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**DETERMINANTS OF THE SHARING ECONOMY
EMERGANCE; AN EXPERIMENTAL STUDY**
Bachelor Thesis

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I hereby declare on my honors that I wrote this bachelor's thesis independently, and I used no other sources and aids than those indicated.

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Prague, 16.05.2016

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Abstract

This thesis explores the emergence of one of the fastest-growing economic phenomena of the modern day – the ‘sharing economy’. The main goal of this paper is to disentangle the two possible channels that may have lead to an increase in use of sharing economy-provided services; Peer-pressure and information-cascades. Moreover, I hypothesize that Peer-pressure and Information-cascades lead to an increase in use of the sharing economy-provided services. To test this hypothesis, an economic experiment has been conducted, in which participants were asked to take part in a lottery game that consists of 12 periods and choose between two options; one of which represented the standard economy, while the other represented the sharing economy. The results of the experiment allowed me to prove my hypothesis as they suggest that both, Peer-pressure and Information-cascades are in fact able to influence participant’s decisions into partaking in the sharing economy-provided services, and thus participate in the emergence of the sharing economy.

Keywords: Experiment, Sharing economy, Peer pressure, risk preference, Information cascades.

JEL classification: C91, C92, D83, O31

Table of Contents

Introduction:	1
1. History of sharing	3
2. The Sharing Economy:	4
3. Enablers of the sharing economy:	8
3.1 Web 2.0:	8
3.2 P2P	9
3.3 The five enablers of the sharing economy	9
4. The economics of the sharing economy:	14
4.1 Transaction costs and theory of extended order:	14
5. Literature review	16
5.1 Risk preference	16
5.2 Peer pressure	18
5.3 Information cascades	20
6. Empirical Part	21
6.1 The experiment	21
6.1.2 Methodology:	21
6.1.3 Design:	21
6.1.4 Participants:	22
6.1.5 Treatments:	22
6.1.6 Results:	23
Conclusion	42
References:	45
Appendix:	51
Appendix I	Experiment instructions for Treatment Baseline (1)..... 51
Appendix II	Experiment instructions for treatment Chat (2) 52
Appendix III	Experiment instructions for Treatment Review (3)..... 53
Appendix IV	Decision making screen in Treatment Baseline (1)..... 54
Appendix V	Decision making screen in Treatment Chat (2)..... 55
Appendix VI	Decision making screen in Treatment Review (3) 56

Introduction:

‘The sharing economy’ has become the buzzword of the current business world. It is defying all the rules of conducting business; not only that, it is also expanding the horizons of asset transfer in ways unprecedented in any other business model.

In a world driven by technological advancement, when the economic environment is unstable due to the never-ending cycle of supply and demand driving growth, online platforms took it upon themselves to change the way that people think, moving from traditional sole ownership of an asset or a service, to the new, rather un-orthodox approach of sharing the asset or service.

Allen Darcy, a Research Fellow at the Institution of Public Affairs, defines sharing economy as "a suite of emerging software platforms acting as an intermediary between private buyers and private sellers, allowing them to share their existing resources – hence, a ‘sharing’ economy" (Darcy, 2015). Moreover, Darcy explains in his article ‘The Sharing Economy’ that, starting from 2008, there have been approximately 25 million guests that chose to use one of Airbnb’s 800,000 listed properties rather than booking hotels, and that in Australia alone, the ride-sharing app "UBER" is signing over 1,100 ridesharing partners every month. Darcy also estimates that the current valuation of p2p models is over \$75 billion. (Darcy, 2015)

In response to the rise of sharing economy-oriented businesses and the threat they pose to major organizations in terms of fewer purchases made by consumers, many established businesses have decided to join the movement by either updating their business models or joining ventures with already existing sharing-oriented companies. Examples of major companies adopting the sharing system include; BMW drive now, the joint venture of Patagonia-eBay, Fed-ex tech connect, etc...

The theoretical part of my paper will focus on the sharing economy as a whole; what is it, the main enablers that contributed to its success, main reasons behind its emergence, and major companies operating within it. In addition, I will discuss the economics behind the sharing economy using the “Transaction costs theory” and the “Theory of extended order”. Furthermore, I will explain the three concepts used in my experiment, relying on previously published papers.

There are, however, pivotal factors that can be used to explain what drives people to participate in sharing economy-provided services. In this paper, I hypothesize that peer-pressure and information cascades (reviews) lead to an increase in use of sharing economy provided services. In order to test my hypotheses; in the empirical part of this paper, I will conduct an experiment that relies on the tools provided by the field of experimental economics, this experiment will aim to disentangle the possible channels that may lead to the increase in use of the sharing economy–provided services .

1. History of sharing

One of the greatest debates to occur in the history of Mankind was the question of "whether we are born cooperative and are corrupted by society later on [e.g. Jean-Jacques Rousseau] or whether we begin egocentric and are then educated by society (e.g. Thomas Hobbes)" (Grassmuck, 2012).

According to Michael Tomasello's empirical findings in his book, *Why We Cooperate* (2009), children from their first birthday show signs of cooperation and helpfulness, these signs come naturally to them, meaning that they do not learn it from adults. Furthermore, he states that later on throughout their lives this borderless cooperation becomes contemplated by influences such as how others see or judge them, and mutual interpersonal feelings. Moreover he adds that as they mature, they increasingly learn culture-orientated habits and norms that affect how they treat others. That being said, I think it is safe to say that human beings are born cooperative, and based on how/where we are raised and what we have faced in our lives, this built-in cooperativeness increases or decreases.

On the other hand, to depart from the psychological theories of Tomasello and head into more philosophical territory, there is such a thing as 'methodological individualism' and the assumption of a 'selfish human nature'. This can be traced back to what is referred to as the 'selfish school', of which the most eminent members were Thomas Hobbes and Bernard Mandeville, who even though they attended the same school had quite different interpretations of its curriculum: "For Hobbes, as he argued in his *Leviathan* (1651), selfish individuals in the absence of an entity which monopolizes power would be stuck in a war of all-against-all. In *Fable of the Bees* (1705), on the other hand, Mandeville argues that self-love can produce "socially desirable outcomes" (Rodriguez-Sickert, C., 2009).

From the prominent philosophers mentioned above comes an economist that took the teachings of the 'selfish school', and applied them to the world of economics. John Stuart Mill and his notion of a *homo economicus*, developed in his essay, "Essays on Some

Unsettled Questions on Political Economy” (1844). A *homo economicus*, or ‘an economic man’, is a self-serving rational economic actor, for whom neither sharing nor cooperating is necessary and who thrives on competing with others. This concept has paved the way for economists for the following half a century, and from it arose another influential essay by Garrett Hardin, “Tragedy of Commons” (1968), preaching that sharing things amongst ourselves will not work, “because freedom in a commons brings ruins to us all” (Hardin, 1968).

2. The Sharing Economy:

An all-encompassing definition of the sharing economy is rather difficult, the reason being that it has many names that were created by different scholars at different times. ‘The sharing economy’; ‘collaborative production’; ‘collaborative consumption’; ‘peer-to-peer’; ‘mesh’; ‘commons-based peer production’; and ‘access economy’ are some of the names given to the phenomenon. This makes it harder for us to reach a concrete definition (Darcy, Berg, 2014). For the sake of simplicity, I will refer to it as ‘sharing economy’ throughout my paper.

The table below defines each name separately:

Manifestation	Definition
Sharing economy	A socio-economic system for production, distribution, trade and consumption of goods and services by different people and organizations.
Peer-to-peer (P2P)	Focuses on the bypassing of intermediaries such as banks and hotels, and on exchange between individuals within civil society.
Collaborative consumption	Using the excess capacity of goods through access over ownership. These can either be Business-to-Consumer (B2C), Business-to-Business (B2B) or Peer-to-Peer (P2P).
Collaborative Production (Commons-Based Peer Production)	Coordination and utilization of a wide number of creative individuals participating in the common goal of a large project. This can involve collaboration to design, produce or distribute goods.
The 'Mesh'	Relationships between technology and allowing individuals to interact in new ways because of these technologies. This focuses on the interconnectedness of social networks (hence the term).

Figure 1

Source: (Darcy, Berg, 2014)

The phrase ‘collaborative consumption’ appeared for the very first time in an article written by Roy Algar on collective bargaining. In his article he writes, “What happens when pricing insights becomes accessible and consumers begin to share knowledge? Welcome to the world of collaborative consumption” (Algar, 2007). However, it was not until Rachael Bostman and Roo Rogers’ book *What’s Mine is Yours* (2010) that the term became popular. The concept gained even more recognition with Lisa Gansky’s book, *The Mesh: Why the Future of Business is Sharing* (2010).

The sharing economy, broadly speaking and according to Bostman and Rogers’ 2010 book (*What’s Mine is Yours*) can be divided into three systems: product service, redistribution markets, and collaborative lifestyle. Product service is a system that makes it possible for individuals to share one or more products that are already owned privately or by a business. Examples of such systems include Zipcar, a car sharing service, and Netflix, an online television and film viewing website.

Secondly, redistribution markets are systems in which re-ownership of a product is facilitated through P2P matching or online through social networks such as Facebook. Further examples of redistribution markets include eBay, an online auction platform, and Freecycle, an online gifting platform.

The third system, collaborative lifestyle, is a system that allows people with similar interests or needs to help each other with intangible assets such as time and money, or errand-running. Examples of collaborative lifestyle systems include SharedEarth.com, a website that connects gardeners to gardens, and Taskrabbit.com, a website for skill sharing.

The reason that sharing economy is gaining so much recognition is that customers are becoming increasingly empowered. Jeremiah Owyang, Christine Tran, and Chris Silva (2013), explain in their paper the three phases driven by new technologies, that account for the rise of the collaborative consumption era and the evolution of consumer power. The first phase is the brand experience era (web), where the internet allows information to be easily accessible, yet holding the ability to publish in the hands of media and corporations. They called this phase a "one-to-many" model because companies communicate with customers solely or mainly through their websites. The power stays with a few, yet many

are affected. The second phase is the customer experience era (social media), where new tools empower people to publish themselves. They called this phase a "many-to-many" model because customers could finally share their opinions and brands were required to listen. As opposed to the previous phase, both customers and companies share power. Lastly, the third phase, which is the collaborative economy era. In this phase customers are empowered to share both goods and services within each other, made possible due to social, mobile and payment systems. Companies lose their position as intermediaries because consumers can now buy directly from each other, rather than buy from companies; thus, power shifts to consumers (Owyang, Tran, Silva, 2013).



Figure 2

Source: "the collaborative economy", Altimeter group (June 2013)

3. Enablers of the sharing economy:

In order for the sharing economy to exist, there had to be facilitators to allow this phenomenon to emerge. In this section of my paper, I will introduce the concepts of WEB 2.0, and P2P. Furthermore I will discuss the five enablers that supported the sharing economy, as described in Michael J. Olson, and Samuel J. Kemp's paper "Sharing Economy; An In-Depth look At Its Evolution & Trajectory Across Industries" (March, 2015).

3.1 Web 2.0:

Most researchers in the world of sharing economy attribute its success to the existence of 'Web 2.0' because it allowed consumers a certain degree of involvement that didn't exist before. Web 2.0 "refers collectively to websites that allow users to contribute content and connect with each other" (Evan and Romano, 2011). This is actually the opposite of Web 1.0, which "primarily involved one-directional provision of information to consumers who did not interact or respond to the website, or to one another" (Belk, 2014). The term 'Web 2.0' was first introduced by Darcy DiNucci in her article "Fragmented Future" (1999). Nevertheless the term did not gain any recognition until its re-introduction five years later by Tim O'Reilly and Dale Dougherty at the Media Web 2.0 conference (2004).

With the introduction of Web 2.0, consumers began to be more empowered, and to have a say in shaping products and services, which in turn gives the customer a sense of

involvement, which is always great for a business. Furthermore, Web 2.0 upgraded the relationship between customers and businesses, allowing customers to rate, comment, or recommend products to others. Additionally from a business's point of view, Web 2.0 made it easier for companies to understand market demand and to become more in touch with their customers. For example, by reading customer's complaints, businesses get to know how they can improve certain products. An example of a business that would not have existed if it was not for Web 2.0 is Yelp; a website that thrives on the mere fact that numerous people both rate and comment on their experience with businesses (Gansky, 2010).

3.2 P2P

Much like Web 2.0, the concept of a peer-to-peer (P2P) marketplace model is one of the pillars on which the sharing economy is built. Some of the pioneers of P2P sharing include Napster, a program that allows total strangers to share music files and movies amongst each other, as well as eBay, Wikipedia, and YouTube. Having said that I cannot fail to mention the forefathers of sharing economy; companies like Couchsurfing.com, a website that connects travelers seeking free accommodation to hosts, and Carpooling.com, a ridesharing company. The aim of these companies is to allow people access to certain goods without having to own them naturally, reducing costs and the need for externalities associated with it.

3.3 The five enablers of the sharing economy

Michael J. Olson and Samuel J. Kemp (2015) have mentioned that there were five main enablers that made the sharing economy possible, as follows:

Enabler #1: Economic and community incentives

The authors believe that the sharing economy gained much of its current popularity following the events of the Great Depression. Spending decreased as customers began to scrimp on their expenses; the result was an increasing number of sharing economy startups subsequent to the worsening economy.

The following figure shows the relation between personal consumption expenditure (PCE) and the foundation of major startups. The figure indicates that the fall in personal consumption leads to an increase in sharing startups.

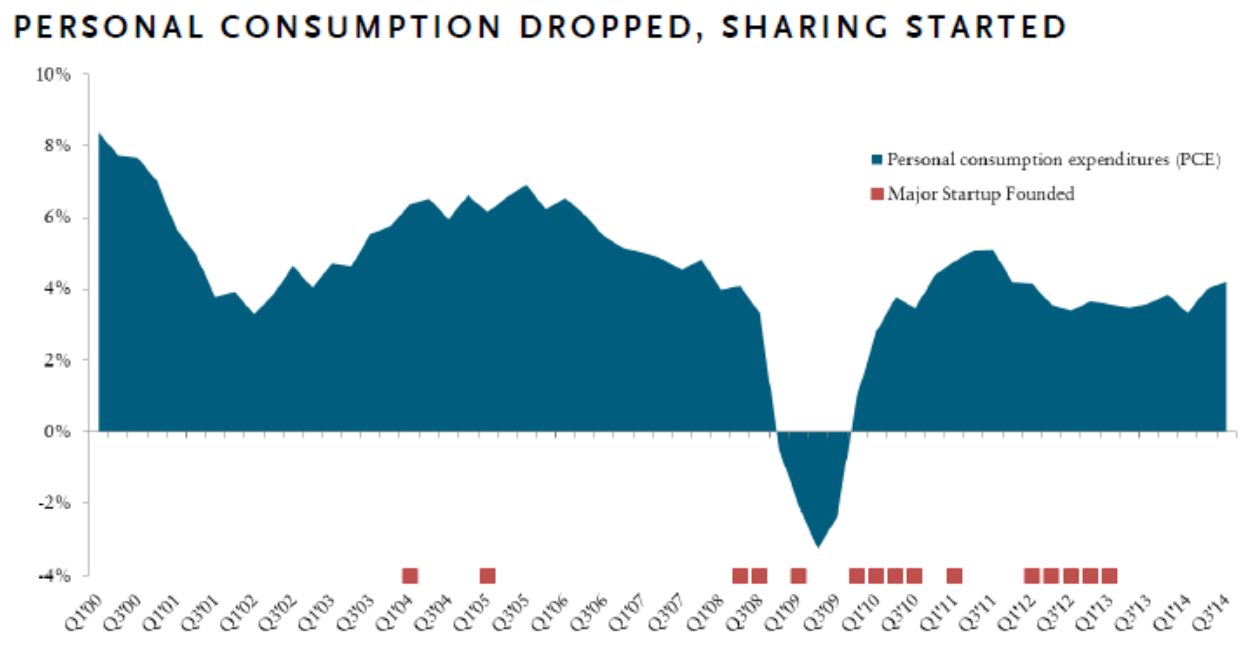


Figure 3

Source: (J. Olson & J. Kemp, 2015)

Furthermore, a sense of community plays a major role in the sharing economy services that is difficult to find elsewhere. Airbnb, for example, provides travelers with a chance that no other hotel can offer; the possibility to stay within a local community and experience life as a local, not just a tourist. Not only that, but Airbnb is, on average, cheaper than hotels.

Enabler #2: Forerunners of sharing and consumer trust

Nowadays the internet is a place where users actively trust one another to a degree that did not exist before. This development of the internet-sharing mentality can be traced to five categories:

- 1) File sharing: one of the first expressions of internet sharing, and the introducer of access over ownership. File sharing is like an online library assembled by users, in the form of peer-to-peer sharing. An example of file sharing would be (even though usually illegal) torrent files.
- 2) Knowledge sharing: much like file sharing, except instead of actual files, users share their knowledge for no expected compensation. Examples of knowledge sharing include: Wikipedia, Ask.com, and IMDB. Knowledge sharing is one of the major players in the sharing economy, since it provides users with reviews and the feedback of other users.
- 3) P2P Asset Sales: the ability of users to buy/sell items over the internet. This concept is lead by companies such as eBay, Amazon, and Craigslist. Furthermore the introduction of the sharing economy allowed users not only to buy or sell unneeded assets, but also under-utilized skill sets such as plumbing, woodworking, and even the assembly of IKEA furniture. Key companies operating in this field include TaskRabbit.
- 4) Homemade entertainment: websites that allow users to share content in the hope of receiving publicity. Pioneers of this industry include YouTube, 9GAG, and BuzzFeed. Those websites contributed to the reinforcement of the sharing nature of the internet, since the majority of them were not expecting remuneration.
- 5) Social Media: as one of the most important contributors to the sharing economy, social media contributed to the elimination of anonymity. Not only that; social media also created a trusted space for people to share their opinions, ideas, and feedback which in turn had a direct impact on the sharing economy. Nowadays many companies operating within the sharing economy spectrum employ social integration as a way to support their users.

Enabler #3: Holistic rating systems

Reviews written by users have been paving a way for trust among users for quite some time, creating transparency and easing decision-making for future users. Furthermore, reviews are able to make or break a site, contributing a great deal to their credibility. Myles Anderson, the founder of BrighLocal.com wrote that “88% Of Consumers Trust Online

Reviews As Much As Personal Recommendations” (Anderson, 2014). With the emergence of the sharing economy, the importance of the rating systems increased dramatically, and users now use those reviews to make far more important decisions, such as sharing a ride with a complete stranger (Uber), staying in strangers’ houses (Airbnb), or even allowing complete strangers to take care of their pets. Naturally when the stakes are high, rating systems become important.

Enabler #4: Payment infrastructure reducing risk

With e-commerce becoming more accepted, users are starting to see online payments as less intimidating, and more as a energy-saving technology. That consumers are more comfortable with making online payments can be credited to payment platforms such as PayPal, BrainTree, and Stripe. The sharing economy has taken advantage of this pre-existing trust and made it work in its favor: payment platforms have reduced the risks of online payments for both sellers and buyers, meaning that online payments are the least of consumers’ concerns when sharing.

Enabler #4: Mobile as a new point of sale

As mobile technology became the easiest means of consumer engagement, it also allowed for the existence of new services and points of sale. Uber, for example, would have never reached its vast popularity if not for its mobile application. Mobile has created a space for the sharing economy in many ways, from ridesharing and home sharing to meal sharing and so on. Moreover, a large number of upcoming sharing economy companies will be mobile-only; based exclusively on mobile applications.

Mobiles also work to the advantage of the sharing economy in that the younger generation – the same generation that is already more willing to participate in the sharing economy’s services – is also predominantly connected to mobiles. The graph below shows us that in 2013 the number of Americans that owned smartphones between the ages of 18-24 was approximately 75%, rising between the ages of 25-34 to approximately 81%; an all-time high in comparison with previous years. It is expected that this dependency on mobile phones will revolutionize the way producers interact with consumers.

MOBILE PENETRATION GROWING QUICKLY ACROSS AGE GROUPS

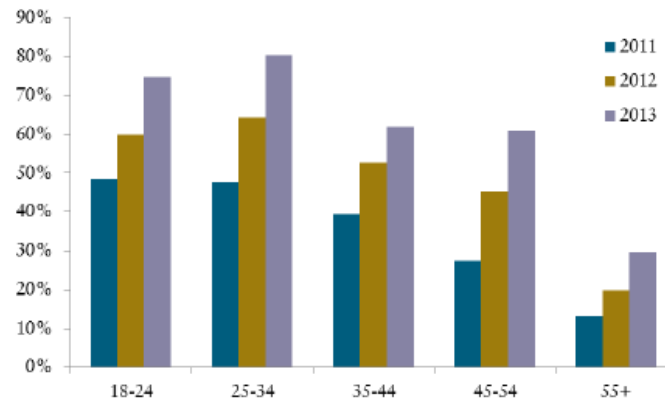


Figure 4

Source: (J. Olson & J. Kemp, 2015)

It is expected that as the younger and more mobile-oriented generation (between 18-34) enter their heavy spending and traveling years (35-64), there will be an increase in the use of sharing economy oriented businesses.

The pie chart below shows consumer expenditure divided into age groups:

CONSUMER EXPENDITURES, BY AGE GROUP SHARE

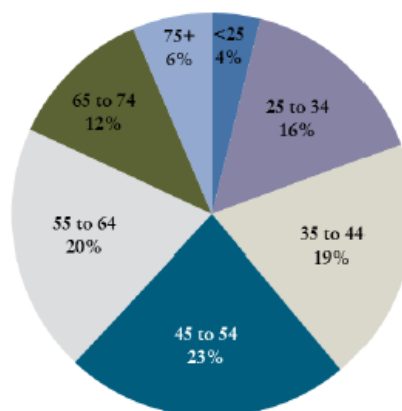


Figure 5

Source: (J. Olson & J. Kemp, 2015)

4. The economics of the sharing economy:

4.1 Transaction costs and theory of extended order:

“We are not facing an economic problem of allocation of resources; instead, we face the ‘problem of utilization of knowledge not given to anyone in its totality’” (Hayek, 1945).

Ronald Coase first introduced the concept of transaction cost in his book ‘*The Problem With Social Cost*’, (1960). Coase defines transaction costs as the costs associated with conducting a market exchange, furthermore he explains that, “In order to carry out a market transaction it is necessary to discover who it is that one wishes to deal with, to inform people that one wishes to deal and on what terms, to conduct negotiations leading up to a bargain, to draw up a contract, to undertake the inspection needed to make sure that the terms of the contract are being observed, and so on.” Transaction costs can be divided into three main categories: search and information costs, bargaining and decision costs, and policing and enforcement costs (Dahlman, C.J, 1979).

Technological advancement has indeed decreased the transaction costs associated with exchange; they have done so by making scattered information both affordable and ubiquitous. Add to that cutting-edge software platform technology, such as those offered by the sharing economy, and we get a far more organized economic exchange (Darcy, Berg, 2014).

Moreover, the decrease of transaction costs, according to Friedrich Hayek’s notion of the ‘extended order of the market’, results in the expansion of trade from a local, to a national, to an international level. According to Hayek, transaction costs have decreased in light of the development of “a great framework of institutions and traditions - economic, legal, and moral - into which we fit ourselves by obeying certain rules of conduct that we never made,

and which we have never understood in the sense in which we understand how the things that we manufacture function” (Hayek, 1988).

Furthermore, those institutions “constitute an information-gathering process, able to call up, and to put to use, widely dispersed information that no central planning agency, let alone any individual, could know as a whole, possess or control” (Hayek, 1988). Hayek argues that a great example of those institutions is the price mechanism, as he states: “I am convinced that if it were the result of deliberate human design ... this mechanism would have been acclaimed as one of the greatest triumphs of the human mind” (Hayek 194). Moreover, he argues that “the price system is just one of those formations which man has learned to use (though he is still very far from having learned to make the best use of it) after he had stumbled upon it without understanding it.”

Both the sharing economy and the price mechanism are similar in the way of how they emerged; both have spontaneously emerged in the shape of institutions with a common goal of arranging knowledge that is not known in full for everyone. Platforms such as Uber are expanding the taxi market in a rather unorthodox way: “It is in this way that the sharing economy is a market; an emergent ‘new, super-individual, spontaneous pattern’ facilitating the exchange of resources.” (Darcy, Berg, 2014)

5. Literature review

5.1 Risk preference

Risks preferences are a very important factor in the decision-making process. Risk preferences are the amount of risks people are willing or able to take. There are three types of attitudes towards risk, which can be explained using a game of fair gamble¹:

- **Risk-averse**, if faced with a fair gamble, refuses to partake or chooses only the sure option.
- **Risk-neutral**, if faced with a fair gamble, is indifferent to any alternatives yielding the same expected value.
- **Risk-seeking**, if faced with a fair gamble, chooses the less certain (more risky) option with a certain expected value to a more certain (less risky) option with the same expected value – hence ‘risk-loving’.

One of the most prominent theories that have been used in explaining the decision-making process under uncertainty and risk is ‘Utility Maximization Theory. It dates back to the 18th century when Daniel Bernoulli used it in an attempt to explain his famous ‘St. Petersburg paradox’ (1738). Advocates of the utility maximization theory include Freidman and Savages, who argue that: “choices among riskless alternatives are explained in terms of utility: individuals are supposed to choose as they would if they attribute some common quantitative characteristic-designated utility-to various goods and then select the combination of goods that yielded the largest total amount of this common characteristic”

¹ A fair gamble is a gamble in which the expected monetary gain is equal to zero

(1948). Another advocate of the utility maximization theory of explaining uncertainty and risk is Leonard J. Savage, with his book *The Foundations of Statistics* (1954). Savage “advanced a theory of decision making under uncertainty and used that theory to define choice-based subjective probabilities. He intended these probabilities to express the decision maker’s beliefs, thereby furnishing Bayesian statistics with its behavioral foundations” (Karni, 2005). He also introduced the theory of ‘subjective expected utility’. The utility maximization theory has faced its fair share of criticism, coming as a result of the theory of diminishing marginal utility (Friedman, Savage, 1948).

Another theory that could be seen as an alternative to the expected utility theory is the ‘prospect theory’. Daniel Kahneman and Amos Tversky introduced this in their paper “Prospect Theory: An Analysis of Decision under Risk” (1979). In their paper, they have criticized the expected utility theory and presented a number of choice problems where preferences violate the expected utility axioms, including the ‘certainty effect’, and the ‘isolation effect’. They argued that the “utility theory, as it is commonly interpreted and applied, is not an adequate descriptive model”.

Risk preferences can be used to understand why consumer preferences lean towards the sharing economy. In a situation where consumers are faced with the decision of whether to use a standard service or a sharing economy provided service; for example hailing a taxi or ordering an Uber; a risk-averse consumer will most probably avoid ordering an Uber, and will go for the safer and surer option of hailing a taxi. On the other hand both risk-neutral and risk-averse consumers are likely to go for the second option of ordering an Uber ride. The former would do so due to the fact that it would yield him a higher expected value (cheaper), while the latter would do it due to the mere fact that it is the riskier option.

5.2 Peer pressure

Another factor in the decision-making process is peer pressure. Put simply, peer pressure refers to how the actions of individuals can be affected by the behavior of their peers.

Peer pressure may be defined in many different ways, one of which is the “social interaction effect.” According to Armin Falk, Urs Fischbacher, and Simon Gächter’s paper “Living in Two Neighborhoods – Social interaction Effects in the Lab” (2009), the social interaction effect occurs “if an individual changes his or her behavior as a function of his or her respective group-members’ behavior”.

Considerations of the effect of peer quality and peer behavior of student outcomes have been present for a long time, including in the Colman Report (1966), the Brown vs. Topeka Board of Education (1954) Supreme Court decision, and various other researches.

However, the impact of peer pressure has been proven in the works of many researchers, such as Betts and Morell (1999) who found that the attributes of high school peer groups have an impact on undergraduate grade point average (GPA). In addition, Case and Katz (1991) have found that peer pressure has an impact on both drug abuse and criminal behavior. There has been a large amount of literature on the impact of neighborhood location, including Katz, Kling, and Liebman (2001) in which they show that adults and children can be affected by neighborhood peer groups. Other literature on the topic can be found in Jencks and Mayer (1990), and Rosenbaum (1992). Sacerdote, B (2000).

When measuring the effects of peer-pressure, the standard method is as follows: first, obtaining observational data, and second, regressing outcomes or behaviors on peer outcomes or behaviors (B. Sacerdote, 2000).

Manski (1993) argues that there are several problems that arise with that method:

#1 The self-selection problem

People tend to self-select, meaning that individuals usually place themselves within their desired surroundings (peer-groups, housemate, or neighborhood). This makes it harder to distinguish whether results are due to the selection problem or peer influence.

#2 The reflection problem

According to Manski (1993) the reflection problem “arises when a researcher observing the distribution of behavior in a population tries to infer whether the average behavior in some group influences the behavior of the individuals that comprise the group”. In other words; if individuals affect each other simultaneously, it is hard to disentangle a causal impact on one another.

#3 The difficulty of empirically distinguishing contextual effects from endogenous effects

The former refers to environmental or social backgrounds that can impact a person’s behavior, while the latter refers to peer effects that can have an impact.

Many scientists attempted to avoid the reflection issue by “designing instruments for peer behavior which are assumed to be exogenous” (B. Sacredote, 2000). Examples of how authors have attempted to avoid the reflection problem can be found in the works of Case and Katz (1991), and Gaviria and Raphael (1999). These authors aim to avoid the reflection problem by using the average behavior of the peer’s parents as a control. Additionally Bjoras (1992) tried to avoid the reflection problem by taking the average human capital of previous generations of individuals’ ethnic groups and then regressing it on the subjects’ behavior (1992).

Even, Oates, and Schwab (1992) attempted to avoid the selection problem by using an equation that explicitly shows that teens self-select their peer groups.

Peer-pressure may affect the sharing economy similarly to word-of-mouth marketing². If one person within a particular peer group has taken part in a sharing economy-provided service and was satisfied, he might want to recommend it to his peers, thus increasing the use of sharing-economy provided services.

5.3 Information cascades

The theory of information cascades is used mostly in the field of behavioral economics, together with other social sciences. Information cascades theory may be found in financial markets, business strategies, and politics, as well as other sectors (P. Jain, 2015). The information cascade occurs, as Bikhchandani, Hirshleifer & Welch's 1992 paper describes, "When it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information."

A particularly peculiar form of information cascade is the so-called 'reverse cascade', where followers detrimentally mimic their peers' decisions, as Anderson & Holt write: "The initial decision makers are unfortunate to observe private signals that indicate the incorrect state, and a large number of followers may join the resulting pattern of mistakes" (1997).

One significant type of information cascade is "herding" or "herd behavior", which signifies "people with private, incomplete information make public decisions in sequence. Hence, the first few decision-makers reveal their information and subsequent decision-makers may follow an established pattern even when their private information suggests that they should deviate" (Anderson & Holt, 2008).

A large part of the sharing economy relies on information cascades in the form of reviews and rating systems. Reviews provide consumers with information regarding a service or a product provided by previous users, while rating systems help consumers assess the quality of a product or service based on how well they are rated. Both contribute to shaping the opinions of consumers, and may lead to the increase of sharing economy service usage.

² An oral/written recommendation from one satisfied customer to another prospective customer on a good/service

6. Empirical Part

6.1 The experiment

6.1.2 Methodology:

In order to disentangle possible channels that may have lead to an increase in use of sharing economy-provided services, I have decided to conduct an experiment using tools provided by the field of experimental economics. In this experiment, my main goal is to determine whether peer pressure and information cascades contribute to the increase in use of sharing economy-provided services.

6.1.3 Design:

The experiment was presented in the form of a lottery game, in which participants had to choose between two options: option A³ which represents the standard economy, or option B which represents the sharing economy. In option A, participants were able to see both their potential payoffs (represented as whole numbers) and their chances of obtaining this particular payoff (represented in percentage point). In option B, participants were only able to see their potential payoffs, not their chances of obtaining that payoff. This was done in order to mimic real-life circumstances in which the sharing-economy (option B) is the riskier option.

Option A offered an 80% percent chance of obtaining 120 CZK and a 10% chance of obtaining 10 CZK, while option B yielded a 55% chance of obtaining 120 CZK and a 45% chance of obtaining 10 CZK.

³ the name "Option" has been chosen due to negative connotation of the lottery word in Czech language

I used three treatments to test the effect of peer-pressure and information cascades on the use of the sharing-economy provided services: Base-line (control group); Chat (peer-pressure); and Review (information cascades).

The experiment consisted of 3 sessions and 3 treatments. Each session tested one treatment, which was in-turn, divided into two groups of participants (group A and group B), who took the experiment simultaneously. Each session consisted of 15 periods with 2 minutes assigned to each period and a payoff-relevant period that was drawn at random. Additionally, in order to highlight the fact that the sharing economy becomes less risky and more lucrative overtime, we increased the probabilities on the use of the sharing-economy services in option B to an 85% percent chance of obtaining 120 CZK and a 15% chance of obtaining 10 CZK, beginning from the 8th period. This was done without the knowledge of the participants, in order to test whether participants would notice the change and start choosing option B.

The experiment was programmed using z-Tree⁴, and the strategy method⁵ has been applied.

Instructions of the experiment can be found in Appendix.

6.1.4 Participants:

In order to conduct this experiment, we recruited 60 participants through ORSEE⁶ software, with no more information than that of an offer to participate in an economic experiment. Each participant was promised a 50 CZK show-up fee and had the opportunity to earn a maximum of 190 CZK.

Out of the 60 participants, 51.7% were male and 48.3% were female. Additionally the majority of participants were of Economics students (81.7%), while the rest studied political science (6.7%); computer science (3.3%); medicine (3.3%); business administration (1.7%); or others (3.3%).

6.1.5 Treatments:

As aforementioned, the experiment consisted of three treatments: Base-line (control group), Chat, and Review. However each treatment differed slightly from the other, in order to

⁴ A software for developing and conducting and developing economic experiments (Fischbacher, 2007)

⁵ A form of strategy used in economic experiment where “responder makes conditional decisions for each possible information set” Brandts, and Charness (2009).

⁶ ORSEE is a web-based Online Recruitment System, specifically designed for organizing economic experiments

measure different effects. In the control group treatment – Base-line – participants were asked to refrain from any sort of collaboration or communication. The aim of this treatment was to measure consumer preferences together with their attitude towards risk if required to decide whether to partake in a sharing-economy provided service, ultimately to be compared to the results of the two other treatments. In the second treatment – Chat – participants were provided with a chat window and encouraged to communicate with each other. This was done to test whether peer-pressure would affect consumer behavior towards participating in sharing economy-provided services (option B). Finally in the third treatment – Review – participants were provided with the average potential earnings of other participants for the other options undertaken in the previous round. This was done in order to measure the impact of information cascades on the decision making process of participants. Screenshots of the decision making screen can be found in Appendix

6.1.6 Results:

In this part of my paper, I will present the results of the experiment in the form of graphs, outputs, and comment on them. Since there were got two groups of participants that took the experiment simultaneously, I will first present the results of each group individually and then compare results between the two groups.

The plan of this part is as follows; **first**, I will present the number of option (B) selected in each group of each treatment, and comment on it. **Second**, I will present the average number of choice (B) chosen in each treatment (within the same group) and compare it between different periods. **Third**, I will provide the hypothesis, the econometric model, and the results I obtained after running the econometric regression.

For the sake of simplicity; Base-line treatment will take the number 1, Chat treatment will take the number 2, and Review treatment will take the number 3. Moreover, each treatment will be divided into two groups: group A and group B.

The number of option (B) selected in each group of each Treatment:

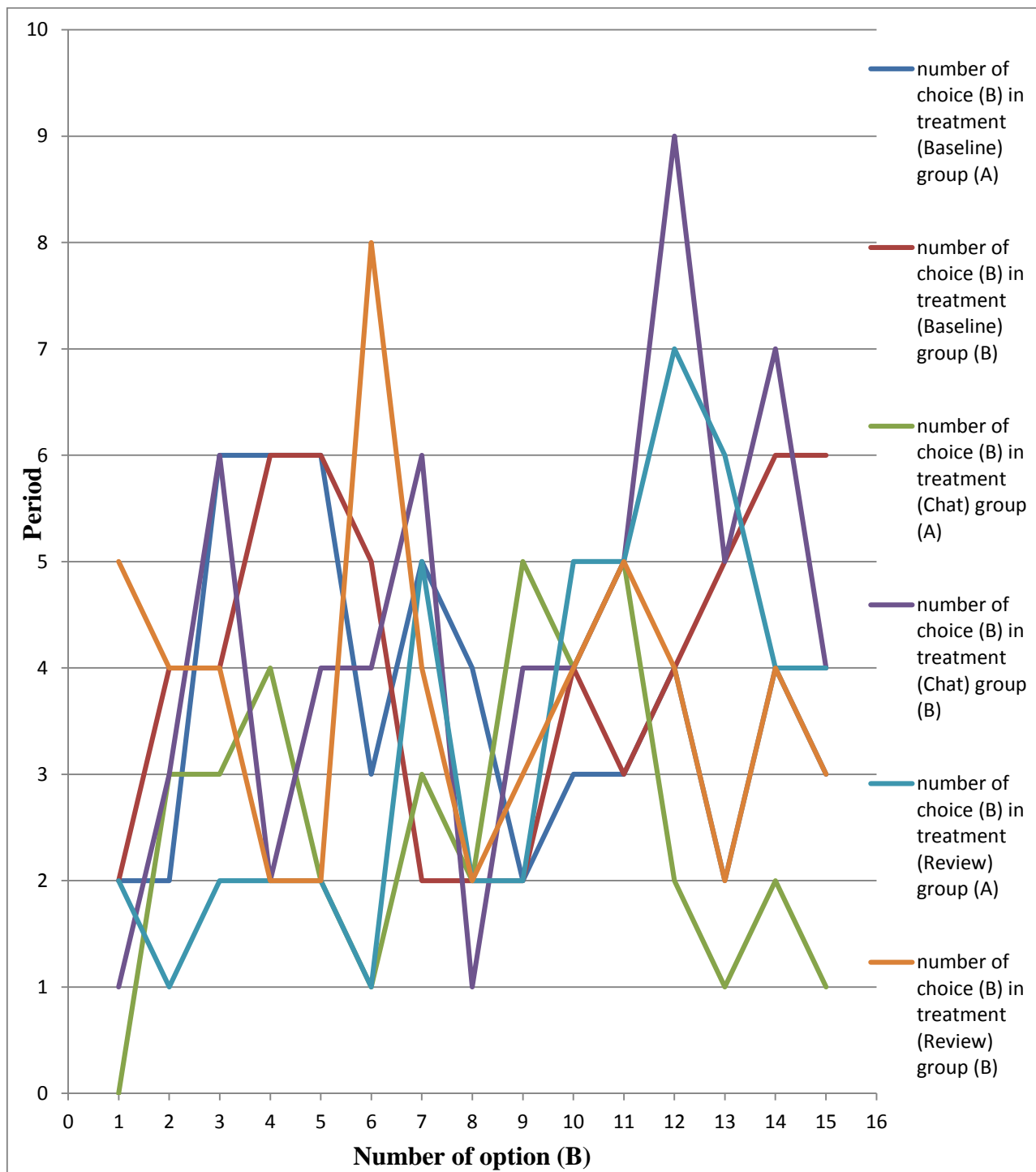


Figure 6

In treatment Baseline (1) both groups (A) represented in navy blue and (B) represented in dark red; preferred choosing the standard economy option (A) to the more risk bearing, sharing-economy option (B) throughout the 15 periods. However, group (B) showed a more frequent choice of option (B) than that of group (A), as it can be seen on the graph. Additionally, in group (A), during the 3rd, 4th, and 5th period, participants did choose option (B) more frequently, but quickly returned to the safer option after that. It can also be seen that participants in group (A) did not respond to the increase in probabilities that took place after the 7th period, and still stuck with the safer option (option (A)). While participants in group (B) did respond to the change, which can be seen on their decisions in periods 11, 12, 13, 14, and 15.

Treatment chat (2) represented in green for group (A) and purple for group (B); shows the participants response after introducing the chat window that allowed participants to communicate. As depicted on the graph, it can be seen that for both groups (A) and (B), participants still preferred the standard economy option (A) to the sharing-economy option (B). However, both groups (A) and (B) show an increase in choice (B) after the 7th period. The former's periods of increase are 8th, 9th, 10th, and 11th. While the latter's periods of increase are 8th, 9th, 10th, 11th, and 12th. This could be seen as the result of the participant's response to the increase in probabilities that occurred after the 7th period.

Treatment review (3) represented in turquoise for group (A) and orange for group (B); shows the participants response after providing them with the average potential earnings of other participants for both options in the previous period. As depicted on the graph above, for both groups (A) and (B); the standard economy option (A) dominates the sharing-economy option (B). However, as the result of the increase in probabilities that took place after period 7, both groups seem to have responded. For group (A); periods 9, 10, 11, and 12 witness an increase in choice (B) chosen, in response to the increase of probabilities, while group (B); periods 8, 9, 10 and 11 witness an increase in choice (B) chosen for the same reason.

In order to measure the effects of peer-pressure and information cascades I have decided to calculate the average number of choice (B) chosen in each treatment (within the same group) and compare it between different periods.

Comparison of all treatments:

Periods 1-7 to 8-15:

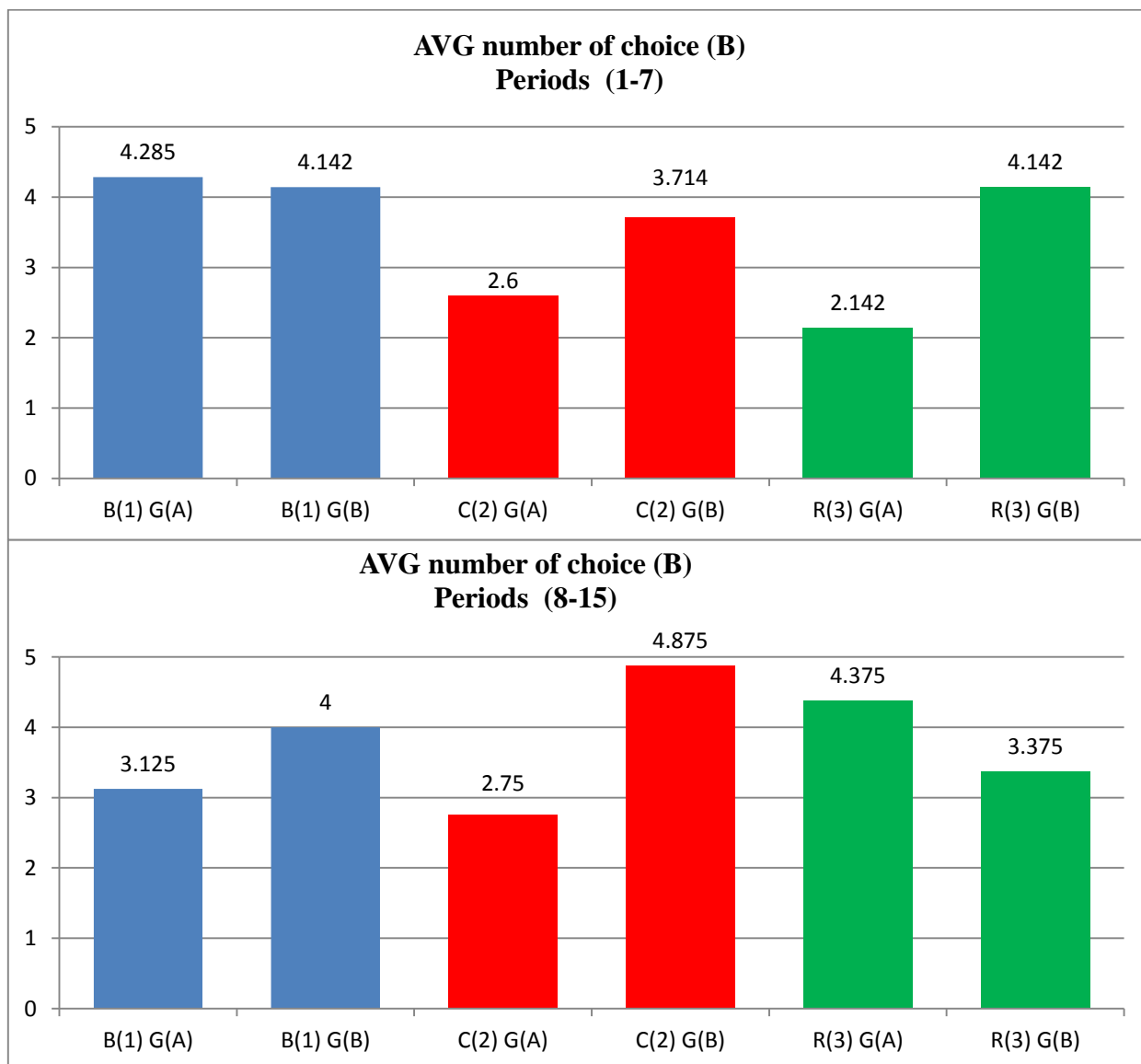


Figure 7

From figure (7), we can deduce that for both groups of treatment Baseline (1) and for group (B) of treatment review (3); the average number of choice (B) has declined from periods (1-7) to periods (8-15). On the other hand, we can see an increase of choice (B) in both groups of treatment chat (2) together with group (A) of treatment review (3).

Due to the fact that participants in periods (1-7); (8-15) may need more time to adapt to the experiment, and understand the task in hand – which in turn may negatively affect the results of the experiment; the results of those periods will not be taken into account. Instead, I have decided to compare between periods: (3-7); (10-15) and (4-7); (11-15).

Periods 3-7 to 10-15:

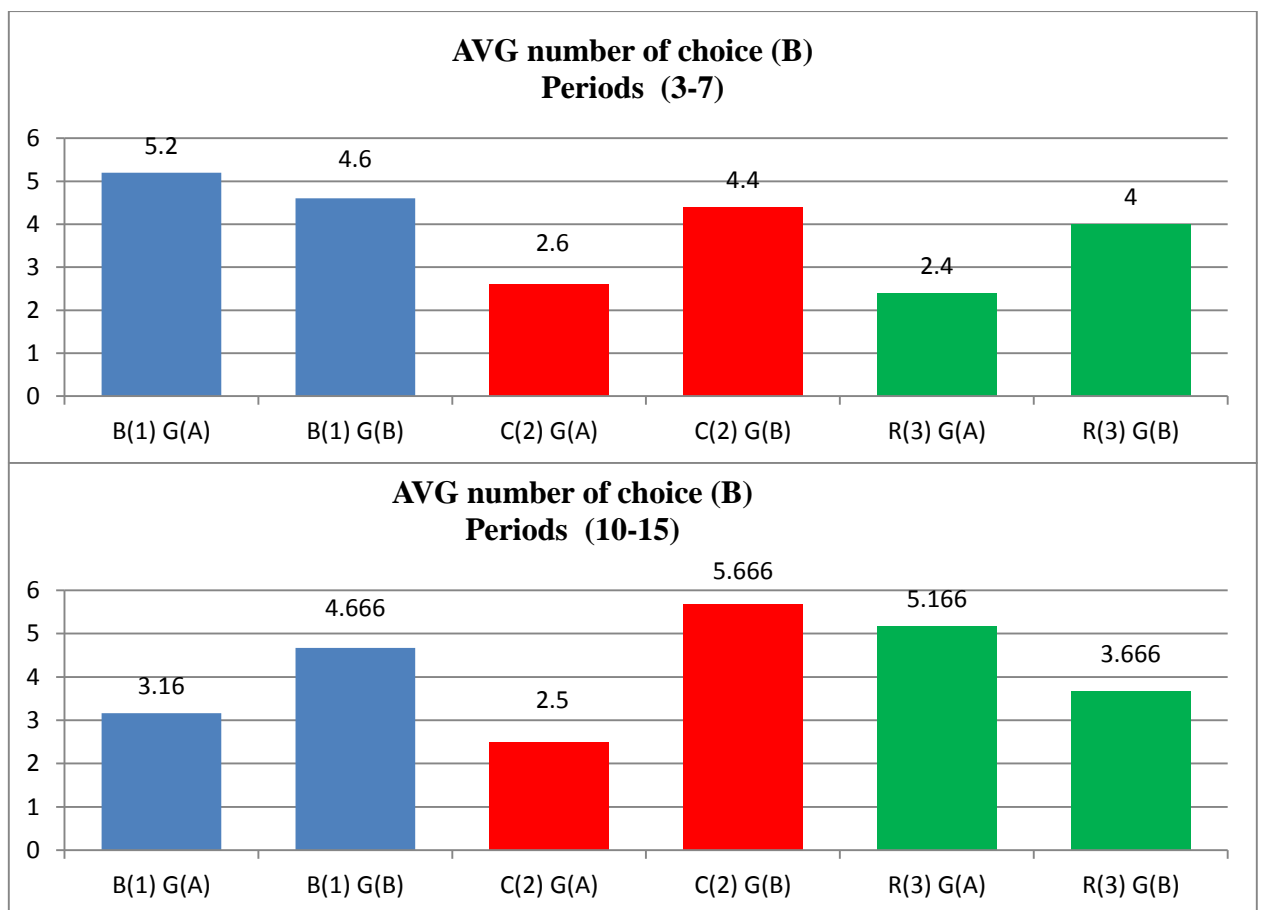


Figure 8

From figure (8) we can deduce that; in treatment Baseline (1), group (A) – the average number of choice (B) decreased in periods (10-15), while in group (B), the average number of choice (B) increased by a very small margin. This could be explained as a result of risk preferences shifting throughout later periods. Moreover, in treatment Chat (2), group (A) – the average number of choice (B) decreased, while for group (B) – the average number of choice (B) increased. For the former; this could be the result of peer-pressure on participant's choices throughout the periods, while for the latter, this could be the result of both; peer-pressure and the change in probabilities that occurred after the 7th period. Finally, in treatment Review (3), Group (A) – the average number of choice (B) increased, while for group (B) – the average number of choice (B) decreased. For the former; this could be the result of both; information cascades and the increase in probabilities that occurred after the 7th period, while for the latter, this could be the result of information cascades on participant's choices throughout the periods.

Periods 4-7 to 11-15:

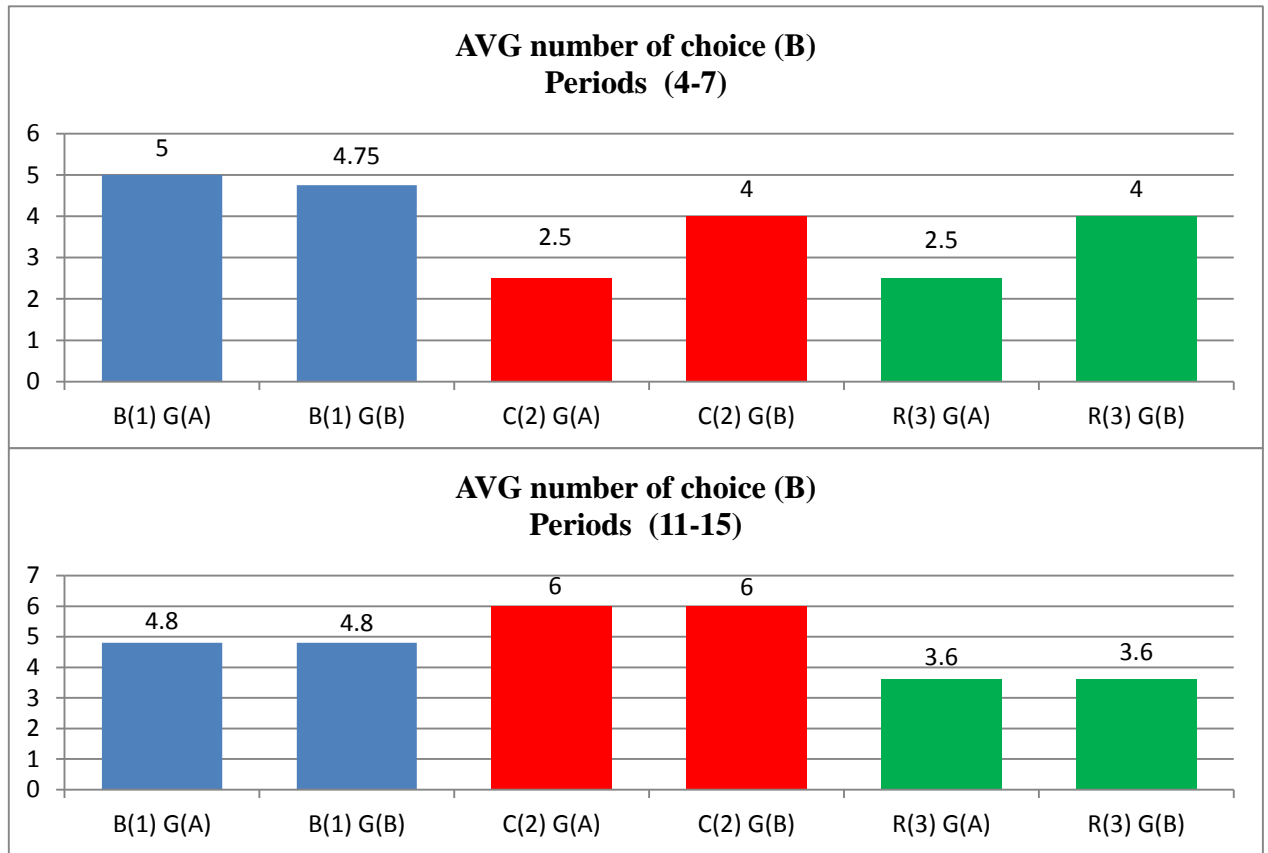


Figure 9

From figure (9), we can deduce that; in treatment Baseline (1), group (A) – the average number of option (B) slightly decreases, while for group (B) – the average number of choice (B) increased. This could be explained as a result of risk preferences shifting throughout later periods. Moreover, the increase of choice (B) that occurred in group (B), could be explained as a result of the increase in probabilities that took place after the 7th period. Furthermore, in treatment Chat (2) – both groups witness an increase in the average number of choice (B) from rounds (4-7) to (11-15), which could be the result of both, peer-pressure and the increase in probabilities that occurred after the 7th period. Finally, in treatment Review (3), group (A) – the average number of choice (B) increased, while for group (B) – the average number of choice (B) decreased. For the former; this could be the result of both; information cascades and the increase in probabilities that occurred after the

7th period, while for the latter, this could be the result of information cascades on participant's choices throughout the periods.

In order to test the significance of my results, I have decided to create an econometric model and run it using the statistical software: STATA. By doing so; I aim to test my hypothesis of whether peer-pressure, and information cascades (reviews); lead to an increase in the use of sharing economy provided services.

The model:

$$\begin{aligned} choice = & \beta_0 + \beta_1 peer\ pressure + \beta_2 review + \beta_3 late\ period + \\ & \beta_4 (peer\ pressure \times late\ period) + \beta_5 (review \times \\ & late\ period) + \beta_6 group1 + \beta_7 group3 + \beta_8 group + \varepsilon \end{aligned}$$

My Hypothesis:

$$H_0: \beta_4 = 0, \beta_5 = 0$$

$$H_1: \beta_4 \neq 0, \beta_5 \neq 0$$

The explanation of the model is as follows:

- **choice:** is a dummy variable that equals to zero if the participants choice is option (A), and equals to one if the participants choice is option (B).
- **β_0 :** is a constant variable
- **β_1 peer pressure:** is a dummy variable that equals to one if we are testing the peer-pressure treatment, and equals to zero otherwise
- **β_2 review:** is a dummy variable that equals to one if we are testing the information cascades (review) treatment, and zero otherwise
- **β_3 late period:** since in my model we are testing between periods (ex: periods 1-7;8-15), so I have created this dummy variable that equals to one for selected periods and zero otherwise
- **β_4 (peer pressure \times late period):** is an interaction term that tests for joint significance of peer pressure and late period interaction
- **β_5 (review \times late period):** is an interaction term that tests for joint significance of information cascades (review) and late period interaction
- **ε :** is an error term
- **$\beta_6, \beta_7, \beta_8$:** Dummy variables equal to one if testing for group (A) and zero if testing for group (B). those variables have been added in order to control for group fixed effects

Linear regression for periods (1-7; 8-15):

Linear regression				Number of obs = 900		
				F(8, 59) = 1.52		
				Prob > F = 0.1706		
				R-squared = 0.0205		
				Root MSE = .47745		
(Std. Err. adjusted for 60 clusters in id)						
choice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
peer_pressure	-.0514286	.1291496	-0.40	0.692	-.3098563	.2069992
review	-.1509524	.1097998	-1.37	0.174	-.3706612	.0687564
late_period1	-.0651786	.0474332	-1.37	0.175	-.1600922	.029735
peer_late1	.1464286	.0630865	2.32	0.024	.0201928	.2726643
review_late1	.1455357	.0770279	1.89	0.064	-.0085967	.2996681
g1	-.04	.1373044	-0.29	0.772	-.3147456	.2347456
g3	-.18	.1158102	-1.55	0.125	-.4117357	.0517357
g6	.0333333	.1077316	0.31	0.758	-.1822372	.2489038
_cons	.4414286	.0961731	4.59	0.000	.2489866	.6338706

Figure 10

From the figure above, the variable (peer_pressure) shows how peer-pressure influences the overall amount of choice (B) for all participants. Moreover, by looking at its corresponding coefficient, we can deduce that; peer-pressure decreases the overall likelihood of choosing option (B) for all participants, which goes against my suggested hypothesis. The variables corresponding p-values show its insignificance at both; 5% and 10% levels of significance, and thus, does not affecting my result.

The variable (review) shows how information cascade (reviews) influences the overall amount of choice (B) for all participants. Moreover, by looking at its corresponding coefficient, we can deduce that; information cascades (reviews) decreases the overall likelihood of choosing option (B) for all participants, which goes against my suggested hypothesis. The variables corresponding p-values show its insignificance at both; 5% and 10% levels of significance, and thus, does not affecting my result.

The variable (late_period1) shows how periods (8-15) influences the overall amount of choice (B) for all participants, in comparison to periods (1-7). Moreover, by looking at its

corresponding coefficient, we can deduce that; choice (B) decreased in periods (8-15) in comparison to periods (1-7) for all participants. However, the variable's corresponding p-values prove that it is not significant at both; 5% and 10% significance levels.

The variable (g1) shows how group (A) of treatment Baseline (1) influences the overall amount of choice (B) for all participants. Moreover, by looking at its corresponding coefficient, we can deduce that group (A) of treatment Baseline (1) decreases the overall amount of choice (B) for all participants. However, the variable's corresponding p-values prove that it is not significant at both; 5% and 10% significance levels.

The variable (g3) shows how group (A) of treatment chat (2) influences the overall amount of choice (B) for all participants. Moreover, by looking at its corresponding coefficient, we can deduce that group (A) of treatment Chat (2) decreases the overall amount of choice (B) for all participants. However, the variable's corresponding p-values prove that it is not significant at both; 5% and 10% significance levels.

The variable (g6) shows how group (B) of treatment Review (3) influences the overall amount of choice (B) for all participants. Moreover, by looking at its corresponding coefficient, we can deduce that group (B) of treatment Review (3) decreases the overall amount of choice (B) for all participants. However, the variable's corresponding p-values prove that it is not significant at both; 5% and 10% significance levels.

Furthermore, by looking at the corresponding coefficient of the interaction term: (peer_late1), we can deduce that peer pressure increases the likelihood of choosing option (B) in periods (8-15) in comparison to periods (1-7), for all participants.. Additionally, by looking at the corresponding p-values ,we can deduce that the interaction term is indeed significant at both 5% and 10% significance levels. This allows me to reach the conclusion of rejecting the null hypothesis.

Similarly, by looking at the corresponding coefficient of the interaction term: (review_late1), we can deduce that information cascades (reviews) increases the likelihood of choosing option (B) in periods (8-15) in comparison to periods (1-7), for all participants. Additionally, by looking at the corresponding p-values we can deduce that the interaction term is only significant at 10% significance level. This allows me to reach the conclusion

of failing to reject the null hypothesis at 5% significance level, and rejecting the null hypothesis at 10% significance level.

Linear regression for periods (3-7; 10-15):

Linear regression				Number of obs = 660		
				F(8, 59) = 1.71		
				Prob > F = 0.1151		
				R-squared = 0.0357		
				Root MSE = .4847		
(Std. Err. adjusted for 60 clusters in id)						
choice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
peer_pressure	-.04	.1381189	-0.29	0.773	-.3163753	.2363753
review	-.1927273	.1167292	-1.65	0.104	-.4263018	.0408473
late_period2	-.0983333	.050248	-1.96	0.055	-.1988793	.0022126
peer_late2	.1566667	.0769872	2.03	0.046	.0026155	.3107178
review_late2	.22	.0857853	2.56	0.013	.0483441	.3916559
g1	-.0545455	.1444929	-0.38	0.707	-.343675	.2345841
g3	-.2545455	.1271411	-2.00	0.050	-.5089542	-.0001367
g6	-.0090909	.1136062	-0.08	0.936	-.2364163	.2182345
_cons	.5172727	.1011969	5.11	0.000	.3147781	.7197673

Figure 11

From the figure above, by looking at the corresponding p-value of the variable (review), we can deduce that it falls at the margin of the 10% significance level. Moreover, by looking at its corresponding coefficient, we can deduce that information cascades (reviews) decreases the overall likelihood of choosing option (B), for all participants.

Moreover, by looking at the corresponding p-value of the variable (late_period2) we can deduce that it falls at the margin of the 5% significance level and that it is significant at the 10% significance level. Subsequently, by looking at its corresponding coefficient, we can

deduce that; choice (B) decreased in periods (10-15) in comparison to periods (3-7) for all participants

The corresponding p-value of the variable (g3), fall at the margin of the 5% significance level, while being significant at the 10% significance level. Subsequently, by looking at its corresponding coefficient, we can deduce that group (A) of treatment Chat (2) decreases the overall amount of choice (B) for all participants.

Furthermore, by looking at the coefficient of the interaction term: (peer_late2), we can deduce that peer pressure increases the participant's likelihood of choosing option (B) in periods (10-15) in comparison to periods (3-7). Additionally, by looking at the p-values, we can deduce that the interaction term is indeed significant at both 5% and 10% significance levels. This allows me to reach the conclusion of rejecting the null hypothesis.

Similarly, by looking at the coefficient of the interaction term: (review_late2), we can deduce that information cascades (reviews) increases the participants likelihood of choosing option (B) in periods (10-15) in comparison to periods (3-7). Additionally, by looking at the corresponding p-values, we can deduce that the interaction term is indeed significant at both 5% and 10% significance levels. This allows me to reach the conclusion of rejecting the null hypothesis.

However, the remaining variables are not significant at both: 5% and 10% levels of significance.

Linear regression for periods (4-7; 11-15):

Linear regression

Number of obs = 540

F(8, 59) = 1.56

Prob > F = 0.1553

R-squared = 0.0411

Root MSE = .48414

(Std. Err. adjusted for 60 clusters in id)

choice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
peer_pressure	-.0625	.1427588	-0.44	0.663	-.3481597	.2231597
review	-.1722222	.1273696	-1.35	0.181	-.4270882	.0826437
late_period3	-.0875	.0595552	-1.47	0.147	-.2066696	.0316696
peer_late3	.1725	.0882067	1.96	0.055	-.0040011	.3490011
review_late3	.19	.0913241	2.08	0.042	.0072608	.3727392
g1	-.0777778	.1499777	-0.52	0.606	-.3778824	.2223268
g3	-.2777778	.1263659	-2.20	0.032	-.5306353	-.0249203
g6	-.0333333	.1197376	-0.28	0.782	-.2729277	.206261
_cons	.5263889	.1045464	5.03	0.000	.3171921	.7355857

Figure 12

From the figure above, by looking at the corresponding p-value of the variable (g3), we can deduce that it is significant at both 5% and 10% significance levels. Subsequently, by looking at its corresponding coefficient, we can deduce that group (A) of treatment Chat (2) decreases the overall amount of choice (B) for all participants.

Furthermore, by looking at the coefficient of the interaction term: (peer_late3), we can deduce that peer pressure increases the participant's likelihood of choosing option (B) in periods (11-15) in comparison to periods (4-7). Additionally, by looking at the p-values, we can deduce that the interaction term falls at the margin of the 5% significance level, while being significant at the 10% significance level. This allows me to reach the conclusion of rejecting the null hypothesis.

Similarly, by looking at the coefficient of the interaction term: (review_late3), we can deduce that information cascades (reviews) increases the participants likelihood of choosing option (B) in periods (11-15) in comparison to periods (4-7). Additionally, by looking at the p-values, we can deduce that the interaction term is indeed significant at both 5% and 10% significance levels. This allows me to reach the conclusion of rejecting the null hypothesis.

However, the remaining variables are not significant at both: 5% and 10% levels of significance.

Due to the fact that my dependant variable (choice) is a binary choice variable (dummy variable). It might be the case that a linear regression is not the best fit for my data. That is why I have decided to run a robustness check, using Probit regression model.

Probit regression for periods (1-7; 8-15):

Probit regression			Number of obs = 900			
			Wald chi2(8) = 11.65			
			Prob > chi2 = 0.1675			
Log pseudolikelihood = -578.6205			Pseudo R2 = 0.0161			
(Std. Err. adjusted for 60 clusters in id)						
choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
peer_pressure	-.1448787	.331995	-0.44	0.663	-.7955771	.5058196
review	-.4080819	.2888619	-1.41	0.158	-.9742408	.158077
late_period1	-.1710403	.1237054	-1.38	0.167	-.4134984	.0714178
peer_late1	.398067	.1693978	2.35	0.019	.0660533	.7300806
review_late1	.3914422	.2040025	1.92	0.055	-.0083954	.7912798
g1	-.1058379	.3589782	-0.29	0.768	-.8094223	.5977466
g3	-.498343	.3275039	-1.52	0.128	-1.140239	.1435528
g6	.0951308	.2876795	0.33	0.741	-.4687106	.6589722
_cons	-.1453959	.2452693	-0.59	0.553	-.626115	.3353231

Figure 13

Marginal effects for Probit regression (1-7; 8-15):

Marginal effects after probit							
y = Pr(choice) (predict)							
= .35739816							
variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]
peer_p~e*	-.053535	.12151	-0.44	0.660	-.291691	.184621	.333333
review*	-.1473739	.10173	-1.45	0.147	-.346765	.052018	.333333
late_p~1*	-.0638924	.0461	-1.39	0.166	-.154238	.026453	.533333
peer_l~1*	.1534454	.06646	2.31	0.021	.023193	.283698	.177778
review~1*	.1508468	.08015	1.88	0.060	-.006249	.307943	.177778
g1*	-.0389507	.13012	-0.30	0.765	-.293985	.216084	.166667
g3*	-.1713447	.10095	-1.70	0.090	-.369202	.026513	.166667
g6*	.0358842	.10984	0.33	0.744	-.179395	.251163	.166667

Figure 14

Similar to the linear regression of periods (1-7; 8-15), coefficients for both interaction terms: (peer_late1) and (review_late1) are significant. The former is significant at both the 5% and 10% levels of significant, while the latter falls at the margin of the 5% significance level and is significant at the 10% significance level. However, due to the fact that I am using a Probit model, the coefficients cannot be interpreted right away. Instead, marginal effects must be used in order to interpret the coefficients. Moreover, by looking at the marginal effects for both interaction terms, we can deduce that peer-pressure and information cascades (reviews) increase the participant's likelihood of choosing option (B) in periods (8-15) in comparison to periods (1-7) – As was the case with the linear regression model. This allows me to confirm the rejection of the null hypothesis.

However, the remaining variables are not significant at both: 5% and 10% levels of significance. Thus, does not need to be commented on.

Probit regression for periods (3-7; 10-15):

Probit regression		Number of obs		=	660	
		Wald chi2(8)		=	13.34	
		Prob > chi2		=	0.1008	
Log pseudolikelihood = -432.56145		Pseudo R2		=	0.0271	
(Std. Err. adjusted for 60 clusters in id)						
choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
peer_pressure	-.1084769	.3473447	-0.31	0.755	-.78926	.5723061
review	-.503591	.2990457	-1.68	0.092	-1.08971	.0825278
late_period2	-.2512607	.1272283	-1.97	0.048	-.5006235	-.0018979
peer_late2	.4086804	.2066053	1.98	0.048	.0037415	.8136192
review_late2	.5718913	.2197058	2.60	0.009	.1412758	1.002507
g1	-.1410888	.3683687	-0.38	0.702	-.8630781	.5809006
g3	-.6839045	.3579213	-1.91	0.056	-1.385417	.0176084
g6	-.0186841	.297011	-0.06	0.950	-.600815	.5634468
_cons	.0454835	.2529841	0.18	0.857	-.4503562	.5413232

Figure 15

Marginal effects for Probit regression (3-7; 10-15):

Marginal effects after probit							
y = Pr(choice) (predict)							
= .39823528							
variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		X
peer_p~e*	-.0416399	.13262	-0.31	0.754	-.301568	.218288	.333333
review*	-.1877474	.10789	-1.74	0.082	-.399205	.023711	.333333
late_p~2*	-.0969993	.04898	-1.98	0.048	-.19299	-.001009	.545455
peer_l~2*	.160612	.08141	1.97	0.049	.001049	.320175	.181818
review~2*	.2244494	.08522	2.63	0.008	.057416	.391483	.181818
g1*	-.0536887	.13792	-0.39	0.697	-.324011	.216634	.166667
g3*	-.2388954	.10727	-2.23	0.026	-.449148	-.028642	.166667
g6*	-.0071982	.11421	-0.06	0.950	-.231036	.21664	.166667

Figure 16

Similar to the linear regression of periods (3-7; 10-15), the variable: (review) falls at the margin of the 10% significance level, and by looking at the marginal effects, we can deduce that information cascades (reviews) decreases the overall likelihood of choosing option (B), for all participants. The variables: (late_period2) and (g3) remain significant at both 5% and 10% significance levels. While by looking at the formers marginal effects we can deduce that choice (B) decreased in periods (10-15) in comparison to periods (3-7) for all participants. Meanwhile, by looking at the latters marginal effects we can deduce that group (A) of treatment Chat (2) decreases the overall amount of choice (B) for all participants.

Furthermore, both interaction terms: (peer_late2) and (review_late2) remain significant at both: 5% and 10% levels of significance – as s was the case with the linear regression model for periods: (3-7; 10-15). Moreover, by looking at the marginal effects for both interaction terms, we can deduce that peer-pressure and information cascades (reviews) increase the participant's likelihood of choosing option (B) in periods (10-15) in comparison to periods (3-7) – As was the case with the linear regression model. This allows me to confirm the rejection of the null hypothesis.

However, the remaining variables are not significant at both: 5% and 10% levels of significance.

Probit regression for periods (4-7; 11-15):

Probit regression				Number of obs	=	540
				Wald chi2(8)	=	11.41
				Prob > chi2	=	0.1795
Log pseudolikelihood = -352.37694				Pseudo R2	=	0.0315
(Std. Err. adjusted for 60 clusters in id)						
choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
peer_pressure	-.1692007	.3603355	-0.47	0.639	-.8754453	.5370439
review	-.4454128	.3246876	-1.37	0.170	-1.081789	.1909633
late_period3	-.2239777	.1502563	-1.49	0.136	-.5184747	.0705192
peer_late3	.4556146	.239265	1.90	0.057	-.0133361	.9245654
review_late3	.4912671	.232708	2.11	0.035	.0351678	.9473664
g1	-.1998866	.3813878	-0.52	0.600	-.947393	.5476199
g3	-.7572878	.3646683	-2.08	0.038	-1.472025	-.0425509
g6	-.0836336	.3112532	-0.27	0.788	-.6936786	.5264115
_cons	.0685612	.2606243	0.26	0.793	-.442253	.5793753

Figure 17

Marginal effects for Probit regression (4-7; 11-15):

Marginal effects after probit							
y = Pr(choice) (predict)							
= .39787101							
variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		X
peer_p~e*	-.0647058	.13651	-0.47	0.636	-.332267	.202855	.333333
review*	-.1668772	.118	-1.41	0.157	-.398153	.064398	.333333
late_p~3*	-.0865122	.05788	-1.49	0.135	-.199946	.026921	.555556
peer_l~3*	.179028	.09385	1.91	0.056	-.004915	.362971	.185185
review~3*	.1930044	.09116	2.12	0.034	.014337	.371672	.185185
g1*	-.0755166	.14054	-0.54	0.591	-.350974	.199941	.166667
g3*	-.2604858	.10493	-2.48	0.013	-.466137	-.054835	.166667
g6*	-.0320126	.11805	-0.27	0.786	-.263387	.199362	.166667

Figure 18

Similar to the linear regression of periods (4-7; 11-15), the variable: (g3) remains significant at both: 5% and 10% levels of significance, and by looking at the marginal effects we can deduce that group (A) of treatment Chat (2) decreases the overall amount of choice (B) for all participants.

Furthermore, both interaction terms: (peer_late3) and (review_late3) remain significant at both: 5% and 10% levels of significance – as was the case with the linear regression model for periods: (4-7; 11-15). Moreover, by looking at the marginal effects for both interaction terms, we can deduce that peer-pressure and information cascades (reviews) increase the participant's likelihood of choosing option (B) in periods (10-15) in comparison to periods (3-7) – As was the case with the linear regression model. This allows me to confirm the rejection of the null hypothesis.

However, the remaining variables are not significant at both: 5% and 10% levels of significance.

Conclusion

This thesis explores the emergence of the newest type of economy – the ‘sharing economy’, one of the fastest growing economic phenomena in contemporary times. This thesis cites numerous research papers that encompass the sharing economy, alongside other papers in different fields such as marketing and experimental economics. The main goal of this thesis is to disentangle possible channels that may have led to the increase in use of the sharing economy-provided services. To do so, we conducted an experiment using tools provided by the field of experimental economics.

In the theoretical part of this thesis, the main aim was to broadly explain what the sharing economy is, as well as introduce the concepts to be used in the practical part. At the beginning, I focus on defining the sharing-economy concept, including its many definitions, when it first appeared, and the three phases that account for its emergence. I then explain the sharing economy concept, providing the reason it is gaining worldwide

recognition, as well the main enablers behind it, major companies involved with it, the three main systems operating within it, and the economics behind it. Finally, I explain the many angles associated with its success, such as the concepts of Web 2.0 and P2P. Towards the end of the theoretical part, I introduce the concepts that are relevant to the practical part and the experiment, including risk-preferences, information cascades, and peer-pressure.

The practical part of this thesis focuses on the experiment, including methodology, designs, treatments, results, etc. In the practical, I present the hypothesis and the econometric model used for running the regression in order to test my hypothesis. Lastly, I present the outputs I have obtained after running the regression, and comment on their significance and relevance to my hypothesis.

The results, specifically the number of option (B) selected in each group of each treatment, show that participants overall chose the standard-economy option rather than the sharing-economy option. This could be explained as a result of the participants being more risk-averse, because participants did not thoroughly understand the task they were asked to do, or due to the small sample size. However, due to financial constraints it was not possible to recruit more participants. Moreover, the results obtained after comparing all treatments (within specific periods) are inconclusive as participants did not demonstrate any certain pattern of choice. Again, this is a result of having a small sample size; had I tested more participants, I would expect a more conclusive result.

Lastly, the results I have obtained after running both the linear regression and the probit regression are in fact in line with my hypothesis. Since I have found that the interaction term that tests for joint significance of peer pressure and late period interaction, and information cascades and late period interaction to be both significant and positive throughout all the regressions that I have ran. In other words, the increase in probabilities that took place after the 7th period (making the sharing economy more appealing) together with information-cascades and peer-pressure caused an increase in participant's choice of the sharing-economy option (B). This allowed me to successfully reject my null-hypothesis. Moreover, it has been found that other variables also influence the participants' choice, including period and group fixed effects.

The interaction term that tests for joint significance of peer pressure and late period interaction, and information cascades and late period interaction to be both significant and positive throughout all the regressions that I have ran

Suggestions for further research on the impact of peer-pressure and information cascades on sharing economy-provided services include factors that I did not include in my research due to time limitations, such as cultural backgrounds, age, education, wage, and sex. I do believe that those factors would make for a better model, and thus, more revealing results. Moreover, other channels that should be explored such as herd behavior, and word of mouth.

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Appendix:

Appendix I

Experiment instructions for Treatment Baseline (I)

Greetings,

You are now taking part in an economic experiment. I would like to thank you in advance for taking the time to participate in this experiment. Should you have any questions or comments, please leave them below.

General overview:

You will be asked to participate in a game that consists of 15 rounds. In each round, you will be asked to choose one (of two) options: option (A) or option (B). The time for each round will be 2 minutes. Please take your time to read the instructions carefully, and do not hesitate to ask any questions before we begin

Specific instructions:

Please do not fail to notice the following:

- In each round, in option (A) the numbers given in whole represent your payoff, while the numbers given in percentage represent the chance of you getting this payoff.
- Bear in mind that in option (B), you are only given payoffs. Meaning that you do not know the chances of getting this payoff. This does not imply that you have zero chance for getting a payoff.
- Random draws are independent between rounds
- Later on throughout the rounds, some percentages (chances) may change for option (B).
- Only 1 (of 15) rounds will be payoff relevant. Meaning that there is only one round, chosen at random where you will be able to earn a monetary compensation. The payoff relevant round will be chosen at the end of the experiment. So you do not know in advance if any actual round will be the payoff relevant one.
- However, after each round you will see your potential payoff from this round. You will earn this at the end of the experiment if the given round is payoff round.
- The payoff relevant round will be the same for everyone.

Feel free to make notes on this paper, but bear in mind that we will be collecting them at the end of the session.

Appendix II

Experiment instructions for treatment Chat (2)

Greetings,

You are now taking part in an economic experiment. I would like to thank you in advance for taking the time to participate in this experiment. Should you have any questions or comments, please leave them below.

General overview:

You will be asked to participate in a game that consists of 15 rounds. In each round, you will be asked to choose one (of two) options: option (A) or option (B). The time for each round will be 2 minutes. Please take your time to read the instructions carefully, and do not hesitate to ask any questions before we begin

Specific instructions:

Please do not fail to notice the following:

- In each round, in option (A) the numbers given in whole represent your payoff, while the numbers given in percentage represent the chance of you getting this payoff.
- Bear in mind that in option (B), you are only given payoffs. Meaning that you do not know the chances of getting this payoff. This does not imply that you have zero chance for getting a payoff.
- Random draws are independent between rounds
- Later on throughout the rounds, some percentages (chances) may change for option (B).
- Only 1 (of 15) rounds will be payoff relevant. Meaning that there is only one round, chosen at random where you will be able to earn a monetary compensation . The payoff relevant round will be chosen at the end of the experiment. So you do not know in advance if any actual round will be the payoff relevant one.
- However, after each round you will see your potential payoff from this round. You will earn this at the end of the experiment if the given round is payoff round.
- The payoff relevant round will be the same for everyone
- You will be provided with a chat window in order to communicate with other participants. Please, restrict your communication to the content of the experiment only.

Feel free to make notes on this paper, but bear in mind that we will be collecting them at the end of the session.

Appendix III

Experiment instructions for Treatment Review (3)

Greetings,

You are now taking part in an economic experiment. I would like to thank you in advance for taking the time to participate in this experiment. Should you have any questions or comments, please leave them below.

General overview:

You will be asked to participate in a game that consists of 15 rounds. In each round, you will be asked to choose one (of two) options: option (A) or option (B). The time for each round will be 2 minutes. Please take your time to read the instructions carefully, and do not hesitate to ask any questions before we begin

Specific instructions:

Please do not fail to notice the following:

- In each round, in option (A) the numbers given in whole represent your payoff, while the numbers given in percentage represent the chance of you getting this payoff.
- Bear in mind that in option (B), you are only given payoffs. Meaning that you do not know the chances of getting this payoff. This does not imply that you have zero chance for getting a payoff.
- Random draws are independent between rounds
- Later on throughout the rounds, some percentages (chances) may change for option (B).
- Only 1 (of 15) rounds will be payoff relevant. Meaning that there is only one round, chosen at random where you will be able to earn a monetary compensation . The payoff relevant round will be chosen at the end of the experiment. So you do not know in advance if any actual round will be the payoff relevant one.
- However, after each round you will see your potential payoff from this round. You will earn this at the end of the experiment if the given round is payoff round.
- You will be provided with the average potential payoffs of other participants for both options (A) and (B) from the previous round, to help you with your decisions.

Feel free to make notes on this paper, but bear in mind that we will be collecting them at the end of the session.

Appendix IV

Decision making screen in Treatment Baseline (1)

Round

1 out of 1

Remaining time (sec): 112

Please, choose either Option A or Option B

Option A

90 % chance of obtaining 100 CZK
or
10 % chance of obtaining 10 CZK

Choose Option A

Option B

unknown chance of obtaining 100 CZK
or
unknown chance of obtaining 10 CZK

Choose Option B

Appendix V

Decision making screen in Treatment Chat (2)

Round

1 out of 2

Remaining time (sec): 65

Please, choose either Option A or Option B. You may use chat window below in order to communicate with other participants.

Option A

90 % chance of obtaining 100 CZK

or

10 % chance of obtaining 10 CZK

Choose Option A

Option B

unknown chance of obtaining 120 CZK

or

unknown chance of obtaining 10 CZK

Choose Option B

Hello world

What did you get in the last period?

Appendix VI

Decision making screen in Treatment Review (3)

Round

2 out of 2

Remaining time (sec): 118

Please, choose either Option A or Option B. Below you can see the average potential payoff of all participants for each chosen option in the last previous round.

Option A
90 % chance of obtaining 100 CZK
or
10 % chance of obtaining 10 CZK

Average potential payoff of participants choosing Option A in the previous period was 100 CZK.

Option B
unknown chance of obtaining 120 CZK
or
unknown chance of obtaining 10 CZK

Average potential payoff of participants choosing Option B in the previous period was 120 CZK.