in decision making for artists to manage their artistic portfolios and the record labels to design their new albums.

In comparison with previous works (Mauskapf et al. 2017, 2018, Berger and Packard 2018), our framework measures individual responses from specific agents, thus exposing the heterogeneity of audiences in how they perceive innovation. This opens up the possibility of more precisely evaluating the career trajectories of individual artists, by examining the responses to their artistic choices from two of the most important cultural intermediaries, radio stations and professional reviewers, which is an interesting question for future research. Our framework can be further applied to manage innovation in other cultural markets like the movies, books and artworks, conceived as a product/service design problem where the innovation degree must be decided. For example, Eliashberg et al. (2014) show how movie scripts can be used to predict box office sales, enabling timely interventions to make the movie more lucrative. Our framework, instead, could provide a more complete picture by incorporating the role of expectations put on the director, movie studio and actors, which are driven by their past works. Another example can be found in the product design decision of electronics companies, which are in the race for producing both ground-breaking and state-of-the-art goods, as well as more incremental updates of their existing models. While plenty of attention is given to how they can navigate this basic, and yet dilemmatic managerial decision (Chan et al. 2018), we can provide a new viewpoint that takes into consideration the position that producers have established in the technological space for themselves and the corresponding expectations that their consumers have about their subsequent products.

Our approach considers the innovation management problem for a single agent with the references formed at the individual level. For scenarios with collaborative production projects such as short-term collaborations in the music industry (as seen in Deshmane and Martínez-de Albéniz 2020) or the aforementioned example of movie production, where the consumers build separate expectations for every participating individual, our framework may prove to be inadequate but could naturally be extended to multi-dimensional reference spaces. Furthermore, one could also incorporate other external factors that may be important in setting expectations. For example, Lady Gaga featured as the lead in Bradley Cooper's 2018 movie 'A Star Is Born' while Kanye West ran an unsuccessful campaign for the US presidency in 2020. These extra-professional activities are bound to have had an effect on the way audiences perceive the subsequently released albums by these two artists which could be captured with an extended model. These extensions suggest that the framework developed in this paper can provide a flexible drawing board for future studies.

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Appendix

A Spotify: Audio Attributes

A.1 Song-Level Attributes

	Features	Scale	Definition
1	Danceability	0-1	Danceability 0-1 Describes how suitable a track is for dancing. This measure includes tempo, regularity of beat, and beat strength.
2	Energy	0-1	A perceptual measure of intensity throughout the track. Typically, energetic tracks feel fast, loud, and noisy like death metal.
3	Key	0-11	The estimated, overall key of the track, from C through B.
4	Loudness	-60-0 dB	The overall loudness of a track measured in decibels.
5	Mode	0 or 1	Whether the song is in minor (0) or major (1) key.
6	Speechiness	0-1	Detects the presence of spoken word throughout the track. Sung vocals are not considered spoken word.
7	Acousticness	0-1	Measure of the acoustic nature of the track (as opposed to more electronic/electric).
8	Instrumentalness	0-1	Measure of the absence of vocal content in the track.
9	Liveness	0-1	Detects the presence of the live audience during the recording. Higher the value, higher the probability that the track was recorded live.
10	Tempo	Beats per minute	The overall estimated tempo of a track.
11	Valence	0-1	The musical positiveness conveyed by the track. (High valence: Cheerful/Happy songs; Low Valence: Sad/Angry Songs)
12	Time Signature	Beats per bar	Estimated overall number of beats in a bar.

Definitions are taken from $SpotifyforDevelopers$ and Mauskapf et al. (2017)

Table 4: Song-level audio features.

A.2 Album-Level Attributes

	Features	Scale	Definition
1	Avg. Duration	ms	Average duration of songs in an album.
2	% Explicit		Proportion of songs containing explicit language in an album.
3	% Collaboration		Proportion of collaboration songs in an album.
4	# Tracks		Number of tracks in an album.

Table 5: Album-level audio features.

Album j \ Album j	Song 1	Song 2	...	Song S_{ij}
Song 1	-	-	...	-
Song 2	$\Delta SongDist_{ij}^{2,1}$	-	...	-
...	...	...	...	...
Song S_{ij}	$\Delta SongDist_{ij}^{S_{ij},1}$	$\Delta SongDist_{ij}^{S_{ij},2}$	...	-

Table 6: Intra-album Song Level Deviation

A.3 Intra-Album Diversity

To capture the measure of intra-album diversity, we estimate the deviation in the musical attributes of each song on an album with respect to every other song on the same album.

Hence, the deviation between the musical attributes between songs on the same album are calculated to get $\Delta SongDist_{ij}^{s_{ij},s'_{ij}}$ as shown in Table 6.

$$\Delta SongDist_{ij}^{s_{ij},s'_{ij}} = 1 - \frac{< \ a_{ij}^{s_{ij}} \ , \ a_{ij}^{s'_{ij}} >}{||a_{ij}^{s_{ij}}|| \times ||a_{ij}^{s'_{ij}}||}, where \ s_{ij} \neq s'_{ij}, and$$

$a_{ij}^{s_{ij}}$ is a musical attribute from Appendix A of song s_{ij} on album j by artist i. We then get a mean of these deviations for each of the albums to get the intra-album diversity as follows.

$$A_{ij} = \left(\frac{1}{S_{ij}[(S_{ij}-1)!-1]} \sum_{s_{ij}=1}^{s_{ij}=S_{ij}} \Delta SongDist_{ij}^{s_{ij},s'_{ij}} \right).$$

B Observation in the BMAT Dataset

Variable	Value	Variable	Value
Date	30/04/17	Track	Me Enamore
Time	17:24:52	Artist	Shakira
Duration	00:03:51	Label	Sony Music Entertainment
Channel	Cadena 100	Isrc	USSD11700088
Country	Spain	BMATID	53ff1a70-62c5-496e-9475-c0d24f568e11
City	Madrid (Madrid)	Album	

Table 7: Sample observation in the BMAT dataset.

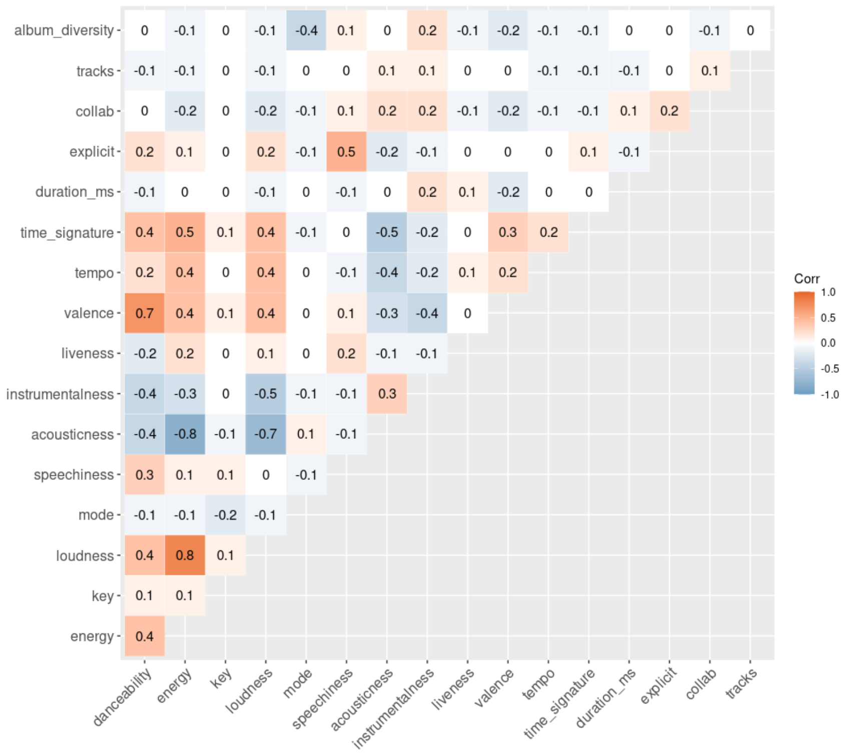

Figure 5: Correlation between the audio features.

C Results

C.1 Focal Plays

	Focal Plays							
	1	2	3	4	5	6	7	8
$log(Focal\_Plays^{k}_{ij-1})$	0.152***	0.155***	0.154***	0.154***	0.155***	0.154***	0.180***	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	
Big_Label_{ij}	0.623***	0.615***	0.597***	0.599***	0.592***	0.594***	0.617***	0.249**
	(0.126)	(0.126)	(0.126)	(0.126)	(0.132)	(0.126)	(0.130)	(0.119)
$Album\_Num_{ij}$	0.026**	0.026**	0.026**	0.026**	0.028**	0.026**	0.030***	0.015
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.013)
$Time\_Diff_{ij}$	0.0002	0.0003	0.0003	0.0003	0.0001	−0.0007	0.0004	0.002**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.001)	(0.0010)	(0.0009)
$Career\_Age_{ij}$					−0.011***			
					(0.199)			
$Danceability_{ij}$	3.680***	3.747***	3.608***	3.606***	3.832***	3.674***	3.384***	2.840***
	(0.750)	(0.743)	(0.743)	(0.744)	(0.760)	(0.745)	(0.771)	(0.685)
$Energy_{ij}$	2.376**	2.338**	2.232**	2.242**	2.586**	2.282**	2.066**	2.962***
	(1.002)	(0.994)	(0.993)	(0.994)	(1.023)	(0.993)	(1.033)	(0.937)
Key_{ij}	−0.3	−0.3	−0.2	−0.2	−0.137	−0.2	−0.1	0.516
	(0.471)	(0.469)	(0.467)	(0.468)	(0.482)	(0.468)	(0.489)	(0.436)
$Loudness_{ij}$	−0.2	−0.6	−0.7	−0.7	−1.23	−0.7	−0.8	−1
	(1.697)	(1.694)	(1.691)	(1.693)	(1.731)	(1.691)	(1.759)	(1.694)
$Mode_{ij}$	0.131	0.035	−0.04	−0.04	0.246	−0.05	−0.1	0.280
	(0.328)	(0.329)	(0.331)	(0.331)	(0.330)	(0.332)	(0.342)	(0.321)
$Speechiness_{ij}$	−5.8***	−5.76***	−5.75***	−5.8***	−6.515***	−5.66***	−6.89***	−4.66***
	(1.070)	(1.064)	(1.078)	(1.080)	(1.045)	(1.080)	(1.102)	(0.929)
$Acousticness_{ij}$	−0.3	−0.4	−0.5	−0.4	−0.3	−0.4	−0.5	0.022
	(0.482)	(0.479)	(0.480)	(0.481)	(0.496)	(0.480)	(0.497)	(0.436)
$Instrumentalness_{ij}$	−0.5	−0.5	−0.4	−0.4	−0.4	−0.4	−0.4	−2***
	(0.492)	(0.491)	(0.489)	(0.494)	(0.492)	(0.489)	(0.504)	(0.447)
$Liveness_{ij}$	−0.98***	−0.88**	−0.87**	−0.86**	−0.69*	−0.78**	−0.69	−0.98***
	(0.379)	(0.390)	(0.389)	(0.392)	(0.405)	(0.388)	(0.400)	(0.357)
$Valence_{ij}$	−0.95*	−1.96**	−0.96**	−0.94**	−1.292*	−1.98**	−1.02	−0.94
	(0.700)	(0.701)	(0.697)	(0.699)	(0.713)	(0.698)	(0.727)	(0.601)
$Tempo_{ij}$	1.495*	1.572*	1.512*	1.511*	1.472	1.554*	1.803*	0.892
	(0.904)	(0.901)	(0.906)	(0.907)	(0.932)	(0.908)	(0.938)	(0.840)
$Time\_Signature_{ij}$	0.229	−0.2	−0.2	−0.2	−0.908	−0.2	−0.03	−1
	(1.337)	(1.338)	(1.335)	(1.341)	(1.373)	(1.334)	(1.366)	(1.237)
$Duration_{ij}$	4.489	3.825	3.612	3.599	3.538	3.848	4.757	−5
	(5.376)	(5.354)	(5.347)	(5.348)	(5.477)	(5.348)	(5.473)	(4.986)
$Explicit_{ij}$	0.210	0.194	0.252	0.262	0.307	0.248	0.389	0.095
	(0.375)	(0.371)	(0.368)	(0.368)	(0.359)	(0.370)	(0.382)	(0.306)
$Collab_{ij}$	0.110	0.277	0.457**	0.450**	0.276	0.463**	0.514**	−0.006
	(0.185)	(0.194)	(0.211)	(0.212)	(0.224)	(0.212)	(0.220)	(0.201)
$Tracks_{ij}$	3.259**	3.084*	2.842*	2.842*	3.109*	2.903*	2.635	1.162
	(1.641)	(1.617)	(1.614)	(1.615)	(1.646)	(1.613)	(1.628)	(1.511)
$Album\_Diversity_{ij}$	7.434***	6.745***	6.189***	6.192***	6.505***	6.140***	5.837***	5.566***
	(1.474)	(1.483)	(1.512)	(1.513)	(1.546)	(1.512)	(1.578)	(1.486)
$Quart\Delta X_{ij}$		−0.2***						
		(0.058)						
ΔX_{ij}			−5.77***	−5	−11.012***	−6.87***	−5.77**	−0.9
			(1.692)	(2.918)	(2.29)	(2.224)	(2.828)	(1.535)
$(\Delta X_{ij})^2$				−5.68				
				(12.18)				
$Career\_Age_{ij} \times \Delta X_{ij}$					0.004***			
					(0.001)			
$Time\_Diff_{ij} \times \Delta X_{ij}$						0.026		
						(0.023)		
$Past\Delta X_{ij}$							18.17***	
							(6.939)	
$Past\Delta X_{ij} \times \Delta X_{ij}$							53.48	
							(44.62)	
$Overdispersion$	0.0873	0.0874	0.0874	0.0874	0.0874	0.0874	0.0862	0.3196
Fixed Effects								
$Artist_i$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
$Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Artist\_Station^{k}_{i}$	No	No	No	No	No	No	No	Yes
Fit statistics								
Observations	20,918	20,918	20,918	20,918	20,918	20,918	19,724	20,918
Adj-pseudo R^2	0.05436	0.05443	0.05449	0.05446	0.05223	0.05448	0.05863	0.06795
Log-Likelihood	−32,882.88	−32,879.03	−32,877.17	−32,877.05	−32,870.00	−32,876.55	−29,657.92	−25,615.18
BIC	82,966.48	82,968.75	82,965.02	82,974.74	82,970.58	82,973.72	74,674.38	135,781.51
AIC	69223.77	69218.08	69214.36	69216.12	68034.08	69215.10	62421.84	68228.36

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Standard Errors in parentheses.

Table 8: Effect of Inter-Album Displacement on Focal Album Plays

C.2 Past Plays

	Past Plays							
	1	2	3	4	5	6	7	8
$log(Past\_Plays^{k}_{ij'-1})$	0.123***	0.122***	0.122***	0.122***	0.125***	0.122***	0.122***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	
$log(FirstYr\_Plays^{k}_{ij'})$	0.711***	0.711***	0.711***	0.711***	0.712***	0.711***	0.711***	
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	
$log(FirstYr\_Plays_{ij'})$								0.4123***
								(0.0057)
Big_Label_{ij}	1.785***	1.784***	1.791***	1.786***	1.797***	1.790***	1.799***	1.229***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.035)
$Album\_Num_{ij}$	0.025***	0.025***	0.025***	0.025***	0.026***	0.025***	0.025***	−0.05***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.0007)
$Time\_Diff_{ij}$	0.005***	0.005***	0.005***	0.005***	0.005***	0.004***	0.005***	−0.003***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0001)
$Career\_Age_{ij}$					0.003**			
					(0.001)			
$Danceability_{ij}$	2.000***	2.018***	2.045***	1.996***	2.226***	2.046***	2.080***	0.149
	(0.277)	(0.277)	(0.277)	(0.278)	(0.282)	(0.278)	(0.278)	(0.195)
$Energy_{ij}$	0.920***	0.943***	0.918***	0.951***	0.785**	0.962***	0.911**	−2***
	(0.356)	(0.356)	(0.356)	(0.356)	(0.362)	(0.357)	(0.356)	(0.272)
Key_{ij}	0.738***	0.709***	0.730***	0.699***	0.685***	0.728***	0.741***	1.139***
	(0.184)	(0.184)	(0.184)	(0.184)	(0.187)	(0.184)	(0.184)	(0.158)
$Loudness_{ij}$	0.770	0.687	0.703	0.675	0.760	0.584	0.687	4.293***
	(0.503)	(0.503)	(0.503)	(0.504)	(0.510)	(0.506)	(0.504)	(0.446)
$Mode_{ij}$	0.208*	0.186	0.187	0.192	0.080	0.204	0.194	0.324***
	(0.125)	(0.125)	(0.125)	(0.125)	(0.126)	(0.125)	(0.125)	(0.100)
$Speechiness_{ij}$	1.663***	1.664***	1.693***	1.664***	1.863***	1.703***	1.719***	−2***
	(0.265)	(0.264)	(0.265)	(0.265)	(0.272)	(0.265)	(0.265)	(0.181)
$Acousticness_{ij}$	−0.7***	−0.7***	−0.7***	−0.7***	−0.7***	−0.7***	−0.7***	−0.9***
	(0.168)	(0.168)	(0.168)	(0.168)	(0.170)	(0.168)	(0.168)	(0.130)
$Instrumentalness_{ij}$	0.060	0.068	0.077	0.060	0.094	0.082	0.087	−0.9***
	(0.151)	(0.151)	(0.151)	(0.151)	(0.153)	(0.151)	(0.151)	(0.097)
$Liveness_{ij}$	0.376**	0.376**	0.380**	0.374**	0.431***	0.376**	0.382***	0.058
	(0.148)	(0.148)	(0.148)	(0.148)	(0.151)	(0.148)	(0.148)	(0.103)
$Valence_{ij}$	−0.98***	−0.98***	−0.97***	−0.96***	−0.96***	−0.95***	−0.95***	0.324*
	(0.258)	(0.258)	(0.258)	(0.259)	(0.263)	(0.259)	(0.259)	(0.168)
$Tempo_{ij}$	−0.98***	−0.98***	−0.97***	−0.96***	−0.76*	−0.95***	−0.94***	−0.08
	(0.371)	(0.371)	(0.371)	(0.371)	(0.378)	(0.371)	(0.371)	(0.296)
$Time\_Signature_{ij}$	−1.96***	−1.95***	−1.94***	−1.95***	−2.98***	−1.98***	−1.99***	−0.14
	(0.401)	(0.401)	(0.402)	(0.402)	(0.410)	(0.403)	(0.403)	(0.363)
$Duration_{ij}$	1.021	1.108	1.058	1.080	2.546*	0.996	1.032	−3**
	(1.370)	(1.365)	(1.362)	(1.367)	(1.427)	(1.368)	(1.358)	(1.038)
$Explicit_{ij}$	−0.2	−0.2	−0.2	−0.2	−0.3	−0.2	−0.3	−0.6***
	(0.182)	(0.181)	(0.181)	(0.181)	(0.181)	(0.181)	(0.181)	(0.090)
$Collab_{ij}$	0.227***	0.230***	0.239***	0.229***	0.306***	0.251***	0.244***	−0.8***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.064)	(0.062)	(0.062)	(0.051)
$Tracks_{ij}$	−0.4	−0.3	−0.2	−0.3	−1	−0.2	−0.2	2.942***
	(0.954)	(0.953)	(0.955)	(0.955)	(0.985)	(0.959)	(0.954)	(0.918)
$Album\_Diversity_{ij}$	0.683	0.597	0.588	0.635	0.899	0.657	0.601	1.468***
	(0.585)	(0.585)	(0.585)	(0.585)	(0.598)	(0.585)	(0.585)	(0.449)
$Quart\Delta X_{ij}$		0.069***						
		(0.017)						
ΔX_{ij}			1.174***	3.000***	0.852*	−0.09	−0.7	0.677**
			(0.308)	(0.764)	(0.484)	(0.559)	(0.905)	(0.263)
$(\Delta X_{ij})^2$				−7.87***				
				(3.160)				
$Career\_Age_{ij} \times \Delta X_{ij}$					0.0001			
					(0.0002)			
$Time\_Diff_{ij} \times \Delta X_{ij}$						0.006***		
						(0.002)		
$Past\Delta X_{ij}$							−0.1	
							(3.341)	
$Past\Delta X_{ij} \times \Delta X_{ij}$							25.44**	
							(11.55)	
$Overdispersion$	0.0977	0.0978	0.0977	0.0978	0.0972	0.0978	0.0978	0.0588
Fixed Effects								
$Artist_i$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
$Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Artist\_Station^{k}_{i}$	No	No	No	No	No	No	No	Yes
Fit statistics								
Observations	110,450	110,450	110,450	110,450	106,462	110,450	110,450	110,450
Adj-pseudo R^2	0.28866	0.28875	0.28874	0.28876	0.28547	0.28877	0.28874	0.15025
Log-Likelihood	−58,744.50	−58,736.36	−58,737.26	−58,733.85	−57,353.81	−58,733.62	−58,734.67	−71,860.12
BIC	135,023.61	135,018.93	135,020.74	135,025.52	131,943.60	135,025.08	135,038.79	145,102.12
AIC	120509.0	120494.7	120496.5	120491.7	117685.6	120491.3	120495.4	143958.3

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Standard Errors in parentheses.

Table 9: Effect of Inter-Album Displacement on Past Album Plays

C.3 Gini Index

	Gini Index							
	1	2	3	4	5	6	7	8
$Gini\_Index^k_{ij-1}$	-0.2^{***}	-0.2^{***}	-0.2^{***}	-0.2^{***}	-0.2^{***}	-0.2^{***}		-0.2^{***}
	(0.0312)	(0.0312)	(0.0312)	(0.0313)	(0.0312)	(0.0312)		(0.0335)
Big_Label_{ij}	0.0144^{***}	0.0141^{***}	0.0144^{***}	0.0143^{***}	0.0137^{***}	0.0145^{***}	0.0041^{***}	0.0164^{***}
	(0.0049)	(0.0048)	(0.0049)	(0.0049)	(0.0049)	(0.0048)	(0.0016)	(0.0052)
$Album\_Num_{ij}$	0.0039^{***}	0.0035^{**}	0.0039^{***}	0.0039^{***}	0.0040^{***}	0.0003	0.0008^{*}	0.0035^{**}
	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0009)	(0.0004)	(0.0015)
$Time\_Diff_{ij}$	0.00004	0.00004	0.00004	0.00004	0.00003	0.00005	0.00004^{***}	0.00006^{*}
	(0.00003)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00006)	(0.00004)
$Career\_Age_{ij}$					0.0001			
					(0.0001)			
$Danceability_{ij}$	0.0614^{**}	0.0656^{**}	0.0616^{**}	0.0612^{**}	0.0586^{**}	0.0570^{**}	-0.003	0.0745^{**}
	(0.0273)	(0.0273)	(0.0273)	(0.0273)	(0.0274)	(0.0272)	(0.0091)	(0.0297)
$Energy_{ij}$	0.0885^{**}	0.0892^{**}	0.0884^{**}	0.0868^{**}	0.0773^{**}	0.0901^{**}	0.0410^{***}	0.0832^{**}
	(0.0363)	(0.0363)	(0.0363)	(0.0364)	(0.0364)	(0.0362)	(0.0113)	(0.0382)
Key_{ij}	0.0418^{***}	0.0402^{**}	0.0418^{***}	0.0411^{***}	0.0412^{***}	0.0392^{**}	0.0093^{*}	0.0382^{**}
	(0.0159)	(0.0158)	(0.0159)	(0.0159)	(0.0158)	(0.0157)	(0.0050)	(0.0171)
$Loudness_{ij}$	-0.2^{***}	-0.2^{***}	-0.2^{**}	-0.2^{**}	-0.2^{***}	-0.2^{***}	-0.05^{**}	-0.2^{**}
	(0.0739)	(0.0743)	(0.0750)	(0.0753)	(0.0754)	(0.0748)	(0.0222)	(0.0792)
$Mode_{ij}$	0.0409^{***}	0.0382^{***}	0.0407^{***}	0.0399^{***}	0.0410^{***}	0.0414^{***}	0.0064^{*}	0.0565^{***}
	(0.0112)	(0.0112)	(0.0113)	(0.0114)	(0.0114)	(0.0114)	(0.0035)	(0.0124)
$Speechiness_{ij}$	0.0313	0.0374	0.0329	0.0241	0.0376	0.0275	0.0107	0.0687
	(0.0411)	(0.0412)	(0.0426)	(0.0451)	(0.0424)	(0.0434)	(0.0121)	(0.0462)
$Acousticness_{ij}$	0.0631^{***}	0.0625^{***}	0.0628^{***}	0.0636^{***}	0.0524^{***}	0.0597^{***}	0.0280^{***}	0.0737^{***}
	(0.0166)	(0.0166)	(0.0168)	(0.0168)	(0.0171)	(0.0168)	(0.0054)	(0.0179)
$Instrumentalness_{ij}$	0.0152	0.0169	0.0154	0.0158	0.0180	0.0105	0.0106^{**}	0.0301^{*}
	(0.0156)	(0.0156)	(0.0157)	(0.0158)	(0.0158)	(0.0157)	(0.0053)	(0.0168)
$Liveness_{ij}$	0.0356^{***}	0.0447^{***}	0.0361^{**}	0.0383^{***}	0.0362^{**}	0.0371^{***}	0.0437^{***}	0.0384^{**}
	(0.0137)	(0.0143)	(0.0141)	(0.0146)	(0.0143)	(0.0141)	(0.0043)	(0.0151)
$Valence_{ij}$	-0.01	-0.01	-0.01	-0.009	-0.010	-0.007	-0.008	0.0048
	(0.0230)	(0.0230)	(0.0230)	(0.0231)	(0.0230)	(0.0229)	(0.0073)	(0.0256)
$Tempo_{ij}$	0.0405	0.0341	0.0398	0.0412	0.0411	0.0425	-0.03^{***}	0.0305
	(0.0290)	(0.0291)	(0.0294)	(0.0295)	(0.0297)	(0.0295)	(0.0101)	(0.0311)
$Time\_Signature_{ij}$	0.0229	0.0145	0.0224	0.0258	0.0407	0.0144	0.0164	0.0937^{**}
	(0.0433)	(0.0434)	(0.0435)	(0.0439)	(0.0441)	(0.0437)	(0.0141)	(0.0461)
$Duration_{ij}$	-0.05	-0.05	-0.05	-0.05	-0.1	-0.10	-0.3^{***}	0.1086
	(0.2070)	(0.2067)	(0.2070)	(0.2070)	(0.2088)	(0.2071)	(0.0617)	(0.2273)
$Explicit_{ij}$	-0.03^{***}	-0.03^{**}	-0.03^{***}	-0.03^{***}	-0.03^{**}	-0.03^{**}	-0.008^{*}	-0.03^{**}
	(0.0126)	(0.0126)	(0.0126)	(0.0127)	(0.0126)	(0.0125)	(0.0039)	(0.0151)
$Collab_{ij}$	0.0086	0.0135^{*}	0.0093	0.0089	0.0126	0.0070	0.0059^{**}	0.0062
	(0.0067)	(0.0071)	(0.0080)	(0.0080)	(0.0082)	(0.0080)	(0.0026)	(0.0086)
$Tracks_{ij}$	1.1327^{***}	1.0982^{***}	1.1308^{***}	1.1249^{***}	1.1128^{***}	1.1069^{***}	0.4270^{***}	1.1214^{***}
	(0.1025)	(0.1035)	(0.1033)	(0.1038)	(0.1035)	(0.1030)	(0.0241)	(0.1069)
$Album\_Diversity_{ij}$	0.2158^{***}	0.1915^{***}	0.2132^{***}	0.2099^{***}	0.1856^{***}	0.2294^{***}	0.0919^{***}	0.2923^{***}
	(0.0543)	(0.0553)	(0.0570)	(0.0573)	(0.0574)	(0.0574)	(0.0177)	(0.0614)
$Quart\Delta X_{ij}$		-0.005^{**}						
		(0.0021)						
ΔX_{ij}			-0.009	-0.07	0.1556^{**}	0.0562	-0.06^{***}	0.0354
			(0.0630)	(0.1218)	(0.0771)	(0.0822)	(0.0187)	(0.1197)
$(\Delta X_{ij})^2$				0.3808				
				(0.6312)				
$Career\_Age_{ij} \times \Delta X_{ij}$				-0.0003^{***}				
					(0.00007)			
$Time\_Diff_{ij} \times \Delta X_{ij}$						-0.0007		
						(0.0007)		
$Past\Delta X_{ij}$								-0.6^{**}
								(0.2587)
$Past\Delta X_{ij} : \Delta X_{ij}$								-2
								(1.8796)
Fixed Effects								
$Artist_i$	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*No*
$Year$	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
$Artist\_Station^k_i$	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*
Fit statistics								
Observations	1,398	1,398	1,398	1,398	1,387	1,398	7,334	1,246
Adj-pseudo R^2	0.03461	0.03393	0.0351	0.0355	0.03469	0.03565	-0.05472	0.0359
Log-Likelihood	2,813.55	2,815.95	2,813.56	2,813.74	2,798.29	2,804.42	18,484.59	2,495.86
BIC	435.12	437.55	442.34	449.22	444.55	402.68	15,088.51	318.40
AIC	-3953.102	-3955.915	-3951.123	-3949.487	-3926.586	-3948.841	-25271.198	-3501.727

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Standard Errors in parentheses.

Table 10: Effect of Inter-Album Displacement on Focal Album Gini Index

C.4 Ratings

	Ratings 1	2	3	4	5	6	7	8
$Rating^k_{ij-1}$	0.1747***	0.1743***	0.1744***	0.1744***	0.1735***	0.1744***	0.1649***	
	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0066)	(0.0065)	(0.0068)	
Big_Label_{ij}	0.2406	0.2690	0.2803	0.2819	0.3205	0.2750	0.4739	0.4163*
	(0.2887)	(0.2888)	(0.2890)	(0.2890)	(0.2940)	(0.2890)	(0.3053)	(0.2275)
$Album\_Num_{ij}$	0.1003	0.0925	0.0901	0.0893	0.1111*	0.0901	0.0551	0.0991*
	(0.0615)	(0.0615)	(0.0616)	(0.0616)	(0.0628)	(0.0616)	(0.0634)	(0.0517)
$Time\_Diff_{ij}$	0.0071	0.0073	0.0068	0.0068	0.0062	0.0013	0.0012	0.0091*
	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0065)	(0.0084)	(0.0071)	(0.0053)
$Career\_Age_{ij}$					−0.006			
					(0.0077)			
$Danceability_{ij}$	−9.87***	−9.88***	−8.98***	−8.92***	−9.91***	−8.98***	−7.88***	−12.310***
	(1.7508)	(1.7506)	(1.7609)	(1.7639)	(1.7907)	(1.7613)	(1.9059)	(1.3837)
$Energy_{ij}$	3.6269*	3.7918*	4.1208*	4.1232*	3.9574*	3.9808*	0.8314	3.3450*
	(2.1660)	(2.1666)	(2.1729)	(2.1729)	(2.2033)	(2.1773)	(2.3405)	(1.7116)
Key_{ij}	−0.3	−0.3	−0.2	−0.2	−0.07	−0.2	−0.2	−0.5
	(0.8943)	(0.8942)	(0.8946)	(0.8994)	(0.9070)	(0.8948)	(0.9592)	(0.6983)
$Loudness_{ij}$	−3.95	−3.94	−3.84	−3.86	−3.87	−3.89	−0.95	−2.88
	(4.8319)	(4.8312)	(4.8334)	(4.8549)	(4.9117)	(4.8337)	(5.0630)	(3.8175)
$Mode_{ij}$	−0.5	−0.4	−0.2	−0.2	−0.07	−0.3	−0.1	−0.4
	(0.6451)	(0.6482)	(0.6536)	(0.6537)	(0.6711)	(0.6553)	(0.6887)	(0.5152)
$Speechiness_{ij}$	4.9992**	4.5374*	3.6259	3.7162	3.4616	3.4294	2.9360	7.2761***
	(2.3164)	(2.3223)	(2.3680)	(2.3877)	(2.3768)	(2.3760)	(2.4681)	(1.8850)
$Acousticness_{ij}$	0.8842	0.8221	0.9224	0.9179	1.1911	0.9022	0.0705	−0.8
	(1.0986)	(1.0986)	(1.0984)	(1.0986)	(1.1130)	(1.0986)	(1.1638)	(0.8606)
$Instrumentalness_{ij}$	4.0958***	3.8958***	3.5983***	3.6006***	4.0065***	3.6583***	3.2666***	4.2698***
	(0.9632)	(0.9659)	(0.9795)	(0.9795)	(1.0170)	(0.9813)	(1.0266)	(0.7724)
$Liveness_{ij}$	−2.98*	−2.98*	−2.97*	−2.96*	−2.96*	−2.94*	−0.65	−1.96
	(1.6958)	(1.6973)	(1.6956)	(1.6994)	(1.7492)	(1.6969)	(1.8077)	(1.3247)
$Valence_{ij}$	3.2041**	3.3506**	3.1005**	3.1394**	3.2326**	3.2203**	2.9536**	3.7431***
	(1.3461)	(1.3470)	(1.3463)	(1.3528)	(1.3718)	(1.3516)	(1.4195)	(1.0517)
$Tempo_{ij}$	4.4576***	4.5777***	4.8560***	4.8179***	4.5576***	4.8691***	5.6553***	4.0579***
	(1.7234)	(1.7237)	(1.7291)	(1.7339)	(1.7623)	(1.7291)	(1.8324)	(1.3607)
$Time\_Signature_{ij}$	−2.95	−3.95	−2.94	−2.99	−3.94*	−2.98	−4.93*	−3.94**
	(2.3917)	(2.3926)	(2.3914)	(2.3960)	(2.4583)	(2.3929)	(2.5639)	(1.8730)
$Duration_{ij}$	8.7165	8.0286	7.7124	7.6390	7.3518	7.6439	8.7171	2.6374
	(5.3865)	(5.3916)	(5.3976)	(5.4033)	(5.4193)	(5.3979)	(5.4661)	(4.0020)
$Explicit_{ij}$	−0.5	−0.5	−0.4	−0.4	−0.3	−0.4	−0.2	−0.4
	(0.5802)	(0.5801)	(0.5809)	(0.5813)	(0.5820)	(0.5809)	(0.6145)	(0.4478)
$Collab_{ij}$	−1.98***	−1.97***	−2.98***	−2.97***	−1.97***	−1.98***	−2.98***	−1.97***
	(0.7185)	(0.7266)	(0.7490)	(0.7492)	(0.7622)	(0.7491)	(0.7857)	(0.5886)
$Tracks_{ij}$	14.960	19.885	24.353	24.040	26.831	23.561	17.063	30.445*
	(20.798)	(20.875)	(21.066)	(21.093)	(21.202)	(21.081)	(22.182)	(16.553)
$Album\_Diversity_{ij}$	−3.98	−3.97	−1.97	−2.97	−4.98	−2.97	−1.98	−1.98
	(3.8239)	(3.8248)	(3.8634)	(3.8682)	(3.9591)	(3.8696)	(4.1045)	(3.0454)
$Quart\Delta X_{ij}$		0.3544***						
		(0.1319)						
ΔX_{ij}			10.520***	12.719	15.457***	6.8202	21.435***	10.570***
			(3.7832)	(8.3580)	(5.3731)	(5.2778)	(6.9554)	(2.9634)
$(\Delta X_{ij})^2$				−12.414				
				(42.069)				
$Career\_Age_{ij} \times \Delta X_{ij}$					−0.008			
					(0.0065)			
$Time\_Diff_{ij} \times \Delta X_{ij}$						0.1385		
						(0.1378)		
$Past\Delta X_{ij}$							23.047**	
							(9.4228)	
$Past\Delta X_{ij} \times \Delta X_{ij}$							−224.71**	
							(111.36)	
Fixed Effects								
$Artist_i$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
$Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Artist\_Station^k_i$	No	No	No	No	No	No	No	Yes
Fit statistics								
Observations	21,830	21,830	21,830	21,830	21,446	21,830	19,727	21,830
Adj-pseudo R^2	0.02791	0.02794	0.02794	0.02793	0.02799	0.02793	0.02777	0.01063
Log-Likelihood	−86,836.32	−86,832.70	−86,832.45	−86,832.41	−85,309.38	−86,831.94	−78,427.81	−78,162.73
BIC	183,244.05	183,246.82	183,246.31	183,256.22	180,053.51	183,255.29	165,519.05	268,145.19
AIC	175588.6	175583.4	175582.9	175584.8	172510.8	175583.9	158607.6	178709.5

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Standard Errors in parentheses.

Table 11: Effect of Inter-Album Displacement on Focal Album Ratings

D Robustness Checks

D.1 Endogeneity Test

	ΔX_{ij}	
	1	2
ΔX_{ij-1}	0.301***	−0.148
	(0.052)	(0.102)
$Plays_{ij-1}$	−0.00001	0.00003
	(0.00001)	(0.00002)
$Ratings_{ij-1}$	0.0001	−0.0003
	(0.0002)	(0.0004)
$Intercept$	0.032*	
	(0.0148)	
$FixedEffects$		
$Artist-level$	No	Yes
$Time-level$	No	Yes
Observations	766	766
Adj R^2	0.041	0.013

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$;
Standard Errors in parentheses.

Table 12: Effect of Inter-Album Displacement on Focal Album Ratings

D.2 Deviation from References as Euclidean Distances

	Focal Plays 1	Past Plays 2	Gini Index 3	Ratings 4
$log(Focal\_Plays^k_{ij-1})$	0.154***			
	(0.013)			
$log(Past\_Plays^k_{ij'-1})$		0.125***		
		(0.009)		
$log(FirstYr\_Plays^k_{ij'})$		0.717***		
		(0.008)		
$Gini\_Index^k_{ij-1}$			−0.2***	
			(0.031)	
$Rating^k_{ij-1}$				0.173***
				(0.007)
Big_Label_{ij}	0.667***	1.773***	0.014***	0.305
	(0.126)	(0.039)	(0.005)	(0.287)
$Album\_Num_{ij}$	0.027**	0.025***	0.004***	0.107*
	(0.011)	(0.002)	(0.001)	(0.061)
$Time\_Diff_{ij}$	0.0005	0.005***		0.007
	(0.0009)	(0.0002)		(0.006)
$Danceability_{ij}$	3.466***	2.007***	0.062**	−9.962***
	(0.741)	(0.277)	(0.027)	(1.751)
$Energy_{ij}$	3.762***	0.880**	0.086**	3.887*
	(0.987)	(0.355)	(0.036)	(2.164)
Key_{ij}	−0.10	0.729***	0.041***	−0.402
	(0.470)	(0.184)	(0.016)	(0.894)
$Loudness_{ij}$	−1.987	0.699	−0.201***	−5.022
	(1.689)	(0.503)	(0.075)	(4.822)
$Mode_{ij}$	0.070	0.190	0.040***	−0.603
	(0.328)	(0.124)	(0.011)	(0.644)
$Speechiness_{ij}$	−5.963***	1.647***	0.033	3.844
	(1.084)	(0.263)	(0.041)	(2.339)
$Acousticness_{ij}$	0.010	−0.8***	0.061***	0.838
	(0.482)	(0.167)	(0.017)	(1.095)
$Instrumentalness_{ij}$	−0.020	0.052	0.017	3.404***
	(0.490)	(0.150)	(0.016)	(0.979)
$Liveness_{ij}$	−0.801**	0.383***	0.040***	−2.986*
	(0.394)	(0.148)	(0.014)	(1.695)
$Valence_{ij}$	−1.987***	−1.022***	−0.008	3.037**
	(0.691)	(0.257)	(0.023)	(1.345)
$Tempo_{ij}$	2.205**	−0.996***	0.037	4.398**
	(0.907)	(0.370)	(0.029)	(1.727)
$Time\_Signature_{ij}$	−0.625	−1.963***	0.018	−3.998*
	(1.333)	(0.401)	(0.043)	(2.391)
$Duration_{ij}$	7.261	1.078	−0.030	7.579
	(5.378)	(1.357)	(0.206)	(5.401)
$Explicit_{ij}$	0.220	−0.202	−0.03***	−0.502
	(0.368)	(0.181)	(0.013)	(0.580)
$Collab_{ij}$	0.311	0.237***	0.012	−2.987***
	(0.217)	(0.062)	(0.008)	(0.756)
$Tracks_{ij}$	3.235**	−0.398	1.118***	26.74
	(1.630)	(0.947)	(0.104)	(21.04)
$Album\_Diversity_{ij}$	6.860***	0.572	0.197***	−3.987
	(1.520)	(0.580)	(0.057)	(3.840)
ΔX_{ij}	−0.753**	0.221***	−0.009	1.994***
	(0.301)	(0.059)	(0.011)	(0.660)
Overdispersion	0.0867	0.0979		
Fixed Effects				
$Artist_i$	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	21,082	111,156	1,401	21,947
Adj-pseudo R^2	0.0537	0.2889	0.0352	0.0278
Log-Likelihood	−33,060.35	−59,098.26	2,820.92	−87,325.01
BIC	83,374.76	135,787.23	443.89	184,256.55
AIC	69586.716	121224.541	−3961.856	176572.032

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Standard Errors in parentheses.

Table 13: Effect of Inter-Album Displacement on Focal Album Ratings with Euclidean Deviation from References

D.3 Variations in Building the Reference Effects

D.3.1 Anchoring on the First Album Release

Here,

$$Refx^n_{ij} = x^n_{i1}.$$

With this consideration, we get the following results.

	Focal Plays	Past Plays	Gini Index	Ratings
	1	2	3	4
$log(Focal\_Plays^k_{ij-1})$	0.1533^{***}			
	(0.0127)			
$log(Past\_Plays^k_{ij'-1})$		0.1255^{***}		
		(0.0087)		
$log(FirstYr\_Plays^k_{ij'})$		0.7169^{***}		
		(0.0078)		
$Gini\_Index^k_{ij-1}$			-0.2^{***}	
			(0.0312)	
$Rating^k_{ij-1}$				0.1733^{***}
				(0.0065)
Big_Label_{ij}	0.6753^{***}	1.7712^{***}	0.0139^{***}	0.2894
	(0.1252)	(0.0394)	(0.0048)	(0.2878)
$Album\_Num_{ij}$	0.0251^{**}	0.024^{**}	0.0040^{***}	0.1179^{*}
	(0.0105)	(0.0024)	(0.0014)	(0.0608)
$Time\_Diff_{ij}$	0.0004	0.0049^{***}	0.00004	0.0017
	(0.0009)	(0.0002)	(0.00003)	(0.0015)
$Danceability_{ij}$	3.3573^{***}	1.9842^{***}	0.0593^{**}	-10^{***}
	(0.7378)	(0.2768)	(0.0273)	(1.7533)
$Energy_{ij}$	3.5226^{***}	0.8533^{**}	0.0874^{**}	3.7875^{*}
	(0.9859)	(0.3549)	(0.0362)	(2.1664)
Key_{ij}	-0.2	0.7447^{***}	0.0417^{***}	-0.2
	(0.4652)	(0.1837)	(0.0158)	(0.8936)
$Loudness_{ij}$	-1.98	0.7792	-0.2^{**}	-5
	(1.6819)	(0.5023)	(0.0742)	(4.8211)
$Mode_{ij}$	-0.08	0.2054^{*}	0.0416^{***}	-0.6
	(0.3305)	(0.1239)	(0.0113)	(0.6476)
$Speechiness_{ij}$	-5.98^{***}	1.6441^{***}	0.0184	4.5844^{**}
	(1.0790)	(0.2632)	(0.0423)	(2.3372)
$Acousticness_{ij}$	-0.05	-0.7^{***}	0.0645^{***}	0.9576
	(0.4817)	(0.1672)	(0.0168)	(1.0943)
$Instrumentalness_{ij}$	0.0713	0.0451	0.0133	3.7304^{***}
	(0.4911)	(0.1503)	(0.0157)	(0.9764)
$Liveness_{ij}$	-0.7^{*}	0.3829^{***}	0.0338^{**}	-2.96^{*}
	(0.3925)	(0.1478)	(0.0139)	(1.6954)
$Valence_{ij}$	-1.97^{***}	-1.0^{***}	-0.008	3.1902^{**}
	(0.6875)	(0.2569)	(0.0229)	(1.3449)
$Tempo_{ij}$	1.9127^{**}	-0.89^{***}	0.0458	4.2142^{**}
	(0.9082)	(0.3702)	(0.0298)	(1.7278)
$Time\_Signature_{ij}$	-0.98	-1.96^{***}	0.0227	-3.96
	(1.3405)	(0.4001)	(0.0433)	(2.3893)
$Duration_{ij}$	7.4648	1.0371	-0.04	8.1023
	(5.3640)	(1.3614)	(0.2067)	(5.4087)
$Explicit_{ij}$	0.2097	-0.2	-0.03^{***}	-0.5
	(0.3672)	(0.1816)	(0.0127)	(0.5805)
$Collab_{ij}$	0.3759^{*}	0.2335^{***}	0.0057	-1.97^{***}
	(0.2062)	(0.0618)	(0.0073)	(0.7482)
$Tracks_{ij}$	3.2367^{**}	-0.5	1.1380^{***}	21.447
	(1.6227)	(0.9471)	(0.1026)	(21.110)
$Album\_Diversity_{ij}$	6.7841^{***}	0.6476	0.2253^{***}	-4.96
	(1.4945)	(0.5802)	(0.0564)	(3.8276)
ΔX_{ij}	-4.98^{***}	0.5246	0.0403	3.9708
	(1.3310)	(0.3279)	(0.0477)	(3.0612)
$Overdispersion$	0.0868	0.0977		
Fixed Effects				
$Artist_i$	Yes	Yes	Yes	Yes
$Year$	Yes	Yes	Yes	Yes
Fit statistics				
Observations	21,082	111,156	1,401	21,947
Adj-pseudo R^2	0.0538	0.28881	0.03519	0.02778
Log-Likelihood	$-33,056.52$	$-59,104.02$	2,820.97	$-87,328.73$
BIC	83,367.11	135,798.75	443.80	184,263.99
AIC	69579.059	121236.054	-3961.948	176579.467

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Standard Errors in parentheses.

Table 14: Effect of Inter-Album Displacement on Focal Album Ratings

D.3.2 Anchoring on the Last Album Released

Here,

$$Refx^n_{ij} = x^n_{ij-1}.$$

With this consideration, we get the following results.

	Focal Plays 1	Past Plays 2	Gini Index 3	Ratings 4
$log(Focal\_Plays^k_{ij-1})$	0.1536^{***}			
	(0.0127)			
$log(Past\_Plays^k_{ij'-1})$		0.1218^{***}		
		(0.0088)		
$log(FirstYr\_Plays^k_{ij'})$		0.7108^{***}		
		(0.0078)		
$Gini\_Index^k_{ij-1}$			-0.2^{***}	
			(0.0312)	
$Rating^k_{ij-1}$				0.1748^{***}
				(0.0065)
Big_Label_{ij}	0.6267^{***}	1.7916^{***}	0.0141^{***}	0.2425
	(0.1260)	(0.0397)	(0.0049)	(0.2887)
$Album\_Num_{ij}$	0.0261^{**}	0.0250^{***}	0.0040^{***}	0.1022^{*}
	(0.0105)	(0.0024)	(0.0014)	(0.0615)
$Time\_Diff_{ij}$	0.0004	0.0049^{***}	-0.00004	0.0065
	(0.0009)	(0.0002)	(0.00003)	(0.0065)
$Danceability_{ij}$	3.7260^{***}	2.0464^{***}	0.0619^{**}	-10^{***}
	(0.7523)	(0.2775)	(0.0273)	(1.7531)
$Energy_{ij}$	2.2740^{**}	0.9216^{***}	0.0870^{**}	3.5007
	(1.0090)	(0.3562)	(0.0363)	(2.1735)
Key_{ij}	-0.2	0.7279^{***}	0.0415^{***}	-0.3
	(0.4726)	(0.1838)	(0.0159)	(0.8951)
$Loudness_{ij}$	-0.02	0.6924	-0.2^{**}	-3.96
	(1.7064)	(0.5035)	(0.0739)	(4.8355)
$Mode_{ij}$	0.1521	0.1863	0.0406^{***}	-0.5
	(0.3291)	(0.1247)	(0.0112)	(0.6457)
$Speechiness_{ij}$	-5.79^{***}	1.6931^{***}	0.0372	5.1812^{**}
	(1.0771)	(0.2648)	(0.0415)	(2.3309)
$Acousticness_{ij}$	-0.4	-0.7^{***}	0.0628^{***}	0.8694
	(0.4851)	(0.1678)	(0.0166)	(1.0987)
$Instrumentalness_{ij}$	-0.4	0.0774	0.0164	4.1480^{***}
	(0.4981)	(0.1506)	(0.0157)	(0.9660)
$Liveness_{ij}$	-0.97^{***}	0.3800^{**}	0.0369^{***}	-2.95^{*}
	(0.3799)	(0.1478)	(0.0138)	(1.6963)
$Valence_{ij}$	-0.98^{*}	-0.96^{***}	-0.01	3.2496^{**}
	(0.7037)	(0.2583)	(0.0230)	(1.3476)
$Tempo_{ij}$	1.5212^{*}	-0.98^{***}	0.0398	4.3613^{**}
	(0.9038)	(0.3706)	(0.0290)	(1.7289)
$Time\_Signature_{ij}$	0.2685	-1.98^{***}	0.0235	-2.99
	(1.3418)	(0.4022)	(0.0433)	(2.3921)
$Duration_{ij}$	4.8553	1.0600	-0.06	8.8305
	(5.3947)	(1.3611)	(0.2071)	(5.3889)
$Explicit_{ij}$	0.2207	-0.2	-0.03^{***}	-0.5
	(0.3789)	(0.1814)	(0.0127)	(0.5804)
$Collab_{ij}$	0.0657	0.2393^{***}	0.0105	-1.94^{***}
	(0.1880)	(0.0622)	(0.0070)	(0.7202)
$Tracks_{ij}$	3.2923^{**}	-0.2	1.1294^{***}	14.359
	(1.6432)	(0.9546)	(0.1025)	(20.815)
$Album\_Diversity_{ij}$	7.6726^{***}	0.5854	0.2108^{***}	-3.98
	(1.4875)	(0.5848)	(0.0545)	(3.8304)
ΔX_{ij}	1.4168	1.1751^{***}	-0.03	-0.96
	(0.9018)	(0.2891)	(0.0336)	(1.9498)
$Overdispersion$	0.0874	0.0978		
Fixed Effects				
$Artist_i$	Yes	Yes	Yes	Yes
$Year$	Yes	Yes	Yes	Yes
Fit statistics				
Observations	20,918	110,450	1,398	21,830
Adj-pseudo R^2	0.05436	0.28875	0.03484	0.0279
Log-Likelihood	$-32,881.63$	$-58,736.26$	2,814.08	$-86,836.07$
BIC	82,973.94	135,018.73	441.29	183,253.56
AIC	69223.276	120494.523	-3952.175	175590.154

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Standard Errors in parentheses.

Table 15: Effect of Inter-Album Displacement on Focal Album Ratings

D.3.3 References as Arithmetic Mean of Past Albums

Here,

$$Refx^n_{ij} = \frac{x^n_{ij-1}}{j-1}.$$

With this consideration, we get the following results.

	Focal Plays	Past Plays	Gini Index	Ratings
	1	2	3	4
$log(Focal\_Plays^k_{ij-1})$	0.1536^{***}			
	(0.0126)			
$log(Past\_Plays^k_{ij'-1})$		0.1236^{***}		
		(0.0088)		
$log(FirstYr\_Plays^k_{ij'})$		0.7108^{***}		
		(0.0078)		
$Gini\_Index^k_{ij-1}$			-0.2^{***}	
			(0.0312)	
$Rating^k_{ij-1}$				0.1744^{***}
				(0.0065)
Big_Label_{ij}	0.5964^{***}	1.7842^{***}	0.0142^{***}	0.2992
	(0.1258)	(0.0396)	(0.0049)	(0.2892)
$Album\_Num_{ij}$	0.0238^{**}	0.0248^{**}	0.0038^{***}	0.0967
	(0.0105)	(0.0024)	(0.0015)	(0.0615)
$Time\_Diff_{ij}$	0.0003	0.0049^{***}	0.00004	0.0016
	(0.0009)	(0.0002)	(0.00003)	(0.0015)
$Danceability_{ij}$	3.6045^{***}	1.9915^{***}	0.0619^{**}	-8.79^{***}
	(0.7403)	(0.2776)	(0.0273)	(1.7624)
$Energy_{ij}$	2.2089^{**}	0.9355^{***}	0.0878^{**}	4.1290^{*}
	(0.9892)	(0.3563)	(0.0363)	(2.1719)
Key_{ij}	-0.2	0.7391^{***}	0.0416^{***}	-0.2
	(0.4662)	(0.1840)	(0.0159)	(0.8947)
$Loudness_{ij}$	-0.7	0.7611	-0.2^{***}	-4
	(1.6880)	(0.5027)	(0.0748)	(4.8339)
$Mode_{ij}$	-0.1	0.2157^{*}	0.0395^{***}	-0.2
	(0.3315)	(0.1247)	(0.0113)	(0.6533)
$Speechiness_{ij}$	-5.89^{***}	1.6507^{***}	0.0415	3.5377
	(1.0705)	(0.2648)	(0.0428)	(2.3652)
$Acousticness_{ij}$	-0.5	-0.7^{***}	0.0616^{***}	0.9012
	(0.4796)	(0.1676)	(0.0167)	(1.0983)
$Instrumentalness_{ij}$	-0.3	0.0530	0.0169	3.5617^{***}
	(0.4889)	(0.1508)	(0.0158)	(0.9788)
$Liveness_{ij}$	-0.7^{*}	0.3730^{**}	0.0387^{***}	-2.94^{*}
	(0.3882)	(0.1478)	(0.0142)	(1.6954)
$Valence_{ij}$	-1.95^{**}	-0.96^{***}	-0.01	3.1488^{**}
	(0.6947)	(0.2586)	(0.0230)	(1.3459)
$Tempo_{ij}$	1.5679^{*}	-0.95^{***}	0.0368	4.9403^{***}
	(0.9095)	(0.3705)	(0.0294)	(1.7303)
$Time\_Signature_{ij}$	-0.2	-1.94^{***}	0.0198	-2.94
	(1.3281)	(0.4013)	(0.0435)	(2.3914)
$Duration_{ij}$	3.6451	1.0334	-0.05	7.4680
	(5.3235)	(1.3708)	(0.2070)	(5.4009)
$Explicit_{ij}$	0.1541	-0.2	-0.03^{***}	-0.4
	(0.3695)	(0.1816)	(0.0128)	(0.5813)
$Collab_{ij}$	0.5895^{***}	0.2238^{***}	0.0128	-2.94^{***}
	(0.2172)	(0.0622)	(0.0083)	(0.7545)
$Tracks_{ij}$	2.9467^{*}	-0.4	1.1194^{***}	25.767
	(1.6031)	(0.9548)	(0.1037)	(21.094)
$Album\_Diversity_{ij}$	5.8426^{***}	0.7080	0.2020^{***}	-1.94
	(1.5140)	(0.5853)	(0.0566)	(3.8572)
ΔX_{ij}	-6.94^{***}	-0.6	-0.06	11.844^{***}
	(1.7728)	(0.4879)	(0.0677)	(3.8921)
$Overdispersion$	0.0874	0.0978		
Fixed Effects				
$Artist_i$	Yes	Yes	Yes	Yes
$Year$	Yes	Yes	Yes	Yes
Fit statistics				
Observations	20,918	110,450	1,398	21,830
Adj-pseudo R^2	0.05457	0.28866	0.03492	0.02795
Log-Likelihood	−32,874.18	−58,743.68	2,813.91	−86,831.69
BIC	82,959.04	135,033.59	441.63	183,244.79
AIC	69208.373	120509.378	−3951.832	175581.384

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Standard Errors in parentheses.

Table 16: Effect of Inter-Album Displacement on Focal Album Ratings

D.3.4 References with Album Success and Memory Effects

$$R_{ij} = (\theta + \theta' Success_{ij-1})R_{ij-1} + (1 - \theta - \theta' Success_{ij-1})X_{ij-1}$$

where, $Success_{ij} = \frac{Plays_{ij-1}}{max\{Plays_{i1}, Plays_{i2}, ..., Plays_{ij-1}\}}$ takes values between 0 and 1.

	Focal Plays	Past Plays	Gini Index	Ratings
	1	2	3	4
$log(Focal\_Plays^k_{ij-1})$	0.0118			
	(0.0217)			
$log(Past\_Plays^k_{ij'-1})$		-0.04		
		(0.0283)		
$log(FirstYr\_Plays^k_{ij'})$		0.6896^{***}		
		(0.0228)		
$Gini\_Index^k_{ij-1}$			-0.09^{*}	
			(0.0502)	
$Rating^k_{ij-1}$				0.2523^{***}
				(0.0161)
Big_Label_{ij}	0.4010	1.1735^{***}	0.0041	-2.615^{*}
	(0.2831)	(0.2695)	(0.0094)	(1.5814)
$Album\_Num_{ij}$	0.1581	0.3909^{**}	0.0018	0.0668
	(0.1592)	(0.1616)	(0.0039)	(0.6722)
$Time\_Diff_{ij}$	0.0036	0.0085^{***}	0.00008	0.0977^{***}
	(0.0024)	(0.0023)	(0.00007)	(0.0351)
$Danceability_{ij}$	4.8676^{**}	1.2961	-0.02	-31.912^{***}
	(2.0909)	(2.1231)	(0.0474)	(9.8642)
$Energy_{ij}$	-0.05	-0.250	0.1145	24.357^{*}
	(2.6050)	(2.4635)	(0.0745)	(14.040)
Key_{ij}	1.8038^{*}	3.4200^{***}	0.0667^{***}	-8.498^{*}
	(1.0470)	(1.1587)	(0.0234)	(4.6940)
$Loudness_{ij}$	9.2683	-1.613	-0.201	-34.814
	(6.1255)	(5.2062)	(0.1682)	(30.622)
$Mode_{ij}$	0.8601	0.4256	0.0350^{**}	-3.892
	(0.7548)	(0.6922)	(0.0165)	(2.8339)
$Speechiness_{ij}$	1.3899	-3.308^{**}	0.0814	31.909^{*}
	(2.4349)	(1.6000)	(0.0815)	(17.610)
$Acousticness_{ij}$	0.3996	-2.691^{**}	0.0277	-0.3772
	(1.2965)	(1.2236)	(0.0311)	(6.1793)
$Instrumentalness_{ij}$	-3.767^{**}	0.4048	-0.02	-1.911
	(1.4628)	(1.2365)	(0.0288)	(7.3409)
$Liveness_{ij}$	1.5927	-2.776^{***}	-0.020	-13.921^{*}
	(0.9786)	(0.8399)	(0.0286)	(7.8742)
$Valence_{ij}$	-2.375	2.9578^{**}	-0.150^{***}	10.980
	(1.5779)	(1.1702)	(0.0355)	(8.4802)
$Tempo_{ij}$	-1.481	-2.495	-0.03	-11.152
	(2.0668)	(2.1254)	(0.0490)	(10.140)
$Time\_Signature_{ij}$	0.3303	2.9515	0.0398	20.215^{**}
	(3.0008)	(3.0571)	(0.0737)	(8.9230)
$Duration_{ij}$	5.0035	-18.988	-1.220^{***}	-90.910
	(16.849)	(15.088)	(0.3637)	(67.300)
$Explicit_{ij}$	0.9794	3.3118^{***}	-0.01	0.3926
	(0.7351)	(0.7876)	(0.0214)	(3.1984)
$Collab_{ij}$	0.117	-1.433^{***}	-0.004	-2.471
	(0.5350)	(0.5148)	(0.0143)	(4.1190)
$Tracks_{ij}$	38.978^{***}	17.441	1.2699^{***}	-53.667
	(12.971)	(12.902)	(0.3916)	(124.14)
$Album\_Diversity_{ij}$	12.440^{***}	5.8918	-0.162^{*}	18.389
	(3.6798)	(3.7838)	(0.0958)	(15.990)
ΔX_{ij}	-6.716^{**}	-4.212	0.0566	30.080^{***}
	(3.0692)	(2.5917)	(0.0846)	(8.1487)
$Overdispersion$	0.110	0.123		
Fixed Effects				
$Artist_i$	Yes	Yes	Yes	Yes
$Year$	Yes	Yes	Yes	Yes
Fit statistics				
Observations	4,019	5,184	444	3,753
Adj-pseudo R^2	0.02038	0.18406	-0.02718	0.02932
Log-Likelihood	$-9,496.44$	$-5,239.77$	1,022.83	$-14,543.98$
BIC	23,623.61	13,439.01	-131.58	32,363.63
AIC	20,108.894	11,171.561	$-1,417.668$	29,883.974
θ	0.9	0.1	0.9	0.8
θ'	0.25	0.85	0.25	0.75

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Standard Errors in parentheses.

Table 17: Effect of Inter-Album Displacement on Focal Album Ratings