Music markets and the adoption of novelty : experimental approaches

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Music Markets and the Adoption of Novelty: Experimental Approaches

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Á mes grand-parents,

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ma soeur,

mon frère,

et mon bien-aimé.

Avertissement

Mis à part l'introduction et la conclusion de cette thèse, les différents chapitres sont issus d'articles de recherche rédigés en anglais et dont la structure est autonome. Par conséquent, des termes "papier" ou "article" y font référence, et certaines informations, notamment la littérature, sont répétées d'un chapitre à l'autre.

Notice

Except the general introduction and conclusion, all chapters of this thesis are self-containing research articles. Consequently, terms "paper" or "article" are frequently used. Moreover, some explanations, like corresponding literature, are repeated in different places of the thesis.

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Abstract **261**

"À trente-cinq ans, j'ai obtenu le prix Nobel de médecine. Rien d'exceptionnel : je n'étais pas si doué, j'avais bénéficié de presque deux existences pour y parvenir. (Et si j'y réfléchis à tête reposée, peut-être que tous les grands génies de l'histoire universelle, d'Archimède ou Euclide jusqu'à Planck ou Darwin, en étaient déjà à leur deuxième vie lorsqu'ils ont découvert ce qui les a rendus célèbres.)

Extrait de «7.», Tristan Garcia.

General Introduction

Preamble

This thesis is composed of four essays analyzing music consumption. It particularly focuses on the consumption of non functional novelty using behavioral and experimental economics. This introduction puts in perspective the questions developed within each essay and provides an overview of the thesis.

The following introduction uses the terminology of "cultural economics" without debating the limits of its definition. Cultural economics hereafter encompasses performing arts and reproducible art goods. The former refers to original art works (prototypes) that are not reproducible on a large scale and for which access is limited such as concert, theater, dance performance etc. The latter involves prototypes that can be reproduced such as music, movies and books. In others words, those are goods that can be digitized.

Mentions will also be made about the quality of cultural goods. The quality of an art piece is not easily quantifiable since it results from aesthetic, social, psychological and historical judgments. In this thesis, quality refers to the maximum satisfaction consumers derive from the consumption of an art good and how it is distributed across them.

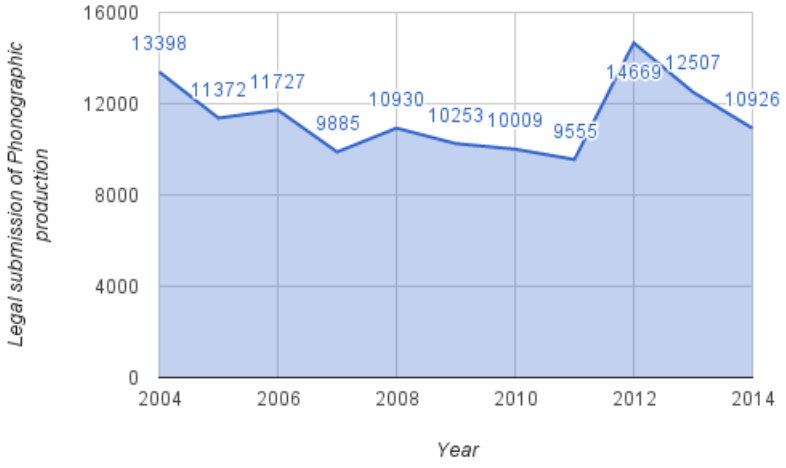
0.1. Cultural goods and Novelty

Markets for cultural goods such as music, cinema, live performances or books are inherently highly differentiated markets and new creations are produced every day. Take for instance the music market: on average, around 11400 phonographic productions were submitted each year to the French legal deposit of the Bibliothèque Nationale

de France between 2004 and 2014 (see Figure 0.1). According to Nielsen data, the number of new music products brought to market tripled between 2000 and 2008 [1]. This increase is closely linked with the reduction of production costs (Hansen, 1997, Aguiar and Waldfogel, 2016). Cultural markets seek many new products quickly, causing strong supply and demand dynamics. If artists and labels keep on producing new pieces of creation, it is certainly because they are able to reach a demand for novelty.

The main objective of this thesis is to understand (i) the determinants of novelty consumed for a given menu of musical goods (Part I) (ii) the willingness to pay to increase the size of the menu of goods via crowdfunding (Part II). This introduction first presents a reflexion on the definition of novelty (Section 0.1), on demand and supply of novelty on music markets (Section 0.2) then describes how experimental economics are well-suited to study such a problematic (Section 0.3). Finally, the outline of the thesis is laid out (Section 0.4).

Figure 0.1 – Legal submission of phonographic production in France



1. http://www.musicsupervisor.com/just-how-many-releases-these-numbers-may-scare-you/

0.1.1. What is novelty?

Novelty seeking behaviors are not generally taken into account in economic models, especially if this novelty does not lead to functional improvements (Bianchi, 2002). The question is thus to understand why consumers need new products in the case of cultural goods. To do so, let us first define what is novelty or "newness", and more precisely what is non-functional novelty.

Novelty and innovation To define novelty in the context of cultural markets, one has to distinguish functional and non-functional innovations. In many industries, like cars, personal computers or mobile phones, new goods and innovation generally refer to functional improvements [2].

Such an analysis is not well-suited for cultural goods since the functional part of those goods is extremely limited. Art goods are specific as they are not required to be functional like most economic goods, and are sought for immediate pleasure and arousal. In other words, the value of a cultural good is hedonic and refers to the experience of enjoyment or pleasure. Blood and Zatorre (2001) conclude from an fMRI study on music that music is linked with biologically-relevant, survival-related stimuli via their common recruitment of the brain circuitry involved in pleasure and reward. As each piece of art is different, each consumption of a cultural good is associated with a different arousal, and thus a different hedonic value. Non functional newness does not refer to a technical improvement but to a different level of arousal.

The only way for a consumer to discover the hedonic value of a cultural good is by experiencing it: listening to a piece of music, watching a movie, reading a book. Trying a new piece of art, such as a new music track, consists in consuming an experience good, that is, a good that you cannot rate before consuming it (Nelson, 1970). Novelty is closely related to the notion of experience and exposure.

2. Note that this distinction between functional and non-functional appears through the distinction between copyright, applied to artistic creations, and patents, applied to technical innovations.

Novelty and exposure Each consumer has a stock of music experiences that are extracted from a set of highly differentiated available goods. Depending on ones own experience, the set of new goods will be of greater or lesser size. In other words, a piece of music that is new for a given consumer may not be new to another. In this perspective, a new cultural good need not be a new production. At the individual level, novelty may refer to a good that already existed in the market but was just not experienced by the consumer.

Novelty also provides arousal but not in a constant manner. If one listens to a music track for the first time, will it not be new if one listens to it a second time? What about the hundredth time? The arousal and satisfaction derived from the consumption of a piece of music varies over time and exposure: the taste for a specific musical song often increases with exposure and then decreases through over-exposure (Hunter and Schellenberg, 2011). It can be assumed that, if it takes some time to discover the whole potential of its newness, up to some point, the more we consume a cultural good the more its novelty erodes. In this perspective, a quality criterion for a new good, understood as the potential satisfaction one may derive from it, is the maximum arousal it can provide, before the latter diminishes.

Novelty and familiarity Even when a consumer has never experienced a good, the level of novelty varies. Novelty is intimately linked with the notion of familiarity. For instance, a consumer may listen to the new album of her favorite singer. While this album is new *per se*, she is likely to have a similar experience, in terms of arousal, from what she experienced before.

To sum up, novelty for cultural goods is defined through two dimension: experience and familiarity. The notion of novelty is thus closely linked to the notion of diversity that can be defined according to three dimensions (Stirling, 1998): variety (the size of the set of goods), disparity (the number of sub-categories of goods) and repartition

(how goods are distributed across these categories). Increasing variety leads to an increase of new goods since the probability that a given consumer was exposed to it is lower. Higher disparity is also related to a higher level of novelty since consumers are less likely to be familiar with all the set of goods. The question is now to understand how demand reacts to novelty.

0.1.2. Why do (or don't) we consume new cultural goods?

Novelty and boredom In *The Joyless Economy: The Psychology of Human Satisfaction*, Scitovsky highlights the importance of arousal and stimulation:

"What does an organism do when all its needs are satisfied, all its discomforts eliminated? The original answer, nothing, is now generally recognized to have been wrong. Perfect comfort and lack of stimulation are restful at first, but they soon become boring; then disturbing."

In his theory of consumption, Scitovsky stresses the crucial role of "pursuit of novelty" as a main driver. A consumer finds satisfaction in novelty. According to him, a possible remedy to low arousal is found in mental stimulation like entertainment, sports, arts etc. There is something intrinsically satisfying in newness and surprises.

The hedonic nature of new goods Psychologist Berlyne (1960, 1971) establishes an explanatory link between the hedonic value of various experiences and stimuli potential such as novelty, unexpectedness or surprise. These dimensions generate arousal. A moderate increase in the level of arousal induces an increase in pleasantness of a situation. If the arousal is too high, however, it has a negative impact on pleasantness, generating dis-utility. As Bianchi (2002) sums it up:

"Novelty, in other words, is pleasant but within bounds: too low a degree is boring, too high a degree is threatening."

New goods and learning by consuming Stigler and Becker's (1977) economic model of cultural consumption generally assumes that cultural goods are habit-forming goods and that past consumption of such goods increases the utility of present consumption. Their model assumes that past consumption increases the stock of a specific consumption capital and thus, the productivity of the time spent on the good. The model does not however specify if it refers to a single good or the general experience of listening to music, reading literature and watching movies (Bianchi, 2002). In other words, do we become addicted to a unique piece of art? Or to successive experiences?

While acknowledging its richness, Lévy-Garboua and Montmarquette (1996) highlight the limits of such a deterministic approach. They develop a model where consumers discover their preferences through a long process of "learning-by-consuming" encompassing a deterministic and a stochastic component: when consuming a cultural good, satisfaction is a function of past consumption and a stochastic component called "surprise". As they explain:

"The unique nature of each "cultural" experience provides new possibilities for surprise."

Each new experience yields a positive or a negative variation in the consumer's taste for a given good[3]. This model allows for novelty-seeking behaviors since each new experience can potentially cause a positive shock on appreciation. It also includes a rate of obsolescence that accounts for loss of knowledge by forgetting, explaining why we may re experience surprise after a long time of non exposure.

New goods as option values New goods can be attractive to consumers because they bear an option value: the new good may turn out to be more preferred than the goods already experienced (Gazel, Tallon and Lévy-Garboua, 2016). Even though the set of goods and their respective quality is uncertain, economic agent may have an

3. Here again, the model does not specify if it refers to a single differentiated good or a broader class such as music, or musical genres. It is however less of a problem since the stochastic part allows for the great differentiation of cultural goods.

incentive to try a new cultural good to discover their preferences (Armantier et al., 2016).

New goods and uncertainty When facing a new cultural good, consumers are not aware *ex ante* - before consumption- of the nature and quality of this stimulus. Because experience goods are inherently uncertain, markets for cultural goods are markets for which "nobody knows" (Caves, 2000). There is a risk of being disappointed. Consumers are confronted with a large set of (risky) choices. When one has to choose between movies to see or concerts to go to, one may rely on the presence of familiar characteristics (an actor one knows, a musical genre one is used to listen to etc.) or on critics (of experts, of friends etc.) and not take the risk of trying something completely unknown, or, in other words, of uncertain quality. Thus, the risky dimension of novelty counterbalances the attractiveness of a potential positive surprise.

We have presented several arguments suggesting that novelty can be appealing. Of course, this list is not exhaustive and others determinants, that we do not look at, may influence novelty consumption, such as social dominance (Bourdieu, 1979) or snobbery effects (Veblen, 1899). The next section aims at understanding the demand and supply for new goods and how markets failures can arise.

0.2. Novelty supplied and novelty consumed

The concept of cultural diversity can be distinguished between diversity supplied and diversity consumed (Benhamou and Peltier, 2007). While diversity supplied refers to the menu of available goods on a given market, diversity consumed refers to the sub-set of goods that are actually consumed. This distinction can be applied to new goods. While economic theory would predict that the diversity supplied should adapt to the diversity consumed, in cultural economics, the supply side have incentives to

provide a a greater level of diversity than the one that will ultimately be consumed. The rationale is the following: since "nobody knows" which goods will be the next hit (Caves, 2000), suppliers overproduce to maximize the expected profit. This section describe, from the supply and the demand side, the production and consumption of new goods in cultural markets.

0.2.1. The demand for new cultural goods

Demand concentration towards few artists The structure of the creative industry is generally described as being shaped according to the 80/20 Pareto law: 80% of the total revenue is made by 20% of the supply. A "happy few" artists is able to become stars, to capture a large part of the demand and to set higher prices. Such cultural markets are characterized as "superstars" (Rosen, 1981) or "winner-takes-all" (Frank and Cook, 1991) markets. Although new experiences do provide arousal, the demand remains concentrated towards a limited number of artists. Popularity, rather than novelty (in exposure), leads the demand.

Three types of explanation are provided by the economic literature. A first analysis suggests that small differences in talent translate into large differences in earning (Rosen, 1981) assuming that one high quality cultural good is an imperfect substitute to several low quality goods. MacDonald (1988) provides a dynamic version of Rosen's (1981) model studying price differences between established artists and newcomers. The model assumes two periods. During the first one, artists decide to perform and the quality of their performance is observable (either good or bad). At the second period, newcomers enter the market but the quality of their performance is unknown, while artists selected through the first period are known to be good performers. The latter can charge higher prices and supply a larger demand than the newcomers because consumers face less uncertainty about their performance [4]. In this model, consumers

4. Chapter 1 study the effect of prices on demand for novelty.

who choose to attend new artists' performance have a low level of additional utility for good performances. In other words, consumption of novelty here depends on the individual appreciation of music. Rosen's (1981) and MacDonald's (1988) models however disregard the effect of love for variety (Schulze, 2003). Hamlen Jr (1991), by using voice quality of singers, tries to test empirically Rosen's (1981) theory. His results however question the latter: if talent increases sales, it is by less than proportionally.

A second explanation, developed by Adler (1985), assumes that many artists have enough talent to potentially become superstars but that stardom only arises because consumers have an incentive to consume the same cultural goods. His rationale is as follows. Consumers' enjoyment of a given piece of art depends on a "consumption capital" (Stigler and Becker, 1977) that can be increased in three ways: (i) through exposure to art itself, (ii) through discussion with friends and acquaintances and (iii) by reading about it in newspapers and magazines. In other words, consumers' enjoyment of a given piece of art depends on its popularity [5]. Adler (1985) sets a dynamic model where each consumer randomly selects a new artist to be added to her consumption bundle. It is only by chance that only a limited number of new artists is solicited by a larger number of consumers and becomes popular. Others will then switch to these artists because preferences for popular artists is assumed, generating a stardom system. Showing that the distribution of gold record follows a Yule distribution, Chung and Cox (1994) find that differences in success are due wholly to chance and talent need not be invoked to explain the stardom system.

The third explanation suggests that the skewness of demand is due to a lack of information. Demand does not depend only on preferences but also on consumers' knowledge of the product set and of their own preferences. Due to the exacerbated uncertainty regarding the quality of goods, consumers rely on signals of quality. In the case of movies or music, a consumer will base her decision on the reputation and

5. The more a good is consumed, the more people and newspapers talk about it.

level of experience of an artist. As in MacDonald's (1988) model, consumers know that existing artists are there because they have already proven their talent. If the same artists produce new pieces of art, the demand has more confidence in on the potential quality of the production. Consumers also rely on others' choice and opinion. Benefiting from others' knowledge helps facing uncertainty about experience goods. Experts and consumers' opinions can be used to evaluate the quality of a movie *ex ante*[6]. Consumers choose products they hear about, which are product that are already consumed: success brings success and informational cascades arise (Bikhchandani, Hirshleifer and Welch, 1992*a*, 1998), explaining the superstars system. An informational cascade appears when it is optimal, for a given consumer, to disregard her own private information and follow the (observed) behavior of the previous adopter instead. Informational cascades, under certain conditions, can however lead to the wrong choice (the chosen good is not of good quality). In the case of high uncertainty, the choice of others may lead to poor choices.

Initiators versus imitators The basic informational cascade model considers that the signal precision is homogeneous across the population. The liability of an evaluation however depends on the experience of a consumer. Early adopters, who can be called «initiators», select a limited number of goods within a set of new goods. As they receive a more precise signal about their quality, their choice is a good information about quality and others, called «imitators», follow the initiators' decision and adopt the selected new goods. In the case of cultural industries, who are the initiators? Initiators may know the artist personally, in which case they are less exposed to asymmetric information. Friends and family are generally assumed to be the first consumers of a given artist. Secondly, they can be hard consumers of arts. Accumulated knowledge about arts increases one's ability to appreciate it. Experts should thus have a higher ability to evaluate the potential arousal that can be generated by a given piece of art

6. Chapter 1 of this thesis study the effect of others' opinion on the consumption of new goods.

and emit signals of better quality. Finally, initiators can have intrinsic motivations to try new goods. In psychology, novelty-seeking behavior has been widely studied and is related to many psychological concepts: novelty seeking (Cloninger, Svrakic and Przybeck, 1993), sensation seeking (Zuckerman, 2002), and openness to experience (McCrae and John, 1992). Generally speaking, novelty seeking is a vast array of psychological dispositions such as a positive attitude toward novelty, a tendency to express spontaneous exploratory behavior and to manifest curiosity, as well as a relatively high need for change (aversion to repetition). More specifically, in the biological perspective of Cloninger, Svrakic and Przybeck (1993), the concept of novelty seeking is defined by high basal dopaminergic activity and the consequent tendency to have a high sensitivity to cues for reward (gotten from gratifying, pleasurable, fun, or exciting activities). In empirical studies, this trait is found to be mostly correlated with extraversion and impulsivity (De Fruyt, Van De Wiele and Van Heeringen, 2000) and is thus very similar to Zuckerman's (2002) concept of impulsive sensation seeking [7].

The unpredictable demand A well known stylized fact about cultural industries, recognized by researchers as well as practitioners, is that demand for new books, films and music is highly unpredictable. This unpredictability can be explained by the social dimension of novelty adoption. Thanks to a Web-based experiment, Salganik, Dodds and Watts (2006) created an artificial music market where 14,341 users downloaded unknown songs. Two conditions were implemented to study the role of social influence: in the independent condition, participants made their choices knowing only the bands and the names of the songs, while in the social influence condition, participants are also aware of the number of times a song was downloaded. The authors show that the social influence "world" increased both inequality and unpredictability of success.

7. The influence of novelty-seeking preferences on music consumption is further investigated in the present thesis, using the Big Five model of personality traits (McCrae and John, 1992). Chapter 2 examines the substituability of musical genres in the light of consumers' level of openness.

0.2.2. The production of new cultural goods

The supply side is directly impacted by the uncertainty in demand. Because they are facing the "cost desease" and high entry costs, production is organized according to an oligopoly with fringe.

The cost disease In their seminal work, Baumol and Bowen, solicited by the Ford Foundation to explain the poor economic revenues of Broadway musicals, conclude on the ineluctable increase in unit price due to the low degree of productivity in the performing arts industry [8]. As Greffe (2010) points out, to face the increase of unit cost, art industries can either lower prices (and lower artists' wages) reinforcing the participation constraint or maintain the price lowering the supply. This "cost disease" leads to an economic deficit that can be limited at the cost of an artistic deficit. The technical possibility of reproducing a unique art good like a live performance or an artifact at low marginal costs have however considerably weakened Baumol's argument. For instance, movie theaters today propose to see live ballets, and plays are often broadcast on television.

Entry costs Some cultural industries are not really concerned about the cost disease, such as the music and the movie industries since recording equipment and diffusion means are more productive nowadays than ever before. Producers however still face entry costs. First, it is generally assumed that these industries face high fixed costs (related to the creation of the prototype [9]) and low marginal costs [10]. These industries are based on the massive reproduction of an original work. Second, on part of the producer, those goods are prototypes. The success of a given good can only be discovered

8. The number of musicians required to perform to perform a Schubert quintet is the same today as it was two centuries ago. But because other industries are highly productive, wages increase (considering the general economy) and art industries have to keep up with those wages. This argument is often called the "productivity lag argument".

9. In the case of music for instance, these costs refer to recording costs, mastering costs etc.

10. Reproducing a CD or a .mp3 file can be done at almost no cost.

after production due to a high degree of demand unpredictability, while most of the costs are already engaged (sunk costs). To test and maximize the potentiality of a new musical production, producers can invest in "payola" so that radios play their music in priority. Investing in promotion signals to consumers the quality of a production. Promotion implies additional entry costs for new producers. High fixed costs associated with low marginal costs generate natural monopolies in the art industry.

The oligopoly with fringe The supply side is constantly renewed and nonfunctional innovation is "distributed" in cultural industries: new pieces of art (song-writings, manuscripts, movie scenarii) are generated by a large number of artists. Producers, who are willing to invest/bet on a subsample of artists, select projects which most likely meet success. Future demand is however highly unpredictable and industries are structured according to an oligopoly with a competitive fringe: the central oligopoly, the *majors*, targets a wide demand while the firms on the fringe focus on niches and new artists. When the first signals of success appear, the central oligopoly invest on large promotion campaigns to enhance what is called "informational cascades"(Bikhchandani, Hirshleifer and Welch, 1992*b*, Banerjee, 1992) of a few selected artists.

Under-experimentation Traditionally, new artists and talents are discovered by agents. The combined effect of the uncertainty on the artists' talents and the difficulty to establish long-term contracts leads to under-experimentation of new artists (Cabral, n.d.). With this in mind, Terviö (2009) shows that, because long-term contracts with artists are difficult to write, a promoter is exposed to the probability that the artist, once she becomes a superstar, may move to another promoter. In other words, the promoter is exposed to the probability that her initial investment is not recovered and benefit to another one. As a result, the industry continues to invest in established stars and leads to lower efforts in discovering new artists.

0.2.3. Market failures

Lack of information and consumer surplus The lack of information, on the demand and the supply side, leads to potential welfare loss for several reasons. First, on the demand side, consumers may prefer to buy less popular products if they knew about it. Hendricks and Sorensen (2009) provide evidence that consumers miss products they would have bought if they knew about it by studying backward spillovers associated with a newly released albums on past albums. One the supply side, variety may be indirectly affected by the way consumers discover the choice set as producers might favor investments for products with mass-market appeal.

Lack of diversity and consumer surplus Increasing variety and disparity leads to an increase in consumer surplus, as shown theoretically and empirically by Brynjolfsson, Hu and Smith (2003). The basic assumption behind this causal effect is related consumers' taste for diversity as well as diversity in tastes. In addition, a deterioration in diversity leads to a deterioration in demand (Benhamou, 2002), presumably because the marginal utility of consuming cultural goods increases with the level of consumption (Stigler and Becker, 1977).

Is the "long tail" effective? With the digitalization of the industry, Anderson (2004, 2006) predicted that the "long tail" would smooth the distribution of sales as a result of: (i) lower production costs causing an increase of the variety supplied (ii) lower distribution costs easing the access to niche products and (iii) the development of online word-of-mouth upscaling the matching between demand and supply. The long tail effect has been tested for various cultural goods, including books (Brynjolfsson, Hu and Smith, 2003, Peltier and Moreau, 2012), videos (Elberse and Oberholzer-Gee, 2006, Benghozi, 2008) and music (Benghozi and Benhamou, 2010, Bourreau et al., 2013). No consensus is however found, either for theoretical nor empirical, on the existence and magnitude of the long tail effect. Even though digitization can lead to

a better matching between supply and demand, consumers' awareness of the overall supply is not systematically insured and choice overload may limit the long tail effect (Gourville and Soman, 2005, Kuksov and Villas-Boas, 2010). In other words, a higher level variety in supply can lead to lower variety in consumption because it is cognitively costly to choose when facing too many alternatives.

Externalities and novelty as a public good As previously mentioned, the production of a novel good constitutes an option value for potential consumers. Throsby (2010) lists all the characteristics explaining why cultural goods are both private and public goods: the *existence value* (people value the very existence of art), the *option value* (people value the continued existence of art, i.e. the ability to consume art in the future) and the *bequest value* (people value future generations' ability to consume art) [11].

0.2.4. State intervention

To improve information, sustain diversity and consider external effects, State intervention is justified to stimulate cultural innovation. Two main types of public policies can be implemented: quotas and subventions.

Broadcasting quotas The basic idea of broadcasting quotas is to protect and promote productions which are hurt by the stardom system. As accessibility and visibility of products increase their probability of success, the State can orientate demand towards a selected set of products. Generally, it aims at promoting domestic production as it is the case with French quotas in music. Established in 1996, French regulation imposes a quota of 60% of French-speaking music, with at least 20% of new songs. The literature however shows the limited effectiveness of such measures suggesting

11. The existence of these non-market values has been stressed by several researchers in cultural economics (see for instance Hansen (1997) for an estimation in the case of a theater and Noonan (2003) for a review.)

that, while radios did broadcast more French songs, diversity was harmed because radios reacted by increasing the rotation rate (Perona, 2011). For instance, 75% of the French radio NRJ's broadcasting rotation was composed of 10 songs in 2013 [12]. In 2016, the French Parliament adopted the bill on "Freedom of Creation, Architecture and Heritage" in which an act specifies that, if more than half of the broadcasting is concentrated on ten French songs, additional broadcasts of these songs are no longer accounted for the quotas. In the meantime, quotas were eased for radios dedicated to discovering new talents, which have to broadcast only 15% of French productions or talents.

Subventions Baumol and Bowen (1966) already suggested that, because of the "cost desease", performing art industries can only be sustainable if they receive State support and/or donations. As new artists' production is undertaken by small firms in the fringe, public policies aiming at promoting innovation should subsidy, directly (subventions) or indirectly (tax credit) these small firms (Benhamou and Peltier, 2010). The State can also take the lead on producing new artists through automatic or selective subventions. In France for instance, this particular role is taken by the Centre national du cinéma (CNC) in the film industry.

0.2.5. Crowdfunding as an alternative to State support

State intervention, however, is not the only way to help the novelty production process. As mentioned earlier, donations sustain art industries production. With Web 2.0 technology came the rise of crowdfunding, often presented as an alternative to formal and public financing, whereby consumers fund the production themselves, usually by pre-ordering the good (Belleflamme, Lambert and Schwienbacher, 2013).

Definition Crowdfunding can be defined as:

12. According to Yacast report of 2013.

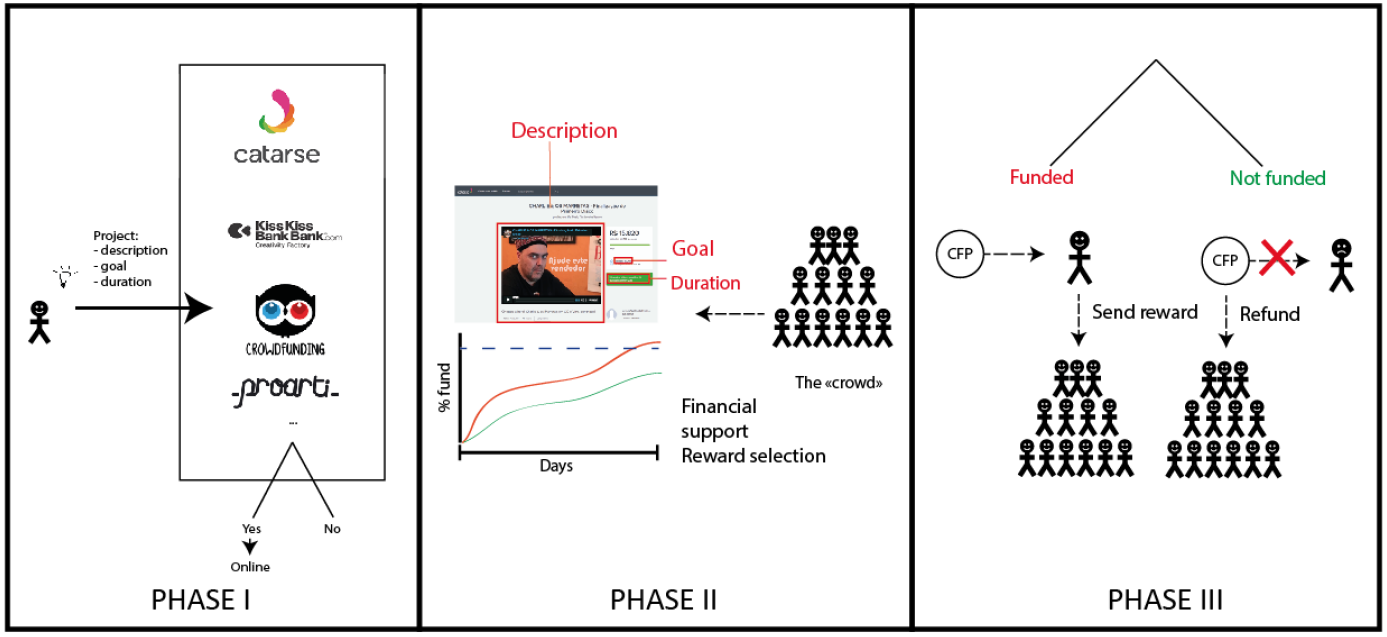
"an open call through the internet for the provision of financial resources either in form of donation or in exchange for some form of reward and/or voting rights in order to support initiatives for specific purposes" (Belleflamme, Lambert and Schwienbacher, 2014*a*).

The concept is straightforward: an artist wishes to produce her creation (a musical album, a video, a book). She first submits her project to a crowdfunding platform. Each submission is generally composed of a project description (text and videos), a financial objective, a campaign duration and a reward schedule (see Phase I in Figure 0.2). If the project is selected by the platform, it goes online and during the time window previously defined, the platform users, called *backers*, can decide to contribute (see Phase II in Figure 0.2). The outcome of the campaign is then determined according to the platform's rule:

— either the artist is facing the All-or-Nothing (AoN) rule, according to which she will only get the collected funds if her financial objective is met before the deadline, otherwise the contributions are redistributed to the backers (see Phase III in Figure 0.2).

— either the artist is facing the Keep-it-all (KiA) rule, according to which she will get the collected funds regardless of the initial objective.

Figure 0.2 – Schematic of a crowdfunding campaign - the "All-or-Nothing" case



Note: In Phase I, an artist/entrepreneur/creator submits her project to a crowdfunding platform. The latter either accepts the project or rejects it. Phase II is the campaign itself: within a time window (generally between 30 and 90 days), backers can financially contribute to the project. In Phase III, after the campaign ended, the project has to send the selected rewards if the threshold (the financial objective) is reached, otherwise backers are reimbursed. "CFP" yields for crowdfunding platforms.

Crowdfunding as an alternative to fund arts Crowdfunding artistic projects has become popular in the past few years and is generally presented has an opportunity to counterbalance the lack of financial public support. Cultural goods, such as music, films, comics, books, performing arts etc. represent an important share of the projects found on reward-based (see Table 0.1).

Table 0.1 – Share of artistic projects on reward-based crowdfunding

Platform	Country	Share of artistic projects	Share of successful artistic projets	Total number of projects
Ulule	France	47.9%	59.0%	23329
KissKissBankBank	France	62.3%	67.1%	22613
Kickstarter	USA	66.4%	45.2%	323501

Note: Statistics publicly displayed by crowdfunding platforms. Numbers were updated in November 2016. The selected categories are: Music, Films, Comics, Arts, Photography, Live performance (theater, dance), Edition (for Ulule, the Edition category also includes Journalism), Fashion

Still, not all artistic projects can be easily crowdfunded and a main distinction should be made with respect to the nature of the product. Performing arts, for instance, offer unique prototypes in limited supply. Other cultural industries, however, relate to markets where products are designed for reproduction (music, videos, books) [13]. These industries are well-suited for reward-based crowdfunding since artists can offer rewards yielding a low marginal cost (digital copy of a new album or a new film, e-books, physical CD/DVD etc.). Regarding performing arts, the supply is more limited and a project holder may not be able to offer theater invitations to all its potential backers [14].

13. Such products can be considered as information goods since they are goods that can be digitized (Varian, 1999). Information goods are defined by three criteria: (i) they are experience goods (ii) they yield high fixed costs and low reproduction costs (iii) they are non-rival and sometimes non-excludable. This difference is crucial as for information goods industries, marginal cost is close to zero and unlimited copies can be produced.

14. In this thesis, we focus on crowdfunding for music.

Crowdfunding as a way to reduce unpredictability? Crowdfunding appears as a good way to lower this uncertainty about demand by allowing individuals to reveal their private valuations of a new product. This is especially true in the case of reward-based crowdfunding as backers actually pre-order the product, and crowdfunding should thus reveal their preferences. This question has recently motivated theoretical articles (Strausz, 2016, Chemla and Tinn, 2016) and an empirical study by Viotto da Cruz (2016) shows that entrepreneurs use reward-based crowdfunding to learn about market demand.

Crowdfunding artistic projects as a public good with private gifts Reward-based crowdfunding, when applied to art, resembles a public good in many ways. Firstly, backers voluntarily decide to financially support the production of a new cultural good. Without the crowd's contribution, it is likely that the good would not be put on the market: the public good *per se* is the ability to purchase a product on the open market (the option value). Thus, (some) consumers may want to participate in crowdfunding to ensure the provision of novelty and obtain the good. One can expect that this type of consumer is particularly cooperative and may exhibit pro-social preferences such as altruism or reciprocity.

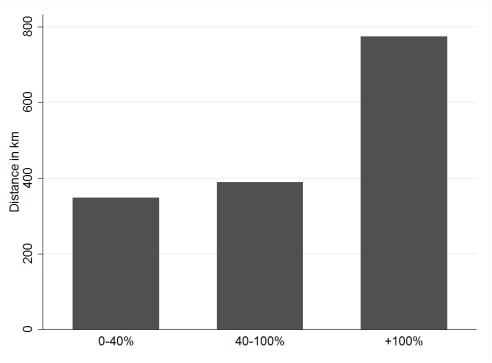
Reward-based crowdfunding: between donation and consumption Belleflamme, Lambert and Schwienbacher (2014*b*) propose a model of reward-based crowdfunding with pre-orders and show that a necessary condition for crowdfunding relates to the idea that contributors derive additional community gains, increasing their willingness to pay for the good. Crowdfunding is often presented as a way to help artists [15], and helping artists is indeed a central motivation for contributors (Gerber and Hui, 2013). Pro-social motivations, based on the idea that an individual's utility depends

15. For example, proarti, a French crowdfunding platform specialized in cultural projects, edits tax receipts for their backers to benefit from tax reductions, assimilating crowdfunding with cultural patronage.

directly on the utility of other people, mixed with contributors' interest in rewards, should thus be at stake [16].

Crowdfunding, friends, family and distance An important feature of crowdfunding is the role played by friends and family (Agrawal, Catalini and Goldfarb, 2015), as an important share of the funding usually comes from close relation (Belleflamme, Lambert and Schwienbacher, 2013): the so-called "love money". Friends and Family (F&F) are those who back a project at the beginning of a campaign and are contributors that are geographically close to the project holder. In Figure 0.3, one can see the average distance between contributors and the creator of the project they are backing on the Brazilian platform Catarse.

Figure 0.3 – Average distance between contributors and artists



Note: The sample corresponds to 473 contributions made on the Brazilian platform Catarse. It only corresponds to contributions for musical projects.

Risk and crowdfunding [17] There are two dimensions of uncertainty when backing a project. First, there is a coordination issue that the project reaches the financial target that would enable the artist to produce the good. If the artist correctly estimate the funds needed for production, there is a risk the project never come true if the funds

16. Chapter 4 investigates the pro-social foundation of backing decisions.
17. Chapter 3 investigates the effect of these two types of risk on the level and the timing of contributions.

are not collected, especially since there are multiple projects competing (Corazzini, Cotton and Valbonesi, 2015*a*). Contributors need to coordinate on projects while facing uncertainty about others' choice and valuation. If coordination is not reached, backers may miss potential positive payoffs.

Secondly, the main particularity of crowdfunding relies on the initial state of production: contributors participate in the production phase and the value of the outcome is unknown, especially when it comes to experience goods. Besides the uncertainty of whether or not a contributor will like the product, there is an hidden information regarding the artist's ability to realize what she announced. One of the 30 musicians interviewed by Galuszka and Brzozowska (2016) in their article on crowdfunding explains:

" 'the money [...] surely gave us a chance to record in a professional studio [...] we wouldn't have recorded it otherwise [...] It was the first time we recorded, we had no experience, there was no really good equipment [...] We surely had no such thing as a producer. Such a person sits there and says 'Okay, play this another way, play this like that' and gives advice."

Artist on crowdfunding platforms are generally amateurs, sometimes unskilled ones. The ex-post success of crowdfunding projects has not been investigated in the literature. In a working paper, Mollick (2015) focuses on factors that led to projects failing to deliver their promised rewards. His results show that 9% of the projects failed to deliver the promised rewards, with a possible range from 5% to 14%. The study, however, does not discuss the success in the realization and the quality of the product itself. The literature in crowdfunding has shown that backers react to signals of quality to face uncertainty. For instance, contributors respond to the quality of the description (Mollick, 2014), the accumulated fundings as a herding behavior (Agrawal, Catalini and Goldfarb, 2015) or the artists's social capita (Colombo, Franzoni and Rossi-Lamastra, 2015).

In this section, we have seen why consumers seek for novelty in cultural markets and the challenges in terms of diversity of consumption that these markets face. We have also seen that consumers themselves can decide to take part in the production of novelty. This thesis aim to study several aspects of what has been developed. Understanding the demand for novelty on music markets can be hazardous. The work presented in this thesis adopts methodologies derived from experimental economics.

0.3. On the use of experimental methods to study cultural economics

In this section, we describe the experimental methodologies applied in this thesis. The first part of this thesis, composed of two chapters, uses in-lab experiments to replicate musical consumption (Chapters 1 and 2). The second part of the thesis, composed of two other chapters, links experimental data to online data on actual behaviors on a crowdfunding platfom (Chapters 3 and 4).

0.3.1. Lab experiments applied to cultural economics

Controlled environment, incentives and causal effects Experimental economics was inspired by experimental psychology and was initially used to test theoretical predictions. Experiments are generally implemented in the controlled environment of the laboratory, allowing for the identification of causal effects. Experimenters must follow 3 main rules: participants must have incentives, they have to make their decisions in a context-free environment and they should not be deceived (Croson, 2005). In addition, if she is aiming to test a theory,, the experimenter specifically needs to take good care of the internal validity of the experiment, meaning that the lab situation should exactly capture theoretical assumptions.

Music: a good candidate for experiments Music is often used in psychology or marketing experiments to study the effect of exposure on satisfaction (Hunter and Schellenberg, 2011), variety-seeking behaviors (Brickman and D'Amato, 1975, Ratner, Kahn and Kahneman, 1999, Galak, Kruger and Loewenstein, 2011) and novelty versus familiarity seeking behaviors (Ward, Goodman and Irwin, 2014).

It is much less often used in experimental economics, despite meeting the field's methodological needs. Participants can make repeated choices within a short amount of time and actually consume privately the good (i.e., listen to the songs they chose). Inclination for music is universal (Peretz, 2006) and songs are sufficiently heterogeneous to avoid boredom and satiety related to repeated consumption (Armantier et al., 2015). Finally, music choices are naturally incentivized: because participants actually consume the good, they have an incentive to choose in accordance with their preferences. Note that while in experimental economics, monetary incentives are generally used, here, music provides an original, but still valid, incentive. We can however mention a few experimental articles using music in an experimental setting to study social contagion (Salganik, Dodds and Watts, 2006), novelty consumption (Berlin, Bernard and Fürst, 2015) [18] or the process of discovering preferences (Armantier et al., 2015).

Implementing and studying novelty consumption in the laboratory The operationalization of artistic novelty in the laboratory is far from trivial, as it requires knowledge of participants' prior exposure to cultural goods as well as their cultural habits. Novelty is implemented in two ways in the experiments of this thesis. In a first experiment (Chapter 1), we distinguish new goods from the others by an exposure criteria. Two categories are defined: the first one is composed of songs from the Top 30 registered at the time of the experiment while the second one is composed of pieces of music created by unknown artists made available on an online platform specialized in artist discovery. In a second experiment, we use the second criteria of

18. Chapter 1 of this thesis is composed of this article.

novelty, namely differenciation (or disparity) by using four musical genres (Pop/Rock, Classical, Rap/Rnb and Bles/Jazz).

0.3.2. Linking data

The second part of this thesis uses a burgeoning methodology that consists in linking experimental data with real-world data, a methodology considerably eased by the use of online experiments (Hergueux and Jacquemet, 2015).

Online experiments Internet is a very attractive tool to implement experiments, including (i) the possibility to reach a larger, more diverse population (ii) a higher flexibility (in schedule) and (iii) reduced costs. Notwithstanding these advantages, the use of online experiments raises internal validity issues (Horton, Rand and Zeckhauser, 2011) [19]. Implementing an online experiment thus requires a self-contained interface that provides multiple support instructions (text, videos and simulators) as the one proposed by Hergueux and Jacquemet 2015. Online experiments are well-suited to couple experimental measures with observational data.

Online behaviors and cultural consumption Since digitization, consumers can acquire contents online. In the case of music, movies and books, goods can be downloaded (on iTunes, Amazon etc.) or consumed on dedicated streaming platforms (Spotify, Netflix, Youbooks etc.).

Individual support to cultural projects can also be observed thanks to crowdfunding platforms. Some actually argue that crowdfunding already existed before Internet. The pedestal for the Statue of Liberty was funded in 1884 by Joseph Pulitzer through an open call to the American people and raising small donations from hundreds of

19. Hergueux and Jacquemet (2015) list the following drawbacks: the lack of information regarding participants' identity, whether they carefully read and understand the instructions and the reasons why they may drop out, the lack of participants' trust regarding payments and the fact that they are playing with real humans, the potential lack of anonymity due to payment.

residents [20]. Web 2.0 has nevertheless provided a critical boost for crowdfunding since artists and crowds can be more easily matched (formalization of existing transactions, reduction of transaction costs etc). Thanks to online crowdfunding, backing decisions are observable both to the researcher and to other Internet users. This thesis makes use of this fact by studying real online decisions to crowdfund artistic projects (see Chapters 3 and 4).

Do experimental measures predict field behaviors? This thesis uses the linking data methodology consisting in coupling observational data with experimental data. Originally, experimental economists studied in-lab behaviors under the assumption that subjects bring their real life preferences inside the lab. Since Karlan's (2005) seminal research where he predicts loan repayment among participants in a microcredit program with the Trust game, experimenters recently brought experimental results outside the lab by studying the correlation between in-lab and out-lab behaviors. There is however a strong debate on whether experimental data have a predictive power with respect to real-life behaviors. Some articles take notice of the existence of a correlation (see Karlan (2005), Laury and Taylor (2008), Benz and Meier (2008), Barr and Serneels (2009), Carpenter and Seki (2011), Fehr and Leibbrandt (2011), Potters and Stoop (2016) for a non exhaustive list [21]) while others find a poor relationship (Galizzi, Navarro-Martínez et al., 2015, Stoop, Noussair and van Soest, 2009).

Levitt and List (2007) highlighted the limits of such an approach. They raise concerns regarding:

— the experimenter demand effect involving a change in subjects' behavior due to cues about what constitutes appropriate behavior (Zizzo, 2010) [22];

20. Joseph Pulitzer decided to launch a fundraising campaign in his newspaper The New York World. Eventually, 160,000 residents donated to build the pedestal, gathering $101,091.

21. See Galizzi, Navarro-Martínez et al. (2015) for a comprehensive list.

22. This issue is crucial when experiments deal with pro-social preferences since acting altruistically or cooperatively is socially desirable. Subjects might act pro-socially towards the experimenter or to please the experimenter.

— non-anonymity, especially between the subject and the experimenter that may induce pro-social behavior not by preference for fairness but by concerns about what an outside observer might think about one's decisions;

— selection effects, suggesting that volunteers are "do-gooders" who "readily cooperate with the experimenter and seek social approval" (Levitt and List, 2007)

In opposition to this claim, Camerer (2015) argue that there is not evidence that experiments aiming at reproducing a specific environment yield no external validity. Despite this debate around laboratory games' external validity, and although it was not the initial purpose of such experiments, there is a burgeoning literature linking experimental measures with field behaviors. It relies on the assumption that in-lab behaviors are good proxies for actual behaviors and that experimental measures can have a predictive power for real behaviors. In other words, individuals act in-lab approximately as they would out-lab. Of course, by construction, experimental conditions are controlled and the environment is everything but natural. But they are still informative of how an individuals would react in a naturally-occurring situation.

Chapter 3 uses an experimental elicitation of attitudes towards risk, following the Holt and Laury (2002) procedure, which consists in a list of 10 choices between a safe lottery and a risky one. This procedure can be used to estimate coefficients of risk aversion and thus to elicit attitudes towards risk. Previous articles highlight the predictive power of such a measure for real behaviors in finance (Fellner and Maciejovsky, 2007), health (Anderson and Mellor, 2008) or food consumption (Lusk and Coble, 2005). Another benefit in using this procedure within the context of reward-based crowdfunding platform is that the amounts at stake are similar.

Chapter 4 uses experimental measures of pro-social preferences. Games have long been used by experimental economists to study altruism, reciprocity, cooperation or inequity aversion (for a review see Fehr and Fischbacher (2002)). Several articles highlight the predictive power of pro-social preferences elicited experimentally. Karlan

(2005), in the context of a microcredit program in Peru, shows that decisions in the Trust game -though not in the Public goods game- predict the loan repayment rate. Trustworthiness in the Trust game is also correlated with students' donations to their faculty (Baran, Sapienza and Zingales, 2010). Social preferences exhibited in the Public goods game predict actual behaviors such as the productivity of fisherman in Japan (Carpenter and Seki, 2011, Englmaier and Gebhardt, 2016), the overextraction of fish (Fehr and Leibbrandt, 2011) or the number of contributions on Wikipedia (Algan et al., 2013).

We presented the methodological tools that are used in this thesis as well as the advantages of experimental economics to study cultural economics. The next section presents the outline of the thesis.

0.4. Outline of the dissertation

The first two chapters focus on the determinants and characteristics of demand for novelty using in-lab experiments. Specifically, Chapter 1 studies demand concentration between popular and new songs while Chapter 2 develops a methodology to estimate price and income elasticities for four musical genres within the lab.

The second part of this thesis investigates the willingness-to-pay to increase the variety of the supply via crowdfunding, linking experimental data and archive data provided by a Brazilian crowdfunding platform, Catarse. Chapter 3 presents a dynamic model of demand for crowdfunding and studies the role of risk aversion while Chapter 4 studies the role of social preferences in crowdfunding activities.

0.4.1. Demand for novelty: in lab experimental approaches

Chapter 1 is a joint work with Noémi Berlin and Guillaume Fürst. We implemented a lab experiment to study the demand structure between bestsellers and new artists' productions in the music industry. In this paper, novelty is defined as a piece of

art that has not yet been experienced by the consumer. We set up an experiment where participants faced real-choice situations and were to decide how to allocate their available time between popular songs (known music) and new songs (novelty).

We created three treatments to isolate the effect of information (specifically "word-of-mouth") and price incentives on novelty diffusion. In a first treatment, music was consumed for free without information. This treatment is the benchmark. Interestingly, we find that, on average 40% of the whole time is allocated to novelty. This first result supports the idea according to which new songs can attract the demand, even if they represent a riskier choice. In a second treatment, subjects received prior information on others' evaluation of the songs to study the effect of word-of-mouth. Finally, in a third treatment, a real market was introduced where music could be bought. Our experiment shows that, when replicating a music market with prices, the aggregate demand is more diversified. We found that with incentives in favor of the new artists' category, the demand structure changes toward more diversity. The price sensitivity between popular songs and new artists' songs is an important result because it is not easy to uncover using field data. Our design enabled us to incentivize decisions, to control the set of choices between popular and unknown music and to isolate the effect of information and price incentives on consumption.

Chapter 2 is a joint work with Louis Levy-Garboua, Laëtitia Placido and Claire Owen. This chapter is aiming several objectives. First, it develops a methodology to estimate demand functions using an Almost Ideal Demand System model (Deaton and Muellbauer, 1980) in a lab controlled environment. Thanks to this methodology, we are able to estimate own and cross price as well as expenditure elasticities for four musical genres, namely Pop/Rock, Classical, Rap/Rnb and Blues/Jazz. In addition, we study differences in estimations for sub-samples of demand, that is by gender, by age and by level of openness for new experiences using the Big Five personality traits. Finally, we apply the methodology to Chapter 1's experiment in order to estimate price elasticity

for known and unknown songs. Results suggest that new music is an necessity good while popular music is a luxury one and that both categories are imperfect substitutes.

0.4.2. When consumers finance the production of novelty: a behavioral approach on Crowdfunding

Chapter 3 studies the timing and the level of contributions for musical projects when contributors are subject to the two types of risk described above (risk of coordination failure and risk of non-delivery). We develop a theoretical model showing that, in order to understand why people may be either early or late contributors, the notion of illusion of control over others' contributions is crucial. It refers to the belief that one's decision will induce others do likewise. Because contributors are exposed to uncertainty, the chapter also focuses on the role of risk aversion in backing decision. We use the Holt and Laury's (2002) procedure to measure individual risk aversion. An important results of our study shows that the higher the level of risk aversion of late contributors, the lower the contribution, while the effect is opposite for early contributions. One way to understand it is that highly risk averse are ready to pay a premium to ensure coordination over a given project.

Chapter 4 is a joint work with Marco Gazel. It aims to study the pro-social foundations of contributions to cultural crowdfunding projects. We study the correlation between experimental measures of altruism, reciprocity and cooperation on the extensive margins of contributions (the number of projects backed) ans the intensive margins of contributions (the average amount contributed) for musical projects. We find that altruism and reciprocity positively predicts the number of projects backed. Experimentally elicited measures of cooperation however poorly predict the average amount of contributions for musical projects. The decision to contribute seems to fall within a donation logic while the decision on how much to contribute within a consumption logic.

Part I

Demand for novelty: in-lab experimental approaches

Chapter 1

Time spent on New Songs: Word-of-Mouth and Price Effects on Teenager Consumption

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This chapter is a joint work with Noémi Berlin and Guillaume Furst. It is an extension version of a published version in the *Journal of Cultural Economics*.

1. Introduction

The structure of the creative industry is generally described as being shaped according to the 80/20 Pareto law: 80% of the total revenue is made by 20% of the supply. Four types of explanation suggest why demand is concentrated towards a limited number of artists. First, skewness may reflect differentiation in talents (Rosen, 1981) under the assumption that one high quality performance is an imperfect substitute to several low quality ones. Secondly, consumer value popularity (Adler, 1985): consumers benefit from network effects when imitating others' consumption. According to Adler (2006), "consumers prefer the most popular artist and therefore even an artist who is as talented as the star cannot entice audiences away from the star, not even by offering a lower price". In other words, price incentives do not outweigh the prior advantage of settled artists. Third, cultural goods are highly uncertain since they are experience goods (Nelson, 1970). Lack of information enhances mimicry behaviors, leading to potentiel "informational cascades" (Bikhchandani, Hirshleifer and Welch, 1992*b*, Banerjee, 1992). Finally, because demand is highly unpredictable, new artists face more difficulties when entering the market that can only be compensated by higher fixed costs to increase visibility and lower prices (MacDonald, 1988). In other words, the skewness in demand is related to a limited number of easily accessible goods.

With the digitalization of the industry, Anderson (2004, 2006) predicted that the "long tail" would smooth the distribution of sales as a result of: (i) lower production costs causing an increase of the variety supplied (ii) lower distribution costs easing the access to niche products and (iii) the development of on-line word-of-mouth upscaling the matching between demand and supply. The long tail effect has been tested for various cultural goods, including books (Brynjolfsson, Hu and Smith, 2003, Peltier and Moreau, 2012), videos (Elberse and Oberholzer-Gee, 2006, Benghozi, 2008) and music (Benghozi and Benhamou, 2010, Bourreau et al., 2013). No consensus is however

found, either for theoretical nor empirical, on the existence and magnitude of the long tail effect. Even though digitization can lead to a better matching between supply and demand, consumers' awareness of the overall supply is not systematically insured and choice overload may limit the long tail effect (Gourville and Soman, 2005, Kuksov and Villas-Boas, 2010). In other words, a higher level variety in supply can lead to lower variety in consumption because it is cognitively costly to choose when facing too many alternatives.

This article aims at studying the drivers that push consumers to try unknown music using an original in-lab experiment. It remains difficult to analyze the ins and outs of novelty consumption since data are difficult to gather. Even in the case where data are accessible, one cannot know what drives consumers' choices: are people influenced by others' opinion, others' consumption, products accessibility, marketing promotion etc. when they decide what to consume? Experimental economics present several assets to overcome these difficulties: the set of supplied goods can be controlled as well as the conditions of consumption. We choose to study musical consumption as it is private consumption, it is easy to reproduce in an experimental laboratory and listening to music inside and outside the laboratory is similar.

Consumers are looking for novelty because cultural goods are semi-durable goods (Bianchi, 2002). According to a IFOP sondage (Institut Francais d'Opinion Publique, French Institute of Public Opinion) in 2014, 72% of the young radio listeners (15/34 years old) think that radio channels broadcast the same songs too often and that the music programming is not enough diversified. The arousal and satisfaction derived from the consumption of a piece of music varies over time and exposure: the taste for a specific musical song often increases with exposure and then decreases through over-exposure (Hunter and Schellenberg, 2011) [1]. But, because it can be costly or risky

1. Hunter and Schellenberg find that Openness-to-Experience- a personality trait measured in psychology that characterizes people who have a general appreciation for art, emotion, adventure, variety of experiences etc.- is correlated with the shape of the function of exposure (linking number of exposures and liking ratings): while low openness leads to an inverted U-shape function, high openness

to try new artists, novelty-seeking behavior might not be enough to counterbalance the stardom structure of the market.

In terms of public policies, it is crucial to promote creative innovation. A deterioration of cultural diversity may lead to a decrease in the demand (Benhamou, 2002). In France, radio channels have the obligation of broadcasting 40% of its songs in French, half of which has to be new in order to compensate for the stardom structure of the music industry. Exposure to new entrants can facilitate the demand for novelty since it eliminates uncertainty about its quality.

In this paper, we study the effect of information and monetary incentives on the distribution of sales (concentration versus diversity) between bestsellers and new artists in the music market. According to the literature, word-of-mouth between consumers should concentrate the demand on artists that are already settled. Regarding prices, there are no important differentiation in the physical nor digital music market (Peitz and Waelbroeck, 2003). Still, in the concert market, prices are differentiated and artist-related characteristics explain the level of prices: the career and the popularity of an artist explain higher concert prices (Decrop and Derbaix, 2014) such that new entrants set lower prices. But, according to the literature, price incentives would not have any important impact on consumption of novelty.

In a controlled online experiment, Salganik, Dodds and Watts (2006) found that observing other individuals' behavior actually increases the skewness of the distribution of the demand. Experimental methods can be used to isolate the effect of peers' information (word-of-mouth) and price incentives on the concentration of consumption toward bestsellers. We propose an experiment that simulates an environment where subjects face real choices between different types of musical songs (best selling songs and new artists' productions). We run this experiment on teenagers because they like music (North, Hargreaves and O'Neill, 2000), they are prone to the stardom system and

is linked with a decreasing liking rating function according to the number of exposures.

they are influenced by peers' opinions (Berns et al., 2010). We create three treatments, the first being an isolated choice treatment (the Benchmark treatment), a second where subjects receive information about others' evaluation (the Word-of-Mouth treatment) and a third where a real market including prices is established (the Market treatment). Our experimental design has two main advantages: we can precisely measure demand for both categories, and, by comparing treatments, we can isolate the effect of information and pecuniary incentives on the structure of demand in an experiment without search costs.

We find effects of the two treatments on diversity. Regarding the global consumption, we find that the Word-of-Mouth has a negative impact on diversity. Conversely, the Market treatment has a positive impact on diversity since half of the demand is dedicated to bestsellers and the other half to the new artists' songs. We then find that the demand is sensitive to the nature of the information and the variability of prices.

This article is organized as follows. Section 2 describes the experimental design. Section 3 presents the results, describing the effect of the Word-of-Mouth and the Market treatments on diversity and the reactions of the demand to the nature of the word-of-mouth and the level of prices. Section 4 discusses and concludes.

2. Experimental design

2.1. New Artists versus Bestsellers

To implement new artists' and stars' products, participants face two track categories. On one hand, the "Top 30" category, the bestsellers' category, gathers the 30 French top selling singles from the 29th of October to the 4th of November 2012 [2]. One can expect that teenagers, regarding their age, are mostly exposed to this category. On

2. The SNEP (Syndicat National de l'édition Phonographique, French union of the phonographic edition) establishes each week the official chart of the best selling singles in France. It takes into account the physical and the digital sales.

the other hand, the new artists' category is composed of the most popular songs of the French website *Noomiz*. *Noomiz* is a website that enables new artists, who did not sign a contract with a music label yet [3], to offer their production, such that one can assume that these tracks have never - or at least rarely - been experienced by the participants. We call this category the "New Artists'" category since it is only composed of unknown artists. During the experiment, we control for habits regarding the use of websites like Noomiz and results show that the majority of the sample actually do not use this type of online platforms [4]. This confirms our assumption according to which subjects are not familiar with the songs that New Artists' category is composed of.

Both categories are composed of 30 songs each and are characterized by the same language and genre distribution [5].

At each period of choice, participants are facing two songs, one of each category. [6] Both songs belong to the same genre such that we can implement differences in popularity: the Top 30 category represents songs for which teenagers are exposed while the New Artists' category is composed of songs that the participants could like (they are of the same genre and of an expected comparable quality as we chose them according to Noomiz popularity ranking, but they are unknown) [7].

3. A popularity ranking allows them to encounter professionals of the music industry.

4. During our experiment, the subjects were asked : "How do you discover new music?". One of the proposed answer was "By visiting websites like Noomiz that specialize in offering music from new artists". Subjects had to answer on a five-point frequency scale. 54% answered "Never", 22% "Rarely", 13% "From time to time", 5% "Often" and 6% "Very Often".

5. Each category is composed of 24 Anglo-Saxon tracks and 6 French ones. In terms of genres, there are 13 electro/dance/remix's songs, 10 pop/rock/folk and 7 Rap/RnB/Hip-hop/Soul. Songs are classified by genre by both the SNEP and Noomiz.

6. All participants are facing the same set of songs in the same order.

7. Throughout the experiment, the Top 30 is actually better evaluated than the New Artists' category. This corroborates the idea that people prefer what they have already experienced or frequently experienced (Bornstein, 1989).

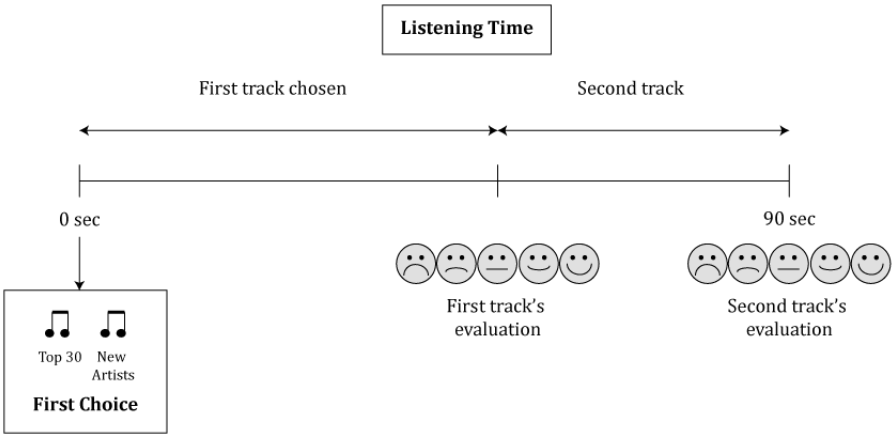
2.2. Procedure

The experiment consists of 30 listening periods of 90 seconds each. At each period, participants are asked to choose between two songs, one from each foregoing category, knowing that both songs belong to the same musical genre. The countdown starts and they listen to the chosen song. During the 90 seconds, participants are allowed to switch only once to the other song, the one that was not initially chosen:

— If a subject decides to switch, she is asked to evaluate the song that she just listened to on a five-point-scale illustrated by smileys. Then, at the end of the period, she is asked to evaluate the second song that she listened to (see figure 1.1).

— If a subject decides not to switch, she is only asked to evaluate the only song she listened to at the end of the 90 seconds period.

Figure 1.1 – Period summary



The experiment consists in three distinct treatments. We use a between-subjects design in such way that each participant takes part in only one of the three treatments.

The Benchmark Treatment Subjects ($n = 33$, 2 sessions) are facing the basic procedure described above. This is the control treatment.

The Word-of-Mouth Treatment In the Word-of-mouth treatment ($n = 41$, 2 sessions), subjects know the mean evaluation of every song which was observed in the Benchmark treatment. It appears as a five-star-scale (with mid-stars). This is to simulate Word-of-Mouth information that can theoretically lead to an informational cascade. If one song has no evaluation - simply because no one, in the benchmark market, listened to it - participants are told so.

The Market Treatment In the Market treatment ($n = 36$, 2 sessions), in each session, two participants are randomly chosen to play the role of sellers, while the others are buyers.

The supply side

Two subjects are randomly designed to sell one category of music to the others in order to implement a monopolistic competition : one seller is to offer songs from the Top 30 category while the other is to offer songs from the New Artists category all along the experiment. At the beginning of the experiment, this situation is described to them. When the experiment starts, each seller is assigned to one of the two categories and will only sell this specific category during the whole session (Top 30 or New Artists). At each period, the sellers listen to one song of the genre they will have to sell and set a per second price included in a defined range [8].

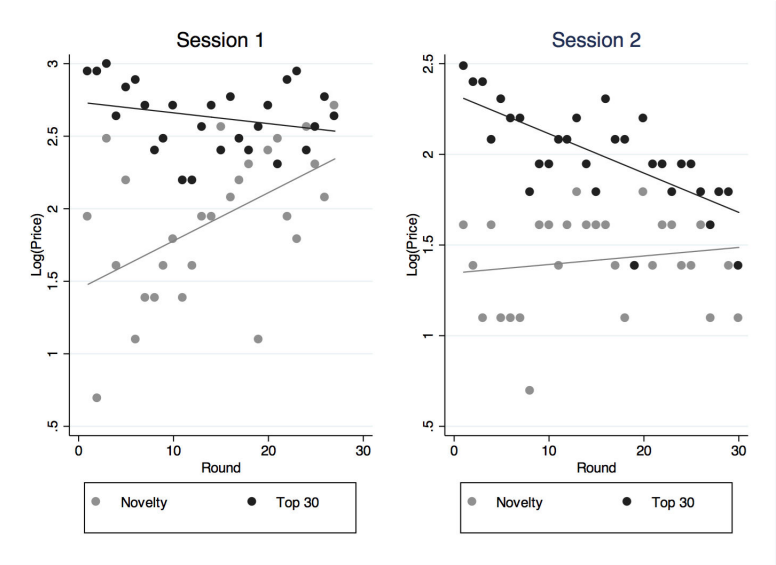
There overall profit of the seller who sells category j is computed as follows:

$$\Pi_j = \sum_{t=1}^{30} p^{t,j} \sum_i \tau_{t,j,i}$$

where $p^{t,j}$ is the price set by seller who sells genre j at period t and $\tau_{t,j,i}$ is the time

8. In the Market Treatment, prices are set to be in an experimental money - the ECU - convertible in candies. Sellers have to set a price from 0 to 20 units of ECU.

Figure 1.2 – Level of prices for each session of the Market treatment



Note: The lines represent linear regressions of the logarithms of prices by sessions and categories.

allocated for genre j by the buyer i at period t. Figure 1.2 represents the Market sessions and the prices that are set by the sellers. Not surprisingly, we can see that for both sessions the Top 30 price is almost always higher than the New Artists' price such that there are incentives to consume the New Artists' category. This result is confirmed by Table 1.1 presenting summary statistics for aggregated prices for all sessions. Prices set by the New Artists' sellers are always significantly lower than prices set by the Top 30 sellers, except for the last 5 periods. Further, Figure (1.2) and Table (1.1) suggest a convergence path of prices.

The demand side

Besides the two selected sellers, all the other participants from each session are music buyers. At each period t, they are offered one song of each category j at a price $p^{t,j}$. They also have a per period budget of 1800 ECU that diminishes according to the

Table 1.1 – Price comparisons between New Artists and Top 30

		Price		Mann-Whitney test	Time spent on
		Top 30	**New Artists**	**p-value**	**New Artists (in sec)**
Rounds	All	10.8	5.8	< 0.001	47.1 (35.0)
	1 to 5	14.1	5.5	< 0.001	52.5 (33.5)
	5 to 10	10.9	4	< 0.001	52.6 (34.1)
	10 to 15	9.5	6.1	0.004	50.3 (32.3)
	15 to 20	10.5	6.3	0.017	42.8 (35.0)
	20 to 25	10.5	7	0.043	43.3 (36.7)
	25 to 30	8.1	6.2	0.300	41.0 (36.5)

Standard deviation in parenthesis.

song - and the associated price - they are listening to. The budget of 1800 is fixed such that even if one buyer listens to a song set at the maximal price of 20 ECU, she can listen to it during the 90 seconds of the period. At the end of the 90 seconds, what is left from the individual i's budget is to be saved [9], such that his/her overall saving is:

$$S_i = \sum_{t=1}^{30}(1800 - \sum_{j=1,2} p^{t,j} * \tau_{t,j,i})$$

At the end of the experiment, S_i is converted into candies in weight [10].

2.3. Sample comparison

110 high-school students were recruited from three distinct French schools' Academies (Paris, Versailles and Créteil which are French education authorities for the Île-de-France area) and participated in the experiment, which was conducted in the Parisian Experimental Economics Laboratory (LEEP) in November 2012. Each of the participants faced an individual screen with headphones. At the end of the experiment, they were asked to fill in a questionnaire. Table 1.2 presents the descriptive statistics of our

9. It is important that the buyers can save experimental currency in order to control for income allocation and preference for saving.

10. The conversion rate is 2gr. of candies for 1000ECU.

sample.

Variables	**Benchmark** $n = 33$	**Word-of-mouth** $n = 41$	**Market** $n = 36$	**p-value** [11] two-sample t-test
Mean age	15.06 (0.6)	15.22 (0.52)	15.1 (0.46)	ns
Gender (% female)	51.51	51.21	50	ns
Music exposure				
Exposure to mainstream music media	1.61	1.64	2.05	$p_{BvsM} = 0.07$ $p_{WoMvsM} = 0.07$
Music listening habits				
(0: rarely, 4: very often)				
Hip-hop/Rap	3.13(1.00)	2.49(1.42)	2.97(1.27)	$p_{BvsWoM} = 0.04$
RnB	3.06(0.98)	2.68(1.39)	3(1.07)	ns
Zouk, Dancehall, Raggeaton	1.94(1.43)	1.67(1.30)	2.06(1.43)	ns
Pop	2.70(1.07)	2.51(1.12)	2.38(1.30)	ns
Rock	1.81(1.33)	1.97(1.41)	1.65(1.50)	ns
Heavy Metal	0.81(1.31)	0.90(1.22)	0.47(0.83)	$p_{WoMvsM} = 0.08$
Jazz/Blues	0.76(1.03)	0.93(0.96)	1.24(1.16)	$p_{BvsM} = 0.08$
Classical	0.45(0.71)	0.98(1.08)	0.71(0.94)	$p_{BvsWoM} = 0.03$

Table 1.2 – Sample comparison

The participants were high-school students who were participating in an open day organized by the University of Paris 1. Several high-schools were invited to participate in order to introduce research in economics to the students. Besides the conferences, one of the main activity of this event was to take part in our experiment. Groups were allocated randomly to the three treatments. Nevertheless, the three Academies were not present on the same day in such way that each session was composed of students from the same Academy [12]. The fact that participants are not coming from the same Academy can explain the difference in musical listening habits. These differences can also be due to the fact that we are using a relatively small sample. However, we control afterwards for musical tastes and it does not change our results.

11. ns means that all the two-sample t-tests are non significant. Only significant ttests' p-values are reported.

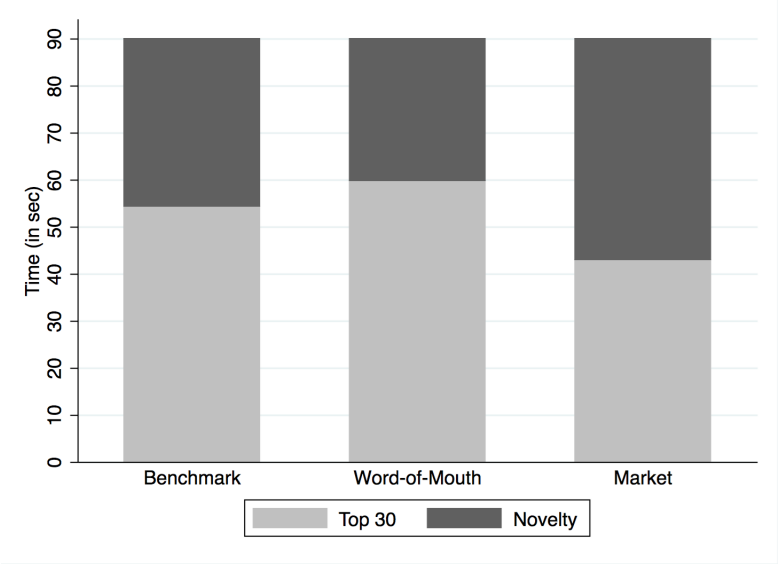
12. A table describing the distribution of participants by treatment can be found in the Appendix.

3. Results

3.1. Descriptive results

First, we study the impact of information and incentives on the overall consumption distribution. In Figure 1.3, we can see that the average demand is skewed toward the Top 30 category for the Benchmark treatment and the Word-of-Mouth treatment while it is almost equally distributed in the Market treatment.

Figure 1.3 – Average consumption of the New Artists and the Top 30 categories by treatment (in sec)



The Word-of-Mouth treatment has a negative impact on the demand for novelty: while subjects listen to 36 seconds (40%) of the New Artists' category on average in the Benchmark treatment, they only listen to 30 (33%) seconds of it in the WoM treatment (a Mann-Whitney test yields $p<0.001$). On average, the Top 30 category was better rated than the New Artists' category along the experiment except for only one period. Hence, the average consumption in the Benchmark and the Word-of-Mouth

Table 1.3 – All Pairwise Comparisons (per treatment) for Time spent on New Artists (per period)

		p-value	
	DI	**Bonferroni**	**Holm**
Benchmark vs WoM	6***	0.002	0.001
Benchmark vs Market	11***	0.002	0.002
WoM vs Market	17***	0.002	0.000

*** p<0.01, ** p<0.05, * p<0.1
Note: DI refers to "difference in means". For instance, the, on average, subjects listened to 6 more seconds of the New Artists' category (per period).

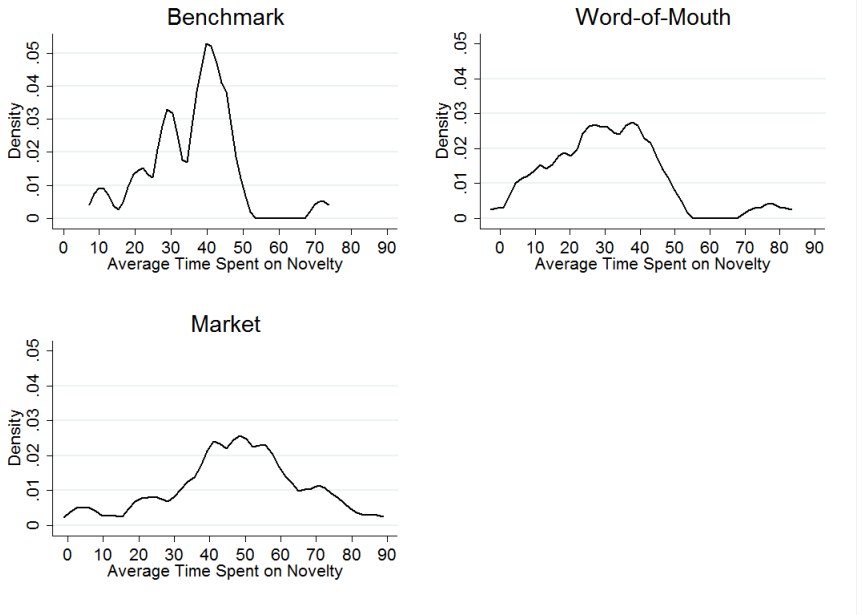
treatments might reflect the quality difference between the two categories. The Market treatment has a positive and strong effect on the demand for new artists' productions. Indeed, subjects listen to 47 (52%) seconds of the New Artists' category on average, versus 36 seconds (40%) in the Benchmark treatment (a Mann-Whitney test yields p<0.001). Since the New Artists' category is always cheaper than the Top 30 category, pecuniary incentives to buy it actually drive subjects to consume more of it. All levels of significance are robust to the Holm-Bonferroni's corrections (see Table 1.3).

Figure (4.1) compares the distribution of the average time spent on New Artists over the 30 periods of the experiment by treatment. The skewness of the distribution in the Benchmark and the Word-of-Mouth treatments shows that very few participants dedicate the majority of their time on New Artists on average. Concerning the Market, we can see that the distribution is more spread such that three consumption profiles appears: consuming relatively more in the Top 30 category, consuming relatively more in the New Artists' category and consuming both categories almost equally.

3.2. Estimation

To confirm these descriptive results, we run an Ordinary Least Square (OLS) regression analysis, clustered on individuals (see Table 1.4). The first column (1) only

Figure 1.4 – Distribution of time spent on New Artists' over the sample by treatment



Note: The distributions are kernel density. The average time spent is calculated at the individual level.

contains two dummies as explanatory variables corresponding to the Word-of-Mouth and the Market treatment. The dependent variable is the time spent listening to the New Artists' category (in seconds) [13] and the OLS regression enhances the effect of the Word-of-Mouth treatment and the Market treatment. In Column (2), we add variables as controls. While the first treatment has a significant negative impact, lowering the expected time dedicated to New Artists (-5.4 seconds), the second has a significantly positive impact, raising the expected consumption (+14 seconds). There is also a significant effect of the beginning of the experiment such that the expected value of the time spent on the New Artists' category is about 6 seconds higher during the first 15 rounds. It seems that there is an exploratory period where subjects wish to try

13. Note that regressing the time spent on the New Artists' category is similar to regressing the time spent on the Top 30 as the two variables are complementary.

more of the New Artists' category. While all the control variables for listening habits do not yield any significant effect, the exposure to mainstream radio channels [14], that generally broadcast the Top 30 songs, has, without surprise, is negatively correlated with the expected time dedicated to the New Artists' category. All things being equal, choosing the New Artists' song first has an important positive impact on the expected listening time (+17.5 seconds). It might be the case that subjects need time to evaluate and experience the first song they chose to listen such that an anchor effect might appear. Finally, the quality difference, which is the difference between the overall mean evaluation of the Top 30 and the New Artists songs per period [15], negatively impacts the time spent on New Artists (-2.2 seconds). By controlling for the quality difference between both songs, we are able to isolate the pure signal effect of the Word-of-Mouth treatment.

14. Mainstream exposure is a continuous variable on a five points scale that combines answers, on a five-point Likert scale each, to the following questions: "how often do you listen to the following radio channels?:"

— NRJ
— Fun Radio
— Voltage
— Virgin Radio
— Skyrock
— Ado FM

These French radio channels are broadcasting mainstream music and top charts.

15. Here, the average evaluations used for the quality difference measure is to be distinguished with the average evaluation used in the Word-of-Mouth treatment. In the first case, it is measured by the overall sample's evaluations while in the second case, the average evaluation is calculated only with the subjects' evaluations of the Benchmark treatment.

Table 1.4 – OLS estimations of Time Spent on New Songs

Time spent on the New Artists' Category		
VARIABLES	(1)	(2)
WoM	-5.440*	-5.371**
	(3.262)	(2.609)
Market	11.417***	14.046***
	(3.901)	(3.380)
Mainstream radio		-3.553*
		(2.093)
New Artists First		17.525***
		(3.441)
Quality difference		-2.275***
		(0.793)
round_1_15		5.061***
		(1.262)
Female		-2.118
		(3.520)
Age		3.351
		(3.226)
Constant	35.702***	-15.931
	(2.057)	(50.436)
Control variables for musical listening habits	NO	YES
Observations	3,129 (106)	3,069 (104)
R-squared	0.054	0.198
Robust standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

Note: WoM and Market are two dummy variables equal to 1 if subjects are respectively in the Word-of-Mouth or Market treatments, 0 otherwise. Maintstream radio is a continuous variable on a 4 points basis. New Artists first is a dummy variable equal to 1 if subject chooses to listen to the novelty song first. Quality difference if a continuous variable. round_1_15 is a dummy variable equal to 1 for the first fifteen rounds, 0 otherwise. Female is a dummy variable equal to 1 for female subjects and age is a continuous variable.

3.3. Gender differences

In this section, we study the effect of word-of-mouth and prices on two sub-samples: female and male. Figure 1.5 shows the average time allocated to the two categories of good by treatment and by gender. In the Benchmark treatment, female participants listen to 37 seconds (41%) of the New Artists' category while male participants listen to 34 seconds (38%) of the New Artists' category (a Mann and Whitney test shows no significant difference with $p = 0.153$). For both sub-samples, the Word-of-Mouth treatment decreases the average consumption of novelty: 33 seconds on average for female versus 27 seconds for male (a Mann and Whitney test shows a significant difference between sub-samples with $p < 0.001$). Finally, in the Market treatment, female participants significantly allocate less of their time to New Artists than male participants (44 seconds versus 50 seconds, a Mann and Whitney test yields $p = 0.006$). These results suggests that, while female and male seem to behave similarly in the Benchmark, they do not react in the same way when information is made available or prices are implemented. All levels of significance are robust to the Holm-Bonferroni's corrections (see Table 1.5).

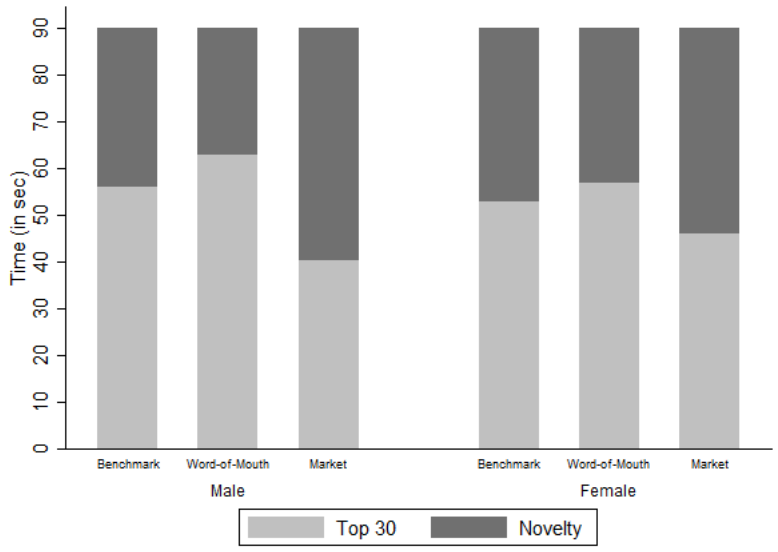
Table 1.5 – All Pairwise Comparisons (per treatment and gender) for Time spent on New Artists (per period)

	Female			Male		
		p-value			**p-value**	
	DI	**Bonferroni**	**Holm**	**DI**	**Bonferroni**	**Holm**
Benchmark vs WoM	4***	0.004	0.004	7***	0.004	0.002
Benchmark vs Market	-7***	0.004	0.000	-15***	0.004	0.003
WoM vs Market	11***	0.004	0.003	23***	0.004	0.001

*** p<0.01, ** p<0.05, * p<0.1
Note: DI refers to "difference in means". For instance, the, on average, female subjects listened to 4 more seconds of the New Artists' category (per period).

Looking at the OLS estimations in Table 1.6, one notices that the effect of word-of-mouth is not significant for female (models (3) and (5)). The effect of prices remains

Figure 1.5 – Average consumption of the New Artists and the Top 30 categories by treatment and gender (in sec)



significant for female: according, to model (5), being in the Market treatment is associated with an expected increase of 9 seconds allocated to the New Artists' category per period (at a 10% level of significance). Looking at male, model (6) suggests that being in the Word-of-Mouth treatment is associated with a decrease of 8 seconds allocated to the New Artists' category per period (at a 5% level of significance) while the Market treatment is expected to increase by 17 seconds per period (at a 1% level of significance). In conclusion, male are more responsive to information and price than female.

Table 1.6 – Time spent on the New Artists' Category - by gender

VARIABLES	(3) Female	(4) Male	(5) Female	(6) Male
WoM	-3.878	-7.063	-5.238	-7.885**
	(4.458)	(4.691)	(3.789)	(3.375)
Market	6.901	15.585***	8.967*	17.458***
	(6.056)	(5.035)	(4.526)	(3.968)
Mainstream radio			-2.585	-3.105
			(2.638)	(2.501)
New Artists first			11.864***	19.130***
			(4.237)	(4.714)
Quality difference			-2.422*	-1.976*
			(1.226)	(1.007)
round_1_15			4.612***	6.106***
			(1.532)	(1.985)
Age			-2.031	9.222**
			(4.420)	(3.514)
Constant	37.125***	34.190***	69.642	-109.949**
	(2.838)	(2.968)	(70.557)	(52.726)
Control variables for musical listening habits	NO	NO	YES	YES
Observations	1,560 (53)	1,569 (53)	1,560 (53)	1,509 (51)
R-squared	0.022	0.095	0.185	0.285
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Note: WoM and Market are two dummy variables equal to 1 if subjects are respectively in the Word-of-Mouth or Market treatments, 0 otherwise. Maintstream radio is a continuous variable on a 4 points basis. New Artists first is a dummy variable equal to 1 if subject chooses to listen to the novelty song first. Quality difference if a continuous variable. round_1_15 is a dummy variable equal to 1 for the first fifteen rounds, 0 otherwise. Age is a continuous variable.

3.4. Demand curves, information and incentives

In the previous section, we found effects of both treatments on the time spent on New Artists. We now look closer to the reaction of the demand to information and incentives.

The scatter diagrams shown in Figure (1.6) suggests a linear and positive relationship between the price ratio [16] and the demand share dedicated to the New Artists' category in the Market treatment (by period). Participants seem to react and adapt the time allocation to relative prices. The higher the price of the Top 30 category compared with the New Artists' category, the higher the demand share for New Artists. Through this relationship, we find that the Top 30 and the New Artists' songs can be considered as normal goods since the demand decreases when prices increase.

Figure (1.7) stresses a linear and negative relationship between the rating ratio [17] and the demand share dedicated to the New Artists' category in the Word-of-Mouth treatment. The higher the word-of-mouth evaluation of the Top 30 category compared with the New Artists' category, the lower the demand share for New Artists.

3.5. Satisfaction and treatments

An important issue is to understand the effect of information and prices on consumers' satisfaction. Even though the latter is not trivial to measure, this section provide some insights on the level of satisfaction of the participants. To properly measure it, we consider that one's satisfaction depends on the rating one assigns to the track she listens to, weighted on the time allocated to it. We thus define the following

16. The price ratio is equal to the price of the Top 30 song divided by the price of the New Artists' song.

17. The rating ratio is equal to the mean rating of the Top 30 song divided by the mean rating of the New Artists' song. These are the ratings appearing on a five-star-scale in the Word-of-Mouth treatment.

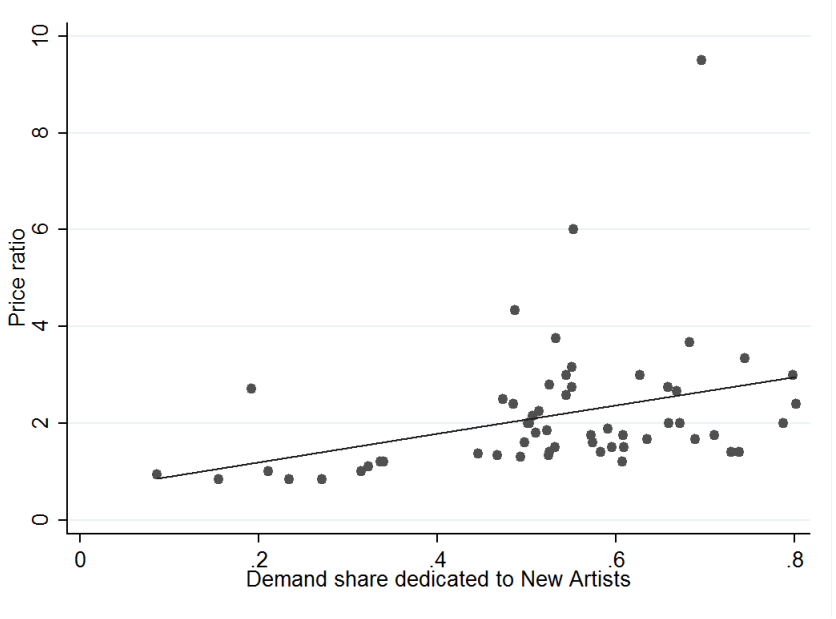


Figure 1.6 – Demand curves in the Market treatment

Note: The price ratio is equal to the price of the Top 30 song divided by the price of the New Artist's song. The line represents a linear regression of the demand share.

measure of satisfaction, at time t and for individual i:

$$S_{i,t} = r^1_{i,t} w^1_{i,t} + r^2_{i,t} w^2_{i,t}$$

where $r^1_{i,t}$ and $r^2_{i,t}$ are respectively the rating made by individual i at period t for the New Artists track and the Top 30 track while $w^1_{i,t}$ and $w^1_{2,t}$ is the share of time allocated to respectively the New Artists and the Top 30 categories. Figure 1.8 presents the empirical distribution function (EDF) of contributions by treatment. Satisfaction indexes are on the x-axis and the cumulated probability of observing a given contribution is on the y-axis. Table 1.7 shows that the score of satisfaction is significantly higher in the Benchmark treatment than in the two other treatments. This result is not surprising for the Market treatment, but one would expect that word-of-mouth would increase subjects' satisfaction by improving the match between their own taste and the

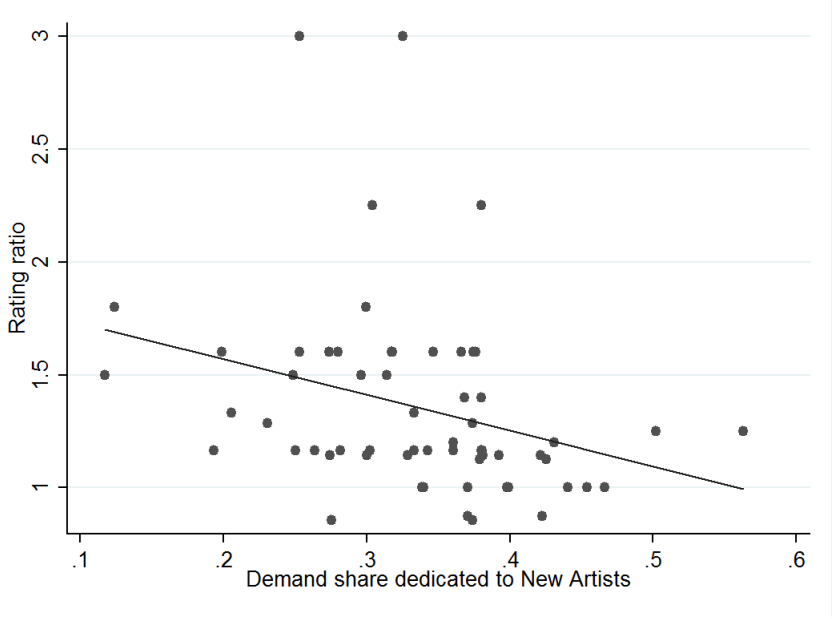


Figure 1.7 – Demand share dedicated to New Artists in the Word-of-Mouth treatment

Note: The rating ratio is equal to the rating (on a five-star-scale) of the Top 30 song divided by the rating (on a five-star-scale) of the New Artists' song. The line represents a linear regression of the demand share.

selected track. It however seems that the role of information may not be that efficient in matching supply and demand according to their tastes.

Figure 1.8 – Distribution of the individual index of satisfaction, by treatment

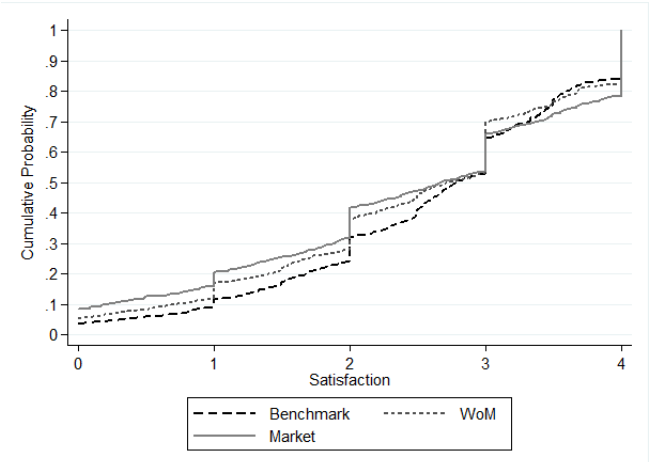


Table 1.7 – All Pairwise Comparisons (per treatment) for Satisfaction

		p-value	
	DI	**Bonferroni**	**Holm**
Benchmark vs WoM	0.121**	0.047	0.031
Benchmark vs Market	0.172***	0.007	0.007
WoM vs Market	0.051	1.000	0.375

*** p<0.01, ** p<0.05, * p<0.1
Note: DI refers to "difference in means". For instance, the satisfaction's score in the Benchmark treatment is, on average, higher by 0.121 units.

We are however not able to disentangle the effect of observed rating and prices on rating. Berns et al. (2010) indeed show that others' rating on songs have an influence on a buyer's own ratings. Lower rating in the Word-of-Mouth treatment can thus be related to the observed ratings. Further investigation should be conducted.

4. Discussion and Conclusion

This paper attempts to replicate choice treatments where demand meets two types of music products: superstars and new artists' productions. A first result of the experiment remains consistent with the existing literature and shows that others' opinion strengthen the stardom effect as the demand concentrates more on the Top 30 category. Indeed, there can be two origins of this phenomenon: either people rely on others' opinions to make the best choice (Bikhchandani, Hirshleifer and Welch, 1992*b*, Banerjee, 1992), or people benefit from coordinating with others thanks to community sharing (Adler, 1985). In the two cases, there is a tendency to imitate others' behavior and to consider others' opinions. With information, popular products tend to be more popular. In our experiment, the word-of-mouth is almost always in favor of the Top 30 category to the detriment of the new artist's demand. Moreover, subjects react to the nature of the information: the better the evaluation of the Top 30 category regarding the New Artists' category, the higher the share of time dedicated to it.

Our experiment also shows that, when replicating a music market with prices, the aggregate demand is more diversified. We find that with incentives in favor of the New Artists' category, the demand structure change toward more diversity. This goes against Adler's theory supposing that new artists cannot entice the demand even with a lower price. Indeed, in our experiment where there are no search cost nor discussion with others, participants only know what songs are produced by popular artists. According to Adler, popular artists are "artists that everybody are familiar with" and popularity constitutes an entry barrier to the market. Thus, one could expect that because of popularity, participants would not be that sensitive to price. However, our experiment shows that it is not necessarily the case when there is only the price and information on popularity (which is of course rarely the case in the real world).

The price sensitivity between popular songs and new artists' songs is an important

result because it is not easy to highlight with field data. Indeed, in the digital and the physical music markets, prices are uniform (Peitz and Waelbroeck, 2003). In the concert market, prices are differentiated but difficulties can be encountered when analyzing the relation between prices and demand. Indeed, some determining data can be unavailable: the prices of resale tickets, the time required to acquire tickets, some characteristics of the concert hall like the geographic distance from consumers etc. Moreover, with an experiment, we can really isolate the effect of prices from the effect of word-of-mouth.

One other important result is that, in an isolated treatment, new artists entice 40% of the demand. This result is not easy to stress in the real industry because there are exogenous variables that determine demand. It is even more surprising that teenagers are usually important consumers of the Top 30. This result lets us think that there are novelty-seeking behaviors and that people actually seek out new musical productions. This result however appears in a particular setting since participants have equal access to both type of goods while in reality, new artists' production may be less accessible [18]. In other words, the probability to encounter a new artist production is likely to be lower in reality. In addition, choosing between only two songs is less likely to occur in reality. Extensions of our experiment could thus be considered to evaluation the effect of search costs on demand concentration. Similarly, regarding the effect of "word-of-mouth", we do not consider the effect of selective "word-of-mouth". In reality, people may wish to communicate their enthusiasm about a given new artist, and not on a popular one such that all opinions are not revealed. The effect of selected word-of-mouth on diversity consumed could be further investigated in-lab.

From these results, we can infer public policy recommendations. Of course, using price incentives in the music market nowadays seems anachronistic with the raise of streaming. Our result remains relevant as soon as it is extrapolated to other activities, as concerts attendance, or to other cultural markets. It is possible to subsidize con-

18. According to the French Conseil de l'Audiovisuel report on music exposure of 2013, 34.4% of the broadcast songs are new (released less than 12 month before).

sumption of new artists' songs, by, for instance promoting new artists' concert. These subsidies can have real incentives to promote diversity. Moreover, we show that reaction to information and price is differentiated by gender: men are more impacted by word-of-mouth and price. This result can be accounted for when deciding on which population to target.

Of course, this experiment was conducted on a very specific population: teenagers. It would be interesting to see if we can replicate these results with adults that may not behave the same when facing information or incentives. In addition, the design of our experiment is based on the definition of novelty by the level of exposure (unknown versus known). This definition of novelty is very specific and does not take into account different level of differentiation (a new good may resemble other existing goods). We could use the same experimental design to evaluate demand reaction to different level of familiarity (conventional versus innovative). This could be made, for instance, thanks to a pre-evaluation of the goods by experts in terms of innovativeness.

The effect of "word-of-mouth" can be understood as a way to select songs of better quality. By acquiring more information, buyers can make better choices. First results suggest that it is not clear that information on others rating increase one's satisfaction (even though it reduces uncertainty). This could be due to heterogeneity or in tastes or to unobserved bias occurring when subjects rate the songs. The main limit of our measure of satisfaction is that the treatments themselves can have an impact on the way buyers make their evaluation. What would be an interesting perspective of research in such a framework is to measure more precisely the level of satisfaction to evaluate the impact of consumed diversity on consumers' well-being. The level of arousal and pleasure are variables that can be measured to approximate satisfaction (Bradley and Lang, 1994), beside the self-declared satisfaction. This way, we could compare the impact of information and incentives on satisfaction and see if diversity alters or improves general well-being. Indeed, it is not sure that introduction of differential prices do not

alter overall well-being.

In this article, we show that using experimental methods, we can study the stardom effect and cultural diffusion. These methods appear to be really useful when data are difficult to gather or analyze. Moreover, even if we used the music market in our experiment for convenience, we believe that, to a certain extend, our result could be applied to other markets such as books or movies.

A. Appendices

A.1. The list of songs

Round	Genre	Artist	Title
1	Rap/Rnb/Hip-Hop/Soul	Kid Cudi	Pursuit of happiness
2	Electro/dance/remix	Psy	Gangnam Style
3	Pop/Folk/Rock	Rihanna	Diamonds
4	Pop/Folk/Rock	BB Brunes	Coups et blessures
5	Electro/dance/remix	Carly Rae Jepsen	Call me maybe
6	Electro/dance/remix	Far East Movement	Turn up the love
7	Electro/dance/remix	Owl City feat Carly Rae Jepsen	Good time
8	Pop/Folk/Rock	Maroon 5	One more night
9	Rap/Rnb/Hip-Hop/Soul	Axel Tony feat Tunisiano	Avec toi
10	Rap/Rnb/Hip-Hop/Soul	Canardo feat Tal	M'en aller
11	Pop/Folk/Rock	Muse	Madness
12	Electro/dance/remix	Asaf Avidian and The Mojos	Reckoning song
13	Rap/Rnb/Hip-Hop/Soul	Shy'm	On se fout de nous
14	Pop/Folk/Rock	Birdy	People help the people
15	Electro/dance/remix	M Pokora feat Tal	Envole moi
16	Electro/dance/remix	Florida	I cry
17	Electro/dance/remix	David Guetta	She wolf (falling to pieces)
18	Pop/Folk/Rock	Emeli Sande	Read all about it
19	Pop/Folk/Rock	Celine Dion	Parler à mon père
20	Rap/Rnb/Hip-Hop/Soul	Ne-Yo	Let me love you
21	Electro/dance/remix	Kavinsky	Nightcall
22	Rap/Rnb/Hip-Hop/Soul	Will I am feat Eva Simons	This is love
23	Electro/dance/remix	Chris Brown	Don't wake me up
24	Electro/dance/remix	Alex Clare	Too close
25	Pop/Folk/Rock	Adele	Skyfall
26	Rap/Rnb/Hip-Hop/Soul	Alicia Keys	Girl on fire
27	Electro/dance/remix	C2C	Down the road
28	Pop/Folk/Rock	One Direction	Live while we're young
29	Pop/Folk/Rock	Fun	We are young
30	Electro/dance/remix	Khaled	C'est la vie

Table 1.8 – Top 30 songs

Round	Genre	Artist	Title
1	Rap/Rnb/Hip-Hop/Soul	Mama's rule	Inspiration
2	Electro/dance/remix	La fèe dèchirèe	Bien des choses
3	Pop/Folk/Rock	Waterfall	Girl!
4	Pop/Folk/Rock	Odyl	Rouge à lèvres
5	Electro/dance/remix	Christine	Fucking Youth
6	Electro/dance/remix	Saycet	Easy
7	Electro/dance/remix	Abigoba	What is the Link
8	Pop/Folk/Rock	Bare Feet Cats	Air in the beginning
9	Rap/Rnb/Hip-Hop/Soul	Jimmy Cena	Jusqu'à ce que la mort nous sépar
10	Rap/Rnb/Hip-Hop/Soul	Panam Panic	Positive Justice
11	Pop/Folk/Rock	Sophie Oz	Promise me again
12	Electro/dance/remix	Wasted Wasted	Alice
13	Rap/Rnb/Hip-Hop/Soul	NJ	Si je pouvais
14	Pop/Folk/Rock	The Octopus	Amazing moment
15	Electro/dance/remix	Yalys	Inside
16	Electro/dance/remix	Lameduza	Clever Monkey
17	Electro/dance/remix	Casper Whirlin	Hope Fool
18	Pop/Folk/Rock	Milamarina	Unlimited race
19	Pop/Folk/Rock	The Cancellers	Out of our cave
20	Rap/Rnb/Hip-Hop/Soul	Adriano	Nothing anymore
21	Electro/dance/remix	Jade Analogic	Creatures
22	Rap/Rnb/Hip-Hop/Soul	Yoan Trade Union	Si tu veux qu'on s'aime
23	Electro/dance/remix	DTWICE	Please to meet you
24	Electro/dance/remix	Bonnie Li	Voodoo Doll
25	Pop/Folk/Rock	Bats on a Swing	No Science-Fiction
26	Rap/Rnb/Hip-Hop/Soul	Robbie and the Gang	Heavenly
27	Electro/dance/remix	Oawl	Pour un rien
28	Pop/Folk/Rock	Jeans	Like a weirdo
29	Pop/Folk/Rock	On a White Lane	Le chemin de ronde
30	Electro/dance/remix	Sexual Earthquake in Kobe	Offshore the World

Table 1.9 – New Artists' songs

A.2. Instructions for the Word-of-Mouth sessions

Welcome,

You are participating to an experiment in economics. At the end of this session, you will receive a FNAC gift card of 15 euros and a bag of candies and chocolate bars.

Please, pay attention and be careful with the instructions. Do not hesitate to raise your hand and ask us any questions. You must not communicate with any other participant during the whole experiment.
Before and after the experiment, you will be asked to fill in a questionnaire with honesty. All the answers will remain anonymous.

The experiment During the experiment, you will listen to songs sorted in two categories:

— The "Top 30" category: These are the 30 bestselling songs of the beginning of November (it can be physical sells, such as CDs bought in any music stores, or digital sells like songs sold on the web).

— The category "New artist": these are 30 songs from artists who are not on the musical market yet.

Both of the categories are composed of the following musical genres: pop, rock, rap, rn'b, electro and dance.
The experiment contains 30 steps of listening time.

— For each step you have 90 seconds during which you can listen to music. You will be able to see the elapsed time and the remaining time on your scree.

— At the beginning of each step, and before listening to music, two songs will appear on the screen:

  — One will be from the Top 30 category

  — The other one will be from the New artist category (that you probably do not know).

  — Both of the songs that appear together on the screen belong to the same musical genre.

For instance, during one step, you can choose between two rap songs (one belongs

to the "Top 30" and the other to the "New artist category, or two pop songs, or two electro songs etc.).

— From one step to another, the songs are different, but you will always know that among the two songs that are proposed to you at a given step, one belongs to the "Top 30" category and the other to the "New artist" category.

— For each song, there is an evaluation on a five stars scale (it will appear next to each corresponding songs). The ratings are based on the songs' evaluations from your schoolmates, this morning.

If there is no star, it means that no one evaluated this song hence nobody listened to it. The worst rating is half a star, the best one is five stars. There can be half stars.

— You will then choose one of the two songs in order to start listening to it.

— At any time, you can decide to switch to the other song. You will then be able to listen to the other song until the end of the 90 seconds.

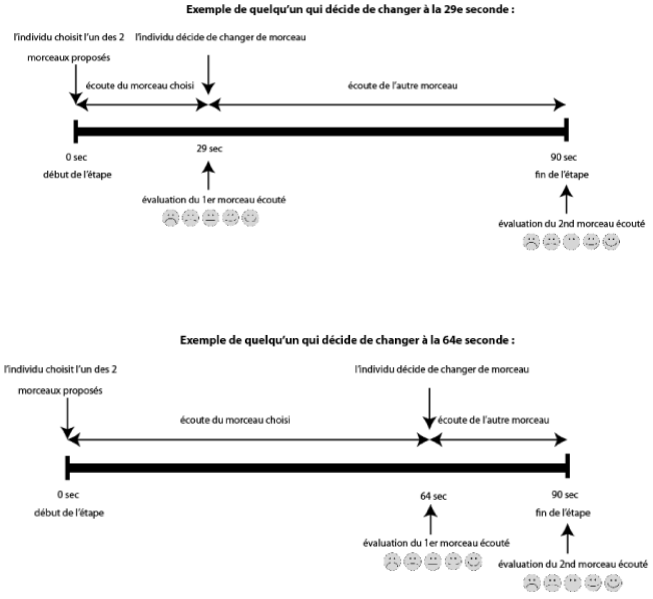
WARNING: You can only switch one time: once you decide to switch, you cannot switch back again.

— If you decide to switch, and when switching to the other song, we will ask you to evaluate the song you just listened to with smileys that will appear on your screen (the happier the smiley is, the more you liked the song you just listened to)

When evaluating the song, music and time count stop. Music listening starts again once you validated your evaluation. At the end of the step, you will be asked to evaluate the second song you listened to with smileys.

If during the whole step, you decide not to switch and to listen to the same song during 90 seconds, then, at the end of the step, you will only have to evaluate the song you chose, with smileys.

These are illustrations of one step:



A.3. Allocation of participants by treatment

The following table describes the number of participants by session. For instance, the Benchmark treatment is composed of 18 participants from the Academy of Versailles and 15 participants from the Academy of Paris. The Market treatment corresponds to two sessions with participants from the Academy of Créteil.

	Benchmark	Word-of-Mouth	Market	Total
Versailles	18	20	0	38
Paris	15	21	0	36
Créteil	0	0	19 & 17	36
Total	33	41	36	110

Chapter 2

Experimental Music Markets: Supply and Demand [1]

This chapter is a joint work with Louis Lévy-Garboua, Laëtitia Placido and Claire Owen.

1. We would like to kindly thank Tim Fry for his advice on the zero replacement technique.

1. Introduction

Empirical analysis of demand function is crucial in economics. It is for instance used in industrial economics to estimate firms market power when production costs are unknown, or in public economics to measure social welfare. Generally, complete demand systems are estimated using time series of aggregate consumption data. This type of data presents several limitations since estimates for income, price and cross-price elasticities are done for aggregated goods and price movements are relatively uniform and limited. In this paper, we use the Almost Ideal Demand System (Deaton and Muellbauer, 1980), a common model used to analyze consumer demand, to estimate demand functions for musical goods using experimental economics.

Experimental data have several advantages over field data (Février and Visser, 2016) and can be used to overcome limitations related to naturally occurring data. First, we can precisely observe all choices and obtain a comprehensive data set. With field data, it may be difficult to collect market data and generally, survey or administrative data only record subsets of commodities. In-lab experiments, consumption is made within a short length of time and the experimenter observes complete consumption and incentivized decisions. On the opposite, field panel data may be incomplete and raise the problem of change in preferences if long term data are collected. Second, one of the main concerns when estimating demand functions is to have sufficient price variations to identify the parameters of the demand function, even if researchers generally use time series data. While with field data prices are relatively stable over time, with experimental economics, the experimenter can control or generate variation over prices and budgets. Third, the experimenter have control over the participant's income (or budget) as well as a control on quality. Finally, we can estimate demand functions for sub-samples defined by individual socio-demographic variables (age, gender etc.) and thus take into account for heterogeneity on the demand side.

The use of experimental methods also raises drawbacks that are mainly related to the external validity of in-lab experiments. The set of goods for which consumption is lab-compatible is limited. Also, consumption decisions are made at a fine level. Even if we aggregate over participants, zero shares on goods can appear due to the limited number of participants [2]. Finally, price variations are more salient in-lab than out-lab and enhance demand responsiveness and thus demand elasticity.

1.1. Measuring demand functions in lab

Historically, in lab settings have been used to test the main assumptions of microeconomic theory, as for instance the general axiom of revealed preferences (GARP) assuming the internal validity of the experiments [3]. First attempts to measure demand function in lab can be dated back to economic experiments with nonhuman animals conducted by John Kagel and Raymond Battalio [4]. They particularly studied consumption changes as a reaction to changes in budget and prices using rats (Kagel et al., 1975) or pigeons (Battalio et al., 1981) as the subjects. A large body of the literature employs experimental settings to tests rationality as college students' and children's consumption of common goods (Sippel, 1997, Harbaugh, Krause and Berry, 2001, Février and Visser, 2004, List, Millimet et al., 2008) or altruism in the dictator game (Andreoni and Miller, 2002) .

Fewer experimental studies aim at actually estimate demand functions for specific goods. Using lab experiments to estimate elasticities requires external validity, meaning that decisions made inside the lab are, to a certain extend, similar to what would happen outside the lab. To ensure external validity, the experimenter has to set a de-

2. These zero shares are however true zeros. Several methods can be adopted to to deal with this phenomenon. We use the zero replacement technique developed by Fry, Fry and McLaren (2000) for robustness checks of our estimates.

3. Internal validity refers to the degree to which the results are attributable to the independent variable and not some other rival explanation. It warranties the identification of a causal effect.

4. See Kagel, Battalio and Green (1995) for a general presentation of their work on animals.

sign such that the population and the environment mirrors an environment of interest. Regarding demand behaviors, this suggests the use of a lab-compatible good. Using fresh strawberries, Brookshire, Coursey and Schulze (1987) find, for instance, that demand behaviors for private goods in an experimental setting are similar to those in a field setting. Even though their experiment is not incentivized, Olmstead et al. (2015) estimate elasticities of demand for heroin with lab and field data and find that experimental estimates are in concordance with field estimates, validating the external validity of their experimental measures. In this article, we study music consumption. Music is an ideal good to estimate demand experimentally since it is privately consumed, inclination for music is universal (Peretz, 2006), it can be consumed within a short time frame and it is less subject to boredom or satiation during the experimental session than other types of goods like food or drinks.

In this article, we aim to estimate demand function for musical genres, assuming that external validity is, to a certain extend, validated. To do so, we used the Almost Ideal Demand system (Deaton and Muellbauer, 1980). To the best of our knowledge, only one article apply structural demand system on experimentally generated data. Février and Visser (2016) use an experimental setting to estimate a translog and a PIGLOG demand systems generating incentivized choices between different types of orange juices. In their design, participants are given the possibility of buying 6 different products under 5 different price/budget configurations set by the experimenters. Authors show that the estimated parameters of the demand equations and tests of the Slutsky restrictions are not influenced by the presence of GARP-inconsistent individuals [5].

5. They also highlight the fact that the translog model is less efficient than the PIGLOG one since the Slustky matrix is only verified with the PIGLOG demand system.

1.2. Demand functions in arts

Only few studies have estimated performing arts elasticities (Seaman, 2006). Generally, empirical works are based on audience or on arts participation surveys (Seaman, 2006) and most of them find low own-price elasticities. The datasets used so far have, however, severe limitations. First of all, the aggregated level over broad categories of arts yields mechanically low price elasticities since substitutes might only exist within each category. As Heilbrun and Gray (2001) note:

> "Elasticity rises with the availability of substitutes. The more, or the closer, the available substitutes for a given good or service, the more readily consumers will switch to something else when the price of that good or service rises relative to other prices"

In parallel, cross-price elasticity evidence for performing arts is relatively weak, especially at a disaggregated level. Gapinski (1986) is the only study that estimates cross-price elasticities between live performing arts, namely theater, opera, dance and symphony. Price inelasticity may also be the result of low pricing strategies of non-profit arts including orchestral and chamber music, opera, ballet and modern dance, and theater (Seaman, 2006). Finally, biases in estimates may arise when based on audience data as prices are not directly observed but proxied using the ratio of audience over attendance. Some empirical works studying the demand for performance arts do not adjust prices by quality of seats or performance and thus find relatively low price elasticities (Lévy-Garboua and Montmarquette, 2011). Abbé-Decarroux (1994) shows in fact that when seats are of high quality, demand for performing arts is price-inelastic while it is price-elastic for reduced price seats [6].

Besides the above mentioned advantages of experimental data over field data, using experimental economics to study demand function for arts helps overcoming these specific limitations. First, we focus on demand for musical genres which are more likely

6. Jenkins and Austen-Smith (1987) even find positive own price elasticity for theater.

to be substitutes and allow us to estimate cross price elasticities. Secondly, by studying music consumption in-lab, we can control the conditions in which the good is consumed and thus quality (of the good itself and of the conditions in which the consumers listen to it). Finally, price variation is easier to implement. We decided not to have a perfect control on prices but to create experimental markets. Studying incentivized experimental markets for music is likely to have better external validity than arbitrary manipulations of prices. In addition, it allows us to create variations in the structure of competition and explore the reactions of consumers to a wider set of consistent price variations. We thus create two types of markets: one in a monopolistic competition framework and the other in a Bertrand competition framework. Thanks to a greater variation in prices, we can obtain better estimates of the demand function within a more natural framework. In addition, implementing different market structures enables us to test some simple predictions of microeconomic theory. Particularly, we can check the validity of the monopolist's inverse elasticity pricing rule according to which a price maker will set a price such that the demand has a unit elasticity (if the good is consumed).

First of all, the main contribution of our paper is methodological by presenting a way to estimate a demand function with experimental markets. This methodology appears as a solution when naturally occurring data are not easy to gather or contains multiple limitations as those mentioned above. Our second contribution is to be considered in the field of cultural economics. Own-price, cross-price and expenditure elasticities are estimated at a fine level using comprehensive experimental data. In line with literature on demand for performing arts, we find relatively inelastic demand for each musical genre, ranged between -0.93 and -0.48. To our knowledge, this study is the first attempt to estimate cross price elasticities between musical genres. We also compare estimates by market structures and by subsamples of consumers, namely by gender, age and personality traits. We then apply the same methodology on the experimental

dataset used in Chapter 1 to study price and expenditure elasticities for popular and new music. Demand for new songs is less elastic than demand for Top 30. Regarding expenditure elasticities, new songs are necessity goods while Top 30 songs are luxury goods.

This article is organized as follows. Section 2 describes the experimental design and the data. Section 3 presents the Almost Ideal Demand System and Section 4, the results. In Section 5, we apply the methodology the market experiment of Chapter 1, estimating elasticities for new music. Section 6 discusses and concludes.

2. Experimental settings

2.1. Design

Each session consists in 20 subjects who are randomly allocated to the role of buyers or sellers. Four musical genres are sold on the market, namely Pop/Rock, Classical, Rap/Rnb and Blues/Jazz. The experiment consists in 50 periods. For each genre, a sequence of 50 tracks is used in a deterministic order [7].

2.1.1. The supply side

The number of sellers depends on the market treatment. Two experimental market structures are implemented in order to generate different price settings: a monopolistic competition structure and a Bertrand competition one.

Monopolistic competition (MC) At the beginning of each session, 4 participants are randomly selected to be the sellers. The market is thus composed of 16 buyers.

7. The selection of samples for the musical genres is based on standardized classifications found in the music market, such as iTunes. To verify the consistency of these musical style classifications, an additional categorization task is conducted before the experiment, in which 3 judges are individually asked to classify 100 music tracks into one of the four categories, or into an additional category labeled 'other'. The respective matching rates between the original classifications and the judges' classifications for Pop/Rock, Classical, Rap/Rnb and Jazz are 90.7%, 96.7%, 88% and 96.7%.

Each of the four music styles is randomly assigned to one seller. Each period comprises the following steps. First, the sellers set the market prices of the music style they are selling without listening to the music that will actually be played. This procedure ensures that sellers have no intrinsic motivation and only seek to maximize their profits. Second, during buyers' one-minute listening phase, sellers are provided with leisurely activities of online gaming, as they never listen to the music themselves. At the end of each period, they receive complete information regarding their profits, the market prices set by other sellers, as well as the number of consumers who have consumed their musical style. The sellers' final gains depend on the prices fixed for their music genre, and on the number of buyers for their product. When the session ends, sellers are payed the ECU equivalent of their profits over the 50 periods (converted based on a 1,000 ECUs = 2 euros exchange rate).

Bertrand competition (BC) The Bertrand competition treatment is similar to the monopolistic one except that 8 sellers are randomly selected at the beginning of each session (2 sellers per music style) [8]. The market is thus composed of 12 buyers. At each period, sellers set a market price for the music style they are selling. For each music genre, only the seller who sets the lowest price is allowed to sell at a given period [9]. As in the MC treatment, during buyers' one-minute listening phase, the 8 sellers are provided with leisurely activities of online gaming. At the end of each period, they receive complete information regarding their profits, the 4 selected market prices of the musical genres, as well as the number of consumers who have consumed their musical style. Of course, for the 4 sellers who are not selected, this number is null. The sellers' final gains depend on the prices fixed for their music genre, and on the number of buyers for their product. When the session ends, sellers are payed the ECU equivalent of their

8. Note that the market structure is a Bertrand competition *per se* but rather a Bertrand game with differentiated goods. For simplicity, we shorten the name to "Bertrand competition".

9. In case of equality between the two sellers of a given music style, we randomly select the seller for the given period.

profits over the 50 periods (converted based on a 1,000 ECUs = 3 euros exchange rate [10]).

2.1.2. The demand side

At each of the 50 periods, buyers are endowed with 200 ECUs (of which 100 ECUs are given as a lump-sum payment) and are asked to buy one music style given the market prices. Each period is partitioned in 3 stages. In stage 1, the subject takes notice of market prices and selects one of four musical styles. In stage 2, wearing closed-back headphones, she has to listen to the entire sample while facing a blank screen. The duration of the sample (one minute) was chosen so as to be sufficiently long to produce a consumption benefit, but enough to avoid ear fatigue. In addition, an acoustic adjustment was applied to homogenize sound levels within and across tracks so that listening experiences were both comfortable and homogeneous. In stage 3, the subject is asked to rate her listening experience on a 10-point scale. This part of the data will not be used here but it plays a role in the incentivization of the experiment [11].

At the end of the experiment, buyers' payment varies according to their savings in ECU (converted based on a 1,000 ECUs = 2 euros exchange rate). Buyers are given the lump-sum (5,000 ECUs = 10 euros) and they receive in addition the cumulated savings from their disposable income, that is, the amount not used for the purchase of music. The experiment also relied on non-pecuniary incentives. In particular, subjects have direct incentives to choose a musical style carefully in stage 1 because they immediately experienced the consequence of their choice (i.e. listening to a one-minute track).

10. The exchange rate for sellers in this treatment is higher as sellers in the competitive market earned very low profits.

11. To encourage truthful reporting in stage 3, each subject received a personalized 10 track digital recording reflecting the experienced utility he reported during the experiment. Specifically, a subject is told that 5 sets of 10 periods would be randomly drawn at the end of the experiment. For each set, we calculate the average experienced utility reported by the subject for the tracks he heard in those periods. The 10 tracks from the set with the highest average experienced utility are then recorded on a device which is offered to the subject. Thus, subjects have extrinsic incentives to rate their listening experience carefully.

2.2. The data

A random sample of 200 individuals (140 buyers and 60 sellers) was recruited via the Parisian Experimental Economics Laboratory (LEEP) website. Half of them were assigned to the monopolistic competition treatment (80 buyers and 20 sellers) while the other half to the Bertrand competition treatment [12] (60 buyers and 40 sellers). We observe 10 sessions over 50 periods each, that is, 500 aggregate data.

Table 2.1 displays summary statistics between treatments. As one notes, in the perfect competition treatment, subjects are significantly younger. Consequently, the declared frequency of listening to classical and Blues/Jazz music is significantly lower in the perfect competition treatment since consumption of these two musical genders are positively correlated with age (Prieto-Rodríguez and Fernández-Blanco, 2000).

Table 2.2 displays the mean budget shares for each musical genre for the whole sample and by treatment. It also shows the proportion of zero expenditure. One notes that Classical music and Blues/Jazz are the musical genres for which corner solutions seems to appear most often. This is consistent with listening frequencies shown in Table 2.1 as these are the least listened genres.

Table 2.3 confirms that monopolistic competition yields higher prices for all musical styles. Figure 2.1 shows the dynamics of prices. For all musical genres, prices converge towards 0 in the Bertrand competition treatment, as predicted by the theory, and towards 20 ECUs in the Monopolistic competition treatment. In other words, the price convergence reflects the market structure implemented. Results also confirm the literature on posted offer markets: prices converge to the competitive equilibrium from above (Davis and Williams, 1986). Figure 2.3 presents scatter of real prices in log and budget shares. Plots seem to show a linear relation between demand and real prices

12. The five sessions of the monopolistic treatment were conducted in March 2011. For the Bertrand competition treatment, three sessions were conducted in May 2013 and two additional sessions were conducted in July 2016. The set of musical tracks remains the same. There might be a change in preferences between the sessions.

Table 2.1 – Summary statistics for buyers by treatment

	Monopolistic Competition		Bertrand Competition		two-sided ttest	
	Mean	Sd	Mean	sd	Difference	p-values
Gender (proportion of female)	0.44		0.55		0.11	(0.190)
Age	26.31	10.60	23.82	5.25	-2.50*	(0.096)
Music listening habits						
Pop/Rock	2.79	1.13	2.67	1.00	-0.12	(0.513)
Classical	2.09	1.02	1.67	0.90	-0.42**	(0.012)
Rap/Rnb	2.49	1.14	2.80	1.22	0.31	(0.121)
Blues/Jazz	2.12	1.04	1.72	0.94	-0.41**	(0.018)
Attitude toward risk, time and preferences						
Risk aversion	0.68		0.70		0.02	(0.755)
Impatience	0.61		0.53		-0.08	(0.351)
Preference for Novelty	0.81		0.70		-0.11	(0.122)
Observations	80		60		140	

Notes: Measures for music listening habits are declared listening frequencies for each musical genre. Music listening habits are measured through the following question "Before this experiment, how often do you listen the [Musical Genre] music?". Participants answered on a 4 points Likert scale (from 0 being "never or rarely" to 4 being "often"). *Risk Aversion* is a dummy variable equal to 1 if subject declared she prefers winning 5 euros with certainty over playing a lottery with chances of winning 10 euros with an unknown probability or nothing otherwise, *Impatient* is a dummy variable equal to 1 if the subject declared she prefers to receive 10 euros now rather than 11 euros tomorrow, *Preference for Novelty* is a dummy variable equal to 1 if the subject declared that, in general, she prefers to listen to novel music rather than music that she already know.

since the curve follows the logarithm representative curve. This is especially true for Pop/Rock, Classical and Blues/Jazz.

Table 2.2 – Summary of budget shares

	Whole Sample		Monopolistic Competition		Bertrand Competition	
Music i	Mean	% of Zeros	Mean	% of Zeros	Mean	% of Zeros
Pop/Rock	0.299	0.052	0.310	0.032	0.288	0.072
	(0.243)		(0.170)		(0.300)	
Classical	0.170	0.236	0.249	0.192	0.090	0.280
	(0.182)		(0.199)		(0.117)	
Rap/Rnb	0.317	0.086	0.282	0.076	0.352	0.096
	(0.259)		(0.195)		(0.307)	
Blues/Jazz	0.215	0.214	0.159	0.196	0.270	0.232
	(0.243)		(0.153)		(0.298)	

Standard deviation in parenthesis.
In total, we count 294 zero shares over 2000 (500*4 musical genres) shares (14.7%)

Table 2.3 – Summary of prices

	Monopolistic competition		Bertrand Competition		Two-tailed ttest	
	Mean	Sd	Mean	Sd	Diff.	p-values
P1 (Pop/Rock)	29.50	24.66	5.91	13.31	-23.59***	(0.00)
P2 (Classical)	27.97	21.98	4.56	8.33	-23.41***	(0.00)
P3 (Rap/Rnb)	23.64	21.73	4.84	8.76	-18.79***	(0.00)
P4 (Blues/Jazz)	21.41	20.13	8.11	11.89	-13.30***	(0.00)
Observations	250		250		500	

Figure 2.1 – Price per Period and market structure

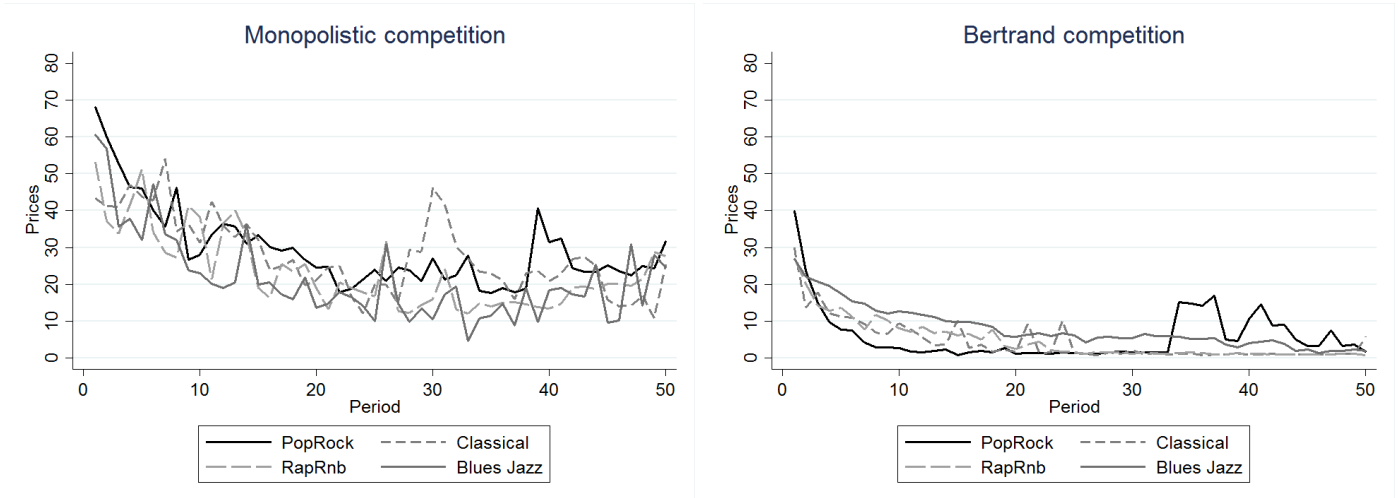
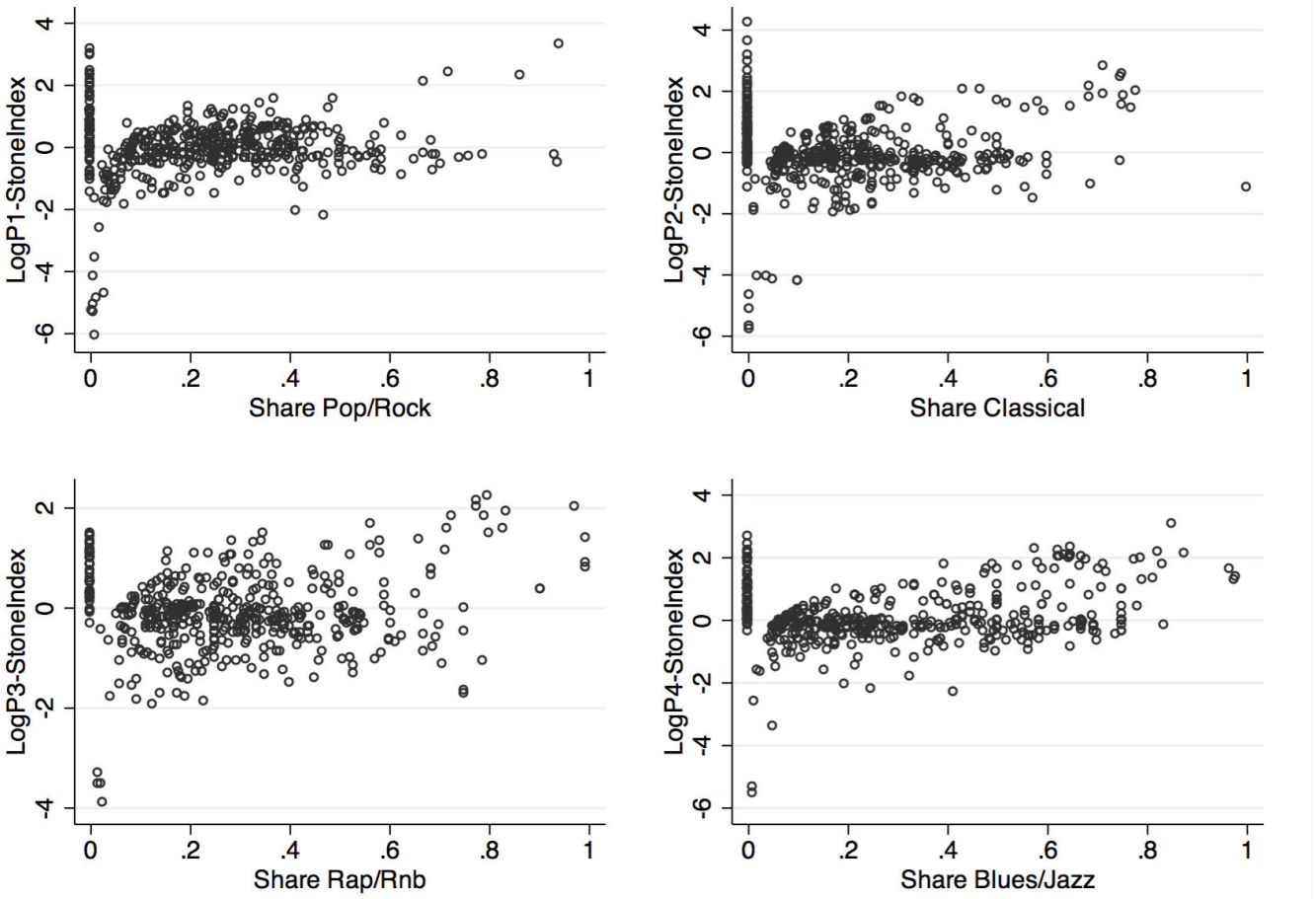


Figure 2.2 – Scatter plot of Real Prices (in log) and Budget Shares



Note: LogP1, LogP2, LogP3 and LogP4 respectively refers to the log prices of Pop/Rock, Classical, Rap/Rnb and Blues/Jazz. The Stone Index used is the average Stone Index (see Section 2). We correct price by the average Stone Index in order to consider real prices.

3. The model

3.1. The AIDS model

The Almost Ideal Demand System developed by Deaton and Muellbauer (1980) is based on a particular class of preferences: the price-independent generalized logarithmic (PIGLOG) class. The PIGLOG expenditure function is defined as:

$$ln\ c(u,p) = (1-u)ln\{a(p)\} + uln\{b(p)\} \tag{2.1}$$

where $c(u,p)$ is the cost or expenditure function; u is the utility; p is a price vector and:

$$ln\{a(p)\} = a_0 + \sum_k a_k lnp_k + \frac{1}{2}\sum_k\sum_j \gamma_{k,j} lnp_k lnp_j$$
$$ln\{b(p)\} = ln\{a(p)\} + \beta_0 \prod_k p_k^{\beta_k}$$

According to Deaton and Muellbauer's (1980) model, $a(p)$ and $b(p)$ can be regarded as the cost of subsistence and the cost of bliss, respectively. As a result, the expenditure function is specified by:

$$lnc(u,p) = \alpha_0 + \sum_k a_k lnp_k + \frac{1}{2}\sum_k\sum_j \gamma_{k,j} lnp_k lnp_j + u\beta_0 \prod_k p_k^{\beta_k}$$

The PIGLOG preferences allow aggregation across households.

The AIDS (Deaton and Muellbauer, 1980), in budget share form [13], is given by:

$$w_{it} = \alpha_i + \sum_j \gamma_{ij}\, ln\, p_{jt} + \beta_i\, ln\frac{X_t}{P_t} + u_{it} \tag{2.2}$$

13. We aggregate individual choices at the period level such that $w_{i,t}$ represents the market budget share at a given period.

where

$$lnP_t = \alpha_0 + \sum_j \alpha_j lnp_{jt} + \frac{1}{2}\sum_j \sum_i \gamma_{i,j} lnp_{it} lnp_{jt}$$

and p_{jt} is the nominal price of the i^{th} good [14], X_t the overall expenditure for music, and $w_{it} = \frac{p_{it}x_{it}}{X_t}$ the share of consumption of good i in a market at period t.

Because of the specificities of our experimental design, one should be cautious about the meaning of the total expenditure variable. Since participants receive a fixed endowment per period and are however asked to choose at least one of the four musical genres, they are given the possibility to choose their expense for music given the minimal expense (choosing the cheapest musical genre). We use a two-stage budgeting to separate the decision of allocating the period's income between consumption and saving. To do so, we first estimate the individual total expenditure using the following equation in the first stage:

$$E_{k,s} = d_0 + d_1 \text{MinExpense}_s + M_k d_3 + \eta_{k,s} \tag{2.3}$$

where $E_{k,s}$ is the total expenditure of individual k over the session s, MinExpense_s is the minimal total expenditure over the session s and M_k are socio-demographic individual data (see Table 2.22 in Appendices for full details of the regression). We then estimate the total expenditure of period t, denoted X_t in equation 2.2, using the following specification:

$$X_{s,t} = a + b_1 p_{\min_{s,t}} + b_2 p_{\max_{s,t}} + b_3 W_{s,t} + \sum_k \hat{E}_{k,s} \mathbb{1}_{k,s} + \epsilon_{s,t} \tag{2.4}$$

where $W_{s,t}$ is the accumulated savings at time t of session s, $p_{\min_{s,t}}$ and $p_{\max_{s,t}}$ are respectively the minimum and the maximum prices at period t of sesson s. $\mathbb{1}_{k,s}$ equal one if k is in session s, 0 otherwise. Then, the predicted real expenditure $\hat{X}_t$ is used to

14. $i = 1, 2, 3, 4$ respectively refers to Pop/Rock, Classical, Rap/Rnb and Blues/Jazz

proxy the disposable total expenditure X_t in Equation 2.2. This approach enables to treat any potential problem of endogeneity in total expenditures [15].

We estimate model 2.2 for each musical genre using Ordinary Least Square regressions. Estimated coefficients $\hat{\beta}_i$ and $\hat{\gamma}_{ij}$ are used to determine the expenditure, own-price and cross price elasticities. The expenditure, uncompensated own-price and uncompensated cross-price elasticities of each musical genre i are derived respectively by $dlnw_i/dlnX$, $dlnw_i/dlnp_i$ and $dlnw_i/dlnp_j$ while compensated elasticities are determined using the Slutsky equation (see in A.4.2 in Appendices for calculation)).

Thus, total expenditure elasticity of genre i (for $i \in [\![1,4]\!]$) is equal to:

$$\eta_i = 1 + \frac{\beta_i}{w_i} \tag{2.5}$$

One has to note however that total expenditure elasticities are to be interpreted with cautious since subjects do not have a real income but are given a fixed amount per period. The uncompensated price elasticities (own and cross price) of genre i with respect to j for $(i,j) \in [\![1,4]\!]^2$ are:

$$\epsilon^U_{i,j} = -\delta_{i,j} + \frac{\gamma_{i,j}}{w_i} - \beta_i \frac{\alpha_i}{w_i} - \frac{\beta_i}{w_i} \sum_k \gamma_{k,j} lnp_k \tag{2.6}$$

where $\delta_{i,j}$ is the Kronecker delta, which is equal to 1 if $i = j$ and 0 if $i \neq j$.

Finally, the compensated price elasticities (own and cross price) of genre i with respect to j for $(i,j) \in [\![1,4]\!]^2$ are:

$$\epsilon^C_{i,j} = \epsilon^U_{i,j} + w_i \eta_i \tag{2.7}$$

The AIDS model is constructed to represent a system of demand functions which are homogeneous of degree zero in prices and total expenditures. These rationality

15. Note that since price and per period budget are exogenous, one can however challenge the possibility that expenditure is endogenous. Further estimations could be done to test this assumption.

conditions are summarized by the following equations:

— additivity: $\sum_i \hat{\alpha}_i = 1$, $\sum_i \hat{\gamma}_{i,j} = 0$, $\sum_i \hat{\beta}_i = 0$ for all $i = 1, 2, 3, 4$

— homogeneity: $\sum_j \hat{\gamma}_{i,j} = 0$

— symmetry: $\hat{\gamma}_{i,j} = \hat{\gamma}_{j,i}$

The additivity condition says that the sum of the estimated constant terms, across the different goods, equals one; for a given good i, the sum of the estimated price terms, $\hat{\gamma}_{i,j}$, equals zero; across genres, the sum of the estimated coefficients for real income, equals zero. The homogeneity condition says that across goods j, the price effects for a specific good i also sum to zero. The symmetry restrictions require that compensated demand effects be symmetric. The following estimations use a constrained model on these assumptions.

4. Results

4.1. Estimated elasticities

4.1.1. Estimations with zero shares

We use the command "aidsills" in Stata, recently introduced by Lecocq, Robin et al. (2015) to estimate the AIDS model constrained on homogeneity and symmetry. Estimated coefficients are presented in Table 2.4 [16] and Table 2.5 lists own-price, cross-price and total expenditure elasticities derived from estimated coefficients. One can first notice that Blues/Jazz's total expenditure elasticity is significantly greater than 1 (luxury good) while it is significantly lower than 1 for Rap/Rnb (necessity good). Uncompensated price elasticities are ranged between -0.93 for Classical and -0.48 for Rap/Rnb. Demand for Classical is more elastic than for the three other musical

16. We replicate estimation for the whole sample using the linear and the quadratic versions of the AIDS model, respectively the LA/AIDS (Deaton and Muellbauer, 1980) and the QAIDS (Banks, Blundell and Lewbel, 1997). Results are displayed in Appendix A.1and seem robust to the different estimation procedures.

Table 2.4 – Estimations of the AIDS model (constrained model)

	Pop/Rock	Classical	Rap/RnB	Blues/Jazz
	$i = 1$	$i = 2$	$i = 3$	$i = 4$
	w_1	w_2	w_3	w_4
$\gamma_{i,1}$	0.066***	-0.012	-0.074***	0.020
	(0.013)	(0.009)	(0.011)	(0.018)
$\gamma_{i,2}$	-0.012	0.010	0.013	-0.010
	(0.008)	(0.007)	(0.011)	(0.011)
$\gamma_{i,3}$	-0.074***	0.013	0.091***	-0.030**
	(0.011)	(0.009)	(0.016)	(0.015)
$\gamma_{i,4}$	0.020	-0.010	-0.030**	0.020
	(0.013)	(0.010)	(0.015)	(0.017)
β_i	-0.041	-0.005	-0.117***	0.163***
	(0.025)	(0.022)	(0.026)	(0.021)
N	500	500	500	500

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: "contrained model" means the model is constrained on the homogeneity and the symmetry conditions.

Table 2.5 – Own and cross price elasticities - All sample (constrained model)

	AIDS			
	Shares	Expenditure	U price	C price
Pop/Rock	0.292***	0.860***	-0.718***	-0.467***
	(0.01)	(0.088)	(0.03)	(0.033)
Classical	0.169***	0.970***	-0.934***	-0.770***
	(0.009)	(0.129)	(0.054)	(0.041)
Rap/Rnb	0.306***	0.617***	-0.479***	-0.291***
	(0.01)	(0.089)	(0.053)	(0.035)
Blues/Jazz	0.234***	1.697***	-0.812***	-0.415***
	(0.009)	(0.093)	(0.034)	(0.027)

	AIDS							
	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.718***	-0.017	-0.174***	0.048	-0.467***	0.128***	0.090**	0.250***
	(0.030)	(0.036)	(0.048)	(0.033)	(0.033)	(0.029)	(0.036)	(0.026)
Classical	-0.061	-0.934***	0.092	-0.066	0.221***	-0.770***	0.388***	0.161***
	(0.04)	(0.054)	(0.072)	(0.048)	(0.047)	(0.041)	(0.053)	(0.039)
Rap/Rnb	-0.095***	0.110***	-0.479***	-0.153***	0.085***	0.215***	-0.291***	-0.009
	(0.027)	(0.036)	(0.053	(0.032)	(0.032)	(0.028)	(0.035)	(0.028)
Blues/Jazz	-0.184***	-0.171***	-0.531***	-0.812***	0.311***	0.116***	-0.012	-0.415***
	(0.035)	(0.045)	(0.056)	(0.034)	(0.045)	(0.039)	(0.043)	(0.027)

Standard errors in parentheses. Standard errors are calculated using the Delta method. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

genres. Blues/Jazz is a net substitute (positive compensated elasticity) for Pop/Rock and Classical. Surprisingly, Rap/Rnb and Classical yield a relatively high compensated cross-price elasticity. Finally, Rap/Rnb and Pop/Rock are the lowest substitute.

4.1.2. Robustness checks: corner solutions and zero replacement procedure

Our dataset contains 14.7% zero expenditure shares (see Table 2.2 for more details). One can easily consider that large markets would yield non-zero expenditures as one

buyer suffices to obtain a positive expenditure. Our experimental procedure however implies small market sizes (16 buyers in the monopolistic competition treatment and 12 buyers in the Bertrand competition one) which facilitates the appearance of corner solutions.

There are many econometric techniques to address this issue like Box-Cox transformations or Tobit regressions. Compositional data analysis literature also provides several solutions that are econometrically less costly but prove to be efficient (Fry, Fry and McLaren, 2000, Koch, 2007) [17]. To see if our results are robust to the presence of zero shares, we reestimate the AIDS model using the modified zero replacement technique based on Aitchison's (1986) procedure and developed by Fry, Fry and McLaren (2000) [18]. The main idea is to replace zero shares by very small values. Fry, Fry and McLaren (2000) suggest that sensible minimum and maximum values for zero shares are respectively determined by $\frac{0.01}{\text{Max of Total Expenditure}}$ and $\frac{0.01}{\text{Min of Total Expenditure}}$ since 0.01 (1 ECU) is considered as a minimal expenditure.

The technique consists in changing the values of null shares as well as non zero shares as follows. Considering that a composition (here a period) has M zeros and $(N - M)$ non zero components (here budget shares), null budget shares are replaced by:

$$\tau_A = \frac{\delta(M+1)(N-M)}{N^2} \tag{2.8}$$

17. Authors report 3 types of solutions. First, amalgamation consists in a reduction of the number of components in the composition by grouping together certain components. Second, the zero replacement simply replaces the observed zeros with small values and adjusts the non zero components. A third solution is to use the Box-Cox transformation in place of the log-ratio transformation. This approach can be used in situations where one of the goods always has a share which is non-zero which is hardly the case in microeconomic data.

18. In their paper, Fry, Fry and McLaren (2000) successfully apply this technique to Australian household data enabling them to estimate a demand system for budget shares.

In order to preserve ratio, non zero are reduced by $\tau_S * w_{i,t}$ [19] where:

$$\tau_S = \frac{\delta(M+1)M}{N^2} \tag{2.9}$$

and δ is called the "maximum rounding error" [20]. In this case, δ is the small share that we cannot observe due to the limited size of our sample while $\frac{(M+1)(N-M)}{N^2}$ is used to normalize τ_A with respect to the number of zero shares and non zero shares [21]. According to the technique, δ and τ_S are derived using equations 2.8 and 2.9. We test the robustness of our results using the minimum and the maximum zero replacement values. Comparing results from Table 2.6 with those of Table 2.5, we notice that results are robust. We thus use our initial data (without the zero replacement technique) for the rest of the article.

19. Indeed, $\frac{w_i(1-\tau_S)}{w_j(1-\tau_S)} = \frac{w_i}{w_j}$

20. In other words, the amount taken from the non zeros is proportional to the size of that non zero value. For a detailed description of Aitchison's (1986) zero replacement technique, see A.2 in the Appendices

21. Explanations for these formulas are given in the appendix.

Table 2.6 – Elasticities estimations with the zero replacement technique (constrained model)

	AIDS ($\tau_{S,min}$)				**AIDS** ($\tau_{S,max}$)			
	Shares	Expenditure	U price	C price	Shares	Budget	U price	C price
Pop/Rock	0.292***	0.860***	-0.718***	-0.467***	0.292***	0.862***	-0.720***	-0.469***
	(0.01	(0.088	(0.03	(0.033	(0.01	(0.087	(0.030)	(0.033)
Classical	0.169***	0.970***	-0.934***	-0.770***	0.170***	0.965***	-0.932***	-0.768***
	(0.009)	(0.129)	(0.054)	(0.041)	(0.008)	(0.126)	(0.053)	(0.040)
Rap/Rnb	0.306***	0.617***	-0.479***	-0.291***	0.306***	0.621***	-0.483***	-0.293***
	(0.010)	(0.089)	(0.053)	(0.035)	(0.010)	(0.088)	(0.053)	(0.035)
Blues/Jazz	0.234***	1.697***	-0.812***	-0.415***	0.232***	1.699***	-0.812***	-0.418***
	(0.009	(0.093	(0.034	(0.027	(0.009)	(0.093)	(0.034)	(0.027)

	AIDS ($\tau_{S,min}$)							
	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.718***	-0.017	-0.174***	0.048	-0.467***	0.128***	0.090**	0.250***
	(0.030)	(0.036)	(0.048)	(0.033)	(0.033)	(0.029)	(0.036)	(0.026)
Classical	-0.061	-0.934***	0.092	-0.066	0.221***	-0.770***	0.388***	0.161***
	(0.040)	(0.054)	(0.072)	(0.048)	(0.047)	(0.041)	(0.053)	(0.039)
Rap/Rnb	-0.095***	0.110***	-0.479***	-0.153***	0.085***	0.215***	-0.291***	-0.009
	(0.027	(0.036)	(0.053)	(0.032)	(0.032)	(0.028)	(0.035)	(0.028)
Blues/Jazz	-0.184***	-0.171***	-0.531***	-0.812***	0.311***	0.116***	-0.012	-0.415***
	(0.035)	(0.045	(0.056)	(0.034)	(0.045)	(0.039)	(0.043)	(0.027)
	AIDS ($\tau_{S,max}$)							
	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.720***	-0.017	-0.173***	0.048	-0.469***	0.130***	0.091**	0.248***
	(0.030)	(0.036)	(0.047)	(0.032)	(0.033)	(0.029)	(0.036)	(0.026)
Classical	-0.059	-0.932***	0.09	-0.063	0.222***	-0.768***	0.385***	0.161***
	(0.039)	(0.053)	(0.071)	(0.047)	(0.046)	(0.040)	(0.052)	(0.038)
Rap/Rnb	-0.094***	0.109***	-0.483***	-0.153***	0.087***	0.215***	-0.293***	-0.008
	(0.027)	(0.035)	(0.053)	(0.032)	(0.031)	(0.028)	(0.035)	(0.027)
Blues/Jazz	-0.184***	-0.172***	-0.531***	-0.812***	0.311***	0.118***	-0.011	-0.418***
	(0.035)	(0.045)	(0.056)	(0.034)	(0.045)	(0.038)	(0.043)	(0.027)

Standard errors in parentheses. Standard errors are calculated using the Delta method. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

4.2. Market structure and elasticities

Microeconomic theory predicts different profit maximization program on part of the sellers depending on the structure of the market. While in the monopolistic competition sellers are "price makers", in the Bertrand competition, they are, eventually, "price takers". Price elasticity should be greater the less the degree of competition as firms raise prices to reach a more elastic portion of the demand curve (Becker, 1971). The negative effect of price competition on own-price elasticity (in absolute value) has been shown empirically (Pagoulatos and Sorensen, 1986). However, when considering demand elasticity, it is empirically challenging to disentangle what is due to preferences (the curvature of the demand curve) and what is due to the market structure (the part of the curve the equilibrium stands on). Experimental data enable to isolate the effect of the market structure on demand elasticity while controlling for preferences. When firms are in a monopolistic competition framework, sellers should fix prices such that demand elasticity is equal to -1. Indeed, let $x_{i,j,t}$ be a binary variable equal to 1 if individual i decides to consume musical genre j at period t and to 0 elsewhere. At each period, the firm/seller of musical genre j chooses the price $p_{j,t}$ such that its profit is maximized, accounting for the prices $p_{-j,t}$ of its competitors:

$$\max_{p_{j,t}} D(t) p_{j,t} \sum_{i=1}^{n} x_{i,j,t}(p_{j,t}, p_{-j,t})$$
$$\text{s.t. } p_{j,t} \geq 0$$

where n is the number of buyers for a given market, $D(t)$ is a discount factor which is not necessarily exponential.

The first order condition implies:

$$D(t)[C_{j,t} + p_{j,t}\frac{dC_{j,t}}{dp_{j,t}}] + \lambda_j = 0$$

or equivalently:

$$D(t)C_{j,t}[1 + e_{j,t}] + \lambda_j = 0$$

with $C_{j,t}$ being the demand for genre j at period t, λ_j the Lagrange multiplier associated with the price constraint and:

$$e_{j,t} = \frac{p_{j,t}}{C_{j,t}}\frac{dC_{j,t}}{dp_{j,t}}$$

denoting the own-price elasticity of demand for j. If $p_{j,t} = 0$, $\lambda_j \geq 0$ and $e_{j,t} \leq -1$, while if $p_{j,t} > 0$, $\lambda_j = 0$ and $e_{j,t} = -1$. Hence, the firm determines the price of j such that any increase in price creates a decrease of the demand in the same proportion.

Table 2.7 displays the estimated coefficient by market structure (Monopolistic Competition versus Bertrand Competition). Table 2.8 shows price and total expenditure elasticities estimates by treatment. Comparing compensated own price elasticities, we notice that they are significantly lower (in absolute value) in the more competitive market for all genres except Classical. Looking at the uncompensated own price elasticities in the Monopolistic Competition treatment, they are either close to -1 (Pop/Rock and Classical) or slightly larger than -1 in absolute value (Rap/Rnb and Blues/Jazz). In the Bertrand competition treatment, uncompensated own-price elasticities are relatively low (-0.54, -0.35 and -0.42 for respectively Pop/Rock, Rap/Rnb and Blues/Jazz). Demand for Classical is the most elastic one in the Bertrand competition (the uncompensated elasticity is -0.97). This result can be explained by the fact that consumers substitute more easily Classical with other musical genres such that even with low prices, demand is not drastically inelastic. This hypothesis seems plausible since cross-price elasticities for Classical music are relatively high.

Another interesting results is that musical genres seem to be more substitutes in the Monopolistic Competition than in the Bertrand Competition treatment, as confirmed in Figure 2.3 where the volatility of shares seems higher in the Monopolistic competition. Cross price elasticities are significantly greater in the Monopolistic market than with Bertrand competition. Since demand is more price elastic in the Monopolistic market, the additivity restriction mechanically sets cross price elasticities with higher values.

Table 2.7 – Estimations by Market Structure (constrained model)

	Monopolistic Competition (MC)				**Bertrand Competition (BC)**			
	Pop/Rock	Classical	Rap/RnB	Blues/Jazz	Pop/Rock	Classical	Rap/RnB	Blues/Jazz
	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 1$	$i = 2$	$i = 3$	$i = 4$
	w_1	w_2	w_3	w_4	w_1	w_2	w_3	w_4
$\gamma_{i,1}$	-0.105***	0.075**	0.017	0.012	0.171***	-0.018*	-0.097***	-0.057***
	(0.029)	(0.032)	(0.019)	(0.018)	(0.015)	(0.009)	(0.015)	(0.013)
$\gamma_{i,2}$	-0.075**	-0.152***	0.037	0.040	-0.018	-0.020*	0.031*	0.007
	(0.033)	(0.045)	(0.033)	(0.029)	(0.019)	(0.011)	(0.018)	(0.012)
$\gamma_{i,3}$	0.017	0.037	-0.084***	0.029*	-0.097***	0.031***	0.171***	-0.105***
	(0.018)	(0.030)	(0.022)	(0.016)	(0.016)	(0.009)	(0.017)	(0.010)
$\gamma_{i,4}$	0.012	0.040	0.029*	-0.081***	-0.057***	0.007	-0.105***	0.155***
	(0.018)	(0.029)	(0.016)	(0.017)	(0.014)	(0.008)	(0.016)	(0.010)
β_i	-0.127***	0.210***	-0.052	-0.031	0.029	0.035*	0.125***	0.062***
	(0.040)	(0.034)	(0.042)	(0.038)	(0.038)	(0.018)	(0.027)	(0.019)
N	241	241	241	241	234	234	234	234

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2.3 – Demand shares by treatment and period

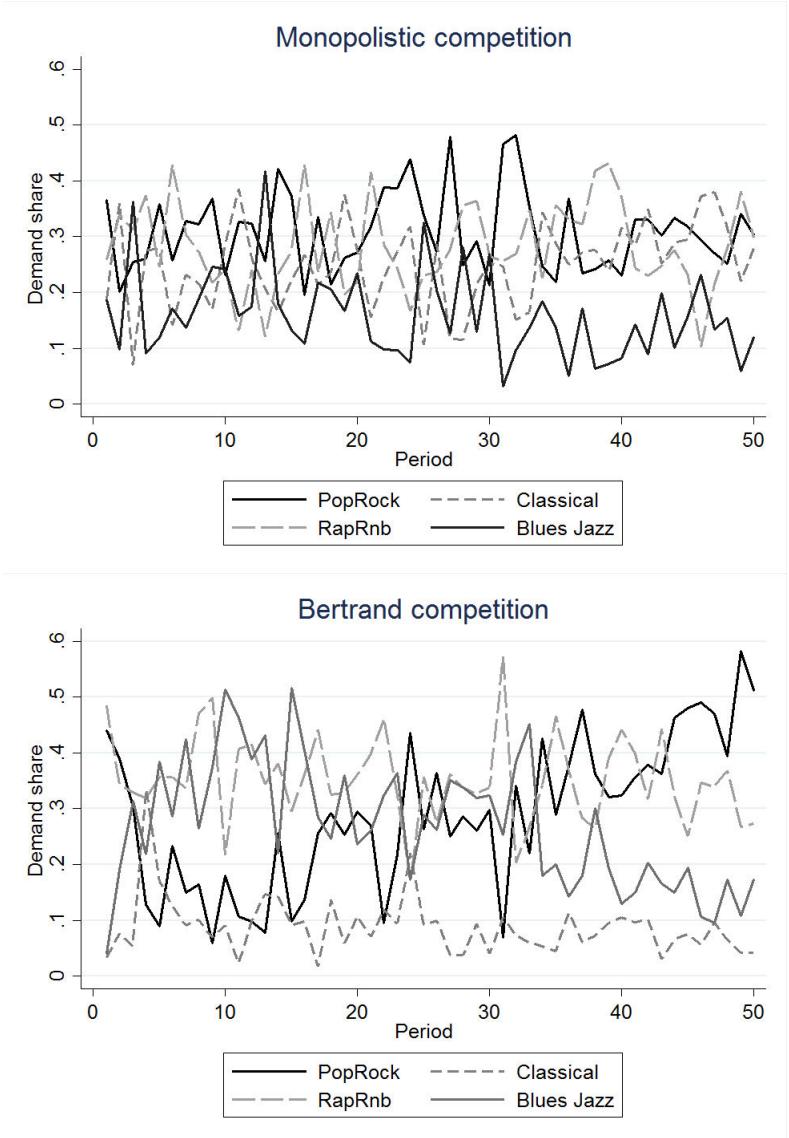


Table 2.8 – Elasticities estimations by Treatment (constrained model)

	AIDS (MC)				**AIDS (BC)**			
	Shares	Expenditure	U price	C price	Shares	Budget	U price	C price
Pop/Rock	0.306***	0.648***	-0.868***	-0.669***	0.307***	1.057***	-0.541***	-0.216***
	(0.011)	(0.104)	(0.037)	(0.043)	(0.018)	(0.101)	(0.048)	(0.043)
Classical	0.264***	1.013***	-1.061***	-0.793***	0.089***	1.192***	-0.971***	-0.864***
	(0.014)	(0.150)	(0.088)	(0.052)	(0.009)	(0.170)	(0.068)	(0.065)
Rap/Rnb	0.294***	1.728***	-1.280***	-0.771***	0.365***	0.689***	-0.354***	-0.103**
	(0.014)	(0.128)	(0.067)	(0.061)	(0.013)	(0.077)	(0.061)	(0.037)
Blues/Jazz	0.135***	0.187	-1.272***	-1.247***	0.238***	1.330***	-0.420***	-0.103*
	(0.011)	(0.210)	(0.111)	(0.130)	(0.008)	(0.074)	(0.054)	(0.042)

AIDS (MC)

	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.868***	0.079	0.124*	0.017	-0.669***	0.250***	0.315***	0.105**
	(0.037)	(0.067)	(0.059)	(0.035)	(0.043)	(0.046)	(0.045)	(0.040)
Classical	-0.020	-1.061***	-0.058	0.126**	0.290***	-0.793***	0.240***	0.263***
	(0.052)	(0.088)	(0.076)	(0.045)	(0.041)	(0.052)	(0.060)	(0.055)
Rap/Rnb	-0.202***	-0.241***	-1.280***	-0.006	0.327***	0.215***	-0.771***	0.228***
	(0.061)	(0.068)	(0.067)	(0.049)	(0.057)	(0.053)	(0.061)	(0.051)
Blues/Jazz	0.18	0.464***	0.441***	-1.272***	0.237***	0.513***	0.497***	-1.247***
	(0.098)	(0.134)	(0.126)	(0.111)	(0.070)	(0.090)	(0.096)	(0.130)

AIDS (BC)

	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.541***	-0.072*	-0.283***	-0.161***	-0.216***	0.023	0.103**	0.090**
	(0.048	(0.040)	(0.066)	(0.043)	(0.043)	(0.040)	(0.048)	(0.039)
Classical	-0.289***	-0.971***	0.008	0.059	0.078	-0.864***	0.443***	0.343***
	(0.079)	(0.068)	(0.121)	(0.086)	(0.093)	(0.065)	(0.087)	(0.075)
Rap/Rnb	-0.125***	0.047*	-0.354***	-0.257***	0.087**	0.108***	-0.103***	-0.093***
	(0.033)	(0.028)	(0.061)	(0.033)	(0.035)	(0.027)	(0.037)	(0.032)
Blues/Jazz	-0.293***	0.01	-0.628***	-0.420***	0.117**	0.129***	-0.142***	-0.103**
	(0.040)	(0.033)	(0.053)	(0.054)	(0.048)	(0.033)	(0.046)	(0.042)

Standard errors in parentheses. Standard errors are calculated using the Delta method.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

4.3. Estimated elasticities in sub-markets

Measuring experimentally demand functions enables us to compare estimations between sub-samples. This approach provides new insights by exploring heterogeneity of demand. We thus make a comparison of demand function by segmenting the market according to gender, age and level of openness.

4.3.1. Gender

Looking at Table 2.9, one can first notice that women significantly listen to less Pop/Rock ($p < 0.001$) and more Rap/Rnb ($p = 0.037$) than men.

Table 2.9 – Average shares by Gender

	Women	**Men**	**Mann-Whitney test (p-value)**
Pop/Rock	0.26 (0.29)	0.33 (0.26)	$p < 0.001$
Classical	0.18 (0.23)	0.17 (0.20)	$p = 0.505$
Rap/Rnb	0.35 (0.32)	0.28 (0.24)	$p = 0.037$
Blues/Jazz	0.22 (0.29)	0.21 (0.25)	$p = 0.298$

On the whole, as one can notice in Table 2.11, there seems to be little difference in the music demand functions of men and women (coefficients are shown in Table 2.10). This suggests that demand curves are similar.

4.3.2. Age

In this section, we divide our sample according to the median age (median age is equal to 24). As shown in Table 2.12 above 24 subjects listen to more Pop/Rock and less Rap/Rnb than below 24 subjects (at a 1% level of significance). Table 2.14 compares demand functions for the below versus above median age subjects. Estimated coefficients are listed in Table 2.13. Results show that demand for Blues/Jazz is slightly more elastic for older subjects.

Table 2.10 – Estimations by Gender (constrained model)

	Women (W)				**Men (M)**			
	Pop/Rock	Classical	Rap/RnB	Blues/Jazz	Pop/Rock	Classical	Rap/RnB	Blues/Jazz
	$i=1$	$i=2$	$i=3$	$i=4$	$i=1$	$i=2$	$i=3$	$i=4$
	w_1	w_2	w_3	w_4	w_1	w_2	w_3	w_4
$\gamma_{i,1}$	0.065***	-0.009	-0.047***	-0.009	0.046***	-0.024***	-0.034***	0.012
	(0.010)	(0.009)	(0.012)	(0.010)	(0.010)	(0.007)	(0.008)	(0.010)
$\gamma_{i,2}$	-0.009	-0.032***	0.004***	0.004	-0.024***	-0.018**	0.017**	0.025***
	(0.011)	(0.011)	(0.012)	(0.010)	(0.009)	(0.009)	(0.008)	(0.009)
$\gamma_{i,3}$	-0.047***	0.037***	0.074***	-0.064***	-0.034***	0.017*	0.080***	-0.062***
	(0.012)	(0.011)	(0.014)	(0.011)	(0.011)	(0.009)	(0.009)	(0.010)
$\gamma_{i,4}$	-0.009	0.004	-0.064***	0.069***	0.012	0.025***	-0.062***	0.025**
	(0.011)	(0.009)	(0.012)	(0.010)	(0.010)	(0.008)	(0.008)	(0.010)
β_i	-0.003	-0.098***	0.070***	0.032*	-0.032**	-0.073***	0.030**	0.076***
	(0.032)	(0.026)	(0.028)	(0.032)	(0.018)	(0.015)	(0.019)	(0.018)
N	491	491	491	491	500	500	500	500

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4. By level of openness

During the experiment, participants were asked to fill in a French version of the Brief Big Five inventory (Barbot, 2008). The Five-Factor Model (FFM) of personality traits is dominant in psychology and assumes a structure of human personality according to five dimensions: agreeableness, conscientiousness, extraversion (vs. introversion), emotional stability (vs. neuroticism), and openness. In this section, we focus on

"openness to new experience" which refers to "needs intellectual stimulation, change, and variety" (McCrae and John, 1992). Hunter and Schellenberg (2011) stress that high openness (measured by the same Brief Big Five) decreases one's preferences for a same musical stimuli. Consumers who exhibit higher level of openness seek to try different experiences. Applied to our study, one can assume that high openness leads to higher own and cross price elasticities : buyers who are more opened to new experiences can more easily switch from a genre to another. Overall, results show that there seems to be little differences between the two samples.

Table 2.15 first presents average shares by musical genres. Subjects who exhibit a higher level of openness listen to more Pop/Rock and less Rap/Rnb and Pop/Rock than others (at a 1% level of significance).

Looking at Table 2.16 and 2.17, we can see however that our hypothesis is only confirmed for Blues/Jazz (higher demand elasticity for subjects who exhibit a higher level of openness). Blues/Jazz and Classical is also more substitutable for subjects who have a higher score of openness. In the meantime, for subjects who have a lower score of openness, the cross-price elasticity of Pop/Rock and Classical is higher.

Table 2.11 – Elasticities estimations by Gender (constrained model)

	AIDS (Women)				**AIDS (Men)**			
	Shares	Expenditure	U price	C price	Shares	Expenditure	U price	C price
Pop/Rock	0.259***	0.988***	-0.747***	-0.492***	0.346***	0.909***	-0.829***	-0.514***
	(0.015)	(0.078)	(0.046)	(0.040)	(0.011)	(0.043)	(0.027)	(0.027)
Classical	0.136***	0.279*	-0.986***	-0.948***	0.187***	0.612***	-0.964***	-0.850***
	(0.012)	(0.157)	(0.064)	(0.063)	(0.009)	(0.060)	(0.040)	(0.039)
Rap/Rnb	0.373***	1.188***	-0.843***	-0.401***	0.273***	1.109***	-0.731***	-0.428***
	(0.016)	(0.055)	(0.041)	(0.036)	(0.010)	(0.049)	(0.037)	(0.033)
Blues/Jazz	0.232***	1.136***	-0.725***	-0.461***	0.193***	1.386***	-0.881***	-0.613***
	(0.013)	(0.075)	(0.055)	(0.040)	(0.011)	(0.080)	(0.046)	(0.042)

	AIDS (Women)							
	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.747***	-0.030	-0.177***	-0.033	-0.492***	0.104***	0.191***	0.196***
	(0.046)	(0.039)	(0.050)	(0.047)	(0.040)	(0.039)	(0.048)	(0.042)
Classical	0.126*	-0.986***	0.431***	0.150**	0.198***	-0.948***	0.535***	0.215***
	(0.067)	(0.064)	(0.094)	(0.076)	(0.061)	(0.063)	(0.071)	(0.059)
Rap/Rnb	-0.175***	0.034	-0.843***	-0.203***	0.132***	0.196***	-0.401***	0.073**
	(0.031)	(0.030)	(0.041)	(0.034)	(0.034)	(0.033)	(0.036)	(0.033)
Blues/Jazz	-0.075*	-0.029	-0.307***	-0.725***	0.219***	0.126***	0.116**	-0.461***
	(0.042)	(0.040)	(0.052)	(0.055)	(0.043)	(0.041)	(0.051)	(0.040)
	AIDS (Men)							
	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.829***	-0.037	-0.080**	0.037	-0.514***	0.133***	0.169***	0.212***
	(0.027)	(0.026)	(0.034)	(0.029)	(0.027)	(0.026)	(0.032)	(0.027)
Classical	0.034	-0.964***	0.171***	0.147***	0.246***	-0.850***	0.338***	0.266***
	(0.038)	(0.040)	(0.049)	(0.041)	(0.037)	(0.039)	(0.046)	(0.038)
Rap/Rnb	-0.170***	0.024	-0.731***	-0.232***	0.214***	0.232***	-0.428***	-0.018
	(0.030)	(0.028)	(0.037)	(0.034)	(0.031)	(0.030)	(0.033)	(0.031)
Blues/Jazz	-0.100**	-0.002	-0.404***	-0.881***	0.380***	0.258***	-0.025	-0.613***
	(0.046)	(0.044)	(0.063)	(0.046)	(0.049)	(0.045)	(0.055)	(0.042)

Standard errors in parentheses. Standard errors are calculated using the Delta method.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table 2.12 – Average shares by Age

	Above 24	**Below 24**	**Mann-Whitney test (p-value)**
Pop/Rock	0.33 (0.28)	0.28 (0.27)	$p = 0.003$
Classical	0.19 (0.25)	0.18 (0.21)	$p = 0.134$
Rap/Rnb	0.27 (0.28)	0.34 (0.30)	$p < 0.001$
Blues/Jazz	0.21 (0.27)	0.21 (0.27)	$p = 0.960$

Table 2.13 – Estimations by Age (constrained model)

	Above 24				**(Strictly) Under 24**			
	Pop/Rock	Classical	Rap/RnB	Blues/Jazz	Pop/Rock	Classical	Rap/RnB	Blues/Jazz
	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 1$	$i = 2$	$i = 3$	$i = 4$
	w_1	w_2	w_3	w_4	w_1	w_2	w_3	w_4
$\gamma_{i,1}$	0.020	-0.024**	-0.029**	0.033**	0.044***	-0.012	-0.038***	0.006
	(0.015)	(0.010)	(0.011)	(0.015)	(0.012)	(0.008)	(0.011)	(0.010)
$\gamma_{i,2}$	-0.024**	-0.026**	0.009	0.041***	-0.012	-0.011	0.021**	0.002
	(0.010)	(0.011)	(0.010)	(0.012)	(0.009)	(0.008)	(0.010)	(0.009)
$\gamma_{i,3}$	-0.029**	0.009	0.077***	-0.057***	-0.038***	-0.021**	0.090***	-0.074**
	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.010)	(0.013)	(0.011)
$\gamma_{i,4}$	0.033**	0.041***	-0.057***	-0.017	0.006	0.002	-0.074***	0.065***
	(0.013)	(0.011)	(0.012)	(0.014)	(0.010)	(0.008)	(0.010)	(0.009)
β_i	-0.067***	-0.081***	0.019	-0.129***	-0.064***	-0.043***	0.074***	0.033**
	(0.022)	(0.019)	(0.021)	(0.018)	(0.016)	(0.013)	(0.016)	(0.015)
N	500	500	500	500	500	500	500	500

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.14 – Elasticities estimations by Age (constrained model)

	AIDS (Above 24)				**AIDS (Below 24)**			
	Shares	Expenditure	U price	C price	Shares	Budget	U price	C price
Pop/Rock	0.318***	0.788***	-0.836***	-0.585***	0.278***	0.768***	-0.742***	-0.529***
	(0.013)	(0.072)	(0.035)	(0.035)	(0.011)	(0.058)	(0.037)	(0.035)
Classical	0.175***	0.540***	-0.976***	-0.881***	0.177***	0.759***	-0.993***	-0.859***
	(0.012)	(0.120)	(0.058)	(0.053	(0.009)	(0.074)	(0.044)	(0.043)
Rap/Rnb	0.272***	1.070***	-0.731***	-0.440***	0.335***	1.221***	-0.765***	-0.356***
	(0.012)	(0.076)	(0.052)	(0.041)	(0.012)	(0.050)	(0.038)	(0.033)
Blues/Jazz	0.235***	1.549***	-1.027***	-0.662***	0.210***	1.158***	-0.709***	-0.466***
	(0.012)	(0.078)	(0.040)	(0.041)	(0.011)	(0.073)	(0.045)	(0.038)

AIDS (Above 24)

	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.836***	0.004	-0.044	0.087**	-0.585***	0.143***	0.170***	0.272***
	(0.035)	(0.034)	(0.044)	(0.036)	(0.035)	(0.032)	(0.038)	(0.032)
Classical	0.087	-0.976***	0.154**	0.195***	0.259***	-0.881***	0.300***	0.322***
	(0.055)	(0.058)	(0.074)	(0.058)	(0.051)	(0.053)	(0.062)	(0.050)
Rap/Rnb	-0.141***	0.006	-0.731***	-0.205***	0.200***	0.194***	-0.440***	0.047
	(0.036)	(0.037)	(0.052)	(0.039)	(0.037)	(0.036)	(0.041)	(0.036)
Blues/Jazz	-0.125***	-0.031	-0.367***	-1.027***	0.368***	0.240***	0.054	-0.662***
	(0.044)	(0.046)	(0.057)	(0.040)	(0.048)	(0.046)	(0.052)	(0.041)

AIDS (Below 24)

	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.742***	0.021	-0.099**	0.053	-0.529***	0.156***	0.158***	0.214***
	(0.037)	(0.033)	(0.044)	(0.035)	(0.035)	(0.032)	(0.040)	(0.032)
Classical	0.035	-0.993***	0.157***	0.042	0.246***	-0.859***	0.412***	0.201***
	(0.043)	(0.044)	(0.057)	(0.045)	(0.041)	(0.043	(0.051	(0.042)
Rap/Rnb	-0.209***	0.001	-0.765***	-0.248***	0.131***	0.217***	-0.356***	0.008
	(0.030)	(0.029)	(0.038)	(0.031)	(0.031)	(0.030)	(0.033)	(0.030)
Blues/Jazz	-0.039	-0.036	-0.375***	-0.709***	0.283***	0.169***	0.013	-0.466***
	(0.042)	(0.043)	(0.059)	(0.045)	(0.043)	(0.042)	(0.052)	(0.038)

Standard errors in parentheses. Standard errors are calculated using the Delta method.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table 2.15 – Average shares by level of Openness

	High O	**Low O**	**Mann-Whitney test (p-value)**
Pop/Rock	0.36 (0.31)	0.26 (0.28)	$p < 0.001$
Classical	0.18 (0.25)	0.15 (0.19)	$p = 0.561$
Rap/Rnb	0.27 (0.30)	0.37 (0.30)	$p < 0.001$
Blues/Jazz	0.19 (0.26)	0.23 (0.27)	$p < 0.001$

High O and Low O respectively refer to above and below median score of openness.

Table 2.16 – Estimations by Level of Openness (constrained model)

	High Openness Score				**Low Openness Score**			
	Pop/Rock	Classical	Rap/RnB	Blues/Jazz	Pop/Rock	Classical	Rap/RnB	Blues/Jazz
	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 1$	$i = 2$	$i = 3$	$i = 4$
	w_1	w_2	w_3	w_4	w_1	w_2	w_3	w_4
$\gamma_{i,1}$	0.079***	-0.031*	-0.058***	-0.010	0.086***	0.006	-0.074***	-0.019
	(0.019)	(0.016)	(0.018)	(0.016)	(0.015)	(0.011)	(0.015)	(0.013)
$\gamma_{i,2}$	-0.031**	0.006	0.026*	-0.001	0.006	0.001	0.013	-0.020*
	(0.015)	(0.013)	(0.015)	(0.012)	(0.013)	(0.010)	(0.024)	(0.011)
$\gamma_{i,3}$	-0.058***	0.026**	0.078***	-0.047***	-0.074***	0.013	0.113***	-0.053***
	(0.015)	(0.013)	(0.014)	(0.013)	(0.013)	(0.010)	(0.013)	(0.011)
$\gamma_{i,4}$	0.010	-0.001	-0.047***	0.038***	-0.019	-0.020**	-0.053***	0.091***
	(0.015)	(0.013)	(0.014)	(0.013)	(0.012)	(0.009)	(0.012)	(0.011)
β_i	-0.032	-0.001	-0.042*	0.074***	-0.030	0.029**	-0.034*	0.035**
	(0.026)	(0.023)	(0.025)	(0.022)	(0.018)	(0.014)	(0.019)	(0.016)
N	369	369	369	369	390	390	390	390

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.17 – Elasticities estimations by level of Openness (constrained model)

	AIDS (High O)				**AIDS (Low O)**			
	Shares	Expenditure	U price	C price	Shares	Budget	U price	C price
Pop/Rock	0.338***	0.904***	-0.728***	-0.422***	0.262***	0.887***	-0.635***	-0.403***
	(0.015)	(0.080)	(0.050)	(0.053)	(0.013)	(0.070)	(0.056)	(0.054)
Classical	0.201***	1.005***	-0.972***	-0.770***	0.161***	1.180***	-1.015***	-0.826***
	(0.013)	(0.117)	(0.080)	(0.068)	(0.010)	(0.088)	(0.068)	(0.063)
Rap/Rnb	0.255***	0.834***	-0.641***	-0.428***	0.351***	0.903***	-0.638***	-0.322***
	(0.015)	(0.103)	(0.068)	(0.055)	(0.013)	(0.054)	(0.043)	(0.037)
Blues/Jazz	0.205***	1.360***	-0.849***	-0.569***	0.227***	1.154***	-0.624***	-0.362***
	(0.013)	(0.115)	(0.064)	(0.054)	(0.011)	(0.077)	(0.054)	(0.046)

AIDS (High O)

	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.728***	-0.074	-0.140***	0.037	-0.422***	0.108**	0.091**	0.223***
	(0.050)	(0.051)	(0.048)	(0.046)	(0.053)	(0.046)	(0.045)	(0.042)
Classical	-0.158**	-0.972***	0.129*	-0.004	0.182**	-0.770***	0.386***	0.202***
	(0.071)	(0.080)	(0.074)	(0.064)	(0.080)	(0.068)	(0.067)	(0.060)
Rap/Rnb	-0.161***	0.136**	-0.641***	-0.168***	0.121*	0.304***	-0.428***	0.003
	(0.062)	(0.067)	(0.068)	(0.058)	(0.071)	(0.059)	(0.055)	(0.052)
Blues/Jazz	-0.093	-0.075	-0.343***	-0.849***	0.367***	0.198***	0.004	-0.569***
	(0.067)	(0.073)	(0.069)	(0.064)	(0.077)	(0.065)	(0.063)	(0.054)

AIDS (Low O)

	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.635***	0.035	-0.235***	-0.052	-0.403***	0.178***	0.076	0.149***
	(0.056)	(0.053)	(0.053)	(0.048)	(0.054)	(0.049)	(0.050)	(0.045)
Classical	-0.019	-1.015***	0.010	-0.155**	0.290***	-0.826***	0.424***	0.112**
	(0.065)	(0.068)	(0.066)	(0.056)	(0.068)	(0.063)	(0.062)	(0.055)
Rap/Rnb	-0.180***	0.049	-0.638***	-0.134***	0.057	0.194***	-0.322***	0.071**
	(0.041)	(0.040)	(0.043)	(0.038)	(0.043)	(0.038)	(0.037)	(0.035)
Blues/Jazz	-0.130**	-0.106**	-0.295***	-0.624***	0.173***	0.079	0.110**	-0.362***
	(0.055)	(0.054)	(0.055)	(0.054)	(0.058)	(0.050)	(0.051)	(0.046)

Standard errors in parentheses. Standard errors are calculated using the Delta method. High O and Low O respectively refer to above and below median score of openness.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

5. Application to the Novelty experiment

In this section, we use data from the experiment described in Chapter 1 where subjects have to allocate their time between music produced by unknown artists (the New Artists category) and music produced by popular artists (the Top 30 category) (see Berlin, Bernard and Fürst (2015) for the detailed design). One of the treatments, the Market treatment, consists in implementing a real market where two subjects were randomly assigned to be the sellers (one for the New Artists category, the other one for the Top 30 category). The experiment consists in 30 periods of 90 seconds of listening time. For each period, participants, facing per second prices, decide how to allocate the 90 seconds between the two categories.

The methodology developed in this article can be applied to this type of data as the experimental design is really similar to the one used to far. One advantage of this setting is that chances of facing zero shares expenditure problems are really low: here demand per period is not discrete but almost perfectly continuous (participants allocate seconds and do not face a discrete choice).

Results show that the New Artists category is always sold at a lower price than the Top 30 category [22]. Own price elasticity for New Artists should be found to be low in absolute value as prices are low while it is the opposite for Top 30. Let the New Artists' category be denoted by $i = 1$ and the Top 30 category by $i = 2$. The mean expenditure shares for the two categories are respectively $\bar{w}_1 = 0.383$ and $\bar{w}_2 = 0.617$. Table 2.18 gives the results of the estimated coefficient of the AIDS model.

Table 2.19 provides the estimated elasticities. Results show that New artists goods are necessity goods while top songs are luxury goods. As subjects accumulate earnings, their consumption of new songs diminishes. Consequently, the two categories yield a

22. These results are in line with the literature. For instance, Mixon and Ressler (2000) conducted a study on own price elasticity comparing demand for old albums with new releases. They find that new releases are sold at lower price than old albums.

Table 2.18 – Estimations of the AIDS model (constrained model on homogeneity)

	New Artists	Top 30
	$i = 1$	$i = 2$
	w_1	w_2
$\gamma_{i,1}$	0.074**	-0.074**
	(0.037)	(0.037)
$\gamma_{i,2}$	0.013	-0.013
	(0.048)	(0.048)
β_i	-0.729***	0.729***
	(0.146)	(0.146)
N	57	57

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

positive cross-price elasticity.

Several limitations can be however formulated. First, one concern about this dataset is that sellers listened to each track before selling it. Thus, price can be a signal of quality. In our setting, demand may be also sensitive to quality, and not only tastes for novelty. Results are however robust when controlling for average ratings of the songs. Second, although these results provides new insights regarding demand for novelty in music markets, one needs to stay cautious with their interpretation as the sample size is quite limited. Robustness checks using additional experimental sessions should be conducted.

Table 2.19 – Estimated elasticities - All sample (constrained model on homogeneity)

	AIDS			
	Shares	Expenditure	U price	C price
New Artists	0.416***	0.224***	-0.733***	-0.640***
	(0.016)	(0.05)	(0.075)	(0.077
Top 30	0.584***	1.552***	-1.362***	-0.455***
	(0.016)	(0.05)	(0.071)	(0.066)

	Uncompensated cross price elasticities		**Compensated cross price elasticities**	
	New Artists	**Top 30**	**New Artists**	**Top 30**
New Artists	-0.733***	0.510***	-0.640***	0.640***
	(0.075)	(0.089)	(0.077)	(0.077)
Top 30	-0.190***	-1.362***	0.455***	-0.455***
	(0.052)	(0.071)	(0.066)	(0.066)

6. Conclusion

Estimating demand elasticities for cultural goods or performing arts is generally a difficult undertaking because of the lack of precise data, price stability and quality differences. We propose an experimental methodology bypassing these issues in order to estimate demand function for music within a controlled environment using the well-known Almost Ideal Demand System model by Deaton and Muellbauer (1980). The estimated uncompensated own price elasticities are ranged between -0.48 (for Rap/Rnb) and -0.93 (for Classical music). Our results are actually in line with price elasticities for performing arts found in the literature (see Seaman (2006)).

Total expenditure elasticities are between 0.84 (for Pop/Rock) and 1.70 (for Blues/Jazz). The interpretation of total expenditure elasticities is however limited as our experiment are not real expenditure for musical goods, but rather expenditure of the endowment provided during the experiment. It is however informative on the way subjects react as their experimental endowment increases.

To our knowledge, this study is the first attempt to estimate cross price elasticities between musical genres. On the whole, we find that Classical music is a net substitutes for all other genres (Pop/Rock, Blues/Jazz and Rap/Rnb music). Pop/Rock and Blues/Jazz are also net substitute. On the contrary, Rap/Rnb and Blues/Jazz are not substitutes as well as Pop/Rock and Rap/Rnb. Our methodology also allows us to compare estimates between sub-samples and to take into account heterogeneity on part of buyers.

Finally, using different market structures, we can also study the impact of market power on demand elasticities showing that more market power yields close to unit price elasticity. Consequently, demand is less price elastic in a more competitive framework. This results has important implications in public and industrial economics as it justifies using own price elasticity estimations to measure well-being and market power.

Even though music is a good candidate for estimating demand functions, several limitations can be expressed. First, changes in price is made salient within the lab and may induce overreaction to prices on part of buyers. Outside the lab, as we mentioned, prices do not vary drastically in the short term. Demand may be less responsive to a change in price simply because buyers do not remember previous prices or do not necessarily notice the change in prices. This dimension is not taken into account in our experimental setting but opens possible extensions of the experimental design that could be explored. In addition, estimations made with experimental data do not take into account the time factor which is an additional cost. Considering demand for performing arts, buying tickets is time consuming.

Since participants of our experiments were to make several choices, it could also be interesting to add a learning-by-consuming process. As consumers discover their true preferences about musical genres (Armantier et al., 2016), past consumption - within the experiment - can determine one's decision for a given round. Dynamic versions of the Almost Ideal Demand System model has been implemented in the literature to study consumption of addictive goods like alcohol (Gil and Molina, 2009) or sugar-sweetened beverages (Zhen et al., 2010). Such approach could be a promising extension of our econometric model.

Although we use music as an ideal good to implement our methodology, other types of goods can be considered, in the field of cultural goods - such as movies or short novels - but also for different types of goods such as food or brands. Several conditions must however be respected such as in-lab private consumption. To limit the costs of such experimentation, goods for which consumption can be repeated have to be preferred.

A. Appendices

A.1. LA/AIDS and QAIDS estimations

We replicate estimation for the whole sample using the linear and the quadratic versions of the AIDS model, respectively the LA/AIDS and the QAIDS.

Table 2.20 – Estimated elasticities - All sample (constrained model)

	LA/AIDS			
	Shares	Expenditure	U price	C price
Pop/Rock	0.216***	1.186***	-0.642***	-0.386***
	(0.021)	(0.059)	(0.055)	(0.046)
Classical	0.089***	1.457***	-0.827***	-0.697***
	(0.017)	(0.169)	(0.089)	(0.083)
Rap/Rnb	0.469***	0.839***	-0.713***	-0.320***
	(0.02)	(0.013)	(0.021)	(0.023)
Blues/Jazz	0.226***	0.975***	-0.626***	-0.405***
	(0.02)	(0.037)	(0.035)	(0.034)
	QAIDS			
	Shares	Expenditure	U price	C price
Pop/Rock	0.287***	0.784***	-0.614***	-0.389***
	(0.011)	(0.088)	(0.049)	(0.036)
Classical	0.182***	1.080***	-0.976***	-0.780***
	(0.011)	(0.118)	(0.078)	(0.066)
Rap/Rnb	0.318***	0.792***	-0.592***	-0.341***
	(0.01)	(0.077)	(0.039)	(0.035)
Blues/Jazz	0.213***	1.532***	-0.835***	-0.508***
	(0.013)	(0.102)	(0.046)	(0.039)

Table 2.21 – Own and cross price elasticities - All sample (constrained model)

LA/AIDS

	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.642***	-0.032	-0.365***	-0.147*	-0.386***	0.073	0.191***	0.122**
	(0.055)	(0.036)	(0.068	(0.06)	(0.046)	(0.039)	(0.05)	(0.046)
Classical	-0.137	-0.827***	-0.18	-0.314*	0.178*	-0.697***	0.503***	0.016
	(0.079)	(0.089)	(0.114)	(0.146)	(0.073)	(0.083)	(0.095)	(0.109)
Rap/Rnb	-0.093***	0.021	-0.713***	-0.053*	0.088**	0.095***	-0.320***	0.136***
	(0.017)	(0.017)	(0.021)	(0.022)	(0.028)	(0.026)	(0.023)	(0.027)
Blues/Jazz	-0.095**	-0.080*	-0.174***	-0.626***	0.116**	0.006	0.283***	-0.405***
	(0.032)	(0.032)	(0.049)	(0.035)	(0.038)	(0.036)	(0.046)	(0.034)

QAIDS

	Uncompensated cross price elasticities				**Compensated cross price elasticities**			
	Pop/Rock	**Classical**	**Rap/Rnb**	**Blues/Jazz**	**Pop/Rock**	**Classical**	**Rap/Rnb**	**Blues/Jazz**
Pop/Rock	-0.614***	-0.063	-0.131**	0.023	-0.389***	0.080**	0.118**	0.191***
	(0.049	(0.035	(0.04	(0.039	(0.036	(0.031	(0.04	(0.033
Classical	-0.183**	-0.976***	0.041	0.039	0.126*	-0.780***	0.383***	0.270***
	(0.06	(0.078	(0.054	(0.059	(0.059	(0.066	(0.053	(0.051
Rap/Rnb	-0.121**	0.076*	-0.592***	-0.155***	0.106**	0.220***	-0.341***	0.014
	(0.046	(0.033	(0.039	(0.035	(0.038	(0.03	(0.035	(0.034
Blues/Jazz	-0.183**	-0.049	-0.465***	-0.835***	0.256***	0.231***	0.021	-0.508***
	(0.063	(0.067	(0.049	(0.046	(0.062	(0.062	(0.052	(0.039

A.2. Aitchison's (1986) zero replacement technique

In statistics, compositional data refers to the vectors with strictly positive components whose sum is constant, such as fractions or proportions. A typical example in economics is income and expenditure distribution. 3-parts compositions can be depicted using a ternary diagram, an equilateral triangle, whose vertices represent the three elements of the composition. Compositions that are dotted at the center are equally distributed across the three components.

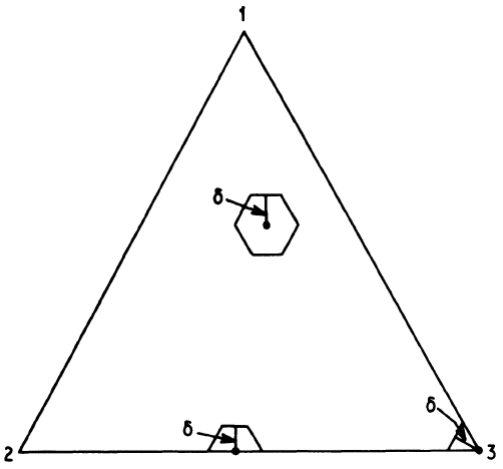
Such data are constrained by the "sum constraint" - and thus imposing constraints on the variance-covariance matrix - which invalidates standard statistical approaches like regression analysis. Log transformation is generally used to conduct statistical analysis on compositional data. It however does not allow for zero shares.

Compositional data literature distinguishes two main reasons why we observe zero proportions. On one hand, zeros can appear because of measurement errors. In this case, zero proportions actually are non-zeros, but are so small that, because of detection limits, they appear as zero in the dataset. These are called "trace zeros". On the other hand, zero proportions can be genuine zero, or "essential zeros". In household data for instance, it may be the case that some households decide not to consume specific goods, such as tobacco or alcohol.

The zero replacement technique consists in replacing zeros by very small values. This methodology is specifically implemented in the case of trace zeros. Fry, Fry and McLaren (2000) however argue that it can be applied whatever the nature of the zero proportions. It assumes that measuring is subject to a maximum rounding measurement error δ. To understand the technique, the following illustration is taken from Aitchison's (1986) seminal work. The 3-part composition $(0.54, 0.19, 0.27)$ could be any composition within the hexagon shown in Figure 2.4. Since the point is at the center of the hexagon, there is no need to replace shares. Consider now the following composition $(0.00, 0.53, 0.47)$. It is associated with the half-hexagonal region of possible

unrounded compositions. The composition can be replaced by any interior point within this area for which the vector equals $(0.00 + \epsilon, 0.53 - \frac{1}{2}\epsilon, 0.47 - \frac{1}{2}\epsilon)$. ϵ can be chosen such that the new composition is in the center of the half-hexagonal region, i.e. $\epsilon = \frac{4}{9}\delta$. Consider now the composition $(0.00, 0.00, 1.00)$. The unrounded composition is within a triangular area and has the following composition $(0.00 + \epsilon, 0.00 + \epsilon, 1.00 - 2\epsilon)$, with ϵ taken for a geometric center as $\frac{1}{3}$ times the maximum possible rounding error. The general procedure to change any composition with M zeros and N components is thus to replace zeros by $\delta\frac{(M+1)(N-M)}{N^2}$ and to reduce non zeros by $\delta\frac{M(M+1)}{N^2}$ where δ is the maximum rounding error.

Figure 2.4 – Ternary diagram



Regions of possible unrounded compositions corresponding to recorded, rounded compositions, with δ as the maximum rounding error.
Source: Aitchison (1986)

A.3. Estimation results for individual total expenditure

Table 2.22 – OLS regression on individual total expenditure

OLS estimates	TotalExpense
Ref=Student	
Employed	5,702
	(4,087)
Unemployed	-574.2
	(5,420)
Retired	-7,728
	(7,728)
Female	-893.5
	(2,203)
Age	116.6
	(162.6)
PrefNov	4,813*
	(2,504)
Risk Aversion (proxy)	-395.7
	(2,354)
Impatience (proxy)	814.3
	(2,254)
Freq All	-342.4
	(684.4)
Minimal Total Expense	60.97***
	(2.607)
Constant	-790.2
	(7,583)
Observations	140
R-squared	0.839

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Employed=1 if the subject declared being employed, Unemployed=1 if the subject declared being unemployed, Retired=1 if the subject declared being retired, Female=1 if the subject is female, Age is the age in years, PrefNov=1 if the subject declared that, in general, she prefers to listen to novel music rather than music that she already know, Risk Aversion=1 if subject declared she prefers winning 5 euros with certainty over playing a lottery with chances of winning 10 euros with an unknown probability over , Impatient=1 if the subject declared she prefers to receive 10 euros now rather than to receive 11 euros tomorrow, Freq All is the sum of declared frequencies of listening for each genre (each frequencies are measured with a 4 points Likert scale from "never or sometimes" to "very often") and the Minimal Total Expense is the Total Expense corresponding to a subject who would have systematically chosen the minimum price over the session.

A.4. Calculation for elasticities

Consider the share equation of the AIDS model:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \, ln \, p_j + \beta_i \, ln \frac{X}{P} + u_i \tag{2.10}$$

where P is the price index and $w_i = \frac{p_i x_i}{X}$, x_i being the demanded quantity for good i and X the total expenditure.

A.4.1. Total expenditure elasticity

The total expenditure elasticity for musical genre i is:

$$\eta_i = \frac{\frac{d(p_i xi)}{dX}}{\frac{p_i x_i}{X}}$$

From Equation 2.10, we have:

$$\frac{dw_i}{dlogX} = \frac{dw_i}{dX}\frac{dX}{dlnX} = \frac{X\frac{d(p_i x_i)}{dX} - p_i x_i}{X^2} X = \frac{d(p_i x_i)}{dX} - w_i = \beta_i$$

Hence:

$$\frac{d(p_i w_i)}{dX} = -\beta_i + w_i$$

We can thus conclude that the total expenditure elasticity for musical genre i equals:

$$\boxed{\eta_i = 1 + \frac{\beta_i}{w_i}}$$

A.4.2. Uncompensated elasticities

The uncompensated (or Marshallian) elasticity of demand with respect to the price of good j can be expressed as:

$$\begin{aligned}\epsilon^{U}_{i,j} = \frac{dlnx_i}{dlnp_j} &= -\delta_{i,j} + \frac{dw_i/dlnX}{w_i} \\ &= -\delta_{i,j} + \frac{1}{w_i}[\gamma_{i,j} - \beta_i \frac{dlnP}{dlnp_i}]\end{aligned}$$

where $\delta_{i,j}$ is the Kronecker delta, which takes on the value 0 and 1 when $i \neq j$ and $i = j$.

Since $lnP = \alpha_0 + \sum_j \alpha_i lnp_j + \frac{1}{2}\sum_j \sum_i \gamma_{i,j} lnp_i p_j$:

$$\boxed{\epsilon_{i,j} = -\delta_{i,j} + \frac{\gamma_{i,j}}{w_i} - \beta_i \frac{\alpha_i}{w_i} - \frac{\beta_i}{w_i} \sum_k \gamma_{k,j} lnp_k}$$

A.4.3. Compensated elasticities

Compensated (or Hicksian) elasticity of demand are obtained from the Slutsky equation:

$$\boxed{\epsilon^{C}_{i,j} = \epsilon^{U}_{i,j} + \eta_i w_j}$$

A.5. List of songs per musical genre

Table 2.23 – List of Pop/Rock Songs

Round	Artist	Title
1	The Verve	Sonnet
2	Elton John	Daniels
3	Offspring	Arent alright
4	Pixies	Brick is Red
5	Alkemy	Underwater
6	Syd Matters	Middle class men
7	Green Day	Waiting
8	Queen	Killer Queen
9	Divine Comedy	Absent Friends
10	Phil Collins	You Known what Time
11	Metallica	To live is to die
12	Radiohead	Let Down
13	Chuck Berry	Orangutang
14	Evanescence	Imaginary
15	Neil Young	Words
16	K's Choice	Another Day
17	U2	Desire
18	Nirvana	Lithium
19	Police	King of Pain
20	Madonna	Static Process
21	Rammstein	Sonne
22	Travis	Writing to reach you
23	Dido	Don't think of Me
24	Texas	In demand
25	Supertramp	Child of vision
26	Red Hot Chili	Road Trippin
27	Bob Dylan	Rainy Day Women
28	Eels	Not Ready Yet
29	Depeche Mode	In Your Room
30	George Mickael	Freedom
31	Springsteen	Working on the Highway
32	Muse	Apocalypse Please
33	DreamTheater	Solitary Shell
34	Cranberries (&Rammstein)	Under to the night
35	David Bowie	Thru' These Architects' Eyes
36	REM	What's the Frequency, Kenneth
37	Charlotte Gainsbourg	Beauty Mark
38	Rolling Stones	Laugh, I Nearly Died
39	Eric Clapton	I've Got a Rock 'N' Roll Heart
40	The Cure	Just Like Heaven
41	Pearl Jam	Jeremy
42	Genesis	Burning Rope
43	John Lennon	Whatever Gets You Thru the Night
44	Cake	Opera singer
45	Mickael Jackson	You Are Not Alone
46	Jeff Buckley	How Long Will It Take
47	Oasis	Who Feels Love
48	Moby	Lift Me Up
49	Justin Timberlake	Cry Me A River
50	No Doubt	Sunday morning

Table 2.24 – List of Classical Songs

Round	Artist	Title
1	Schubert	Fantaisie 4m - Mvt 1
2	Debussy	Mer Orch - Mvt2
3	Rameau	Contredanse
4	Bach	L'art de la fugue
5	Grieg - PeerGynt Orch	Anitra Dance
6	Schoenberg	op. 11 n° 3
7	Haendel	Trionfo Voc
8	Ravel	Tzigane
9	Delibes	Clochettes (Lakme)
10	Bartok	The miraculous Mandarin - Beginning
11	Satie	Gnossienne n° 1
12	Lizst	BACH Orgue
13	Boulez	Le marteau sans maître
14	Vivaldi	Gloria Voc
15	Mahler	Symphony n° 5 (Adagietto)
16	Stockhausen	Klavierstück 8
17	John Williams	Harry Potter (Chamber of secrets)
18	Wagner	Wesendonk Lieder
19	Varese	Ionisation
20	Beethoven	Trio Piano/Violon/Cello "L'archiduc"
21	Fauré	Sicilienne (Peleas et Melisande)
22	Barber	Concerto Cello - Mvt2
23	Strauss	Metamorphose
24	Moussorgsky	Tableaux
25	Crumb	Makrokosmos: La Gondole Phantom
26	Puccini	La Tosca
27	Brahms	Symphony n° 1 - Mvt4
28	Tchaikovsky	StrQuartett op.30 n° 2
29	Messiaen	Sortie Orgue
30	Moussorgsky	Boris Goudonov
31	Offenbach	La belle Hélène - Invocation à Vénus
32	Bruckner	Symph n° 7 - Mvt4
33	Schostacovitch	Quartett in Fa m l
34	Prokoviev	Scythian Suite
35	Brahms	Sextett Cordes
36	Stravinsky	L'oiseau de feu
37	BachBusoni	Chaconne
38	Mozart	Requiem (confutatis) Voc
39	Berio	Cinque Variazioni
40	Dany Elfman	Edward Scissorhands (Intro)
41	Bartok	Contraste - Mvt3
42	Genesis	Burning Rope
43	Haydn	Trio Flute/piano/cello in ré m - Mvt1
44	Purcell	Dido et Aneas
45	Saint Saens	Symphony n° 3 for Organ - Mvt3
46	Rachmaninov	Suite for 2 pianos op.17 n° 2
47	Schumann	Scherzo (Ouverture, Scherzo et Final)
48	Ligetti	Atmospheres Orch
49	Gluck	Iphigenie in Aulis - Graumsame Götter
50	Chant Ambrosien	Cantus Officiorum

Table 2.25 – List of Rap/RnB Songs

Round	Artist	Title
1	Destiny's child	Survivor
2	Ice Cube	A bird in the hand
3	Joe	I understand
4	Monica	Angel of mine
5	Shola Ama	Granny's Yard
6	Coolio	Gangsta's paradise
7	Veronica	Show me love
8	Sinclair	It's over
9	Ruby Turner	Chinese whisper
10	Snoop Doggy Dog	The Fatha Figga
11	Pussycat Dolls	When I grow up
12	Cobra	Mary J
13	Boyz II Men	The color of love
14	Kayliah	Caractere
15	Mac Mall feat Eklypse and Do-Right	Real friends
16	Fat joe	Breathe and stop
17	Neresa Maye	Step'n up
18	Public Enemy	Public Enemy n° 1
19	Alicia Keys	No one
20	Cypress Hill	Insane in the brain
21	Seal	Crazy
22	Ashanti	Foolish
23	Cooly's Hot Box	It's alright
24	Melissa M	Elle
25	T.I.	whatever you like
26	Aaliyah	Age ain't nothing but a number
27	Alibi Montana feat Diam's	Loin des yeux loin du coeur
28	Jungle style	This is your night
29	Rihanna	Disturbia
30	Elijah	Someday
31	Shima	Girlfriend
32	Next	Butta love
33	India T	Keep it up
34	Beyonce	If I were a boy
35	Kinece Senegal	You Don't Want No Funk
36	Seek	Loving heart
37	Amel Bent	Tu n'es plus la
38	Tee	Here we go again
39	Club nouveau	Situation n° 9
40	Lisa Stansfield	All Woman
41	50 cent	Wanna lick
42	Chris Brown feat T-pain	Kiss Kiss
43	Denis Taylor	Bad as you wanna be
44	Donna Gardier	Colour of my Soul
45	Down Low	Hit me right
46	Leah Mc Crae	Who I am
47	Jag	I Couldn't Keep It To Myself
48	D influence feat Louise Ros	32 flavours
49	Wu Tang Clan feat Erykah Badu	The Heart gently Weeps
50	Tasha's World	Nothing really matters

Table 2.26 – List of Blues/Jazz Songs

Round	Artist	Title
1	Charlie Parker	April in Paris
2	Ella Fitzgerald	You'll Have To Swing It
3	Thelonious Monk	Off Minor
4	Coleman	The Twelve Powers
5	Grappelli	Blues
6	Davis & Evans	Song so our country
7	Nina Simone	My Baby Just Cares For Me
8	Lucio Dalla	Flying Home
9	Cole Porter	I get a kick ou of you
10	Woody Herman	RoseRoom
11	Wes Mongomery	Airegin
12	AbbeyLincoln	The Masquarade Is Over
13	Abdullah Ibrahim	The Mountain
14	John Coltrane	Giant Step
15	Mulligan	Apple Core
16	Chet Baker	How I the Moon
17	Dinah Washington	Why Was I Born
18	Chick,Corea & Origin	Change
19	Joshua Redman Quartett	The Oneness of Two (in Three)
20	Corea	Early Afternoon Blues
21	Bill Evans	Time Remembered
22	Judy Gardland	Lucky Day
23	James Cotton	Blue in my Sleep
24	Dave Brubeck	Koto Song
25	Rodgers & Hart	Blue Room
26	Strayhorn	Take the Train
27	Nancy Wilson	Prelude To A Kiss
28	Stitt	Sonny's Blues
29	Michael Brecker	El Nino
30	Joshua Redman Quartett	The Oneness of Two (in Three)
31	Meldhau	Blame it on my Youth
32	Peggy Lee	Fever
33	Jerome Kern	The Way you look tonight
34	Getz&Horn	Nature Boy
35	Mickael Urbaniak	Softly As The Morning Sunrise
36	Dexter Gordon	Seven Come Eleven
37	Rachel Ferell	You Send Me
38	Scofield	Lets say we did
39	Kenny Garrett	Two Down & One accross
40	Johnny Griffin	Hush a Bye
41	Keith Jarrett	La Scala
42	Sarah Vaughan	Over The Rainbow
43	Dizzie Gillepsie	Slew Foot
44	Gary Burton	African Flower
45	Petrucciani	Colors
46	Mingus	Slop
47	Diane Reeves	Softly, As In Morning Sunrise
48	Maceo Parker	Going in Circles
49	Wynton Marsalis	Majesty of Blues
50	Lionnel Hampton	Take The 'A' Train

A.6. Instructions (Monopolistic competition treatment

A.6.1. General instructions

You are about to take part in a scientific experiment where you are going to make decisions. Each participant makes decisions individually in front of his/her assigned computer.

20 participants.

The conduct of the experiment Four participants are randomly assigned at the beginning and until the end of the session as sellers of a musical genre and will stay sellers. Sellers will stay anonymous and will not be informed about prices and profits of other sellers.

The rest of the participants are buyers. While sellers will have to decide the price of the musical genre they are selling, buyers will choose the musical genre they want to listen and pay for it (in ECUs). The price for a given track cannot be higher than 100 ECUs. Each buyer will be endowed with 200 ECUs at each period. Choosing one musical genre is mandatory. The budget that will not be spent is saved and the accumulated savings will be converted in euros.

The experiment consists in 50 periods of approximatively 1 minute.

If you are a seller, you will have to decide for each period the price you want to set ranged between 0 and 100ECUs (no cents allowed) for your musical genre. For each period, you will have to sequentially: i. indicate the chosen price on a first screen, ii. wait about a minute long while you will have access to readings and games on a second screen, iii. take note of your gains for the period and the accumulated gains over the past periods on a third screen.

If you are a buyer, at each period, you will have to choose a musical genre among 4 styles. The 4 styles remain the same all along the experiment. You will receive two types of gratification: by listening the music you buy among the 4 genres ; and by

receiving the converted monetary budget you will save during the experiment.

Each period of musical choices comprises 3 steps:

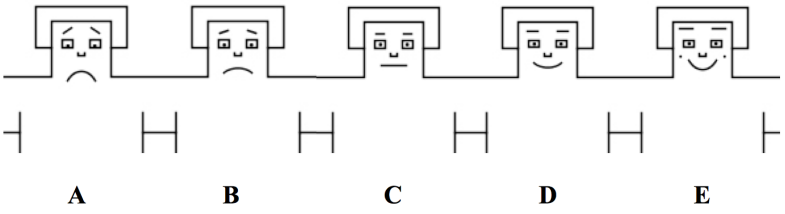
— First comes the choice itself, indicating the musical genre you wan to hear after taking note of the prices proposed for a given period (the prices are ranged between 0 and 100 ECUs).

— This is followed by a listening of a one-minute excerpt of the musical genre you have chosen.

— Finally, you will be asked to make an evaluation of the excerpt you have heard, which will be based on 3 grades:

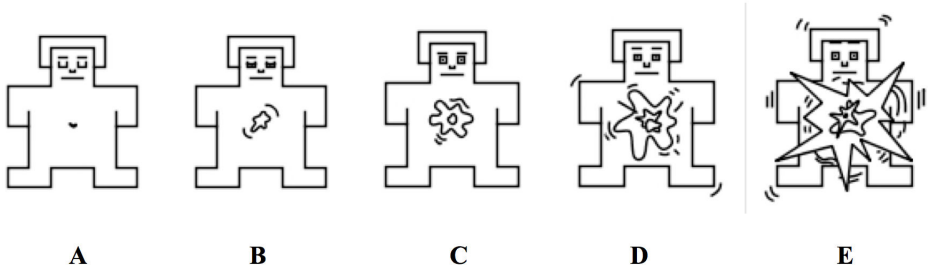
  — a global grade from 1 to 10 will initially estimate the excerpt you have listened to. Give 1 if you hated it, 2 if you really disliked it, and so on up to 10 if you adored it.

  — second comes an evaluation of the pleasure/displeasure you derived from listening to the excerpt. Pick the facial drawing which best expresses your pleasure/displeasure. By checking the drawing to the far right, you are expressing maximum pleasure, and by checking the one the far left you express maximum displeasure. The drawings in between indicate various levels of pleasure/displeasure.



  — thirdly, you are asked to evaluate your level of excitement. Check the drawing that best expresses it. Likewise, by checking the drawing to the

far right, you express maximum excitement whereas by checking the one to the far left you indicate a feeling of complete calmness.



The experiment ends with two questionnaires. All information which you provide us with remain strictly anonymous. Once you fill in the questionnaires, you will be informed of your gains in euros.

Compensation A the end of the experiment, you will receive a compensation determined by your decisions over the session. This amount will be given to you at the end if you do not interrupt it, you listen to the musical excerpts entirely (if you are a buyer) and you fill in the questionnaires. Payment modalities are explained in additional instructions specific to each role.

A.6.2. Buyers' instructions

For buyers, conversion rate is the following: 100ECU=0.20€.

If you are a buyer, the amount of your compensation depends on your consumption over the 200 ECUs per period budget. At each period, your budget is composed of 100 ECUs (a budget that you will have independently of your decision), and a variable part of 100 ECUS (the budget that can be used to buy music giving the prices set by the sellers). Your final remuneration is ranged between 5 000 and 10 000 ECUs.

A personalized CD will also be send to you within 15 days after the experiment. Its composition will be determined according to the following procedure: the computer

will randomly pick 10 tracks among the 50 tracks that you listened to during the experiment. 5 independent and random draws will be made. Your personalized CD will be the draw yielding the highest overall evaluation based on your own evaluations, without taking into account for the prices.

Headphones We ask that you turn off your mobile phones, and that you put on your headphones in the right direction (with the earphone "G" on your left ear, and the earphone "D" over your right ear). We also kindly ask you that you raise your hand if your headphones do not work, or if you have a computer problem during the experiment. Please note that the volume of your musical listening cannot be changed, and that you cannot go back to previous pages.

Sellers' instructions For sellers, conversion rate is the following: 100ECU=0.20€.

If you are a seller, your compensation, determined at the end of the experiment, is based on a fixed amount of 100ECUs per period, plus benefits you realized over the 50 periods. For a given period, your benefits equal the price you set times the number of buyers that chose the musical genre you were assigned to.

You are asked not to communicate during the experiment. If you have any question regarding these instructions, please raise your hand and the person in charge of the experiment will answer you individually.

Part II

When consumers finance the production of novelty: a behavioral approach on Crowdfunding

INTRODUCTION TO PART II

In the first part of this thesis, we have studied the determinants and characteristics of demand for novelty. The next two chapters aim at understanding contributors' decisions to support new musical projects on a the Brazilian crowdfunding platform Catarse. While in the first part of this thesis we employ lab experiments, the following two chapters use coupled data combining experimental and observational data are used. As a preamble to this part, this section presents Catarse, the crowdfunding platform providing the field data, and the implementation of the online experiment.

1. Background on Catarse

1.1. The first crowdfunding platform in Brazil

Created in 2011, Catarse is one of the first crowdfunding plateform in Brazil and is specialized in creative and artistic projects (70% of the projects). In 2016, Catarse recorded more than 240000 backers registered and raised more than R$35 millions. Since 2011, 2000 projects managed to collect the necessary funds (23% of music projects).

The platform works as a typical reward-based crowdfunding plateform: a project holder uses Catarse to present her idea, fixes the financial goal, the duration of the campaign and the offered rewards. At the time of our study, Catarse followed the "All-Or-Nothing" (AoN) scheme such that the artist can only receive the amount collected when reaching the announced threshold [23]. Figure II.1 shows the schematic view of a project webpage on Catarse.

As shown in Figure II.1, when backers visit a project web-page, they have access to a description of the project (based on various materials such as videos, texts or

23. Since 2015, the platform also enables project holder to adopt a "keep-it-all" mechanism.

Figure II.1 – Schematic view of the Catarse website. (http://catarse.me/centrodaterra)

embedded music player). They can also know the level of previous contributions, the number of previous backers and the number of days left before the end of the campaign.

1.2. Musical projects on Catarse

Success of the campaign At the time we received Catarse's dataset, 817 campaigns for musical projects were conducted. Among them, 485 succeeded to reach their threshold, 317 failed, 15 were still ongoing projects. Table II.1 provides descriptive statistics on projects. As we can see, failed projects are, on average, radically under the threshold (they are funded at 12% on average).

The success rate for musical projects is thus of 60.5% for musical projects and goes up to 99.9% for projects reaching 60% of their goal (see Table II.2).

Table II.1 – Descriptive statistics for musical projects ($n = 802$)

	Successful coordination $n = 485$	**Failed coordination** $n = 317$	**Both** $n = 802$
Project Goal (in R$)	13690 (14754)	16697 (16680)	14869 (15603)
Pledged (in R$)	15714 (20475)	1828 (2789)	10203 (17394)
Nb. contributions	148.2 (216.3)	22.5 (26.7)	98.4 (179.8)
Nb. backers	147.2 (216.3)	21.5 (26.7)	97.5 (179.8)
Percent fund	117.9 (95.9)	11.7 (12.8)	75.9 (91.2)

Note: Standard deviation in parenthesis.

Table II.2 – Success rates by percent funded for musical projects on Catarse

Percent funded (in %)	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
% of successful projects	60.5	80.6	89.3	95.1	97.8	99.4	99.9	99.9	99.9	99.9
Nb. of projects (music)	802	602	543	510	496	488	486	486	486	486

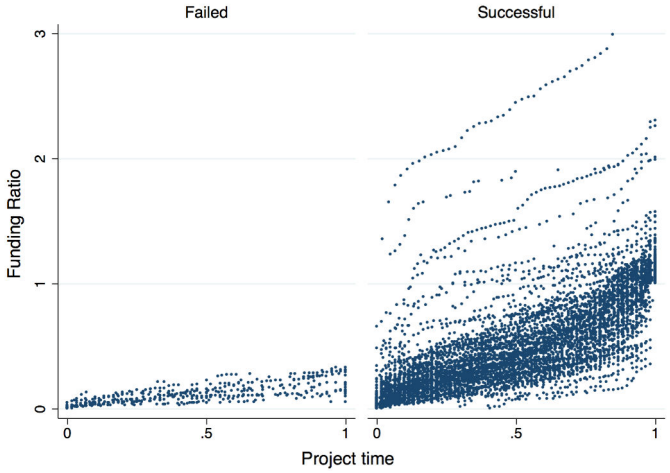
Note: Based on data from April 2011 to February 2016 on Catarse.

Dynamics of a campaign Figure II.2 provides scatter plots of all pledges split by the project categories (successful versus failed). This graphical representation over time illustrates that, except for few projects, the process towards success, shown on the right plot, is slow but eventually boosts. Table II.3 confirms a stylized fact in reward-based crowdfunding: the bath-tub shaped curve of the number of contributions (Kuppuswamy and Bayus, 2015). Figure II.4 shows the average number of backers for musical projects reaching their goal: one can notice that it is not uniformly distributed.

Contributions Contributions for musical project equal, on average, 96.4R$ (sd = 335). When removing particularly high contributions (more than 1000R$ [24].), the average contribution falls down at 72R$ (sd = 86.1). Contribution values before and after the threshold are not significantly different (a two-sample test yields a p-value of $p = 0.574$) and are on average respectively 96.2R$ (sd=332) and 98.0R$ (sd=350) [25]. As it can be noticed in Figure II.5, contribution values have quite the same distribu-

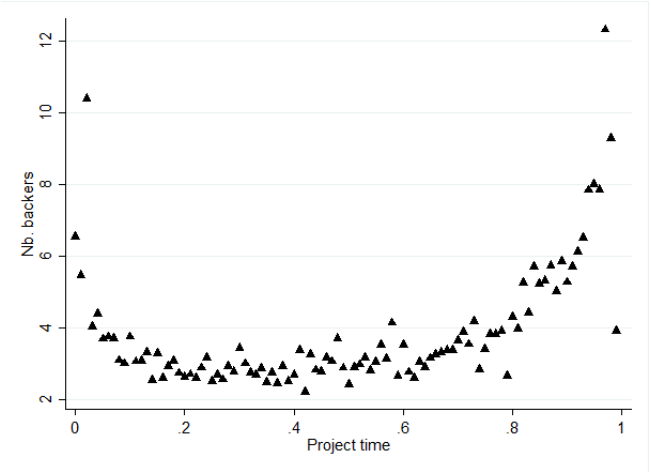
24. This value corresponds to approximatively 320 US $
25. For all statistics on contributions, we remove contributions made by the project holder herself.

Figure II.2 – Funding process for successful and unsuccessful musical projects



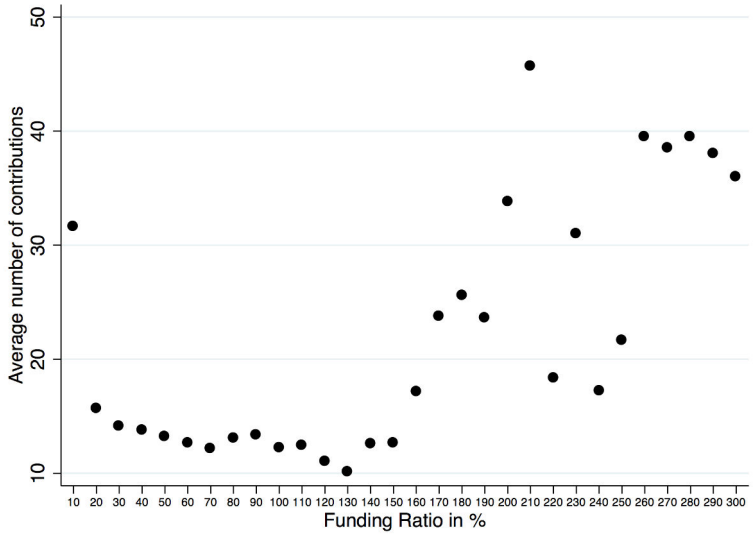
Note: The sample is composed of all musical projects of Catarse at the time we received Catarse's dataset.

Figure II.3 – Average number of backers and project time



tion before and after the threshold is reached. Among the 66323 contributions made on musical projects reaching their goal, 82% are made before reaching the threshold while 18% after reaching the threshold. 89% of the contributions are unique contributions to the same project.

Figure II.4 – Average number of contributions and Funding ratio (for successful projects)

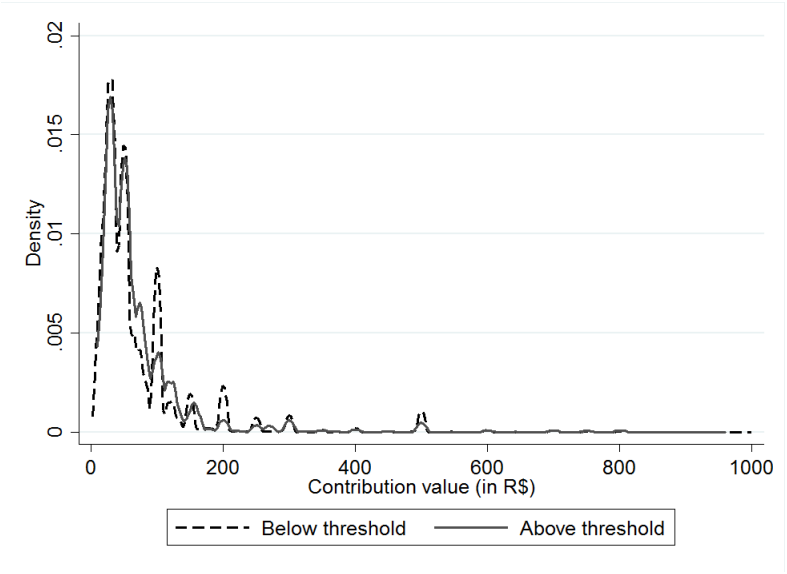


1.3. Backers' account on Catarse and information disclosure

This section provides a description of information disclosure, as these variables are used in Chapter 4. Having a profile on Catarse is mandatory in order to back a project. One's account list all projects a given backers contributed to and created (see Figure II.6 for a schematic view of a backer's profile). When creating a profile, one has to provide her name and/or a nickname. Users can decide to disclose their photo and links to personal social media accounts (Facebook, Twitter or personal website). Uploading one's photo can be done manually or by logging in with a Facebook account [26]. This latter procedure does not however imply that the Facebook account is displayed on the backer's Catarse profile: this has to be done manually. But if a backer decides to log in with Facebook, her profile picture is automatically displayed. We cannot distinguish

26. In this case, Catarse directly upload Facebook profile picture.

Figure II.5 – Distribution of contribution values before and after the threshold is reached for successful projects



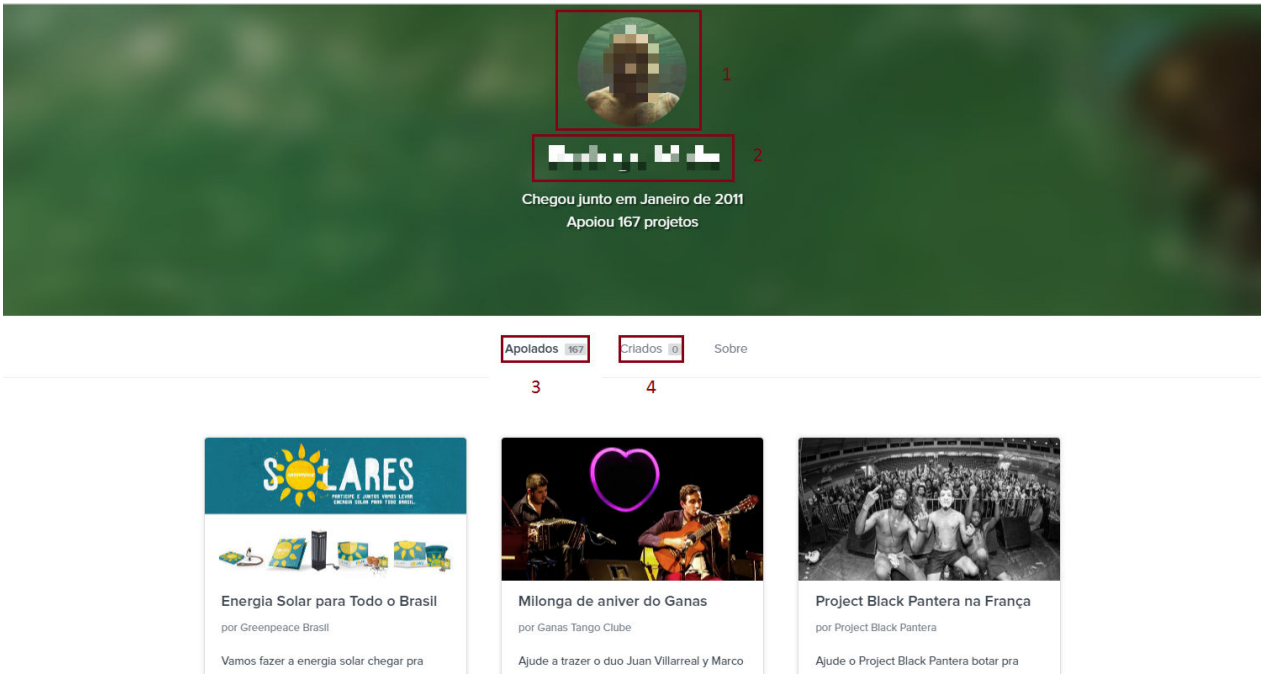
Note: we only consider here contributions that are below 1000R$. We removed contributions made by the project holder to her own project.

between backers who decide to use their Facebook's photo for convenience [27] or to actually reveal their identity.

For a given project, the identity of the backers is revealed but not the amount of the contribution (see Figure II.7). Each time a backer makes a contribution, it is added on her account. In other words, one can observe a backers' whole activity (the number of project she backed) but not the overall amount contributed.

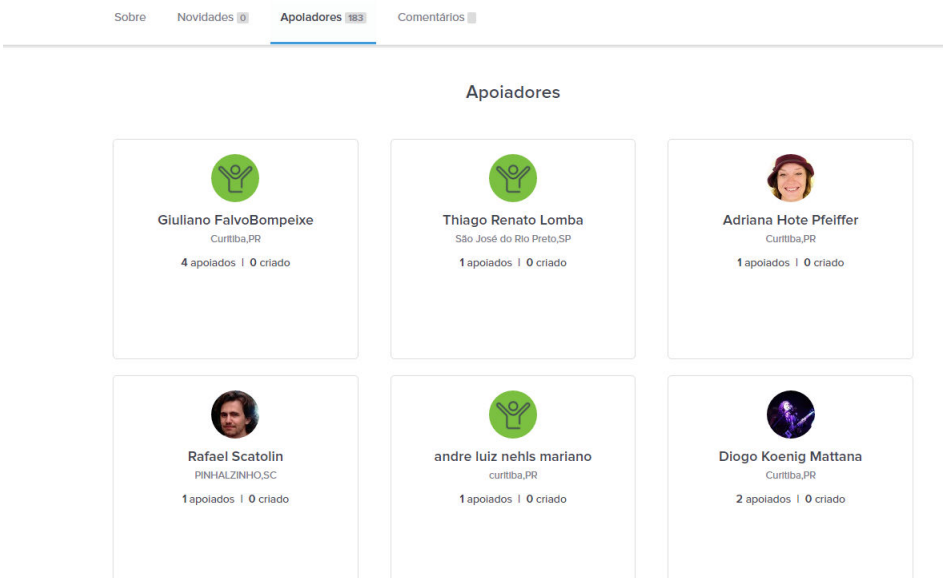
27. It is relatively easy to create an account using Facebook and it does not require to publicly link one's Catarse account with Facebook.

Figure II.6 – Schematic view of an account.



Personal information is blurred on purpose.
(1): photo, (2): name or pseudo, (3): projects backed, (4): projects created

Figure II.7 – Schematic view of the list of backers for a given project



2. Design of the online experiment

This section presents the online experiment we implemented in partnership with Catarse. It consists in incentivized experimental games conducted online thanks to a self-contained platform we created for the purpose.

2.1. Participants selection

We first define a stratified random sample of 20 musical projects. These projects correspond to 4680 users who backed the selected list of projects and Catarse randomly invited 2723 of them [28] to participate in our experiment. This way, we are sure to have backers who contribute to at least one musical project. As the stratification is made according to the project goals, we also ensure variations in the artist's ambition.

2.2. The online procedure

Our online implementation requires a self-contained interface. The selected sample received an email by Catarse as an invite to our experiment. Each potential participant was endowed with a unique log-in allowing them to log in to our experimental platform. The welcome page provides general information regarding the experiment.

2.3. The tasks order

Participants completed 6 tasks [29], namely:

- 2 versions of the Public Goods game: the standard Public goods game and a Public goods game with threshold (Chapter 4)
- 2 versions of the Dictator game: the standard Dictator game and a Dictator game

28. Before the launch of our experiment, Catarse preferred to limit the number of invitations. The invitation process was implemented as follows. 5 waves of invitations were launch from March to June 2015. We commonly decided to stop the invitation process after the 5th wave.
29. Details on the games are provided in the two following chapters.

where the recipient has a positive endowment (Chapter 4)

- the Trust game (Chapter 4)
- the Holt and Laury's (2002) lotteries choice procedure (Chapter 3)

Order effects may influence decisions so we consider different orderings. Following Hergueux and Jacquemet (2015) methodology, participants first complete the two versions of the Public Goods games. Then, participants play the two Dictator games and the Trust game in a random order. After playing all these games, we also elicit risk preferences using the multiple price list choices of Holt and Laury (2002). To sum up, the possible orders are:

- Order 1 [30]: Public Goods games - Trust game - Dictator games - Lotteries choice
- Order 2: Public Goods games - Dictator games - Trust game - Lotteries choice

After completing the tasks, participants are asked to fill-in a Big Five inventory (John, Donahue and Kentle, 1991) that enables us to measure personality traits. With this questionnaire, we are able to have scores for 5 personality traits, namely Extraversion, Openness, Emotional Stability, Agreeableness and Conscientiousness (Table II.3 provides definitions by McCrae and John (1992)). This questionnaire consists of a list of 100 adjectives. For each adjective, subjects declare on a five-point Likert scale if the adjective describes her totally or not at all, with three intermediate possibilities. The test provides scores on a 1 to 5 scale. A higher score for a given personality trait will characterize the subject.

2.4. Online instructions and materials

We also follow Hergueux and Jacquemet's (2015) methodology to ensure participants' understanding of each task. The first screen of each task describes the instructions of the game subjects are about to play (see Figure II.8). In addition, participants

30. The order between two versions of the Public goods game and the order between the two Dictator games are randomized. When players play both role, the order is randomized.

Table II.3 – The Big Five personality traits (McCrae and John, 1992)

Traits	**The degree to which a person...**
Openness to experience	...needs intellectual stimulation, change, and variety
Conscientiousness	...is willing to comply with conventional rules, norms, and standards.
Extraversion	...needs attention and social interaction.
Agreeableness	...needs pleasant and harmonious relations with others.
Neuroticism	...experiences the world as threatening and beyond his/her control.

have access to a video illustrating and commenting (thanks to a voice over) the instructions [31]. Finally, participants can test each task before making their decision thanks to a simulator (See Figure II.10).

31. To limit anchoring effects, several versions of the video are created. For each participants, one of these versions is randomly selected.

Figure II.8 – The instruction screen of the Public Goods game

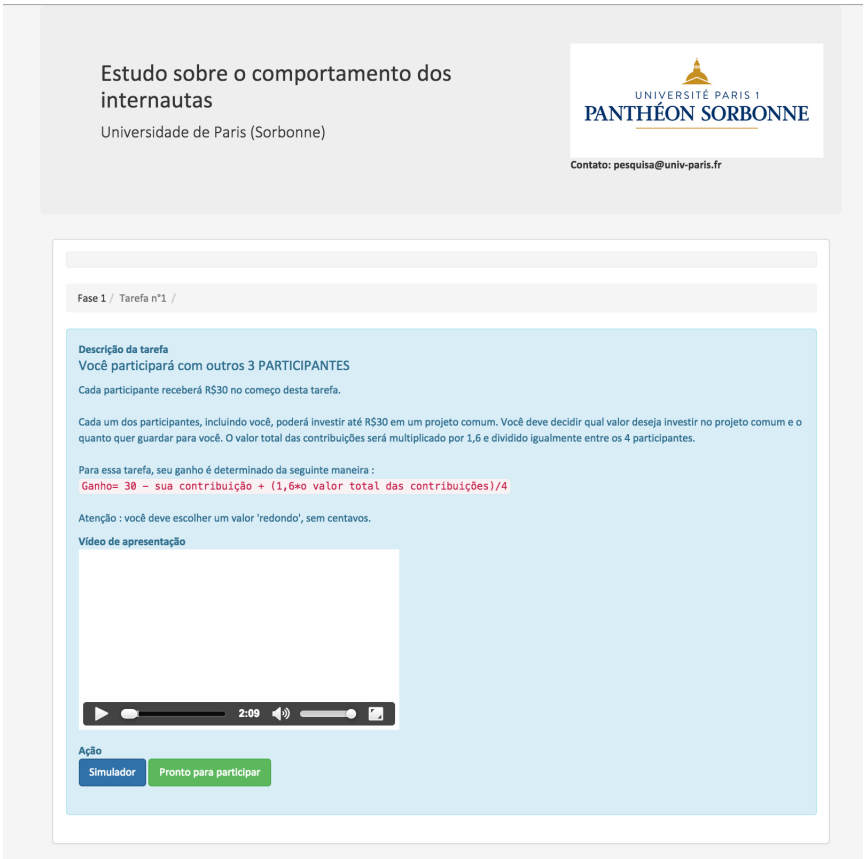
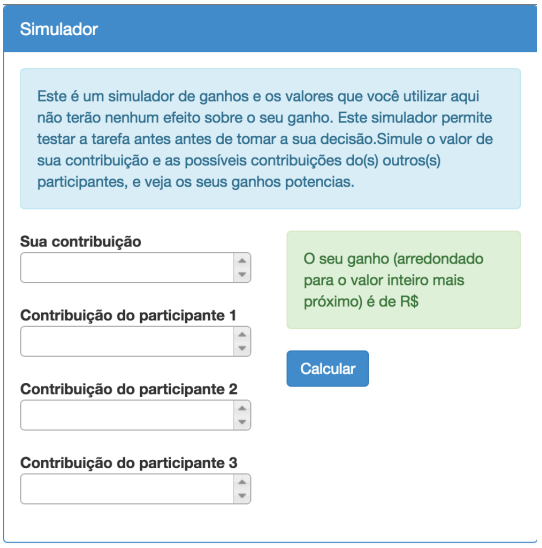


Figure II.9 – The instruction video of the Public Goods game

Figure II.10 – The simulator of the Public Goods game



3. Participants characteristics

We conducted the online experiment from March to June 2015. Over the invited sample, 154 individuals participated. Our response rate is pretty low (5.7%) and this may be due to several things. First, users may not always open and read Catarse's email. Secondly, sharing banking information might undermine users' motivation to participate [32]. Finally, the complexity of the experiment may discourage participants to complete it: over 190 connections to our interface, 36 gave up during the experiment.

3.1. Sample representativeness

Regarding the representativeness of our sample, Table II.4 provides comparison between our participant and users who responded to a survey conducted by Catarse in 2012. We use data from the survey because Catarse does not have information on socio-demographic variables like age or income since these informations are not required for registration. Table II.5 compares numbers and amounts of contributions between our sample and the overall sample of Catarse. Unique contributors are less represented in our sample while "serial" contributors are of higher proportion. This is probably due to the fact that unique contributors are less reactive to invite emails sent by the platforms while "serial" contributors are more reactive.

32. We considered paying participants using Paypal but at the time of our experiment, it was not possible to use the private transfers device from France to Brazil.

Table II.4 – Sample comparison with Catarse's survey

		Our sample $n = 154$	Catarse's survey $n = 3336$
Gender			
	Female	32%	41%
	Male	68%	59%
Age			
	<18	2%	1%
	18-24	23%	19%
	25-30	42%	31%
	31-40	24%	25%
	+41	9%	24%
Monthly Income			
	<1500R$	25%	21%
	1500R$ to 3000$	15%	24%
	3000R$ to 10000$	38%	43%
	>10000R$	20%	12%

Table II.5 – Sample comparison with Catarse and Invited samples

	Catarse	Invited sample	Participants
Number of users/participants	$n = 65930$	4560	111
Proportion of Cat. 1 (1 contribution)	75%	68%	36%
Proportion of Cat. 2 (2 to 5 contributions)	22%	27%	34%
Proportion of Cat.3 (6 or more contributions)	3%	5%	30%
Number of contributions	74712	6597	357
Proportion of contrib. made by Cat.1	52%	47%	11%
Proportion of contrib. made by Cat.2	32%	37%	25%
Proportion of contrib. made by Cat.3	16%	16%	65%

3.2. Extensive margins

Table II.6 compares the distribution of the number of musical projects backed for our final sample, the invited sample and Catarse's sample. As we can see, our sample is composed of more active contributors who back more musical projects.

3.3. Intensive margins

In our sample, contributions are on average equal to 56R$ (sd =63) for 471 contributions for 171 projects. Table II.7 presents the proportion of rewards in our sample.

Table II.6 – Distribution of the number of musical projects backed for the sample, the invited sample and Catarse's sample.

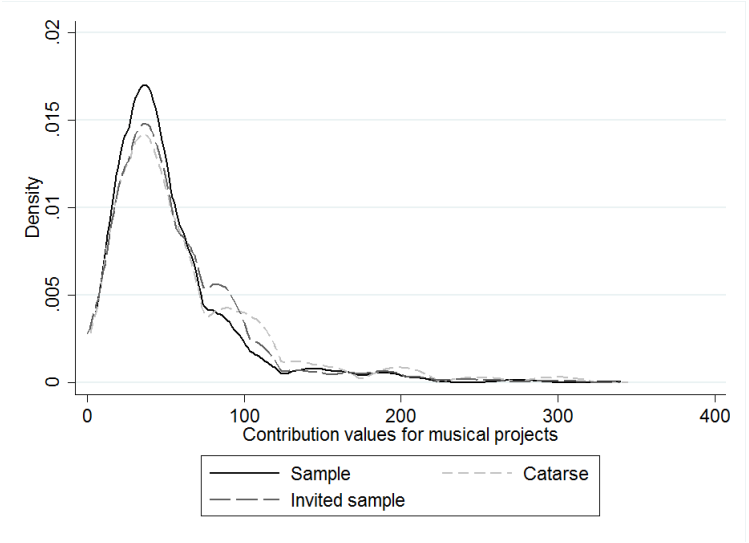
	Sample $n = 154$	Invited $n = 2,740$	Catarse $n = 63,649$
Distribution in % (by number of,musical projects backed)			
1 project backed	64%	81%	90%
2 projects backed	13%	10%	7%
3 projects backed	9%	4%	1.5%
4 projects,backed	5%	2%	0.5%
5 projects,backed	1%	1%	0.2%
More than 6 projects	8%	2%	0.8%
Average number	2.44	1.46	1.15

As we can notice, the majority of the selected pre-orders.

Table II.7 – Rewards

$(n = 473)$	**Preorder**	**Show**	**Pre-order & Show**	**No reward**	**Other**
Share (in %)	83.9	1.4	6.4	6.2	2.1

Figure II.11 – Distribution of contribution value in R$ for the sample, the invited sample and Catarse's sample.



Notes: The sample corresponds to the 154 participants that we consider for our analysis ($n = 368$). The invited sample corresponds to contributions made by all users that were invited to our experiment ($n = 4003$). The Catarse's sample is composed of all the contribution made for musical projects on Catarse since creation ($n = 73199$). We excluded for all samples contributions made by the project holder to her own project.

3.4. Descriptive statistics

Table II.8 provides the descriptive statistics of our entire sample.

Table II.8 – Summary statistics on participants

Variable	**Definition**	**Mean** ($n = 154$)
Photo	Equal to 1 if the subject displays her photo on Catarse	0.48
Personal link to Facebook or Twitter	Equal to 1 if the subject displays a personal link to a social media profile	0.24
Full name	Equal to 1 if the subject uses her full name (first + last name)	0.65
Female	Equal to 1 if the subject is a female	0.32
Age	Declared age of the subject (in years)	29.55 (9)
Cultural budget	Amount of the cultural expenses per month (in R$)	198.63 (212)
Creator	Equal to 1 if the subject declared she have already been a project holder in a CFP	0.11
F&F	Equal to 1 if subject declared she have already back a project from a friend or a family member	0.61
Population (city)	Number of inhabitants of the subject's city (in millions)	4.83 (4.85)
GDP/capita	Gross Domestic Product per capita of the subject's city (in reals)	43,280 (62547)
Registration date	Number of days elasped between Catarse's creation date and subject's registration date	764 (315)
Multiple switch	Equal to 1 if subject j switched several times in the H&L procedure	0.26
Time_hl	Time to complete the H&L procedure (in seconds)	175 (137)
Time_bp	Time to complete the Public Goods game (in seconds)	981 (9700)
Time_bp2	Time to complete the Public Goods game with threshold (in seconds)	231 (333)
Time_d	Time to complete the Dictator (in seconds)	44 (42)
Time_d2	Time to complete the Dictator game 2 (in seconds)	60 (67)
Time_tgb	Time to complete the Trust game (Player B, in seconds)	292 (262)

Note: Standard deviations are in parenthesis.

Chapter 3

Risk and Voluntary Contributions to Crowdfunding[1]

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1. I would like to kindly thank Louis Lévy-Garboua for helping me with the model developed in this chapter.

I haven't received ANYTHING at all. I was tripping at first and then I bought the album on iTunes. I thought I'd be receiving something in the mail as I provided my address and email address. I have received NOTHING. I'm never doing anything like this again. Thanks for nothing. I want my $50 back.

(*A contributor's comment on Elzhi's campaign on Kickstarter*)

1. Introduction

In September 2013, rapper Elzhi launched a crowdfunding campaign on Kickstarter asking for $25000 to produce his new album. His project reached more than $37000 after only a few weeks. Two years later, the album was still not ready. Many backers have left comments on the project webpage, expressing their anger for the rapper's failure. One of them even promised to prepare a class action lawsuit against the artist.

Reward-based crowdfunding is an attractive solution for music artists who wish to realize their creative project. But Elzhi's failure to honor his promise to produce his album in time is only one in many examples showing the limits of such financing mechanism. The concept is simple: an artist sets a financial target covering the cost of production. She offers tangible (pre-order of the CD, derivative products, memorabilia) and/or symbolical (name credited on the CD sleeve or listed on the artist's website) rewards in counterpart of backers' support.

When contributors decide to "buy" a product (or a reward) on a crowdfunding platform, they are exposed to a risk a non-delivery since the product is at early stage of production. Furthermore, the probability that the product will be produced depends on the amount collected along the campaign. To sum up, potential backers are exposed to two types of risk when voluntary contributing to a project: (i) a risk of coordination failure and (ii) a risk of non-delivery. This article aims at studying the role of both risks on the timing and level of contributions.

The risk of coordination failure During a crowdfunding campaign, projects might not succeed in achieving their goals (Wash and Solomon, 2014): to make sure an artist gathers the required funds, backers need to coordinate. The risk of coordination failure exists whatever the considered crowdfunding mechanism, that is the Keep-it-All (KiA) or the All-or-Nothing (AoN) ones, when fixed costs of production are assumed. Under the first mechanism, the KiA, fundraisers keep the money raised regardless if they reach their funding goal. Under the AoN mechanism, they keep the money they collected during the campaign if and only if they reach or exceed the funding objective they set. Even though the risk of coordination failure is more salient under the AoN mechanism, one can easily assume that insufficient fundings under the KiA mechanism will compromise production of the product.

The risk of coordination failure is a strategic risk, namely a risk associated with others' decision since they face uncertainty about the number of potential contributors and/or the level of their valuation (Hu, Li and Shi, 2015). Competition between projects on crowdfunding platforms amplifies the risk of coordination failure (Corazzini, Cotton and Valbonesi, 2015*b*). Even with the guarantee of a refund if the provision point is not reached in the case of AoN crowdfunding, contributors are exposed to the risk of ending up with a null utility [2]. Hu, Li and Shi (2015) propose an interesting model of coordination considering a two-periods model. In each period, a buyer arrives at the proposed project and participation of both buyers is necessary for the project to succeed. We adopt a similar framework, assuming that contributors are subject to "illusion of control": they believe that their own contribution will induce other similar individuals to do likewise.

Cultural projects encounter relatively high success rate on the main crowdfunding platforms. On Kickstarter for instance, dance, theater, comics and music are the most successful categories with, respectively 62.9%, 60.4%, 50.6% and 50.4% chances of

2. We can even add sunk costs due to the time spent in making a decision, looking at projects etc.

reaching the goal. A successful campaign does not however mean a successful project. Several cases show that backers can be deceived as Elzhi's ones were.

The risk of non-delivery In the case of arts, from the viewpoint of contributors, there is an uncertainty about the product quality. Cultural goods are indeed characterized as "experience goods", namely goods for which one can only know his derived utility after consumption (Nelson, 1970). Any potential backer does not know if the output will satisfy his/her taste (Belleflamme, Omrani and Peitz, 2015). In addition, crowdfunding consists in betting on a good that is not produced yet, generally from an unknown artist. Backers have few cues to estimate the quality of the output and are thus facing uncertainty (Belleflamme, Lambert and Schwienbacher, 2014*b*). Mollick (2014) shows that backers on Kickstarter respond positively to signals about the quality of the project such as the presence of a descriptive video, frequent updates, spelling errors or being featured by Kickstarter on their home page. Backers also face uncertainty about the project holder's capacity to produce her project after gathering her funds[3]. This point is particularly crucial as crowdfunding platforms do not provide reimbursement or compensation in case of failure in providing the product. Except for anecdotal stories, there is however little empirical evidence about the ex-post failure of crowdfunding projects in music.

A puzzling stylized fact about crowdfunding is that contributors back projects even if the threshold is already met. One can wonder why a backer is ready to get exposed to a risk of non-delivery and not wait for the product to be on the market to buy the product. Several explanations including community benefits (Belleflamme, Lambert and Schwienbacher, 2014*b*) or pro-social motives may explain why contributors wish

3. Backers may also face a risk of moral hazard. A principal (the crowd) pays an agent (the project holder) to create a good, which comes with moral hazard problems (Belleflamme, Lambert and Schwienbacher, 2014*b*). The agent's effort can be determinant of the quality of the product, but once the campaign is over, there are little incentives for the agent to provide sufficient effort. We do not consider this problem in this article, assuming that moral hazard problem is limited in the case of musical projects for two reasons: artists have intrinsic motivation to create (Greffe, 2010) and failure can injure online reputation (among the creator's peers and for the musical industry).

to back a project that does not need additional funding. It can also be the case that additional fundings impact the risk of non-delivery in a positive way. In the case of music, a project holder who receives additional fundings will be in the best conditions to produce her album [4].

Several empirical studies have looked at the dynamics of a crowdfunding campaign, investigating the crowding-out effect in donations (Burtch, Ghose and Wattal, 2013), the dynamics of added backer throughout the campaign (Kuppuswamy and Bayus, 2015, 2017) or reactions to quality signals (Agrawal, Catalini and Goldfarb, 2015). To the best of our knowledge, the theoretical literature comparing contributions before and after the threshold is scarce. In Hu, Li and Shi's (2015) model, two buyers, with heterogeneous preferences for the product, decide how much they are willing to contribute to a project. To ensure the project's realization, buyers need to coordinate. Several extensions of the model including exogenous and endogenous arrivals at the two periods, finite number of buyers or uncertainty about the number of contributors. The latter version explains why overfunding may occur: buyers arriving at the beginning of a campaign face uncertainty about the number of future buyers and provide more funds than necessary.

This article aims to understand the impact of these two types of risk on contributors' willingness to pay. To investigate this question, we propose and analyze a multi-periods model of decision to understand the timing and level of contributions. Each period is characterized by different levels of risk of coordination failure and of non delivery. The model helps us understanding the decision to choose the period as well as the level of a backer's contribution. In order to understand why contributors make their decision on the timing of their contribution, we resort to the notion of illusion of control. Individuals have an illusion of control when they overvalue their influence on events correlated with their choices. Kuppuswamy and Bayus (2017) investigate on the idea that people

4. Note that it can also be the case that higher fundings leads to an unexpected number of rewards to deliver, meaning that additional fundings will increase the ex post risk of failure to deliver.

financially support projects when they believe that their contribution matters. Because of the goal gradient effect, they argue that when contributors are closed to the threshold, they feel like their contribution will have a huge impact, explaining why the number of backers increases at that time of the campaign. Likewise, we assume more broadly that a contributor thinks that a fixed portion of other contributors will act as herself. Consequently, those who back a project early in the campaign believe their contribution will bring more contributors to do likewise than those who back later. In other words, the model show that contributors who are more subject to the illusion of control will back earlier.

Thanks to our model, we can make several predictions about patterns of contribution. Specifically, we investigate the role of risk aversion on contributions. To illustrate these results, we use a dataset that couples experimental data measuring attitude towards risk and observational data on a real crowdfunding platform, the Brazilian platform Catarse[5]. We first study the probability of backing a project early in the campaign. Results show that contributors who are more likely to be subject to illusion of control backer earlier. Looking at coefficients of risk aversion, we find that for late contributors, the higher the level of risk aversion, the lower the level of their contribution. However, for early contributors, risk aversion is positively correlated with the level of contributions: the fear of coordination failure dominates the effect of the risk of non-delivery.

The rest of the paper proceeds as follows. Section 2 presents a simple model of backers' demand for crowdfunding music projects. In section 3, we present the design and implementation of the experimental measure. Section 4 presents the data. We report our empirical results in Section 5. Section 6 provides a discussion of our results and concludes.

5. Descriptive statistics on contributions to musical projects are provided in the introduction **??**.

2. A model of demand for crowdfunding

Crowdfunding is a risky activity as it combines the demand for a specific good (e.g. a music album) with a contribution to the collective funding of production and delivery. As we explained in the introduction, the risk associated with crowdfunding is twofold. It consists of a risk of coordination failure and a risk of non-delivery.

In this section, we develop a simple model of backers' demand for crowdfunding music projects on a reward-based platform [6].

2.1. The framework

The model considers the AoN mechanism: project j is only funded if the amount raised exceeds the threshold G_j set by the project holder by the end of the campaign; otherwise, the backer is reimbursed [7]. Let T_j be the number of days before the campaign for project j ends. We assume a large number of agents, N_j, chooses to contribute or not to project j. Each agent i, with $i \in [\![1, N_j]\!]$, assigns a subjective quality $m_{i,j}$ to project j that can be understood as the "taste" for music. We assume that $m_{i,j}$ is randomly distributed across the population. Let I be the available income for consumption.

Consider that contributing more does not provide additional return (additional rewards, benefits related to altruistic motivations etc.). We assume that receiving the product is conditional on the backer's contribution and that the level of the contribution should be higher or equal than a minimal contribution $\underline{c}$. Note that when $\underline{c} = 0$, we are in the context of a public good where everybody can benefit from the product without contributing (if the good is eventually produced).

Since we focus on contributions to a specific project, we hereafter drop index j to simplify notations.

6. The model specifically considers music projects, but can be extended to other areas.
7. We consider that G_j is exogenous.

2.2. *The timing*

We assume that time is discrete and that each agent can contribute to the project at period t, with $t \in [\![1, T]\!]$ where T is the total number of periods [8].

For simplicity, we consider that each contributor makes sequential decisions to either contribute or not for each period starting from $t = 1$. At each period, a contributor i observes the level of previous contributions C_{t-1} and decide whether or not to contribute. Once the contributor decides to contribute, we thus assume that she exits the game [9]. In other words, if a contributor decides to contribute at time t^*, then $c_{i,t} = 0 \, \forall \, t \neq t^*$. Moreover, we consider that contributors have a bounded rationality and that they will decide to contribute as soon as the participation constraint is satisfied. In other words, contributors are myopic and they do not compare decision with future states.

2.3. *Illusion of control*

In this model, we assume that contributors may be subject to the "illusion of control". Illusion of control has been showed to be important in voting decisions. Quattrone and Tversky (1986) attributed the voter's illusion to the belief that the decision to vote might induce others to do likewise. Authors explain:

> If one votes, then one's politically like-minded peers, who think and act like oneself, will also vote. Conversely, if one abstains, then one's like-minded peers will also abstain. Because the preferred candidates could defeat the opposition only if the like-minded citizens vote in larger number than do the unlike-minded citizens, the individual may conclude that he or she had better vote. That is, an individual may regard his or her single

8. The length of a period can be for instance a day, a week, two weeks etc. If we consider days as the time periods, T is generally set between 30 to 60 days on crowdfunding platforms.

9. On Catarse, considering contributions to music projects, 89% of contributions are unique contributions.In other words, contributors only back once a given project.

> vote as diagnostic of millions of votes, and hence as a sign that the preferred candidates will emerge victorious. [p244.]

It has been shown for instance that in small-scale public goods games, cooperators overestimate the probability that their own contribution are critical (Van de Kragt et al., 1986).

To formalize the "illusion of control", we assume that contributor i believe that her own contribution at period t will induce $k_i - 1 = \lambda_i N - 1$ contributors to make the same decision. In other words, λ is the degree of the illusion of control: when $\lambda = 0$, a given contributor is not subject to any illusion of control while when $\lambda = 1$, she believes that her decision will induce all other contributors to do likewise. We assume that k_i is constant over time (and thus, for the rest of the article, we will use k_i instead of $\lambda_i N$ as a preferred notation). In other words, as long as contributor i do not decide to contribute, she thinks that those who will contribute like her did not contribute as well and contributors do not update their illusion of control with past contributions.

2.4. Characterization of the risk of coordination failure and the risk of non-delivery

The risk of coordination failure The risk of coordination failure refers to the risk that the goal G will not be reached, represented by the probability q of coordination failure such that $q \equiv P(c_{i,t} + C_{-i} < G)$ where C_{-i} are all contributions made by others. At period t, q is a function of accumulated contributions $C_{-i,t-1}$ to project j and of the contributor's contribution $c_{i,t}$ times k such that $q(k_i c_{i,t} + C_{-i,t-1})$. For a matter of clarity, the notation q refers to $q(kc_{i,t} + C_{-i,t-1})$, q' to its first derivative with respect to $c_{i,t}$ and q'' to its second derivative with respect to $c_{i,t}$.

The shape of function q is not straightforward. Two opposite effects are at stake. First, higher contributions lead to "information cascades" (Bikhchandani, Hirshleifer and Welch, 1992*a*) suggesting the convexity of q. The goal gradient effect (Kuppuswamy

and Bayus, 2017), according to which efforts increase as the financial goal gets closer, is also in line with this assumption. Second, a crowding out effect may also arise (Burtch, Ghose and Wattal, 2013): contributors are less likely to donate when overall contributions increase. Since contributors receive the product, we assume that the first effect dominates the second one and that q is decreasing with $c_{i,t}$ and $q' = \frac{\delta q}{\delta c_{i,t}} \leq 0$ and convex $q'' = \frac{\delta q''}{\delta c_{i,t}} \geq 0$.

The risk of non-delivery Projects are at a very early stage of production. We assume that there is a probability that the outcome will not satisfy backers or that the reward is simply not delivered to the backer. Let f be the subjective probability that a project will not be of satisfying [10]. We assume that f is a function of the collected fund (the more money an artist manages to collect, the better are the conditions to produce it) such that f can be written as $f\big(k_i c_{i,t} + C_{-i,t-1}\big)$. Note however that f is a conditional probability: it is only when the threshold is reached that the risk of non-delivery comes into play. In other words, we can assume that when $C_t < G$, f is constant and equals f_0. As f_0 is the prior belief about the project holder capacity, one can also assume that f_0 depends on the relationship between the contributor and the project holder (f_0 may be lower for friends and family for instance because they have private information) and on signals of quality (quality of the description and videos, the implication of the project holder, the project goal G etc.).

For simplicity, we assume that contributor i assigns a perceived quality m_i to project j with probability $(1-f)$ and 0 with probability f. Furthermore, f is a function of the contribution of agent i, $c_{i,t}$, and accumulated contributions of other backers, $C_{-i,t-1}$ and $f' = \frac{\delta f}{\delta c_{i,t}} \leq 0$ and convex $f'' = \frac{\delta f'}{\delta c_{i,t}} \geq 0$. In other words, we assume increasing returns of production. For a matter of clarity, the notation f refers to $f(kc_{i,t}+C_{-i,t-1})$, f' to its first derivative and f'' to its second derivative with respect to $c_{i,t}$.

10. In other words, f is the risk of disappointment or the risk of not receiving a reward.

2.5. Preferences

Backer's preferences are defined by a multivariate utility function $U(.)$ that depends on the level of income and the value of the product/reward she may receive. $U(.)$ is such that $U'(.) \geq 0$ and $U''(.) \leq 0$.

2.5.1. Expected utility

If coordination is successful, we assume that backer i receives an expected utility:

$$EU_f(I - c_{i,t}, \tilde{m}_i) = fU(I - c_{i,t}, 0) + (1 - f)U(I - c_{i,t}, m_i)$$

with $\tilde{m}_i = 1$ with probability $(1 - f)$ and $\tilde{m}_i = 0$ with probability f. The framework is similar to the AoN mechanism where the backer get a refund in case of non coordination. Including the risk of non coordination, the expected utility thus becomes:

$$qU(I, 0) + \big(1 - q\big)EU_f(I - c_{i,t}, \tilde{m}_i)$$

2.5.2. Participation constraint

First, we can note that a backer is willing to contribute at period t if:

$$\begin{aligned} & qU(I, 0) + \big(1 - q\big)EU_f\big(I - c_{i,t}, \tilde{m}_i\big) \geq U(I, 0) \\ \Leftrightarrow \quad & EU_f(I - c_{i,t}, \tilde{m}_i) \geq U(I, 0) \end{aligned} \tag{3.1}$$

The optimal contribution must not exceed the willingness to pay for the product. In other words, crowdfunders like the good that they finance and the perspective of receiving m_i is appealing enough in spite of the cost of funding and the risk of failure.

2.5.3. Optimal contributions at period t

At period t, a contributor maximizes her expected utility:

$$\max_{c_{i,t}} qU(I,0) + \big(1-q\big)EU_f(I - c_{i,t}, \tilde{m}_i)$$
$$\text{s.t. } c_{i,t} \geq 0$$

The First Order Condition implies (proof is relegated in Appendix A.1.1) :

$$k_i h_q\big[EU(I - c_{i,t}, \tilde{m}_i) - U(I,0)\big] + k_i h_f(1-f)\big[U(I - c_{i,t}, m_i) - U(I - c_{i,t}, 0)\big] \leq EU'_f(I - c_{i,t}, \tilde{m}_i)\big] \quad (3.2)$$

With $h_q = \frac{-q'}{1-q}$ and $h_f = \frac{-f'}{1-f}$ and $EU'_f = fU'(I - c_{i,t}, 0) + (1-f)U'(I - c_{i,t}, m_i)$.

2.5.4. Corner solution at period t

$c_{i,t} = 0$ if and only if:

$$k_i(h_q + h_f)(1-f)\big[U(I, m_i) - U(I,0)\big] \leq EU'_f(I, \tilde{m}_i) \quad (3.3)$$

Assuming a separable and additive utility function, we obtain $U(I,0) = u(I) + v(0)$ and $U(I - c_{i,1}, m_i) = u(I - c_{i,1}) + v(m_i)$ where $u'(.) > 0$, $u''(.) < 0$ and $v'(.) > 0$, $v''(.) < 0$. Then $c_{i,t} = 0$ iff:

$$k_i(h_q + h_f)(1-f)\Delta v \leq u'(I) \quad (3.4)$$

where $\Delta v = v(m_i) - v(0)$

According to Equation 3.4, a backer contributes at period t if and only if:

$$k_i(h_q + h_f)(1-f)\Delta v > u'(I) \quad (3.5)$$

Proposition 1. *Contribution's likelihood at period t increases with the subjective value of the reward (Δv), the perceived degree of similarity of other potential backers with self (k_i), the level of income (I) for risk averse contributors, the estimated probability of product delivery ($1-f$) and the sum of hazard rates associated with the risk of coordination failure and the risk of non delivery ($h_q + h_f$).*

2.5.5. Interior solution

If Equation 3.5, the First Order condition implies (proof is relegated in Appendix A.1.1):

$$k_i h_q \big[EU_f(I - c_{i,t}, \tilde{m}_i) - U(I, 0)\big] + k_i h_f (1-f)\big[U(I - c_{i,t}, m_i) - U(I - c_{i,t}, 0)\big] = EU'(I - c_{i,t}, \tilde{m}_i)\big] \tag{3.6}$$

Note that assuming $U''(.,.) \leq 0$ is a necessary and sufficient condition for an optimum (see Appendix A.1.3).

Assuming additive separability, Equation 3.6 becomes (proof is relegated in Appendix A.1.2):

$$k_i h_q \big[\big(u(I - c_{i,t}) - u(I)\big) + (1-f)\Delta v\big] + k_i h_f (1-f)\Delta v = u'(I - c_{i,t}) \tag{3.7}$$

Equation 3.7 can be rewritten as:

$$k_i h_q \Delta EU_q + k_i h_f \Delta EU_f = u'(I - c_{i,t})$$

with $EU_q = \big(u(I - c_{i,t}) - u(I)\big) + (1-f)\Delta v$ and $EU_f = (1-f)\Delta v$.

In other words, the sum of the expected utility gain associated with a successful campaign and the expected utility gain associated with a successful delivery must equal the marginal utility of income.

2.5.6. Risk aversion and optimal solutions

Since contributors are subject to different types of risk, attitude towards risk determines the level of contributions. To study the effect of risk aversion, we consider the Taylor's polynomial expansion of the utility function under the assumption that contribution is small relative to income ($c_{i,t} << I$) :

$$u'(I - c_{i,t}) \approx u'(I) - c_{i,t}u''(I)$$
$$u'(I - c_{i,t}) \approx u'(I)(1 + c_{i,t}\frac{RRA(I)}{I})$$

where c is whether $c_{i,1}$ or $c_{i,2}$ and $RRA(I) = -I\frac{u''(I)}{u'(I)}$ is the relative risk aversion.

Applied to the First Order Condition (Equation 3.7), we have:

$$k_i(h_q + h_f)(1 - f)\Delta v - u'(I) = (kh_q + \frac{RRA}{I})u'(I)c_{i,t} \tag{3.8}$$

Let us consider now the particular cases: before (early contributions) and after (late contributions) the threshold is reached.

Early contributions ($C_t \leq G$) For early contributions, $f = f_0$ and $h_f = 0$. Taking the derivative with respect to RRA, we obtain (proof is relegated in Appendix A.1.4):

$$\frac{dc_{i,t}}{dRRA}\left[kh'_q\big(\Delta v(1 - f_0) - u(I - c_{i,t}) + u(I)\big) - kh_q - \frac{RRA}{I}\right] = \frac{u'(I)}{I}c_{i,t} \tag{3.9}$$

where $h'_q = \frac{dh_q}{dc_{i,t}} = -k\frac{q''(1-q)+(q')^2}{(1-q)^2}$

Since $\Delta v(1 - f_0) > u(I - c_{i,t}) - u(I)$ according to Equation 3.1, we have, for risk averse individuals, $\left[k_i h'_q\big(\Delta v(1-f_0)-u(I-c_{i,t})+u(I)\big)-kh_q-\frac{RRA}{I}\right] > 0$ and $\frac{u'(I)}{I}c_{i,t} > 0$. Thus, we must have $\frac{dc_{i,t}}{dRRA} > 0$. This result suggests that risk averse contributors may want to overcontribute in order to insure the success of the campaign.

Proposition 2. *When $C_t \leq G$, for risk averse contributors, the higher the level of risk*

aversion, the higher the contribution.

Late contributions ($C_t \geq G$) For late contributions, $q = 0$ and $h_q = 0$. Taking the derivative with respect to RRA, we obtain (proof is relegated in Appendix A.1.5):

$$\frac{dc_{i,t}}{dRRA}\big[-k^2 f''\Delta v - \frac{u'(I)}{I}RRA\big] = \frac{u'(I)}{I}c_{i,t} \tag{3.10}$$

For risk averse contributors, since $-k^2 f''\Delta v - \frac{u'(I)}{I}RRA < 0$ and $\frac{u'(I)}{I}c_{i,t} > 0$, we must have $\frac{dc_{i,t}}{dRRA} < 0$.

Proposition 3. *When $C_t \geq G$, for risk averse contributors, the higher the level of risk aversion, the lower the contribution.*

To test the several results of our model, we use coupled data combining experimental measures of risk aversion (described in Section 3) and field data from Catarse on dynamic contributions (described in Section 4). To simplify the econometric analysis, we only consider two periods: the first one were both risk are at stake (Period 1) and a second one where contributors are only exposed to the risk of non-delivery (Period 2).

3. Experimental procedure

We conducted our experimental measures on users of the Brazilian platform Catarse to test for the role of risk aversion on the level of contributions (see Section II.0 for more details on the implementation of the online experiment and on Catarse). More particularly, we estimate risk preference of backers using the Holt and Laury's (2002) procedure. We decide to use this measure over other risk aversion elicitation methods since it enables to estimate constant relative risk aversion which relates to our model. Additionally, the Holt and Laury's (2002) procedure can be used to identify subjects with risk-loving or risk neutral preferences, unlike some alternate measures. We also use information on contributors to understand who are the early and late contributors

(summary statistics of participants' characteristics are listed in Table 3.5). In the next section, we describe the experimental procedure.

3.1. Measuring risk preferences

We elicit risk preference using one of the most widely used procedure: the multiple price list choices of Holt and Laury (2002). It presents several advantages as it is context free and incentivized. Previous articles highlight the predictive power of such a measure for real behaviors in finance (Fellner and Maciejovsky, 2007), health (Anderson and Mellor, 2008) or food consumption (Lusk and Coble, 2005). Another benefit in using this procedure within the context of reward-based crowdfunding platform is that amounts at stake are similar.

Participants realize ten paired-lottery choices presented on the same screen (see Table 3.1). The original amounts used by Holt and Laury (2002) are converted to Brazilian Reals and multiplied by 3 [11]. We use the decreasing frame as it may lower the rate of inconsistent choices (Lévy-Garboua et al., 2012) [12]. Each choice is made of a "safe" lottery (option A) and a "risky" lottery (option B). In Choices 1-6, the expected payoff of option B is higher than the one of option A whereas in Choices 7-10 it is the opposite. All choices are displayed on the same screen and multiple switching is allowed during the task. At the end of the experiment, one of the choices is randomly drawn and played.

Results of our experiment are consistent with previous research: the frequency of choosing option A raises when the probability of winning the high payoff lowers (see Figure 3.1). Participants are heterogeneous in terms of preference towards risk. The majority of our 154 subjects choose 4 (17%), 5 (19%) or 6 (24%) times the safe option. The comparable proportions in Holt and Laury (2002) are 26%, 26% and

11. The exchange rate between US dollars and Reals at the time of the experiment is about 1$=3R$.
12. The authors distinguish two types of inconsistency: choosing option A when the payoff is sure (*strong inconsistency*) and multiple switching (*weak inconsistency*). In both cases, the decreasing frame significantly lowers the inconsistency rate.

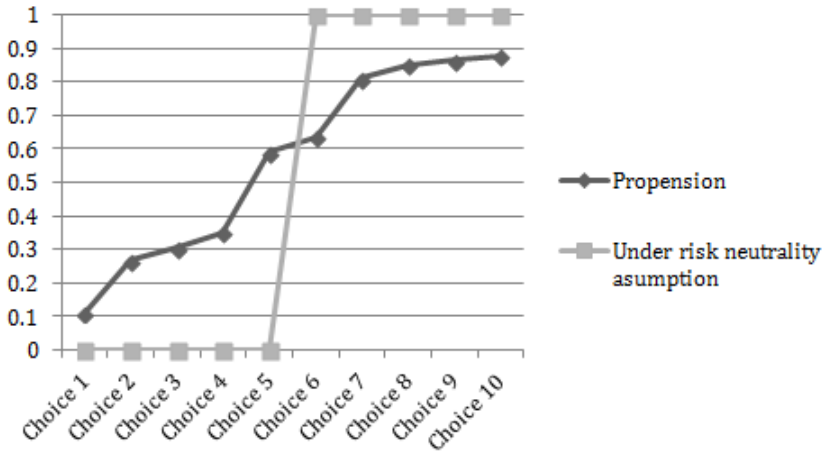
Table 3.1 – Lottery choices list

Choice	Option A: safe lottery (S)				Option B: risky lottery (R)				E(A)-E(B)
	Proba.	Payoff	Proba.	Payoff	Proba.	Payoff	Proba.	Payoff	
1	100%	12R$	0%	9.6R$	100%	23.1R$	0%	0.6R$	−11.1
2	90%	12R$	10%	9.6R$	90%	23.1R$	10%	0.6R$	−9.09
3	80%	12R$	20%	9.6R$	80%	23.1R$	20%	0.6R$	−7.08
4	70%	12R$	30%	9.6R$	70%	23.1R$	30%	0.6R$	−5.07
5	60%	12R$	40%	9.6R$	60%	23.1R$	40%	0.6R$	−3.06
6	50%	12R$	50%	9.6R$	50%	23.1R$	50%	0.6R$	−1.05
7	40%	12R$	60%	9.6R$	40%	23.1R$	60%	0.6R$	0.96
8	30%	12R$	70%	9.6R$	30%	23.1R$	70%	0.6R$	2.97
9	20%	12R$	80%	9.6R$	20%	23.1R$	80%	0.6R$	4.98
10	10%	12R$	90%	9.6R$	10%	23.1R$	90%	0.6R$	6.99

23%. Whereas the authors find that 17% of their sample choose more than 7 times the option A, our proportion is higher (30%) suggesting that our sample is more risk averse. These differences might be due to difference in terms of nationality (Brazilians vs. Americans), occupation (19.5% of our sample are students whereas Holt and Laury (2002)'s sample is only composed of students) and experimental conditions (online vs. in-lab). It can also be due to the fact that the stakes are relatively higher with respect to average income in Brazil compared with the USA [13]. Since, as Holt and Laury (2002) noticed, most individuals become more risk averse as the stakes of the gamble increase, our subjects may be less risk averse.

13. According to the World Bank ranking of 2012, the monthly average revenue in Brazil and in USA are respectively around 970$ and 4200$

Figure 3.1 – Proportion of safe choices in each decision



Note: In dark grey line represents the proportion of participants who chose the safe option A over the option B for each choice. The light grey line represents the proportion of safe A options under the assumption of risk neutrality.

3.2. Estimations of attitude toward risk

Following Holt and Laury (2002), we assume a functional form of a Constant Relative Risk Aversion (CRRA) utility function to define the upper and lower bounds of the risk aversion parameter (r) such that:

$$\begin{cases} U(Y) = \dfrac{Y^{1-r}}{1-r} & if\ r \neq 1 \\ U(Y) = log(Y) & if\ r = 1 \end{cases}$$

where r is the coefficient of CRRA and Y the payoff of the lottery. Besides participants who never switched (4%), most of the participants only switch once from option B to option A (68%), generally choosing the risky lottery for Choices 1-4 then switching for the safe lottery for Choices 5-10. For these individuals, it is possible to estimate intervals for r. To illustrate the calculation, consider an individual who switches from option B to option A at Choice 8. The upper bound corresponds to the parameter of an

individual who is indifferent between option A and B for Choice 7 ($r = -0.15$) while the lower bound corresponds to the parameter of an individual indifferent between the two lotteries for Choice 8 ($r = -0.49$). Negative, null and positive values of r indicate respectively risk-loving preferences, risk neutrality and risk aversion. The ranges are reported in Table 3.2. We further use the midpoint of these range as an explanatory variable. One can notice that, compared with Holt and Laury's (2002) results, our consistent sample contains more risk loving participants (11% versus 8%). This difference can be due to the online conditions of the task completion combined with the specificities of our sample.

For subjects who make multiple switches (26%), we follow Lusk and Coble (2005) and Anderson and Mellor (2008) in determining the range of r. The upper bound is defined by the first switch from option B to option A while the lower bound is determined by the last risky choice the subject makes. Thus, we consider that these individuals have "fat preferences" (Andersen et al., 2006) and are indifferent between lotteries from the first switch to the last.

Table 3.2 – Risk aversion and proportion of safe choices

Number of safe choices	Range of Relative Risk Aversion	Classification	Proportion
0-1	$r < -0.95$	highly risk loving	0.05
2	$-0.95 < r < -0.49$	very risk loving	0.02
3	$-0.49 < r < -0.14$	risk loving	0.04
4	$-0.14 < r < 0.15$	risk neutral	0.18
5	$0.15 < r < 0.41$	slightly risk averse	0.14
6	$0.41 < r < 0.68$	risk averse	0.25
7	$0.68 < r < 0.97$	very risk averse	0.11
8	$0.97 < r < 1.37$	highly risk averse	0.06
9-10	$1.37 < r$	stay in bed	0.16

Note: Proportion are calculated only considering participants who switched less than once and who did not choose option A for Choice 10 (109 participants).

17 of the 154 participants choose option A for Choice 10 and are considered as strongly inconsistent, preferring 12R$ for sure rather than 23.1R$ for sure. The average

time spent on the task for the inconsistent participants is significantly lower than for the consistent ones (119 seconds versus 182, a t-test yields $p = 0.07$). We consider that these subjects do not understand the task and are dropped from the subsequent analysis.

4. Observed contributions of the sample

4.1. Contributions for Period 1 and Period 2

In this article, we focus on the level and the timing of contributions by considering two sequential periods. Hereafter, Period 1 refers to the first period while Period 2 refers to the second one. To ensure a certain homogeneity on part of the projects, we only consider contributions to music projects aiming the production of an album and projects that reached their threshold as we can use the advantages of having a period with no risk of coordination failure. We keep contributions that are lower or equal to 1000R$ as we believe that high contributions are made by special contributors (involved in the project or huge fans of the artist) [14]. We also exclude contributions made by the project holder to her own project since it comes under obvious different motives than buying a project or contributing for its production.

Our sample is thus composed of contributions made for 126 projects with a successful coordination. Table 3.4 gives the summary statistics on projects. As we can see, the average number of contributions is relatively high (240 backers per projects). The maximal number of backers is 3209 while the minimal number is 19.

To test the results of the model, we need to appropriately define the moment when coordination risk disappears. A natural way to distinguish between Period 1 and Period 2 is to consider the moment when the threshold is reached. One can however think that even below this threshold, at a funding ratio of 70% for instance, a contributor

14. 5 contributions fall into this category and are ranged between 1380R$ and 6970R$.

may think it is very likely that the project she is backing will reach the threshold and that her own contribution will not change anything. The probability of coordination failure can be hard to compute as it depends on various variables: the funding ratio, the number of days left, the arrival rate, contributors' valuation etc. We can however use the funding ratio as a good proxy for several reasons: it is probably the main cue a contributor will take into account to estimate the chances of success of a campaign and we can easily compute empirical probabilities using data from the platform (see Table II.2). We thus consider several funding thresholds to separate Period 1 from Period 2, namely 70%, 80%, 90% and 100%. We consider contributions in Period 1 and Period 2. Thus, if a contributor contributed twice during Period 1, we calculate the sum of the two contributions. For instance, for a contributor who backs a given project first by 20R$ then by 15R$ during Period 1, we consider that the level of contribution for this backer in Period 1 equals 35R$. Table 3.3 reports the number of contributions and the average contribution per period. Variables regarding projects that are on our sample are listed in Table 3.4.

Table 3.3 – Contribution level per period

Variables/Period 1 criteria	Below 70%			Below 80%		
	Period 1	Period 2	p-value	Period 1	Period 2	p-value
Nb. of contributions	129	141		141	131	
Average contribution value (in R$)	53.0	55.8	$p = 0.050$	52.9	55.7	$p = 0.054$
sd.	(55.9)	(38.5)		(54.4)	(38.5)	
Average nb. of backers per project	130	110		145	94	
sd.	(123)	(271)		(136)	(261)	

Variables/Period 1 criteria	Below 90%			Below 100%		
	Period 1	Period 2	p-value	Period 1	Period 2	p-value
Nb. of contributions	160	113		178	94	
Average contribution value (in R$)	58.49	56.10	$p = 0.111$	58.90	55.5	$p = 0.277$
sd.	(7.2)	(3.8)		(6.5)	(4.2)	
Average nb. of backers per project	162	77		180	54	
sd.	(155)	(249)		(176)	(238)	

Notes: We use several criteria to define Period 1, namely Below 70%, Below 80%, Below 90% and Below 100%. For instance, when the criterion is Below 70, a contribution is made in Period 1 is the funding ratio is below 70%. Nb. of contributions corresponds to the number of contributions in our sample that were made respectively in Period 1 and 2. Average contribution value is the average contributions made in our sample (without accounting for contributions made by backers outside our sample). Average nb. of backers per project is the average number of contributors for Period 1 and 2 by projects (considering contributions made by backers outside our sample to the projects of our sample). The listed p-value results from non-parametric Mann-Whitney tests.

Table 3.4 – Summary statistics of P_j

Variable	Definition	Mean (corrected sample) ($n = 126$)	sd.
Goal	Financial goal of the project (in R$)	18,432	20,444
Duration	Number of days for which a project accepts funding.	54.3	11.3
Population$_j$	Number of inhabitants of the city where the project is realized	5,790,619	4,984,767
GDP/capita$_j$	Gross Domestic Product per capita of the city where the project is realized (in R$ per year)	42.029	11,720
Budget description	Equal to 1 if the budget is precisely described	0.60	
Nb. of videos	Number of videos in the description of the project	2.48	1.77
Nb. backers	Number of backers at the end of the campaign	240	364
Pledged	Amount raised during the campaign (in R$)	22,966	32,761
Funding ratio	Pledged/Project goal (in %)	135	185

Note: Standard deviations in parenthesis. The corrected sample is the one used in the econometric analysis, taking into account all restriction described in this Section.

Table 3.5 – Summary statistics on X_j

Variable	Definition	Mean (corrected sample) ($n = 111$)	Mean (complete sample) ($n = 154$)
r	Risk aversion parameter (CRRA)	0.43	0.42
Multiple switch	Equal to 1 if subject j switched several times in the H&L procedure	0.21	0.26
Time_hl	Time to complete the H&L procedure (in seconds)	178 (117)	175 (137)
Female	Equal to 1 if the subject is a female	0.36	0.32
Age	Declared age of the subject (in years)	29.20 (8)	29.55 (9)
Cultural budget	Declared amount of the cultural expenses per month (in R$)	197.44 (236)	198.63 (212)
Friends & family	Equal to 1 if the subject declared she have already backed a project of a friend or family on a CFP	0.65	0.62
Population	Number of inhabitants of the subject's city	4,716,267 (4,757,377)	4,826,000 (4,845,717)
GDP/capita	Gross Domestic Product per capita of the subject's city (in millions)	38074 (12,520)	43,280 (62,547)
Creator	Equal to 1 if the subject declared she has already been a project holder in a CFP	0.11	0.11
Extraversion	Score of extraversion at the Big Five inventory	3.23 (0.82)	3.25 (0.82)
Agreeableness	Score of agreeableness at the Big Five inventory	3.68 (0.59)	3.66 (0.56)

Note: Standard deviations in parenthesis. The corrected sample is the one used in the econometric analysis, taking into account all restriction described in Section 4 and 5.

5. Results

5.1. The Choice of backing in Period 1

We first focus on understanding who are those who back in Period 1. According to the model, the choice of backing first is linked to one's perceived similarity with others (k_i), one's belief on the initial risk of non-delivery (f_0) and one's valuation of the product (Δv).

To study the characteristics of early contributors, we run a probit on backing in Period 1 (=1) or in Period 2 (=0). We use the different funding ratio described previously to define this variable, namely below 70%, 80%, 90% and 100%. We use the

following specification for our estimations:

$$probit(P(\text{Period } 1_{i,j} = 1)) = \beta_0 + \beta_1 X_i + \beta_2 P_j + \epsilon_{i,j}$$

where X_i are individual level variables and P_j are project level variables.

Table 3.6 reports the estimated coefficients. Results confirm that those who choose to back a project on Period 1 are those who have a better knowledge on the risk of non delivery ($(1 - f_0)$ is likely to be lower for this type of backers). We use 3 variables to proxy f_0: "First project", "FF", ">50km". The first one is "First Project" that equals 1 if the project is the first one a backer support on the platform: it is likely that contributors register on the platform to support a project held by a friend. From model (1) to model (3), we can see that the first contribution on Catarse is associated with a higher probability of backing at Period 1. The probability of backing in Period 1 is higher for contributors who declared that she has already backed a project of a friend or a member of their family (coefficients of all models being significant at a 5% level). A last variable that might inform us about the social tie between the contributor and the project holder is distance (Agrawal, Catalini and Goldfarb, 2015). Contributors who live far from the project (more than 50km) are less likely to back during Period 1. Results show that when backers live far from the project, they are less likely to back at Period 1.

The declared cultural budget, which should be linked with Δv, does not predict the probability of Period 1.

The perceived similarity with others is not easy to approximate empirically. We however assume that k_i is linked with the backer's sociability. We use measures for Extraversion and Agreeableness with the John, Donahue and Kentle's (1991) version of the Brief Big Five inventory. With this questionnaire, we are able to have scores for 5 personality traits, namely Extraversion, Openness, Emotional Stability, Agreeableness and Conscientiousness. This questionnaire consists of a list of 100 adjectives. For each

adjective, subjects declare on a five-point Likert scale if the adjective describes her totally or not at all, with three intermediate possibilities. The test provides scores on a 1 to 5 scale. A higher score for a given personality trait will characterize the subject. Extraversion is related to a higher degree of sociability, emotional activity seeking and talkativeness while Agreeableness is related to the needs for pleasant and harmonious relations with others. Contributors who yields a higher degree of Extraversion are more likely to back during Period 1 while no correlation is observed regarding the score of Agreeableness.

Risk preferences (r) does not seem to be correlated with the timing of the contribution, except when the threshold for Period 1 is set at 100% (model (4)).

5.2. Risk aversion and contribution values

In this section, we study the effect of preferences towards risk on the level of contributions. We estimate contributions using OLS regressions clustered on the individual level according to the following model:

$$log(c_{i,j}) = \gamma_0 + \gamma_1 r + \gamma_2 \text{Period 1} + \gamma_3 r * \text{Period 1} + \gamma_4 D_{i,j,t}\gamma_5 + P_j\gamma_6 + X_i\gamma_7 + R_{i,j,t}\gamma_8 + \epsilon_{i,j,t}$$

Where r is the coefficient of risk aversion, Period 1 is a dummy that equals 1 if the contribution is made in Period 1, P_j are project level variables, X_i are individual level variables and $R_{i,j}$ are contribution level variables.

As can be seen in Table 3.7, models (1) and (2) show that risk aversion is significantly and negatively correlated with the level of contributions (in log) when contributors back in Period 2 [15]. A one-unit increase in the coefficient of risk aversion r corresponds a 15.1% (model (2), $p = 0.082$) to a 15.3% (model (1), $p = 0.047$) decrease of the contribution value. This results confirms the prediction of the model. The coefficient is no longer significant when Period 1 is defined by backing before 100%.

15. Our results are robust when we exclude participants who made multiple switch.

When contributions are made in Period 1, the correlation between the contribution values and r becomes positive: for instance in model (1), a one-unit increase in r is associated with a 23% increase in the contribution value ($p = 0.023$). The subjective impact of the contribution on the hazard rate of the coordination risk should thus be high enough so that risk averse contributors prefers to have the insurance that the project will reach the threshold. This coefficient is significant for all models except for model (4). This suggests that when approaching the threshold T_j, the two effect of r are counterbalancing and the effect is less obvious.

Interestingly, backers who claimed they have already contributed to a project of a friends or a family contribute less than those who do not (from 23% to 25% less). This result suggest that friends and family are less interested in music (they have a low m_i).

Our sample encompasses all types of rewards and contributions declining rewards. The sample is however quite homogeneous since 88% of the contributions are associated with a pre-order of the product (a CD or an album). Results are robust if we exclude those who do not ask for a reward at all (3% of the contributions of our sample).

As the decision to back a project is likely to be an endogenous variable, we check the previous results thanks to a two stage least squares with a probit first stage. We use predicted value of Equation 3.6 as an instrument for variables "Period 1" and the interaction term "Probit 1 $\times r$", as suggested by (Wooldridge, 2010, p623). Results are robust and coefficient are even of larger amplitude for r and Period $1 \times r$.

Table 3.6 – Estimation on the probability of backing in Period 1 (for successful projects) using a probit model

	(1)	(2)	(3)	(4)
Period 1=1	Below 70%	Below 80%	Below 90%	Below 100%
Variables				
Individual level variables X_i				
Proxies for f				
First project	1.470*	1.469**	1.445*	1.449*
	(0.292)	(0.288)	(0.285)	(0.296)
$>$ 50km	0.714	0.604**	0.608**	0.573**
	(0.158)	(0.133)	(0.150)	(0.148)
FF	1.867**	2.119***	1.992***	1.838**
	(0.468)	(0.515)	(0.444)	(0.450)
Proxy for Δv				
Cultural Budget	1.000	1.000	1.000**	1.000
	(0.000258)	(0.000245)	(0.000236)	(0.000295)
Proxies for k_i				
Agreeableness	0.950	0.933	0.782	0.785
	(0.171)	(0.175)	(0.144)	(0.148)
Extraversion	1.461***	1.357**	1.359**	1.225
	(0.206)	(0.186)	(0.200)	(0.186)
Other variables				
r	1.244	1.319	1.209	1.339*
	(0.240)	(0.260)	(0.203)	(0.234)
Female	0.852	0.870	0.865	0.708
	(0.209)	(0.214)	(0.210)	(0.176)
Age	0.979	0.980	0.957***	0.971**
	(0.0143)	(0.0150)	(0.0126)	(0.0110)
Creator	1.512	1.165	0.844	0.822
	(0.525)	(0.403)	(0.297)	(0.257)
Project level variables P_j				
Budget	0.842	0.888	0.858	0.742*
	(0.152)	(0.157)	(0.142)	(0.134)
Nb. videos	1.202***	1.211***	1.184***	1.132***
	(0.0507)	(0.0554)	(0.0437)	(0.0543)
Project goal	1.000**	1.000***	1.000***	1.000***
	(4.59e-06)	(4.78e-06)	(5.04e-06)	(4.92e-06)
Controls	YES	YES	YES	YES
Constant	0.436	0.721	5.698	5.805
	(0.435)	(0.793)	(6.096)	(6.824)
Observations	271	272	272	271
Cluster	111	111	111	111
AUC	0.83	0.84	0.86	0.86

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: We exclude projects that did not reach their threshold from the sample. Only projects aiming to produce an music album are kept. r is the coefficient of risk aversion, $>$ 50km=1 if the contribution lives more than 50km away from the project location, FF=1 if the contributor declared she already backed a project from a friend or a member of her family, Female=1 if the contributor is female, Cultural Budget is the average amount the contributor declared she spent per month for cultural goods, Agreeableness is a score of agreeableness measured by the Brief Big Five inventory, Extraversion is a score of extraversion measured by the Brief Big Five inventory, Budget=1 if the project holder provides a clear description of how the funds will be allocated. Control variables: Multiple switch, Time_hl
AUC is the area under the roc curve.

Table 3.7 – Estimation on contribution values in log (for successful projects) - OLS regressions

	(1)	(2)	(3)	(4)
Period 1 is defined by:	Below 70%	Below 80%	Below 90%	Below 100%
VARIABLES	$log(c_{i,j})$	$log(c_{i,j})$	$log(c_{i,j})$	$log(c_{i,j})$
r	-0.153**	-0.151*	-0.148	-0.0967
	(0.0763)	(0.0858)	(0.0969)	(0.0876)
Period 1	0.00444	0.0357	-0.00269	0.0954
	(0.0951)	(0.101)	(0.0886)	(0.0836)
Period 1 $\times r$	0.230**	0.211*	0.184*	0.0716
	(0.101)	(0.112)	(0.103)	(0.0970)
Project level variables P_j				
Project goal (in log)	0.159***	0.157***	0.147***	0.150***
	(0.0394)	(0.0386)	(0.0406)	(0.0385)
Budget	1.70e-05	0.00350	0.0106	0.0106
	(0.0657)	(0.0663)	(0.0651)	(0.0637)
Nb. videos	-0.0346	-0.0341	-0.0316	-0.0345
	(0.0271)	(0.0272)	(0.0256)	(0.0270)
Contribution level variables $R_{i,j}$				
First project	-0.129	-0.121	-0.124	-0.158
	(0.0976)	(0.100)	(0.0969)	(0.0960)
$> 50km$	-0.0681	-0.0618	-0.0618	-0.0437
	(0.0914)	(0.0907)	(0.0890)	(0.0900)
Tangible reward	0.866***	0.870***	0.848***	0.830***
	(0.256)	(0.259)	(0.259)	(0.258)
Symbolical reward	-0.0347	-0.0395	-0.0288	-0.0181
	(0.0662)	(0.0687)	(0.0677)	(0.0681)
Two contrib.	0.865***	0.802***	0.901***	0.943***
	(0.185)	(0.190)	(0.189)	(0.179)
Individual level variables X_i				
Female	-0.0194	-0.0211	-0.0156	0.00969
	(0.102)	(0.102)	(0.0999)	(0.102)
Age	-0.0102**	-0.00940*	-0.00941*	-0.00819
	(0.00495)	(0.00515)	(0.00515)	(0.00516)
F&F	-0.242**	-0.252**	-0.230**	-0.252**
	(0.105)	(0.109)	(0.104)	(0.104)
Creator	-0.234	-0.227	-0.230	-0.245
	(0.167)	(0.169)	(0.166)	(0.168)
GDP/capita city user (in log)	0.0887	0.0745	0.0948	0.0912
	(0.0825)	(0.0869)	(0.0852)	(0.0817)
Cultural budget (in log)	0.0322	0.0284	0.0321	0.0285
	(0.0594)	(0.0588)	(0.0598)	(0.0608)
Constant	0.960	1.210*	1.238*	1.200*
	(0.721)	(0.699)	(0.708)	(0.691)
Observations	271	271	272	271
Cluster	111	111	111	111
R-squared	0.284	0.273	0.268	0.275

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: We exclude projects with coordination failure from the sample. Only projects aiming to produce an music album are kept. "Budget" "Two contrib" is a dummy variable that equals 1 if the amount of the contribution is composed of two backing decisions. "Tangible reward" is a dummy variable that equals 1 if the contributors ask for at least one tangible reward ; "Symbolical reward" is a dummy variable that equals 1 if the contributors ask for at least one symbolical reward. Controls: Multiple switches, Temps_hl, Population (city project).

Table 3.8 – Estimation on contribution values in log (for successful projects) - 2SLS regressions

	(5)	(6)	(7)	(8)
Period 1 defined by	Below 70%	Below 80%	Below 90%	Below 100%
VARIABLES	$log(c_{i,t})$	$log(c_{i,t})$	$log(c_{i,t})$	$log(c_{i,t})$
r	-0.297**	-0.187	-0.345**	-0.370**
	(0.122)	(0.199)	(0.145)	(0.164)
Period 1	-0.235	-0.928	-0.305	-0.0409
	(0.528)	(0.789)	(0.478)	(0.413)
Period 1 $\times r$	0.536***	0.370	0.522***	0.477**
	(0.196)	(0.242)	(0.186)	(0.205)
Project level variables P_j				
Project goal (in log)	0.171***	0.121	0.140**	0.166***
	(0.0522)	(0.0824)	(0.0680)	(0.0489)
	(0.0377)	(0.0370)	(0.0389)	(0.0369)
Budget	-0.00850	-0.0485	-0.00660	0.00110
	(0.0755)	(0.0827)	(0.0780)	(0.0827)
Nb. videos	-0.0265	0.0169	-0.0158	-0.0224
	(0.0435)	(0.0526)	(0.0349)	(0.0309)
Contribution level variables $R_{i,j}$				
First project	-0.0659	0.0396	-0.0550	-0.118
	(0.116)	(0.142)	(0.121)	(0.112)
$>$ 50km	-0.104	-0.151	-0.0991	-0.0662
	(0.0913)	(0.113)	(0.0999)	(0.100)
Tangible reward	0.913***	0.817***	0.887***	0.868***
	(0.252)	(0.274)	(0.244)	(0.248)
Symbolical reward	-0.0477	-0.0267	-0.0587	-0.0475
	(0.0708)	(0.0937)	(0.0658)	(0.0694)
Two contrib.	0.837***	0.522	0.976***	1.044***
	(0.299)	(0.328)	(0.202)	(0.179)
Individual level variables X_i				
Female	-0.0485	0.00404	-0.0411	-0.0113
	(0.106)	(0.116)	(0.0955)	(0.0953)
Age	-0.0145**	-0.0174**	-0.0162**	-0.0134**
	(0.00603)	(0.00766)	(0.00818)	(0.00684)
F&F	-0.186	-0.0230	-0.159	-0.211*
	(0.153)	(0.200)	(0.129)	(0.117)
Creator	-0.175	-0.143	-0.191	-0.203
	(0.163)	(0.160)	(0.149)	(0.152)
GDP/capita city user (in log)	0.113	0.314	0.131	0.0667
	(0.154)	(0.242)	(0.153)	(0.128)
	(0.0790)	(0.0832)	(0.0816)	(0.0782)
Cultural budget (in log)	0.0452	0.0699	0.0455	0.0401
	(0.0579)	(0.0726)	(0.0581)	(0.0552)
Constant	0.630	0.767	0.718	0.616
	(0.753)	(0.753)	(0.731)	(0.707)
Observations	270	271	272	271
R-squared	0.284	0.273	0.268	0.275
Week-ID (F)	2.90	2.08	5.02	6.64

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: We exclude projects with coordination failure from the sample. Only projects aiming to produce an music album are kept. "Budget" "Two contrib" is a dummy variable that equals 1 if the amount of the contribution is composed of two backing decisions. "Tangible reward" is a dummy variable that equals 1 if the contributors ask for at least one tangible reward ; "Symbolical reward" is a dummy variable that equals 1 if the contributors ask for at least one symbolical reward. Controls: Multiple switches, Temps_hl, Population (city project).

6. Discussion and conclusion

Crowdfunding appears as a new way for consumer to consume music by participating in the production of new goods. Since creation is at an early phase of contribution, consumers/contributors are however exposed to two types of risk: a risk of non coordination (will the project get funded?) and a risk of non delivery (will a contributor be fully satisfied with the product and delivery after the campaign?). This paper contributes to a burgeoning literature on the role of risk in crowdfunding.

Depending on the timing of one's contribution, exposure to both risks varies. We develop a model of demand for crowdfunding where contributors make sequential decisions on whether or not to contribute and if so, by how much. In order to understand the dynamics of contributions, we include in our analysis the illusion of control. We particularly show that those who back earlier believe their contribution will induce the contribution of a higher number of contributors. Early contributors are also those who have more private information on the risk of non-delivery (especially, friends and family). Finally, the model shows that risk aversion is related to the level of contributions, but in a different manner depending on the timing of the contribution. For early contributors, risk aversion is positively correlated with the level of contribution. More risk averse contributors are willing to over-contribute in order to insure the success of the campaign. The correlation is negative for late contributors. Our theoretical predictions are confirmed empirically thanks to an original dataset coupling experimental/survey data and real data from a crowdfunding platform.

Extensions of the model can be considered. We assumed in our baseline model that there is no quality differentiation for the ordered product: a higher contribution does not yield a higher quality in the reward. We can also consider the case where contributing at a higher level will give the backer the opportunity to reach a reward of higher value. Another way to say this is that a contributor will obtain some kind

of "return on investment" in addition to the value m_i. Results regarding the timing of the contribution should however hold since it does not modify the nature of the two risks and the degree of the illusion of risk. It should however increase the negative effect of the non delivery risk on contributions for more risk averse contributors as higher contributions increase the variance of the "investment". A second possible extension consists in including an altruistic preferences parameter as crowdfunding is likely to spark pro-social motives. A possible extension of the model is thus to include a component in the utility function $\epsilon U(C_t)$ where ϵ is the degree of altruism, conditional on the success of the campaign. It is also possible to add a term of "warm glow"(Andreoni, 1990): contributors receive a direct satisfaction by giving. Note that these components are subject to the risk of non coordination but not the non delivery. Finally, our model is based on a relatively strong assumption that contributors are myopic. Extensions of the model could thus investigate the role of inter-temporal decisions suggesting that one may have an incentive to "wait and see" the evolution of the campaign.

Our model is the first to provide a formalization of the illusion of control which can be extended to voting decisions. Further investigation should be done, especially regarding one's belief update on the number of individuals that will take the same decision. In our model, we assumed that k_i is constant over time for a given individual.

Our empirical test is limited to a particular field, the music market, a particular mechanism, reward-based crowdfunding with threshold and a particular country, Brazil. Further research could be considered in comparing the role of risk aversion depending on the field, country and type of crowdfunding.

Finally, the model can also be tested in lab, using a provision point public good game with private rewards. Beside the fact that we can isolate the decision to contribute and fix the probability of non delivery, the experimenter can easily elicit contributors' beliefs about the probability of a successful coordination.

A. Appendices

A.1. Proofs

A.1.1. Proof of Equation 3.2

The first order condition implies:

$$-kq'\big[EU(I-c_{i,t},\tilde{m}_i)-U(I,0)\big]-kf'(1-q)\big[U(I-c_{i,t},m)-U(I-c_{i,t},0)\big] \leq (1-q)EU'_f(I-c_{i,t},\tilde{m}_i)$$

With $h_q=\frac{-q'}{(1-q)}$ and $h=_f=\frac{-f'}{(1-f)}$, the first order condition becomes:

$$kh_q\big[EU(I-c_{i,t},\tilde{m}_i)-U(I,0)\big]+kh_f(1-f)\big[U(I-c_{i,t},m_i)-U(I-c_{i,t},0)\big] \leq EU'(I-c_{i,t},\tilde{m}_i)\big]$$

A.1.2. Proof of Equation 3.6

If $c_{i,t}=0$, Equation 3.2 becomes:

$$kh_q(1-f)\big[U(I,m_i)-U(I,0)\big)\big]+kh_f(1-f)\big[U(I,m_i)-U(I,0)\big]\leq EU'_f(I,\tilde{m}_i)$$

A.1.3. Second Order Condition

Let $V(c_{i,t})$ be the expected utility function to maximize:

$$V(c_{i,t})=qU(I,0)+(1-q)[\,fU(I-c_{i,t},0)+(1-f)U(I-c_{i,t},m_i)\,]$$

The first derivative is:

$$\begin{aligned} V'(c_{i,t}) = &- kq'[\,EU_f(I - c_{i,t}, \tilde{m}_i) - U(I,0)\,] \\ &- kf'(1-q)[\,U(I - c_{i,t}, m_i) - U(I - c_{i,t}, 0)\,] \\ &- (1-q)EU'_f(I - c_{i,t}, \tilde{m}) \end{aligned}$$

Thus, the second derivative equals:

$$\begin{aligned} V''(c_{i,t}) = &- k^2 q''[\,EU_f(I - c_{i,t}, \tilde{m}_i) - U(I,0)\,] \\ &- k^2 f''(1-q)[\,U(I - c_{i,t}, m_i) - U(I - c_{i,t}, 0)\,] \\ &+ 2kq' EU'_f(I - c_{i,t}, \tilde{m}_i) + 2k(1-q)f'[\,U'(I - c_{i,t}, m_i) - U'(I - c_{i,t}, 0)\,] \\ &+ (1-q)EU''_f(I - c_{i,t}, \tilde{m}_i) \end{aligned}$$

where $EU''_f(I - c_{i,t}, \tilde{m}_i) = fU''(I - c_{i,t}, 0) + (1-f)U''(I - c_{i,t}, m_i)$. If $q', f' < 0$, $q'', f'' \geq 0$, $U' > 0, U'' \leq 0$ and $U(.,.)$ separable, then $V''(c_{i,t}) < 0 \forall c_{i,t}$. Under these conditions, the First Order Condition is a necessary and sufficient condition for an optimum.

A.1.4. Proof of Equation 3.9

According to Equation 3.8, if $f = f_0$ and $h_f = 0$, we have:

$$kh_q(1 - f_0)\Delta v - u'(I) = \big(kh_q + \frac{RRA}{I}\big)u'(I)c_{i,t}$$

Taking the derivative with respect to RRA, we have:

$$\frac{dc_{i,t}}{dRRA}\big[kh'_q\big((1 - f_0)\Delta v - u'(I)c_{i,t}\big) - k_i h_q - \frac{RRA}{I}\big] = u'(I)c_{i,t}$$

Using the first order Taylor's expansion $u(I - c_{i,t}) = u(I) - c_{i,t}u'(I)$, we have:

$$\frac{dc_{i,t}}{dRRA} = \left[kh'_q\big(\Delta v(1-f_0) - u'(I-c_{i,t}) + u(I)\big) - kh_q - \frac{RRA}{I}\right] = u'(I)c_{i,t}$$

A.1.5. Proof of Equation 3.10

According to Equation 3.8, if $q = 0$ and $h_q = 0$, we have:

$$-k_i f'\Delta v - u'(I) = \frac{RRA}{I}u'(I)c_{i,t}$$

Taking the derivative with respect to RRA, we obtain:

$$\frac{dc_{i,t}}{dRRA}\big(-k^2 f''\Delta v\big) = \frac{u'(I)}{I}c_{i,t} + \frac{dc_{i,t}}{dRRA}\frac{RRA}{I}u'(I)$$

Chapter 4

Backers' pro social motives to crowdfund artistic projects: Experimental Evidence

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This chapter is a joint work with Marco Gazel.

And the media asked, "Amanda, the music business is tanking and you encourage piracy. How did you make all these people pay for music?" And the real answer is, I didn't make them. I asked them. And through the very act of asking people, I'd connected with them, and when you connect with them, people want to help you. (*Amanda Palmer*)

1. Introduction

In 2012, female singer Amanda Palmer has raised almost US$1.2 million to release her solo album and was backed by 24,883 contributors. Amanda Palmer's above quote suggests that even if music is nowadays freely available with freemium streaming or piracy, people are ready to pay for a CD even though it is not produced yet in order to help artists. In other words, (some) consumers are ready to pre-pay artists so that they are able to produce cultural goods. Generally, crowdfunding for cultural goods such as music, films or books follows the reward-based rule where contributors, or "backers", are rewarded for their contributions. Generally, first tiers of contributions give access to pre-orders (of the album, the movie, the book) while higher contributions give access to exclusive rewards such as private meeting with the artist, or invitation to a private show [1]. This article aims at studying the hybrid nature of reward-based crowdfunding for musical projects, between donation and consumption, using experimental and field data.

Motivations to back an artistic project on a crowdfunding platform can be manifold. Material rewards are obviously one of the main motives to back a cultural project. In the mean time, contributors can always choose to free-ride on others' contributions and wait for the product to buy it once produced. One explanation, suggested by Belleflamme, Lambert and Schwienbacher (2014*b*), is that backers' willingness to pay

1. In the case of Amanda Palmer's campaign, rewards from $1 to $50 corresponds to a digital or a physical version of the album. 21780 backers (87%) asked for pre-orders of the album.

for a given product is higher than for other consumers because their backing experience provides them with additional community benefits. People seek to help artists, to support an idea and to be part of a community (Gerber, Hui and Kuo, 2012), suggesting that backers are not only interested by the offered rewards but are also driven by social preferences such as altruism or reciprocal motives.

In this article, we explore the pro-social motives to crowdfund artistic projects coupling observational data collected online with experimental data. Our study is the first to investigate the correlation between contributors' activity on a real platform with experimental measures of pro-social preferences. We specifically focus on altruism (Andreoni, 1989, 1990) and reciprocity (Rabin, 1993, Falk and Fischbacher, 2006) using standard games in experimental economics. Eliciting pro-social preferences can be hazardous. Self-assessed measures may be subject to social desirability. Using experimental measures may help the experimenter distinguish between "acts and words". Even though we acknowledge that the experimenter demand effect (Zizzo, 2010) might be a source of bias in measuring pro-social behaviors, we believe that decisions in incentivized games may well reflect cooperative, altruistic and reciprocal behaviors, more than hypothetical answers to surveys. By using an online setting for the experiment, we provide measures of altruism (using the Dictator game) and reciprocity (using the Trust game). In addition, we use two versions of the Public Goods game to study the correlation between in-lab and out-lab cooperation.

This exploratory study helps understanding the hybrid nature of crowdfunding, between consumption and donation, with a special focus on music. We particularly find that backers who exhibit higher levels of altruism and reciprocity back more projects (extensive margins), suggesting that contributors take into account the positive externality they are generating when ordering an artistic product on a crowfunding platform. In parallel, we find that the average level of contributions (the intensive margins) is not correlated with pro-social preferences, suggesting that willingness to pay is adjusted to

the value of the reward.

Section 2 describes the related literature. Section 3 presents the design and implementation of the experimental measures. Section 4 reports empirical measures. Section 5 discusses and concludes.

2. Literature review

Evidence of altruistic behaviors in reward-based crowdfunding is relatively scarce: these marketplaces offer a mix of intangible and tangible incentives (altruism versus rewards) and disentangling mixed motivations is not trivial. In a qualitative survey, Gerber, Hui and Kuo (2012) highlight pro-social motives to crowdfund. Burtch, Ghose and Wattal (2013) show empirically that crowdfunding for journalism projects is subject to partial "crowding-out" [2] such that a 1% increase of the prior frequency of contribution is associated with a 0.31% decrease in subsequent contributions. Their result suggests first that altruism is at stake, and second that both pure and "warm-glow" are involved [3]. In another study of the dynamics of crowdfunding, Kuppuswamy and Bayus (2017) suggest that support increases as a project approaches its target goal because people involve in pro-social behaviors when they believe that their actions make a positive impact. Studying data from the German platform Startnext, Crosetto and Regner (2014) find that a consistent share of pledges are outright donations which are sometimes done after the threshold is reached [4].

The link between pro-social motives and cultural consumption has been observed on behaviors in pay-what-you-want models. For instance, in 2007, the rock band Radiohead self-released their album *In Rainbows* online as a pay-what-you-want download during 2 months. People could decide how much they wanted to pay and were even

2. In the context of donations, others' contributions should decrease (crowd out) the contribution of a pure altruist in a proportional way.

3. If no warm-glow were involved here, perfect crowding-out should occur.

4. On Catarse, 12% of the contributions to music projects are outrigh donations. When considering contributions made after the threshold is reached, this share is of 7%.

able to download the album for free. According to a study from the magazine *Record of the day*, the album was bought 4£ on average and only a third of the consumers downloaded it for free. Regner and Barria (2009) find that consumers willingness to pay is significantly higher than the recommended price on the label and online store Magnatune [5]. Authors argue that consumers have reciprocal motives and wish to reward the artists' work. One can think of a similar decision process in the framework of crowdfunding.

Crowdfunding also triggers social image concerns. The literature in experimental economics has highlighted the role of anonymity and donation (Andreoni and Petrie, 2004) and cooperation: revealing one's identity and/or contribution increases the average contributions in the public goods game (Andreoni and Petrie, 2004, Rege and Telle, 2004) and the average transfers in the dictator game (Bohnet and Frey, 1999). The effect of information privacy in the case of crowdfunding has been studied by Burtch, Ghose and Wattal (2015). They set a randomized controlled experiment to study the priming effect of choosing what information a backer wishes to disclose, i.e. the amount of the contribution and her identity. Results show that when contributors make their decision about information disclosure before payment, the level of conversion [6] is lower but contributions are higher than when this decision is made after payment. These results indicate that social image in pro-social behavior concerns may play into crowdfunder behavior. It is thus important to understand how contributors' identity is disclosed on the platform.

3. Experimental design

The procedure of the experiment is described in the introduction of Part II.0. This section provides details on the games we are using.

5. On average customers pay $8.20, far more than the minimum of $5 and even higher than the recommended price of $8.

6. The conversion rate refers to backers who actually confirm their contribution.

3.1. Measuring social preferences

To elicit social preferences, we use incentivized standard games developed in experimental economics (see e.g. Camerer and Fehr (2004)). We follow Algan et al.'s (2013) and Hergueux and Jacquemet's (2015) methodology to implement an online experiment, except that, for two-players games, participants play both roles (e.g. both *trustor* and *trustee* in the Trust game and both *sender* and *receiver* in the Dictator game [7]). Even though reversing role in standard game may have an influence in decisions (Burks, Carpenter and Verhoogen, 2003), it seems closer to real-world situations since people are generally confronted with both situations, i.e. trustor and trustee, giver and recipient (Bonein and Serra, 2009) and allows us to collect more data.

Altruism We use the standard Dictator game (DG) to measure individual propensity to behave altruistically. This measure however encompasses pure altruism and warm-glow motives. The latter is not easy to measure individually, we thus decide to proxy it using a modified version of the Dictator game (DG 2) where the recipient has an initial positive endowment [8], as described in Table 4.1. In both conditions, Player A, the *sender*, must decide how much of her 30R$ initial endowment [9] is transferred to Player B, the *receiver*. In the second version, the initial endowment of Player B is supposed to crowd out donations compared with the first version. As endowment of Player B is higher is the Dictator game 2, we expect warm-glow to play a greater role in the decision. All subjects play both roles (Player A and Player B) in the two versions [10].

7. For the Trust game, we particularly use Bonein and Serra, Chaudhuri and Gangadharan's (2009, 2007)) methodology.

8. We use Konow's (2010) design which was use to validate the existence of "warm-glow" at the aggregated level. The author uses a between-subject experiment. One of the treatment is the standard dictator game while another one is a modified version where the receiver has a positive endowment. At the aggregated level, the author finds transfers are not perfectly crowded-out in the modified treatment compared with the baseline treatment.

9. The exchange rate is 1€= R$3 (Brazilian real) during the period the experiment was carried out.

10. Subjects play as Player B even if it is a passive condition in the Dictator game.

The proportions of the initial endowment transferred from Player A to Player B in both versions are our measures of altruism.

Table 4.1 – Dictator games: Initial endowment

	Player A	Player B
Dictator game (DG)	R$ 30	R$ 0
Dictator game 2 (DG 2)	R$ 30	R$ 12

Reciprocity Participants are paired to play a Trust game (TG) (Berg, Dickhaut and McCabe, 1995). They play both roles. Since pairing is sequential according to the timing of connexion, they do not play with the same participant when they take the role of *trustor* or *trustee*. Each player is initially endowed with 30R$. Player A (the trustor) decides how much of the initial endowment is transferred to Player B (the trustee). [11]. Player B receives three times the amount transferred by Player A and decides how much she sends back to Player A. Because participants are not logged in our platform at the same time, we use the strategic method: Player B is asked to specify the amount she is willing to send back for ten possible transferred values, without knowing the actual amount chosen by Player A. One of the intended values of Player B is randomly selected in order to determine the payoffs π_a and π_b of, respectively Player A and Player B: $\pi_a = 30 - \text{transfer}_a + \text{return}_b$ and $\pi_b = 3 \times \text{transfer}_a - \text{return}_b$. We take the average proportion over the ten choices of the received amount that is send back by Player B as a measure of reciprocity.

Cooperation We add a third type of game to test the external validity of in-lab cooperation. To elicit backers' propensity to cooperate, we propose two different versions of the Public Goods game to our participants: a standard Public Goods game (PG) and a Public Goods game with threshold (PG 2). In both versions,

11. Player A can choose between ten values: R$3, R$6, R$9, R$12, R$15, R$18, R$21, R$24, R$26, R$30.

participants are grouped by four and each of them receives an initial endowment of R$30. Participants decide how much of their initial endowment they would like to contribute to the common project. The payoff for each member i of the group is: $\pi_i = 30 - \text{contribution}_i + 0.4 \sum_{j=1}^{4} \text{contribution}_j$. The difference between the two versions of the Public Goods game is that, in the threshold version, this payoff is valid only if $\sum_{j=1}^{4} \text{contribution}_j \geq$ R$84. If the total contribution to the common project does not reach this value, each participant keeps the initial endowment as the payoff for this task, this framework is supposed to be more representative to AoN crowdfunding. The proportions of the endowment contributed to the common project are our measures of propensity to cooperate.

3.2. Observed behaviors in the experiments

Table 4.2 – Descriptive statistics of experimental measures

Variable	Definition	Mean (corrected sample) ($n = 151$)	Mean (complete sample) ($n = 154$)	Mean (literature)
Cooperation - Public Goods game (PG)	The proportion of the endowment contributed to the public goods	0.65 (0.26)	0.65 (0.26)	(0.38) [12]
Cooperation - Public Goods game with threshold (PG2)	The proportion of the endowment contributed to the public goods with threshold	0.78 (0.22)	0.78 (0.15)	
Altruism - Dictator game (DG)	The proportion of the endowment transferred to Player B	0.48 (0.15)	0.48 (0.19)	(0.28) [13]
Altruism - Dictator game 2 (DG2)	The proportion of the endowment transferred to Player B	0.36 (0.19)	0.35 (0.20)	
Reciprocity - Trust game (TGB)	Average proportion of amount returned to Player A	0.52 (0.20)	0.53 (0.20)	(0.20) [14]

Note: The corrected sample excludes participants who only backed their own projects. Standard deviations are in parenthesis.

Table 4.2 provides descriptive statistics about our measures of cooperation and pro-social preferences. These measures are particularly high compared with what is usually found in the literature. An interesting feature is that the proportion of subjects who are

12. See Zelmer's (2003) meta analysis.
13. See Engel's (2011) meta analysis.
14. See Johnson and Mislin's (2011) meta analysis. The reported proportion is the one for Trust game version where subjects plays both roles.

fully selfish is very low. For instance, only 3 subjects out of 151 give nothing in the DG and the DG 2. Many confounding variables can explain this difference, including the fact that Brazilians could me particularly generous in general. We can however expect that a share of this difference is due to a self-selection effect: individuals who engage in crowdfunding are particularly reciprocal, cooperative and altruistic. As Table 4.3 shows, levels of cooperation in both Public Goods games are correlated to each other but we find a low correlation with other games [15]. This result is consistent with previous studies: Dreber, Fudenberg and Rand (2014) show that giving in the dictator game does not predict cooperation in a repeated public goods game and Blanco, Engelmann and Normann (2011) find that contributions made in a standard public goods game are significantly correlated with respondent's behavior in a sequential prisoners dilemma, but not to choices made in dictator games. Reciprocity in the Trust game and altruism in the Dictator game yields a positive and significant correlation suggesting that the amount returned in the Trust game is partly motivated by altruism preferences.

Table 4.3 – Correlations between decisions

	Cooperation PG	**Cooperation PG 2**	**Altruism DG**	**Altruism DG 2**	**Reciprocity TG (Player B)**
Cooperation - Public Goods game	1				
Cooperation - Public Goods game 2	0.364***	1			
Altruism - Dictator game	0.127	0.0416	1		
Altruism - Dictator game 2	0.151*	-0.0962	0.540***	1	
Reciprocity - Trust game (Player B)	0.104	0.0727	0.215***	0.103	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Pearson's correlation

15. Only cooperation in PG is correlated with altruism in DG 2 but the correlation is only significant at a 10% level of significance.

3.3. Observed behaviors on Catarse

We exclude from the 473 contributions of the whole sample those made by the project holder, which leaves us with 470 contributions made by 151 backers. Descriptive statistics on these contributors are provided in the Appendix 4.9. The backers of our sample contributed to 168 different musical projects. The average project goal is 20,206R$ (sd. $20,134$) and the average duration of the campaigns was 53.4 days (sd. 12.6). In 93% of the cases, contributors asked for at least one tangible reward (a cd, an album, an invitation for a show etc.), and in 37.8% of the cases, they asked for at least one symbolical reward (a name on the website etc.). For 5% of the contributions, the contributor did asked for nothing (pure donation). 82.1% of the project were aiming to produce an album or a CD, 5.4% a concert and 12.5% both.

3.4. Information disclosure behaviors

Since anonymity plays an important role in pro-social behaviors, we use controls for information disclosure in our econometric analysis. Table 4.4 presents descriptive statistics on information disclosure. Why people decide to disclose their photo is not straightforward. Willingness to reveal one's appearance can be linked with willingness to reveal one's identity and thus be linked with social image concerns. An alternative explanation would be that backers may want to disclose their photo to enhance social presence. The latter can be defined as the extend to which a user experiences other users as being psychologically present (Fulk et al., 1987). Perceived social presence foster trust and cooperative behaviors (Teubner et al., 2013). Thus, displaying one's photo is linked with a backer's will to engage in trustworthy relationship with other members of the community and to signal her will to be part of the community. Lastly, displaying one's photo may be simply more convenient. Backers' can register using Facebook and this procedure spare a new user the time of filling in a form.

Table 4.4 – Information disclosure for the corrected sample*

Displayed information	Percentage of the corrected sample ($n = 151$)
None	41%
Photo only	36%
Facebook or Twitter only	11%
Both	13%

Note: The corrected sample excludes participants who only backed their own projects.

4. Results

This section presents the results regarding the correlation between contributors own pro-social preferences and their actual online activity. More specifically, we study two types of outcome: the extensive and intensive margins of contributions.

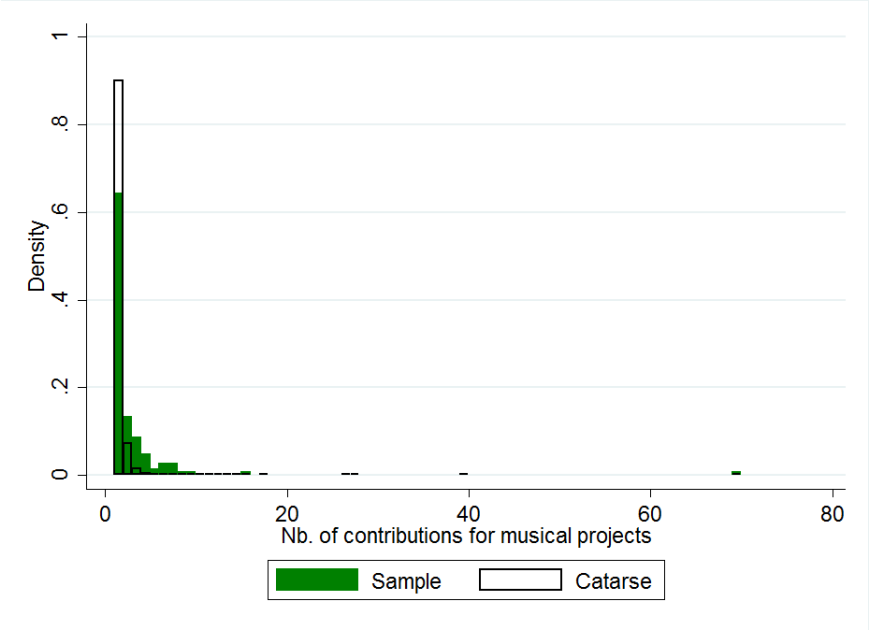
4.1. Extensive margins of contributions

Extensive margins of contributions refers to the number of contributions a backer made on the platform. Adding an altruistic component to the decision weakens the participation constraint. In other words, people exhibiting a higher degree of altruism should back more projects, *ceteris paribus*. Since we focus on musical projects, the outcome variable of interest here is the number of musical projects backed by a given contributor.

The number of musical projects backed follows a strong power law distribution (see Figure 4.1). We use the negative binomial pseudo-likelihood estimators as it takes into account the skewness of our data and is well suited for count data. Negative binomial regressions describe the probabilities of the occurrence of whole numbers greater than or equal to 0. Unlike the Poisson distribution, the variance and the mean are not equivalent, thus this estimator is well-suited for over dispersed count data. With negative binomial regression, we can interpret coefficients as semi-elasticities. This

section is organized as follow: we first present the relationship between demographic variables and activity on the Catarse. We then study the role of pro-social preferences when predicting the number of projects backed.

Figure 4.1 – Distribution of the number of musical projects backed for the corrected sample ($n = 151$) and the invited sample ($n = 63649$)



Note: Catarse's sample is composed of 63649 backers while our sample is composed of 151 contributors.

The effect of control variables on the number of projects backed We first run the negative binomial regressions using demographic variables as independent variables. Estimates are listed in Table 4.5 [16]. The expected number of projects backed is from 32.7% (model (4), $p = 0.059$) to 34.1% (model (1), $p = 0.054$) higher for backers who

16. For robustness check, we also provide estimates for the number of cultural projects, including Films, Comics, Books, Dance, Arts, Theater and Photo, backed on the platform (see Table 4.10 in Appendices). Results are consistent with those presented here except that the coefficient associated with the variable "Photo" is no longer significant (though is it still positive). Displaying one's full name is negatively correlated with the number of projects backed. Those who declared they have already backed a project from a friend of a member of their family (F&F) are expected to back 47% less projects (model(4), $p < 0.001$).

display their photo on their account, *ceteris paribus*. Providing a personal link such as Facebook or Twitter is associated with an increase of 67.2% of the number of musical projects backed (model (2), $p = 0.058$). The coefficient is however not significant when controlling for other information disclosure (model (4)). These results suggest that backers who decide to display more information are more involved on the platform, either because, by disclosing personal information, they demonstrate their will to be part of the community or either because of social image concerns. The coefficients are however weakly significant and the effect of disclosure of information seems limited.

The coefficient for full name disclosure is surprisingly negative: backers who disclose their full name backed, on average, 28.1% less musical projects (model (3), $p = 0.066$). Nevertheless, those who do not provide their full name actually use a nickname. Although surprising, this results suggest that choosing one's full name may be related to the one's will to be engaged in the crowdfunding community, while choosing a nickname is a sign of group belonging.

Coefficients associated with demographic variables are poorly correlated with the dependent variable. Individuals who owns a Ph.D. however back less projects by an expected decrease of 60% in model (3) ($p = 0.036$) [17]. Surprisingly, coefficients associated with the GDP/capita and the monthly budget allocated to cultural goods is close to zero and non significant.

The declared F&F variable does not yield any significant effect. Without surprise, backers who created their account later backed less musical projects: registering one day later since the creation of Catarse is associated with a decrease by 0.16% in the number of projects backed ($p < 0.001$).

Pro-social preferences and extensive margins of contributions We run the same negative binomial regression using the experimental measures of pro-social be-

17. Note that this effect can be correlated with age.

Table 4.5 – Number of musical projects backed (negative binomial estimates)

	(1) Nb. projects backed	(2) Nb. projects backed	(3) Nb. projects backed	(4) Nb. projects backed
Photo	.2934*			.2826*
	(.1525)			(.1499)
Personal link (Facebook or Twitter)		.5142*		.3583
		(.2710)		(.2398)
Full name			-.3298*	-.2628*
			(.1797)	(.1511)
Age	.0241	.0352	.0138	.0306
	(.0377)	(.0351)	(.0331)	(.0338)
Age^2	.0000	-.0001	.0001	-.0001
	(.0005)	(.0004)	(.0004)	(.0004)
Female	.0645	.1331	.1199	.0989
	(.1821)	(.1812)	(.1817)	(.1755)
Registration day	-.0016***	-.0015***	-.0017***	-.0015***
	(.0004)	(.0004)	(.0004)	(.0004)
Degree level (ref: high school)				
Undergraduate	.0761	.1233	.0334	.1109
	(.3123)	(.3137)	(.3200)	(.2984)
Master	.0561	.1011	.0894	.0510
	(.1730)	(.1693)	(.1881)	(.1686)
Ph.D.	-.6822*	-.6988**	-.9062**	-.6632*
	(.3827)	(.3275)	(.4318)	(.3465)
Creator	-.2025	-.4893	-.2134	-.3708
	(.3800)	(.3715)	(.3599)	(.3631)
F&F	-.2415	-.2124	-.2330	-.1618
	(.2389)	(.2147)	(.2272)	(.1988)
GDP/capita city user	-.0009	-.0009	-.0008	-.0006
	(.0007)	(.0006)	(.0005)	(.0006)
Cultural budget (in R$)	-.0003	-.0002	-.0002	-.0002
	(.0003)	(.0003)	(.0003)	(.0003)
Constant	1.2770*	.9258	1.8331***	1.1067*
	(.6904)	(.6749)	(.6558)	(.6503)
Pseudo R2	.0962	.1017	.0974	.1088
Log pseudolikelihood	-279.8083	-278.1118	-279.4447	-275.9102
Observations	151	151	151	151

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Photo=1 if the contributor has a photo on Catarse, Personal link =1 if the contributor gives a personal link to Facebook or Twitter, Full Name=1 if the contributor uses her full name (first and last names), Female=1 if the contributor is female, Age is the individual's age and Age^2 is the square of Age, Registration day equals the number of days that passed between Catarse's creation January the 17th of 2011, F&F =1 if the contributor declares she has already backed a project from a friends or a member of her family, Cultural Budget is the declared amount spent on cultural activities per month.

haviors (see Table 4.6) [18]. Altruism measures and reciprocity seem to be positively

18. We run robustness check on the number of cultural projects backed. Table 4.11 in the Appendices presents the results of those estimations using, as an explanatory variable, the number of project

correlated with the number of musical projects backed (see Models (3) to (6)). Moving from full selfishness (null transfer) to full altruism (full transfer) in the DG and the DG 2 are respectively associated with an increase by 470% (model (2), $p = 0.003$) and by 282% (model (3), $p = 0.006$). Moving from no reciprocity (Player B returns nothing) to full reciprocity (Player B returns all the amount received) is associated with an increase of 371% of the number of musical projects backed (model (5), $p < 0.001$). Regarding propensity to cooperate measured by the two versions of the Public Goods game, we can see that coefficients are not significant.

Looking at margins (see Figure 4.2), for a subject who is not reciprocal at all (null transfer), the average predicted count is about 0.99 while for a subject who is fully reciprocal (full transfer), the average predicted count is about 4.37. A fully altruistic backer (full transfer in the DG) is expected to back 5.5 projects while a fully selfish backer (null transfer in the DG) is expected to back 0.94 projects.

One can finally notice that when all pro-social measures are used in the regression (with model (6)), reciprocity yields the highest level of significance, suggesting that it is the most robust pro-social measure to predict extensive margins.

backed, all cultural categories included. Results suggest that reciprocity is the only experimental measure associated with a significant and positive coefficient. According to model (6), moving from no reciprocity (Player B returns nothing) to full reciprocity (Player B returns all the amount received) is associated with an increase of 708% in the expected number of cultural projects backed. Again, estimations suggest that displaying one's full name is negatively correlated with the number of project backed. Being a creator is associated with a expected decrease of 43.4% in the number of project backed.

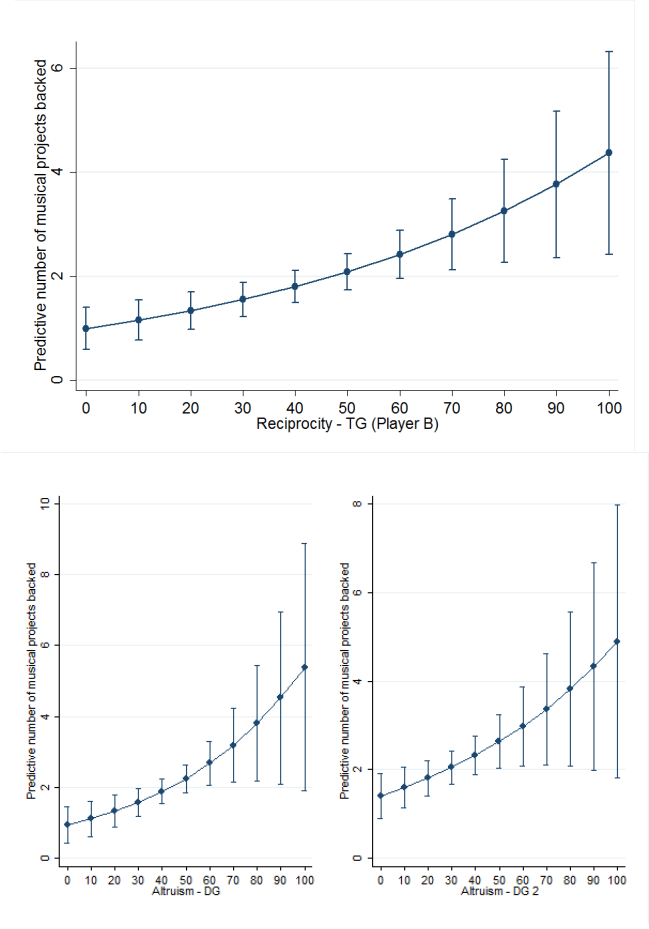
Table 4.6 – Number of musical projects backed (negative binomial estimates)

	(1) Nb. projects backed	(2) Nb. projects backed	(3) Nb. projects backed	(4) Nb. projects backed	(5) Nb. projects backed	(6) Nb. projects backed
Cooperation - PG	.0016					-.0027
	(.0030)					(.0029)
Cooperation - PG 2		.0008				.0010
		(.0034)				(.0036)
Altruism - DG			.0174***			.0065
			(.0059)			(.0047)
Altruism - DG 2				.0134***		.0075*
				(.0048)		(.0041)
Reciprocity - TG (Player B)					.0155***	.0112***
					(.0040)	(.0035)
Photo	.2881*	.2915*	.1921	.2379*	.2553*	.2239
	(.1530)	(.1537)	(.1429)	(.1440)	(.1428)	(.1432)
Personal link (Facebook or Twitter)	.3491	.3360	.1821	.2275	.2860	.1714
	(.2319)	(.2343)	(.2052)	(.1941)	(.2001)	(.1847)
Full name	-.2423	-.2416*	-.2478*	-.2364	-.1608	-.1757
	(.1477)	(.1466)	(.1464)	(.1510)	(.1395)	(.1426)
Creator	-.4749	-.5007	-.3492	-.3309	-.3859	-.4094
	(.3646)	(.3654)	(.3481)	(.3382)	(.2911)	(.2954)
F&F	-.1422	-.1305	-.1233	-.0615	-.0453	-.0108
	(.1899)	(.1834)	(.1717)	(.1766)	(.1736)	(.1582)
Constant	.9063	1.3317*	.6025	.2660	.6671	.3566
	(.6705)	(.7005)	(.5790)	(.5890)	(.7331)	(.7005)
Control Variables	YES	YES	YES	YES	YES	YES
Pseudo R2	.1134	.1158	.1313	.1333		
Log pseudolikelihood	-402.6170	-401.5454	-394.4779	-393.5858		
Observations	151	151	151	151	151	151

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Additional controls are Age, Female, Registration date, Degree level, GDP/capita and cultural budget. Cooperation - PG is the proportion of the endowment transfered in the Public Goods game (in %), Cooperation - PG 2 is the proportion of the endowment transfered in the Public Goods game with threshold (in %), Altruism - DG 1 is the proportion of the endowment transfered in the Dictator game (in %), Altruism - DG 2 is the proportion of the endowment transfered in the second version of Dictator game (in %); Reciprocity - TG (Player B) is the average proportion of amount received that is returned by the subject in the Trust game strategic method.

Figure 4.2 – Predictive margins for the number of musical projects backed for reciprocity and altruism



Notes: Confidence levels at 95%.

4.2. Intensive margins of contributions

In this section, we report results regarding the intensive margins of contribution. We take the average contribution per musical project of each participants, excluding contributions made by the creator to her own project. We use Ordinary Least Square Regression on the average contribution, clustered on individuals.

Demographic variable and average contribution per project We first regress the log transformed average amount of contribution over a set of demographic variables (see Table 4.7). These independent variables however have a poor explanatory power over our variable of interest. Holding all other independent variables constant, the amount dedicated to cultural activities (on the broad sense) is positively correlated with the average contribution: a 1% increase of the monthly cultural budget is associated with a 18.2% (model(1), $p = 0.017$) increase of the expected average contribution for musical project. The average goal of the project backed by a given individual is positively correlated by the average amount.

Pro-social preferences and intensive margins of contributions We run the same OLS regression introducing our experimental measures. Results show that the experimental measures do poorly in predicting the intensive margins of contributions (see Table 4.8). None of the coefficients are significant. Pro-social motives do not seems to be determinant on the level of one's contribution.

Since the only explanatory variable correlated with the extensive margins is the cultural budget, our results suggest that the rational behind the decision on how much to contribute is related to consumption, not donation.

Table 4.7 – Average contribution for musical projects (OLS)

	(1) Average contribution (in log)	(2) Average contribution (in log)	(3) Average contribution (in log)	(4) Average contribution (in log)
Photo	-.1445			-.1199
	(.1261)			(.1277)
Personal link (Facebook or Twitter)		-.0168		-.0576
		(.1517)		(.1654)
Full name			-.1682	-.1605
			(.1398)	(.1537)
Age	-.0222	-.0201	-.0217	-.0258
	(.0183)	(.0181)	(.0186)	(.0195)
Age^2	.0003	.0003	.0003	.0003
	(.0002)	(.0002)	(.0002)	(.0002)
Female	-.0658	-.0819	-.0708	-.0606
	(.1275)	(.1261)	(.1243)	(.1288)
Registration day	.0001	.0001	.0001	.0001
	(.0002)	(.0002)	(.0002)	(.0002)
GDP/capita city user	-.1488	-.1490	-.1331	-.1360
	(.1404)	(.1351)	(.1338)	(.1404)
Degree level (ref: high school)				
Degree level=1	-.1306	-.1155	-.1319	-.1467
	(.2363)	(.2361)	(.2382)	(.2419)
Master	-.2141	-.2397	-.2489	-.2254
	(.1682)	(.1686)	(.1753)	(.1758)
Ph.D.	-.8905***	-.8347***	-.8790***	-.9321***
	(.2762)	(.2649)	(.2740)	(.2925)
Creator	-.1214	-.1052	-.1168	-.0848
	(.1705)	(.2044)	(.1673)	(.2010)
F&F	.0688	.0776	.0774	.0705
	(.1527)	(.1523)	(.1515)	(.1527)
Average project goal (in log)	.1817**	.1868**	.1859**	.1823**
	(.0889)	(.0891)	(.0898)	(.0909)
Cultural budget (in log)	.1672**	.1623**	.1623**	.1675**
	(.0692)	(.0697)	(.0679)	(.0685)
Constant	2.1349*	2.0211	2.1327*	2.2868*
	(1.2462)	(1.2389)	(1.2181)	(1.2242)
R2	.1074	.0986	.1102	.1172
Observations	151	151	151	151

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Photo=1 if the contributor has a photo on Catarse, Personal link =1 if the contributor gives a personal link to Facebook or Twitter, Full Name=1 if the contributor uses her full name (first and last names), Female=1 if the contributor is female, Age is the individual's age and Age^2 is the square of Age, Registration day equals the number of days that passed between Catarse's creation January the 17th of 2011, F&F =1 if the contributor declares she has already backed a project from a friends or a member of her family, Cultural Budget is the declared amount spent on cultural activities per month (in log), Average project goal is the average of the project goal a contributor backed

Table 4.8 – Average contribution for musical projects (OLS)

	(1) Average contribution (in log)	(2) Average contribution (in log)	(3) Average contribution (in log)	(4) Average contribution (in log)	(5) Average contribution (in log)	Average contribution (in log)
Cooperation - PG	.0019					.0020
	(.0028)					(.0030)
Cooperation - PG 2		.0011				-.0003
		(.0038)				(.0041)
Altruism - DG			-.0065			-.0053
			(.0043)			(.0057)
Altruism - DG 2				-.0052		-.0013
				(.0036)		(.0043)
Reciprocity - TG (Player B)					-.0010	.0004
					(.0031)	(.0033)
Photo	-.1347	-.1321	-.1002	-.1335	-.0980	-.1206
	(.1305)	(.1366)	(.1270)	(.1274)	(.1301)	(.1398)
Personal link (Facebook or Twitter)	-.0904	-.0876	-.0247	-.0574	-.0811	-.0798
	(.1688)	(.1660)	(.1697)	(.1738)	(.1683)	(.1811)
Full name	-.1488	-.1648	-.1605	-.1412	-.1641	-.1266
	(.1530)	(.1509)	(.1528)	(.1520)	(.1539)	(.1503)
Cultural budget (in log)	.1921***	.1899***	.1623**	.1579**	.1691**	.1962**
	(.0717)	(.0710)	(.0688)	(.0735)	(.0685)	(.0760)
Creator	.0132	.0220	-.0550	-.0486	-.0638	.0780
	(.2117)	(.2113)	(.2059)	(.2104)	(.2110)	(.2398)
F&F	.0581	.0442	.1019	.0576	.0588	.0586
	(.1460)	(.1473)	(.1594)	(.1681)	(.1660)	(.1663)
Average project goal (in log)	.1534*	.1495	.1956**	.1745*	.1762*	.1500
	(.0896)	(.0905)	(.0911)	(.0925)	(.0959)	(.0964)
Constant	2.3359**	2.2024*	2.3229*	2.6947**	2.4634*	2.9448**
	(1.1686)	(1.1477)	(1.2329)	(1.2736)	(1.2972)	(1.3117)
Control Variables	YES	YES	YES	YES	YES	YES
R2	.1466	.1434	.1294	.1402	.1201	
Observations	151	151	151	151	151	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Additional controls are Age, Female, Registration date, Degree level, GDP/capita (in log) and cultural budget (in log). Cooperation - PG is the proportion of the endowment transfered in the Public Goods game (in %), Cooperation - PG 2 is the proportion of the endowment transfered in the Public Goods game with threshold (in %), Altruism - DG 1 is the proportion of the endowment transfered in the Dictator game (in %), Altruism - DG 2 is the proportion of the endowment transfered in the second version of Dictator game (in %); Reciprocity - TG (Player B) is the average proportion of amount received that is returned by the subject in the Trust game strategic method.

5. Conclusion and discussion

In this article, we study the correlation between experimentally elicited pro-social preferences and actual behaviors on a crowdfunding platform. Our results are twofold. Regarding the extensive margins of contributions (the number of projects backed), contributors who exhibit a higher level of altruism and reciprocity back more musical projects while measures on cooperation do not predict the number of backed projects. Our results confirm that reciprocity plays an important role in music consumption, as Regner and Barria (2009) suggested. Contributors who are reciprocal may want to reward artists for the work they are involved in to maintain innovation in the music market. Regarding the intensive margins of contributions (the average amount of contributions), none of the experimental measures predict online contributions. The decision to back a project and the decision on how much to give seem to be based on two different rationales. Serial backers exhibit a higher degree of altruism and reciprocity. However, the level of contributions, as they are not correlated with pro-social preferences, has to be understood according to a logic of consumption: backers contribute more either because they want to reach rewards of higher value or because they want to ensure the success of a campaign, in order to consume the good afterwards. Practical implications of this results can be inferred. First, it is possible that offering rewards of higher values mitigates altruistic motive to contribute. In other words, project holders may benefit from lowering the value of rewards in order to foster "warm-glow". With this in mind, further investigation should be done on understanding how to optimize the menu of rewards. Secondly, as the intensive margins are correlated with the pro-social preferences of backers, crowdfunding platform can use this information as a signal for users segmentation in order, for instance, to target marketing campaigns.

Our results also show that altruism and reciprocity yield similar results. However, reciprocity is more robust to econometric specification. The similarity between results

comes from the fact that, in the the Trust game, the *trustee* is in a position of a dictator. Player B can always choose not to transfer anything to the *trustor* without being punished for her "betrayal". Likewise in the Dictator game, Player A can decide to keep all the money. The main difference is that, in the Trust game, Player B can choose to reward Player A for the amount she has sent, while in the Dictator game, money "falls from the sky", which may explain why reciprocity is a better predictor. A higher proportion returned means the participant is very willing to reward those who gave her a "gift" (the endowment transfered by the *trustor*) and one can consider that, in the case of crowdfunding, backers reward artists for the effort they provide. In this perspective, the use of the "gift exchange" game to predict crowdfunding behaviors could be considered.

A second contribution of this article concerns the promises of linking experimental data with real-world data. Our results contribute to the burgeoning body of literature related to the external validity of experimental measures. Note that if the Dictator games and the Trust games are correlated with field behaviors, it is not the case for the Public goods games. Two interpretations can be made: either crowdfunding is not related to the motives implied in the Public goods game, either the Public goods game has a low level of external validity. As cooperation in the Public goods game is related to altruism and reciprocity, we believe the latter might be more plausible as the Public goods game is cognitively difficult to understand (Andreoni, 1995), especially using an online experiment. Finally, an important remark to make is that the predictive power of experimental measures cannot be here understood as a direct causal effect. One can think that contributors discovered their pro-social preferences by engaging in crowdfunding and interacting within a community ruled by pro-social norms.

Our article faces several limitations. First, our sample is limited and additional online sessions could be considered. Second, we only study crowdfunding activity conditional on being a contributor. It would be thus interesting to compare our results

to a similar population that is not engaged in crowdfunding.

In this article, we focused on musical projects. Different categories of projects, even in cultural markets, may however involve different motives. For instance, a musical product may be easily accessible by those who did not contribute, enhancing the determinant role of pro-social motives. When the artistic good is more exclusive, as all performing arts, the picture can be totally different.

A. Appendices

A.1. Summary statistic of the corrected sample

Table 4.9 – Summary statistics on participants

Variable	**Definition**	**Mean ($n = 151$)**
Photo	Equal to 1 if the subject displays her photo on Catarse	0.49
Personal link to Facebook or Twitter	Equal to 1 if the subject displays a personal link to a social media profile	0.24
Full name	Equal to 1 if the subject uses her full name (first + last name)	0.65
Female	Equal to 1 if the subject is a female	0.32
Age	Declared age of the subject (in years)	29.60 (11)
Cultural budget	Amount of the cultural expenses per month (in R$)	198.13 (245)
Creator	Equal to 1 if the subject declared she have already been a project holder in a CFP	0.10
F&F	Equal to 1 if subject declared she have already back a project from a friend or a family member	0.61
Population (city)	Number of inhabitants of the subject's city (in millions)	4.80 (4.67)
GDP/capita	Gross Domestic Product per capita of the subject's city (in reals)	43,495 (41,416)
Registration date	Number of days elasped between Catarse's creation date and subject's registration date	767 (327)
Time_bp	Time to complete the Public Goods game (in seconds)	992 (9763)
Time_bp2	Time to complete the Public Good game with threshold (in seconds)	233 (334)
Time_d	Time to complete the Dictator (in seconds)	44 (42)
Time_d2	Time to complete the Dictator game 2 (in seconds)	60 (66)
Time_tgb	Time to complete the Trust game (Player B, in seconds)	293 (263)

Note: Standard deviations are in parenthesis. The corrected sample excludes participants who only backed their own projects.

Table 4.10 – Number of projects backed (negative binomial estimates) - all cultural categories

	(1) Nb. projects backed	(2) Nb. projects backed	(3) Nb. projects backed	(4) Nb. projects backed
Photo	.1306			.2291
	(.2682)			(.2388)
Personal link (Facebook or Twitter)		.4116*		.1250
		(.2389)		(.2411)
Full name			-.8167***	-.8211***
			(.2271)	(.2534)
Age	.0992**	.1106***	.0801**	.0880**
	(.0405)	(.0382)	(.0344)	(.0351)
Age^2	-.0008*	-.0010**	-.0006	-.0007*
	(.0005)	(.0004)	(.0004)	(.0004)
Female	.0339	.0462	.0736	.0461
	(.2182)	(.2046)	(.1903)	(.1905)
Registration day	-.0027***	-.0026***	-.0027***	-.0027***
	(.0004)	(.0004)	(.0003)	(.0003)
GDP/capita city user	-.0016**	-.0017**	-.0010	-.0008
	(.0008)	(.0008)	(.0008)	(.0008)
Degree level (ref: high school)				
Undergraduate	.8471	.8668	.6830	.7131
	(.5310)	(.5406)	(.4709)	(.4752)
Master	.6101***	.6292***	.5290**	.4848**
	(.2281)	(.2336)	(.2383)	(.2391)
Ph.D.	-.8527**	-.8638***	-1.3102***	-1.1976***
	(.3345)	(.3057)	(.4327)	(.4353)
Creator	-.3060	-.5875	-.3082	-.3861
	(.4110)	(.3600)	(.3444)	(.3473)
F&F	-.9035***	-.8992***	-.6636***	-.6283***
	(.2721)	(.2858)	(.2164)	(.2114)
Cultural budget (in R$)	.0001	.0002	.0004	.0003
	(.0004)	(.0004)	(.0004)	(.0004)
Constant	1.4809*	1.1205	2.2471***	1.9387**
	(.8937)	(.8987)	(.7559)	(.8727)
Pseudo R2	.1134	.1158	.1313	.1333
Log pseudolikelihood	-402.6170	-401.5454	-394.4779	-393.5858
Observations	151	151	151	151

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Photo=1 if the contributor has a photo on Catarse, Personal link =1 if the contributor gives a personal link to Facebook or Twitter, Full Name=1 if the contributor uses her full name (first and last names), Female=1 if the contributor is female, Registration day equals the number of days that passed between Catarse's creation January the 17th of 2011, F&F =1 if the contributor declares she has already backed a project from a friends or a member of her family, Cultural Budget is the declared amount spent on cultural activities per month

Table 4.11 – Number of projects backed (negative binomial estimates) - all cultural categories

	(1) Nb. projects backed	(2) Nb. projects backed	(3) Nb. projects backed	(4) Nb. projects backed	(5) Nb. projects backed	(6) Nb. projects backed
Cooperation - PG	.0066*					.0063
	(.0039)					(.0041)
Cooperation - PG 2		.0021				.0009
		(.0052)				(.0046)
Altruism - DG			.0092			-.0034
			(.0092)			(.0089)
Altruism - DG 2				.0092		.0052
				(.0067)		(.0056)
Reciprocity - TG (Player B)					.0209***	.0160***
					(.0043)	(.0044)
Photo	.2418	.2414	.0576	.0825	.0990	.1348
	(.2230)	(.2165)	(.1681)	(.1742)	(.2012)	(.1615)
Personal link (Facebook or Twitter)	.1823	.1826	.0995	.1107	.1861	.2359
	(.2159)	(.2283)	(.2269)	(.2379)	(.2185)	(.2005)
Full name	-.6955***	-.7432***	-.7931***	-.7848***	-.5983***	-.5607***
	(.2195)	(.2277)	(.2502)	(.2565)	(.2054)	(.1885)
Creator	-.6534**	-.7260**	-.4727	-.4449	-.6399**	-.8017***
	(.3294)	(.3391)	(.3206)	(.3275)	(.2523)	(.2512)
F&F	-.5376***	-.5484***	-.6350***	-.6073***	-.5441***	-.4992**
	(.2039)	(.2098)	(.2059)	(.2216)	(.2043)	(.1986)
Constant	.9905	1.9368**	1.7500*	1.3247	1.4479*	.0291
	(.7927)	(.8396)	(.9640)	(1.0566)	(.8486)	(.8967)
Control Variables	YES	YES		YES	YES	YES
Pseudo R2	.1439	.1436	.1391	.1397	.1558	.1604
Log pseudolikelihood	-388.7824	-388.9023	-390.9355	-390.6772	-383.3537	-381.2968
Observations	151	151	151	151	151	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Additional controls are Age, Female, Registration date, Degree level, GDP/capita and cultural budget. Cooperation - PG is the proportion of the endowment transfered in the Public Goods game (in %), Cooperation - PG 2 is the proportion of the endowment transfered in the Public Goods game with threshold (in %), Altruism - DG 1 is the proportion of the endowment transfered in the Dictator game (in %), Altruism - DG 2 is the proportion of the endowment transfered in the second version of Dictator game (in %); Reciprocity - TG (Player B) is the average proportion of amount received that is returned by the subject in the Trust game strategic method.

General Conclusion

The ambition of this thesis is to shed light on (i) the determinants of novelty consumed for a given menu of musical goods (Part I) (ii) the willingness to pay to increase the size of the menu of goods via crowdfunding (Part II). This general conclusion provides an overarching view of the contributions of this thesis and presents some perspectives of research.

The suitability of experimental economics in the field of cultural economics

The work presented in this thesis in based on two experimental approaches to study cultural economics. First, laboratory experiments are conducted in Chapters 1 and 2. Music presents particularities which makes it an ideal good for lab experiments: it provides natural incentives, it is universal and it is not subject to boredom. Thanks to its attributes, the experimenter has the opportunity to bring back the field into the lab. In other words, the out-lab environment can be almost perfectly replicated into the lab. The second methodology used in this thesis is the one of linking data, that consists in investigating the correlation between experimental measures and field behaviors (Chapters 3 and 4). Again, this methodology is ideally suited to study the music. More and more, consumption decisions are made through the Internet, which is convenient for two reasons. First, online field data are precise and generally yield a high level of granularity. Second, Internet is a very attractive tool to implement experiment as the experimenter has the possibility of reaching a specific population, as we did with crowdfunding platform users.

In this thesis, we only consider music. Experimental economics however opens new opportunities to study other cultural markets within the lab. In this vein, Ćwiakowski,

Giergiczny and Krawczyk (2016) use an incentivized choice experiment to investigate willingness to pay for a legal, rather than pirated, copy of full length movie. Lab experiments is however not suitable for all types of goods and the list of lab-compatible goods is limited.

An alternative to lab experiments or coupled data is to directly implement a field experiment, bringing the lab into the field. A burgeoning literature reports results from field experiments in the field of cultural economics. For example, Bakhshi and Throsby (2014), thanks to a quasi-natural experiment, study substitutability between live and broadcast performances at the Royal National Theatre of London. Lattarulo, Mariani and Razzolini (2016) study the effect of incentives on high school teens' museum attendance using a randomized field experiment.

The determinants of demand for new goods

A contribution of this thesis in the field of cultural economics concerns the understanding of demand for novelty based on two experiments (Part I). In an experiment where participants are given the choice to allocate their time between established artists and new entrants (Chapter 1), we confirm that there is something appealing about new goods. In Chapter 1, a non negligible share of demand is allocated to new goods, even though they are riskier than popular ones. Several remarks should be made, each of them leading to several perspectives of research. These results are first conditioned on the specificities of the experiment: subjects are equally exposed to popular and new songs. In reality, there is a higher probability that a given consumer has the opportunity to choose to listen (or not) to popular songs. Moreover, our subjects are exposed, at each period, to only two songs, which is rarely the case. Further research should thus be done by varying the proportion of novelty and popular songs as well as the size of the set of choices. Secondly, in this first experiment, we considered new goods as unknown goods. We however mentioned in the general introduction that novelty is

to be understood through the combined notions of exposure and differentiation. The latter is thus not taken into account in this experiment as we do not measure the degree to which new goods are different from known goods, in terms for instance of innovativeness.

Chapter 1 also confirms that demand appears more skewed when participants have information on others' opinion. In our setting, the "word-of-mouth" boosts the attractiveness of the most popular songs and thus worsens the natural handicap of new songs. We cannot, however, disentangle the effects of quality (established artists are of better quality) from the effect of popularity (popular artists are better rated because they are popular). An interesting extension of our experiment would thus be to compare the effect of experts' critic and consumers' critic in order to differentiate the two effects. Additionally, we do not consider the effect of selective "word-of-mouth". In reality, people may wish to communicate their enthusiasm about a given new artist, not on popular artists and all opinions are not revealed. The effect of selected word-of-mouth on diversity consumed could be investigated in-lab.

Part I finally highlights the role of price incentives and market structure on novelty consumed. As shown in Chapter 1, when a market is implemented, subjects tend to allocate more time to new artists. In other words, thanks to price flexibility, markets support cultural diversity and the exploration of novel artworks in comparison with the free access to goods that strengthens popularity and conformism. In Chapter 2, we conducted another experiment in which subjects are placed in a market where they can buy music of four musical genres and we estimate demand elasticities. This chapter actually suggests that diversity can be promoted when sellers have a certain level of market power. Indeed, we compare two market structures and find that, when sellers have market power, demand is more elastic and more diverse. On the contrary, when prices are lower, demand is less elastic and consumers seem to stick with the musical genre they are initially prefer. Note that, even though the notion of prices

seems somehow anachronistic at a time when the share of streaming consumption is steadily increasing, our result remains relevant as soon as it is extrapolated to other activities, as concerts attendance, or to other cultural markets for which there is a price differentiation.

A perspective of research is to estimate the effect of diversity on consumers' satisfaction and well-being. First results in Chapter 1 suggest that subject are more satisfied when choice are made freely (Benchmark treatment). Our measure of satisfaction is however based on self-declared ratings of the songs, which can be influenced by information on others' opinion. Other measures of satisfaction can thus be considered. In the case of music consumption, arousal can be measured using self assessment manikins or even measures of neurological activation associated with arousal and pleasure using functional magnetic resonance imaging (fMRI) [19]. However, one has to keep in mind that learning to like takes time. Even after a single experience of music, consumers may not perfectly discover their true taste about a new good because discovering one's true taste for music generally takes much longer than that (Armantier et al., 2015). In this perspective, short and long terms effect of consumption of novelty should be studied.

Understanding voluntary contributions to reward-based crowdfunding

Another contribution of this thesis lies on the understanding of contributors' willingness to pay on reward-based crowdfunding platforms. A first result suggests that before the financial goal of the project is secured, contributors who yields a higher level of risk aversion are willing to pay more (Chapter 3) [20]. This conclusion is somehow

19. See, for example, Berns et al. (2010).

20. Our result seem to be reminiscent of the link between overbidding in first-price auctions and risk aversion (see, for example, Cox, Smith and Walker (1988)).

counterintuitive. In a sequential public good game, Teyssier (2012) finds for instance that risk aversion is negatively correlated for first movers. We believe that we find the opposite because of the nature of reward-based crowdfunding which implies covering fixed costs (reaching the threshold) and receiving a private good (rewards). This assumption could thus be tested in-lab using a modified version of the Public goods game. In the same Chapter 3, we provide a formalization of a behavioral aspect in collective decision, namely the "illusion of control". The underlying assumption is that people wish to voluntary contribute as they believe their own contribution will have an induce others to contribute. This behavioral aspect can be applied to understand all situations where one's contribution is not pivotal, like in voting decisions.

This thesis, thanks to an exploratory study (see Chapter 4), provides empirical evidence that crowdfunding for musical projects is related to pro-social preferences, and especially reciprocal motives. More precisely, our results suggest that the decision to contribute falls within a donation logic while the decision on how much to contribute falls within a consumption logic. In other words, a contributor decides to opt in the funding process to reward artists who (may) provide a good at her taste. This results could be extrapolated to traditional consumption of music, as digital piracy enables buyers to listen to music freely. One can think that the decision to buy a CD is thus also related to reciprocal motives.

To sum up, Part II of this thesis highlights the combined role of reciprocity and risk. The former is based on the social contract between consumers and artists while the second leads to a potential *ex post* disappointment. In traditional cultural markets, when artists sign contracts with labels or majors, the incentive constraint (providing the efforts to maximize their chances of success) is generally satisfied since artists have interest in the signing future contracts. In the case of crowdfunding, this incentives are less obvious. The question of the sustainability of crowdfunding is at stake as repetitive *ex post* failure can mitigate the "crowd's" will to voluntary fund artistic projects.

Finally, while acknowledging that individuals are willing to contribute to increase the variety of the supply, this thesis do not question the level of *disparity*, that is differentiation, of crowdfunding projects. The common belief is that crowdfunding frees artists' creativity because it enable them to emancipate from *majors*, associated with profit-seeking behaviors. In the meantime, it is not clear that crowdfunding marketplaces escape from the stardom economy. In line with this possibility, Agrawal, Catalini and Goldfarb (2014) find that funding on the American platform Kickstarter is highly skewed: whereas 61% of all creators did not raise any money, 0.7% of them accounted for more than 73% of the funds raised between 2006 and 2009. Artists may have incentives to propose projects that are not too risky to attract a maximal expected demand.

Contributions to the experimental literature

Finally, this thesis contributes at a wider level to the literature in experimental economics. First, our lab-experiments are in line with experiments that bring the field into the lab, like real-choice experiments. This methodology presents two advantages: decisions are more field-relevant and data can be collected in a controlled environment. For instance, Chapter 2 takes profit of the possibility to control prices and quality to apply the Almost Ideal Demand System (Deaton and Muellbauer, 1980) on experimental data and provide results that are difficult to obtain with field data. We are able to estimate price and cross price elasticities, which are difficult to obtain using field data. This methodology is also used to confirm microeconomic predictions on the effect of market structure on demand elasticities.

Part II of this thesis contributes to the burgeoning stream of literature exploring the predictive power of experimental measures on field behaviors. Both our measures of risk aversion and pro-social preferences yield correlations with field behaviors, suggesting that they are good proxies of real preferences. They can thus be used to investigate

the foundations of a wide array of field behaviors, as it has been done to understanding contributions on Wikipedia for instance (Algan et al., 2013).

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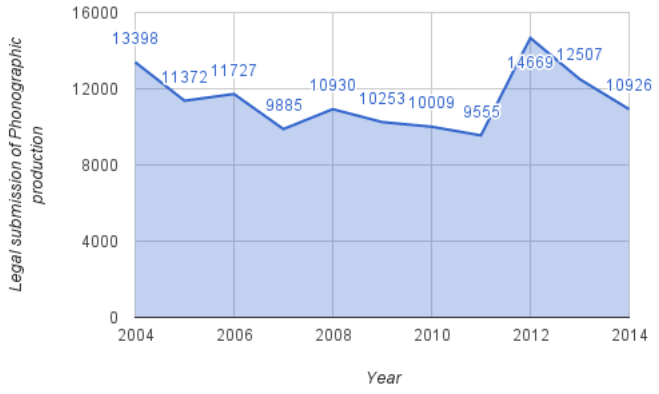
Résumé substantiel

Les marchés des biens culturels, tels que ceux de la musique, du cinéma, des arts de la scène ou des livres sont caractérisés par l'unicité de chaque bien et par l'abondance de l'offre. Cette offre abondante de biens uniques est constamment renouvelée. En France par exemple, c'est autour de 11400 créations phonographiques qui sont déposées chaque an au dépôt légal de la Bibliothèque nationale de France entre 2004 et 2011 (voir Figure 1). D'après les données Nielsen, le nombre de nouveautés musicales a par ailleurs triplé entre 2000 et 2008.

FIGURE 1 – Nombre de dépôts légaux de créations phonographiques en France



Objectifs de cette thèse

Cette thèse a pour objectif d'étudier la consommation et le financement de la nouveauté musicale en adoptant la méthodologie de l'économie expérimentale. Ce résumé décrit d'abord les particularités de la nouveauté sur les marchés culturels, ainsi que les enjeux de la nouveauté offerte et consommée puis la méthode experimentale appliquée à l'économie culturelle. Enfin, il présente l'organisation et les contributions de cette

thèse.

Contexte

Qu'est-ce que la nouveauté ?

La nouveauté artistique a cela de particulier qu'elle n'est pas essentiellement fonctionnelle. Dans la plupart des industries, telles que celles des voitures, des ordinateurs portables ou des téléphones portables, un nouveau bien ou une innovation renvoie à une amélioration technique permettant notamment d'améliorer la productivité d'un ménage. Ce type d'analyse s'applique mal à l'innovation artistique tant il est difficile d'envisager une amélioration fonctionnelle du bien [21].

Si l'on comprend bien ce que la nouveauté culturelle n'est pas, définir ce qu'elle est reste pourtant une tâche difficile. Parce que chaque bien est unique, il est potentiellement nouveau. Ainsi, un bien nouveau se définit d'abord par l'expérience qu'un consommateur en fait et la première fois que l'on écoute un album ne procure pas la même « stimulation » (en anglais « arousal ») que lorsqu'on l'écoute pour la centième fois. La seconde dimension de la nouveauté réside dans la potentielle surprise, positive ou négative, que le bien d'expérience transmet. Cette surprise réside dans le degré de différentiation entre ce bien et les autres biens. Le consommateur ne connaît pas, *ex ante*, son goût pour cette surprise.

Nouveauté et bien-être social des consommateurs

En termes de politiques publiques, la diversité culturelle est souvent présentée comme étant un élément essentiel à préserver. Accroître la variété des produits culturels permettrait améliorer le surplus des consommateurs (Brynjolfsson, Hu and Smith, 2003). La première explication de cette corrélation entre surplus des consommateurs

21. Cette distinction liée à la nature de l'innovation transparaît ainsi dans le cadre légal puisque les œuvres artistiques relèvent du domaine du droit d'auteur quand les innovations techniques relèvent des brevets.

et variété des produits tient d'abord au fait que les biens culturels sont des biens semi-durables (Bianchi, 2002). Les consommateurs sont attirés par de nouveaux biens parce la stimulation procurée par un bien donné diminue avec le nombre d'expositions. Ensuite, la présence de nouveaux biens sur le marché constitue aussi une valeur d'option pour les consommateurs. En écoutant un artiste qu'il n'a jamais écouté, l'agent économique découvre une œuvre qui modifie l'ordre de ses préférences et qui, potentiellement, sera préférée à ce qu'il a écouté jusque-là. Enfin, les consommateurs valorisent la diversité en soi parce qu'elle génère des externalités positives (Throsby, 2010).

Nouveauté offerte et nouveauté consommée

Le concept de diversité culturelle renvoie aux notions de diversité « offerte » et de diversité « consommée » (Benhamou and Peltier, 2007). La diversité « offerte » désigne l'ensemble des biens (albums, films, livres) qui sont proposés aux consommateurs. La diversité « consommée » est le sous-ensemble effectivement consommé. Cette distinction s'applique de façon similaire à la notion de nouveauté.

Les industries de biens culturels font face à une incertitude exacerbée : « nobody knows » (Caves, 2000). Les biens culturels sont des biens d'expérience (Nelson, 1970) et ce n'est qu'en consommant un tel bien que le consommateur découvre l'utilité que ce bien lui procure. Cette incertitude exacerbée peut être à l'origine d'une diversité consommée plus faible qu'à l'optimum social. D'autant plus que, du côté de l'offre, les producteurs de biens culturels font face à une demande imprédictible avant même d'engager les investissements importants de production, distribution et promotion.

La demande de nouveautés La distribution des ventes de biens culturels suit une forme asymétrique selon une loi de Pareto : 80% des revenus totaux sont réalisés par 20% de l'offre. Ce phénomène apparaît pour trois raisons principales : un différence de qualité des biens (ce sont les artistes les plus talentueux qui capturent la majorité de la demande), une préférence pour les biens populaires (les consommateurs préfèrent

les biens qui sont consommés par les autres) et un manque d'information (l'incertitude portant sur la qualité des biens pousse les consommateurs à se concentrer sur un nombre limité de biens populaires).

Le premier argument lié aux différences de qualité a d'abord avancé été par Rosen (1981) qui fait l'hypothèse que de petites différences de talents se traduisent par d'importantes différences de revenus. Selon l'auteur, ce mécanisme tient du fait que plusieurs performances de mauvaise qualité se substituent imparfaitement à une performance de haute qualité. Dans la version dynamique du modèle de Rosen (1981) développée par MacDonald (1988), l'auteur suggère deux périodes d'entrée des artistes sur le marché. Lors de la première période, deux types d'artistes offrent des performances musicales de bonne ou de mauvaise qualité. Lors de la seconde période, des nouveaux artistes entrent sur le marché et les consommateurs ne connaissent pas la qualité de leur performance. Ces nouveaux artistes font concurrence aux artistes sélectionnés lors de la première période dont la qualité des performances est connue. L'incertitude sur la qualité de leur bien étant levée, les artistes établis peuvent fixer un prix plus élevé que les nouveaux artistes.

Adler (1985) propose un deuxième argument permettant de rendre compte de l'asymétrie de la demande sur les marchés culturels. Selon l'auteur, il existe un nombre important d'artistes qui disposent du talent nécessaire pour devenir *superstar*. Mais l'économie du *starsystem* n'émerge que parce que les consommateurs ont intérêt à consommer les biens populaires. Son raisonnement repose sur l'hypothèse que l'appréciation d'un bien culturel dépend du « capital culturel » du consommateur (Stigler and Becker, 1977). Ce capital culturel peut être enrichi : (i) par l'exposition à l'art en soi (ii) et par la discussion avec d'autres consommateurs (iii) par la lecture d'articles portant sur l'art. D'après le modèle dynamique d'Adler (1985), chaque consommateur sélectionne initialement aléatoirement de nouveaux artistes. Ce n'est que par chance que certains artistes sont sélectionnés par un plus grand nombre de consommateurs

et deviennent, par la suite, populaires. Ce sont ces artistes populaires qui seront alors choisis par les autres consommateurs et deviendront des *superstars*.

La concentration de la demande s'explique enfin par le manque d'information auquel les consommateurs font face. Dans ce cadre, les agents fondent leurs décisions à partir du comportement des autres consommateurs, phénomène aboutissant à celui de « cascade informationnelle » (Bikhchandani, Hirshleifer and Welch, 1992*a*, 1998). Une cascade informationnelle émerge lorsqu'il est optimal, pour un consommateur, d'ignorer son information privée et de suivre le comportement des autres. Sous certaines conditions pourtant, les cascades informationnelles aboutissent au mauvais choix.

La production de nouveautés La production de nouveautés sur les marchés culturels est caractérisée par des coûts d'entrée élevés de deux natures. D'abord, la production même d'un prototype unique suppose des coûts de production fixes élevés. Ensuite, le succès du prototype est hautement imprédictible. Ce n'est qu'après avoir produit un album ou un film que les producteurs peuvent observer son succès. Les producteurs investissent alors dans des campagnes de promotion et de diffusion dans la perspective de maximiser le potentiel succès d'une œuvre.

Les industries culturelles sont caractérisées par un système d'innovation distribuée : c'est un grand nombre d'artistes qui proposent de nouvelles créations (paroles d'une chanson, manuscrit d'un livre, scénario d'un film). Face à cette offre initiale abondante, les producteurs qui sont prêts à engager les coûts de réalisation, distribution et promotion réalisent une sélection des projets les plus à même de rencontrer un public. Les industries culturelles s'organisent généralement en oligopole à frange de la façon suivante. L'oligopole central vise une demande large et limite les risques de non rentabilité en misant sur des « recettes » qui fonctionnent telles qu'un album réalisé par un chanteur connu et populaire. Ces entreprises engagent par ailleurs des dépenses de promotion importantes de ces artistes *superstars*. Les entreprises de la frange se concentrent, elles, sur des artistes de niche ou de nouveaux artistes en misant sur leur potentiel succès.

Ce sont ces entreprises qui prennent le rôle de « dénicheurs de nouveaux talents ».

Défaillances de marché Dans le cadre de la production de nouveautés artistiques, deux types de défaillances de marché apparaissent. La première défaillance de marché est due à l'incertitude portant sur la qualité des biens. Cette défaillance joue tant du côté de l'offre que du côté de la demande. Du fait de l'imprédictibilité de la demande et de coûts fixes très importants, certains artistes n'ont pas intérêt à entrer sur le marché, alors même que leur production pourrait rencontrer un succès. Du côté de la demande, les consommateurs peuvent passer à côté de biens qu'ils auraient consommé en situation d'information parfaite (Hendricks and Sorensen, 2009) parce que la nouveauté est risquée et parce qu'ils découvrent leurs préférences. La seconde défaillance de marché est relative au fait que le renouvellement permanent, la richesse et la diversité de l'offre artistique constituent des externalités positives car elles bénéficient à l'ensemble de la société. Ainsi, Throsby (2010) distingue trois caractéristiques des biens culturels justifiant la nature à la fois publique et privée de tels biens : les biens culturels ont une valeur d'existence (les individus sont prêt à payer pour que d'autres personnes puissent le faire également), une valeur d'option (les individus sont prêt à payer pour conserver la possibilité de profiter un jour de ce bien) et une valeur de legs (les individus sont prêt à payer pour que les générations futures puissent le consommer). Ainsi, la production de certains projets artistiques ne peuvent être financés que par des donations ou par l'intervention de l'État. Même si de tels projets n'ont pas de retombées économiques directes, ils peuvent toutefois bénéficier à l'ensemble de la société.

Politiques publiques et soutien aux nouveaux artistes

L'État peut intervenir selon deux modalités principales afin d'enrichir la diversité offerte et consommée. Le premier principe consiste à subventionner les artistes, soit au moyen d'aides automatiques (les artistes demandeurs qui remplissent un certain nombre de critères d'éligibilité peuvent en bénéficier), soit au moyen d'aides conditionnelles

(l'octroi des aides est déterminé par un comité de sélection). En subventionnant la production des nouveaux artistes, l'État permet à des artistes d'entrer sur le marché alors que les conditions de marché ne leur auraient pas été favorables.

Le second principe consiste à favoriser la diversité consommée en régulant la promotion des artistes nouveaux. Il s'agit par exemple de jouer sur la visibilité et l'accessibilité des nouveaux artistes afin de compenser leur handicap. Les quotas de diffusion de radio en France, initialement instaurés en 1996, contraint ainsi les radios françaises à diffuser 60% de production française, dont 20% de nouveaux artistes. Théoriquement, il serait également possible de subventionner la demande pour des nouveaux artistes.

Le financement participatif

Le financement participatif, ou *crowdfunding* en anglais, constitue nouvelle forme de financement des nouveaux artistes par les consommateurs. Selon la définition de Belleflamme, Lambert and Schwienbacher (2014*a*), ce type de financement consiste en :

> « un appel ouvert, majoritairement fait *via* internet, pour obtenir des ressources financières, soit sous forme de don, soit en échange du produit futur, d'autres formes de récompenses et/ou de droits de vote, dans le but de soutenir une initiative pour la réalisation de projets »

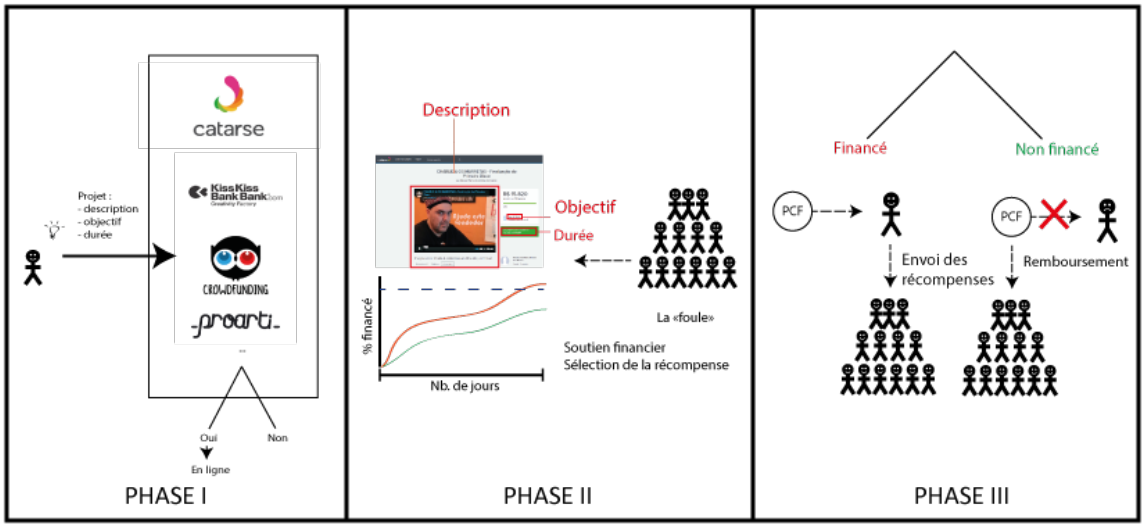
Le concept est simple : un artiste/entrepreneur/créateur souhaite produire l'une de ses créations (un album, un film ou un livre par exemple). Il soumet son projet sur une plateforme de *crowdfunding* telles que Ulule ou KissKissBankBank en France et fixe trois paramètres : un montant minimal à collecter, la durée de la collecte et une liste de contreparties correspondant à différents niveaux de contributions (voir Phase I de la Figure 2). Si le projet est sélectionné par la plateforme, la collecte en ligne commence et les contributeurs décident de soutenir ou non le projet en échange des récompenses. Ces récompenses peuvent être symboliques (une carte de remerciement) ou tangibles

(un préachat, un souvenir, un produit dérivé). À l'issue de la campagne, deux règles peuvent s'appliquer selon le fonctionnement de la plateforme :

— la règle du « tout-ou-rien » (« all-or-nothing ») : l'artiste ne récupère les fonds collectés pendant la campagne de financement que si le seuil initialement fixé est atteint. Dans le cas contraire, les contributeurs sont remboursés (voir Figure 2)

— la règle du « gardez-tout » (« keep-it-all ») : l'artiste récupère les fonds collectés pendant la campagne de financement, que l'objectif financier soit atteint ou pas.

FIGURE 2 – Le financement participatif avec récompenses - Règle du "Tout-ou-rien"



Lecture : Lors de la Phase I, un artiste/entrepreneur/créateur soumet un projet à une plateforme de *crowdfunding* (PCF). Cette dernière sélectionne ou non le projet. Lors de la Phase II, le projet est en ligne : c'est le déroulement de la campagne. Pendant un laps de temps prédéterminé (généralement entre 30 et 60 jours), les contributeurs (la foule) peuvent apporter leur soutien financier au projet (en échange ou non de récompenses). Lors de la Phase III, une fois la campagne terminée, l'artiste initie l'envoi des récompenses si l'objectif financier est atteint, sinon les contributeurs sont remboursés.

Le financement participatif de projets artistiques est généralement présenté comme une solution à la baisse du soutien public, notamment parce que ce type de projets est particulièrement populaire. Ainsi, les catégories culturelles telles que la musique, les films, les bandes dessinées, les livres ou les arts de la scène représentent une part importante des projets sur les plateformes de *crowdfunding* avec récompenses (voir Table 1).

TABLE 1 – Part des projets artistiques dans le *crowdfunding* avec récompenses

Platforme	Pays	Part de projets artistiques	Part de projets artistiques (parmi les succès)	Nb. total de projets
Ulule	France	47.9%	59.0%	23329
KissKissBankBank	France	62.3%	67.1%	22613
Kickstarter	Etats-Unis	66.4%	45.2%	323501

Note : Les statistiques présentées dans ce tableau sont issues des données publiquement diffusées sur les plateformes (données actualisées en novembre 2016). Les catégories sélectionnées sont : Musique, Films, Bandes-dessinées, Art de la scène (théâtre et danse), Edition et Mode.

À l'heure où les industries culturelles sont confrontées au piratage des contenus numérisés, le financement participatif apparaît presque comme un paradoxe. Certains consommateurs, qui peuvent profiter des contenus à des prix compétitifs (voire gratuitement grâce au piratage), sont prêts à financer des projets culturels risqués, car à un stade de production très préliminaire. En effet, soutenir un projet de financement participatif n'assure pas au contributeur d'obtenir ou de profiter du bien culturel ultérieurement. Les contributeurs font en effet face à deux types de risques (Bernard and Gazel, 2017). D'abord, il existe un risque que la coordination échoue et que le projet ne reçoive pas les fonds nécessaires pour produire le bien. Ensuite, le *crowdfunding* consiste à soutenir des projets à l'état très préliminaire de production. Il existe ainsi un risque de non livraison du produit dû, d'une part aux capacités du créateur à mener à bien le projet et d'autre part, à l'incertitude portant sur la qualité du produit. Mais alors, pourquoi certains consommateurs sont-ils prêts à mettre « la main à la poche

» et à porter le risque de l'échec d'une campagne ? Et pourquoi souhaitent-t-ils payer des œuvres culturelles alors même qu'ils pourraient en profiter à un prix très faible sur des plateformes de *streaming* par exemple ? En ce sens, le financement participatif peut être assimilé à un bien public : c'est la possibilité même que le bien soit sur le marché, sa valeur d'option, qui constitue le bien public. En d'autres termes, la foule participe volontairement afin d'assurer la provision de biens nouveaux. Le statut hybride entre donation et consommation suggère une double nature des motivations des contributeurs, entre logique de consommation et logique de don.

La méthode expérimentale appliquée à l'étude des industries culturelles

Les expériences en laboratoire

Une expérience en économie consiste à créer un environnement contrôlé, généralement dans un laboratoire, afin de reproduire une situation permettant de tester une théorie économique. La possibilité de contrôler l'environnement permet à l'expérimentateur, sous réserve de respecter quelques règles, d'évaluer des effets causaux difficilement mesurables avec des données de terrains. Croson (2005) décrit trois principes nécessaires à la validité d'une expérience : les participants doivent être incités, généralement monétairement, l'expérience doit être décontextualisée et l'expérimentateur ne doit pas mentir aux participants. En outre, l'expérience doit être conçue de telle sorte que l'expérimentateur puisse réellement tester l'hypothèse théorique qu'il souhaite vérifier : c'est ce que l'on appelle la « validité interne » d'une expérience. Par exemple, lors de l'étude de l'effet d'un traitement (d'une modification de l'environnement), la validité interne garantit le fait que toute variation statistique observée est bien causée par le traitement étudié.

La musique est peu utilisée en économie expérimentale malgré les nombreux avantages qu'elle présente. En effet, il s'agit d'un bien :

— qui implique de véritables incitations : un consommateur a intérêt à maximiser sa satisfaction espérée en écoutant les musiques qu'il préfère étant donné ses contraintes de budget et de temps ;

— qui respecte le principe de non-satiété : les biens musicaux sont différenciés, limitant ainsi les risques d'ennui ;

— pour lequel le goût pour la musique est universel (Peretz, 2006).

Par ailleurs, les conditions de consommation de la musique en laboratoire sont similaires à celles hors du laboratoire. Ainsi, les décisions prises au cours de l'expérience sont naturelles (les participants sont habitués à faire ce type de choix) et la validité externe de cette dernière est renforcée.

Coupler des données expérimentales à des données de terrain

L'article de Karlan (2005) a initié une littérature en économie expérimentale qui consiste à croiser données de laboratoire et données hors laboratoire. Il y étudie dans quelle mesure les comportements observés dans le jeu de la confiance prédisent les décisions financières réelles des individus. La principale hypothèse de cette littérature est celle de la validité externe des mesures, autrement dit de la généralisation d'une inférence causale d'un contexte à un autre. Si certains travaux ne trouvent peu ou pas de relation entre les données expérimentales et les données réelles (Galizzi, Navarro-Martínez et al., 2015, Stoop, Noussair and van Soest, 2009), de nombreux articles constatent à l'inverse une corrélation (Karlan, 2005, Laury and Taylor, 2008, Benz and Meier, 2008, Barr and Serneels, 2009, Carpenter and Seki, 2011, Fehr and Leibbrandt, 2011, Potters and Stoop, 2016). D'après Levitt and List (2007), la validité externe des mesures expérimentales est limitée par :

— l'effet de demande due à la présence de l'expérimentateur qui est à l'origine d'une modification du comportement de l'agent, ce dernier prenant en compte les indices quant aux décisions appropriées ou attendues (Zizzo, 2010) ;

— les limites de l'anonymat, particulièrement entre les participants et l'expérimentateur, qui orientent particulièrement les comportements dits « prosociaux » [22] ;

— le biais de sélection qui suggère que les participants aux expériences sont aussi des individus plus coopératifs.

Selon Camerer (2015), aucune preuve n'est pourtant faite que les expériences visant à refléter un environnement particulier manquent de validité externe. La validité externe d'une expérience repose sur le fait que l'environnement de décision construit en laboratoire ne mime pas parfaitement celui du terrain et que la population n'est pas similaire. La solution la plus intuitive afin de s'assurer que la population en laboratoire soit similaire à celle étudiée hors du laboratoire est simplement de recruter les participants parmi la population étudiée sur le terrain. Toutefois, cette solution est limitée par la contrainte géographique du laboratoire. Dans cette perspective, la possibilité de mener des expériences en ligne constitue une solution idéale.

Plan de la thèse

La demande de nouveautés musicales : approches expérimentales en laboratoire

Une première partie de cette thèse, composée de deux chapitres, vise à étudier la consommation de biens musicaux au moyen d'expériences en laboratoire.

Le Chapitre 1 est co-écrit avec Noémi Berlin et Guillaume Fürst. Dans ce chapitre, nous étudions ainsi l'effet de l'information et du prix sur la concentration de la demande lorsque les consommateurs peuvent choisir entre des artistes établis sur le marché et des nouveaux entrants. Il s'agit d'une expérience d'allocation du temps d'écoute musicale. Sur un marché expérimental recréé en laboratoire, nous offrons à 110 lycéens de la région parisienne deux chansons de même style : des « tubes » issus du classement

22. Au sens large, un comportement est dit prosocial dès lors que l'agent intègre son l'utilité la situation d'un autre agent.

des meilleures ventes en France et des nouveautés issues du site Noomiz qui accueille de nouveaux artistes. Trois traitements sont envisagés. Un tiers des participants réalise leurs choix d'allocation du temps entre ces deux types d'oeuvres sans aucune information (le traitement « benchmark »). Un deuxième tiers des participants réalise leurs choix en connaissant la satisfaction moyenne que les participants du benckmark associent à chacun de ces titres (le traitement « bouche-à-oreille »). Pour le dernier tiers des participants, un marché est mis en place : pour chaque session, deux participants sont tirés au sort aléatoirement, l'un prenant le rôle de vendeur de la catégorie des « tubes » et l'autre celui de vendeur de la catégorie des nouveautés. Les données utilisées dans ce chapitre ont cela d'original qu'elles rendent compte des réactions de la demande dans des conditions particulières de consommation, celles d'une exposition équitable à des biens populaires et à des biens nouveaux. Un premier résultat de ce chapitre montre ainsi que, dans ces conditions particulières, une part non négligeable de la demande se reporte sur des biens nouveaux, et donc plus risqués. Il semble donc qu'il existe bien un attrait pour la nouveauté et qu'en termes de politiques publiques, il soit possible de soutenir l'innovation en favorisant la visibilité des artistes. Ensuite, l'information concernant l'avis des autres consommateurs défavorise la diversité consommée et réduit l'écoute de nouveaux artistes. L'on ne peut toutefois discerner l'effet de la qualité (les artistes établis sont mieux notés car de meilleure qualité) de l'effet de la popularité (les artistes établis sont mieux notés car populaires). Enfin, le marché, par le biais du prix, lève le handicap des nouveaux entrants et favorise la diversité consommée. Ce résultat semble presque anachronique à l'heure où la consommation de musique sur les plateformes de *streaming* se généralise. Il reste pourtant pertinent dès lors qu'on l'extrapole à d'autres activités telles que la consommation de concerts ou d'autres biens culturels et justifie des politiques publiques de subventions de la consommation de nouveaux artistes.

Le Chapitre 2 est co-écrit avec Louis Lévy-Garboua, Laëtitia Placido et Claire

Owen. Il présente une méthodologie innovante permettant l'estimation de l'élasticité de la demande pour quatre genres musicaux, à savoir le Pop/Rock, le Classique, le Rap/RnB et le Blues/Jazz. L'expérience met en place un marché de la musique en laboratoire dans lequel chaque genre musical est vendu aux participants et ce, pendant 50 périodes. Les prix sont fixés par des vendeurs, aléatoirement assignés à ce rôle, si bien que le design expérimental permet une variation des prix. À partir des données générées, nous réalisons une estimation de systèmes complets de demande (Deaton and Muellbauer, 1980) pour chacun des genres musicaux. Les résultats sont comparables à de nombreux constats empiriques : les élasticités prix de la demande pour ces quatre genres musicaux sont comprises entre -0.5 et -1, la demande de musique classique étant la plus élastique. La méthodologie expérimentale utilisée dans ce chapitre permet par ailleurs d'estimer des élasticités prix croisées. Ainsi, d'après les résultats, certains genres musicaux apparaissent comme étant substituts, tels que le Pop/Rock et le Classique ou le Blues/Jazz et le Classique. Parallèlement, certains genres musicaux s'avèrent peu substituables, tels que le Rap/Rnb et le Pop/Rock. La méthodologie expérimentale permet aussi de comparer les élasticités estimées par sous populations (par genre, âge etc.) et par structure de marché (monopolistique ou compétitive). Nous appliquons enfin cette méthodologie à l'expérence du Chapitre 1. Les résultats montrent que les titres populaires sont des biens de luxe tandis que les titres nouveaux sont des biens de nécessité. Aussi constatons nous un certain degré de subtituabilité entre des deux types de biens.

Quand les consommateurs financent la production de nouveautés : une analyse comportementale du financement participatif

La deuxième partie de cette thèse s'intéresse aux comportements de contributeurs sur une plateforme de financement participatif. L'approche adoptée est celle de l'économie comportementale.

Le Chapitre 3 propose un modèle de décision de contribution au financement participatif de projets culturels. Le modèle repose sur l'hypothèse d'agent soumis à une illusion de contrôle : les contributeurs pensent que leur contribution individuelle entraînera la contribution des autres agents. L'illusion de contrôle permet ainsi d'expliquer la dynamique des contributions lors d'une campagne de financement participatif. Les individus les plus sujets à l'illusion de contrôle endossent le rôle des premiers contributeurs car ils pensent que leur contribution permet la réussite de la campagne. Le modèle suppose aussi que les contributeurs font face à deux types de risques : un risque d'échec de la coordination et un risque de non livraison. L'étude du rôle des préférences face au risque montre que lorsque le risque d'échec de la coordination disparaît, l'aversion au risque est corrélée négativement au niveau des contributions. Cependant, en début de campagne, cette corrélation est positive. Ce dernier résultat suggère que les agents plus averses au risque sont prêts à s'assurer contre l'échec de la campagne.

Le Chapitre 4 est co-écrit avec Marco Gazel. Il s'intéresse au rôle des préférences prosociales des agents dans leurs décisions de contribution. Les résultats suggèrent que l'altruisme et la réciprocité sont à l'origine de la décision de contribuer (les agents plus altruistes et ayant un degré de réciprocité plus élevé financent plus de projets). Toutefois, la décision concernant le montant de la contribution ne semble pas corrélée avec les préférences prosociales mais suivre au contraire une logique de consommation. Ce chapitre montre ainsi l'importance des préférences pro-sociales dans la participation des consommateurs au financement de nouveaux artistes.

Contributions de la thèse et perspectives de recherche

Contributions de la thèse La première contribution de cette thèse est de montrer la pertinence du recours à l'économie expérimentale en économie de la culture. Le bien musical, qui présente de nombreux avantages dans son utilisation en laboratoire, nous a permis de confirmer ou enrichir la littérature en économie de la culture : le rôle de l'in-

formation sur la concentration de la demande, l'estimation inédite d'élasticités croisées entre genres musicaux etc. L'utilisation du couplage entre données expérimentales et de terrain nous a aussi permis de mettre en exergue le rôle fondamental de l'aversion au risque et des préférences sociales chez les contributeurs au financement participatif. La seconde contribution de cette thèse porte sur la méthode expérimentale même. La première partie de cette thèse présente des *designs* expérimentaux innovants, notamment par l'utilisation de la musique comme bien expérimental. La seconde partie présente des résultats qui contribuent à la littérature concernant la validité externe des mesures en laboratoire.

Perspectives de recherche La méthode expérimentale en laboratoire offre des perspectives de recherche dans l'analyse de la diversité consommée. Dans le cadre de la longue traîne par exemple, l'effet de la surabondance de choix sur la diversité consommée pourrait être étudié. Au-delà même de l'intérêt scientifique de telles démarches, les résultats pourraient orienter l'aide à la décision des politiques publiques. Le recours à l'économie expérimentale peut ainsi servir à la définition d'un système de quotas de diffusion permettant efficacement de promouvoir la diversité.

Dans le cadre du financement participatif, cette thèse met en évidence les rôles combinés de la réciprocité et du risque. La première suppose une logique de contrat social entre les consommateurs et les artistes, le second suppose une potentielle déception des contributeurs. Les consommateurs souhaitent soutenir les artistes fournissent des efforts, à condition toutefois qu'ils honorent leur contrat. La question de la pérennité du financement participatif se pose pourtant du fait de l'existence de l'aléa moral. Traditionnellement, lorsque de nouveaux artistes sont signés par des *labels*, ils n'ont pas intérêt à faire défaut (à ne pas produire un album, à ne pas se présenter à un concert) d'une part parce qu'ils sont liés juridiquement par un contrat mais aussi du fait de la perspective de contrats futurs. Or, dans le cas du financement participatif, ces contraintes d'incitations ne sont pas si évidentes. De futures recherches pourraient

ainsi être menées sur l'effet des déceptions des contributeurs sur leurs contributions.

Résumé

Par sa nature prototypique, chaque bien musical, et par extension chaque bien culturel, est un bien nouveau. Cette thèse a pour objectif d'étudier la consommation et le financement de la nouveauté musicale en adoptant deux approches de l'économie expérimentale : les expériences en laboratoire (première partie) et l'interprétation des données de terrain à partir de mesures expérimentales (seconde partie). La première partie explore les déterminants et les caractéristiques de la demande de nouveauté musicale. Dans un premier chapitre, nous étudions l'effet de l'information et du prix sur la concentration de la demande lorsque les consommateurs peuvent choisir entre des artistes établis sur le marché et des nouveaux entrants. Le second chapitre propose une estimation de systèmes complets de demande pour quatre genres musicaux. La seconde partie de cette thèse s'intéresse aux comportements de contributeurs sur une plateforme de financement participatif avec récompenses. Dans le troisième chapitre, nous proposons un modèle rendant compte de la décision de contribuer à un projet musical à partir du constat que les contributeurs font face à deux types de risque : le risque d'échec de la coordination et le risque de non livraison du produit. Dans ce contexte, l'illusion de contrôle permet d'expliquer la dynamique de contribution. L'étude du rôle des préférences face au risque montre que lorsque le risque d'échec de la coordination disparaît, l'aversion au risque est corrélée négativement au niveau des contributions. Cependant, en début de campagne, cette corrélation est positive. Le dernier chapitre se concentre sur la nature hybride du financement participatif. Les résultats suggèrent que la décision de contribution relève d'une logique de don tandis que le niveau de ces contributions relève d'une logique de consommation.

Abstract

By its prototypical nature, each musical good, and by extension each cultural good, is new. The aim of this thesis is two study the consumption and the funding of musical novelty, using two experimental approaches: the use of in-lab experiments to study demand (part I) and the use of experimental measures to understand field behaviors (part II). The first part explores the determinants and characteristics of demand for novelty. In the first chapter, we study the demand concentration when consumers can choose between established artists and new entrants. The second chapter presents estimations of an almost ideal demand system for four musical genres. The second part of this thesis focuses on contributors' behaviors of a reward-based crowdfunding platform. In a third chapter, we propose a model of decision to contribute to a musical project, based on the observation that contributors are exposed to two types of risk: a risk of coordination failure and a risk of non delivery. With this in mind, illusion of control allows to understand the timing of decision. A closer look at the role of risk preferences shows that risk aversion is negatively correlated with contributions when coordination is ensured. On the contrary, the correlation becomes positive at the beginning of a campaign. In the last chapter, we investigate the mixed nature of crowdfunding. Results suggest that the decision to contribute falls within a donation logic while the decision on how much to contribute falls within a consumption logic.

Mots-clés Cultural economics, Experimental economics, Music markets, Novelty, Crowdfunding, Almost ideal demand system, Risk aversion, Pro-social preferences