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Co-Utility in the Digital Economy: Conciliating Individual Freedom and Common Good in the Information Society

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Department of Computer Engineering and Mathematics (DEIM)

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WE STATE that the present study, entitled "*Co-Utility in the Digital Economy: Conciliating Individual Freedom and Common Good in the Information Society*", presented by *Abeba Nigussie Turi* for the award of the degree of Doctor, has been carried out under our supervision at the Department of Computer Engineering and Mathematics of this university.

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Dedicated to the memory of my parents, Nigussie Turi and Tezerash Feleke.

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Abstract

The collaborative economy refers to the digital economy of the millennial era which relies on the information technology as the main catalyst. Mesh, peer or sharing economy are the other terms that are interchangeably used to refer to the hybrid market models of this economy. Financial technologies, including the business lines of peer-to-peer transactions, the crowdfunding and crowdsourcing, innovation and educational marketplaces, are some of the common structures of this economy. This economic system is shaping the trends in consumption, production, distribution and, more generally, utilization of scarce resources. It is mainly characterized by the disintermediation of the traditional centralized form of economic system. The peer-to-peer business models underlying this economic system are enabled by the digital platforms that facilitate direct peer-to-peer transactions. Currently, these new collaborative business models account for a significant segment of the global economy, and they exhibit a fast pace of growth and adoption across different sectors. As this collaborative form of value creation emerges and the economic system gets more complicated, the system becomes prone to many serious problems that hamper its efficiency. Some of the new challenges and uncertainties currently arising in this economic system include privacy risks, security and operational risks (dangers of fraud, cybercrime and operational outages), platform failure, lack of trust between the transacting peers resulting from the information asymmetry, risk of default, usury and systemic financial risks due to liquidity, and credit risks with the business cycle uncertainties. Apart from its externalities to the traditional business models and incumbent players, this economic system also poses a challenge to the government in enacting new rules and regulations that govern the new businesses models and hence disrupts the government revenues at its current stage of growth.

In this work, we aim at approaching this economic system and tackle some of the aforementioned problems associated with it by introducing the notion of co-utility, which adheres to the self-governance principle. By considering specific use cases of the collaborative economy business models and identifying the case-specific problems, we design co-utile protocols through incentive mechanisms that can tackle the underlying problems. More specifically, we consider the crowd-based business models (crowdfunding and crowdsourcing), the P2P online lending market, and further extend our analysis to the e-commerce market. In this class of business models, where collaborations are facilitated by non-physical digital platforms, a standard principle governing selfish agents in an efficient way is needed. Hence, the notion of co-utility which we introduce in this work is helpful to conciliate the individual freedom and common good of the information society encompassing this economic system. In order to deal with the information asymmetry and the resultant mistrust and fear effects inherent to the crowdfunding market, we model potential incentive schemes that may render crowdfunding strictly co-utile. The incentive schemes we propose are community-based reputation and cryptographic mechanisms. Similarly, for the P2P online lending market and e-commerce, in order to tackle the problem of lack of trust between transacting peers, we leverage a distributed reputation protocol based on the co-utility principle. The mechanism relies on the key assumption of transitive trust. This reputation mechanism is cost-effective, anonymous in its computation and robust against tampering attacks; these features make it attractive for these markets. To sum up, the work presented in this thesis contributes to the scanty literature on the collaborative economy and further draws implications to improve the conventional methods at play.

Resum

L'economia col·laborativa fa referència a l'economia digital del segle XXI, que es basa en la tecnologia de la informació com a principal catalitzador. Economia en xarxa, economia d'iguals o consum col·laboratiu són altres termes usats freqüentment per referir-se a aquest model de mercat híbrid. Les tecnologies financeres, incloent-hi les línies de negoci de les transaccions d'usuaris en xarxes d'igual a igual, el micromecenatge i l'externalització de tasques (o col·laboració oberta distribuïda), així com els mercats d'innovació i d'educació, són algunes de les estructures més comunes d'aquest tipus d'economia. Aquest sistema econòmic està donant forma a les tendències actuals en consum, en producció, en distribució i, més generalment, en l'ús de recursos limitats. Es caracteritza principalment per la eliminació d'intermediaris en la cadena de subministrament del sistema econòmic centralitzat tradicional. Les plataformes digitals que faciliten les transaccions entre iguals permeten que funcioni el sistema de negoci de xarxes d'igual a igual que estan subjectes a aquest model. En l'actualitat, aquests nous models empresarials de col·laboració representen un segment important de l'economia mundial i mostren un ritme ràpid de creixement i d'adopció en els diferents sectors. A mesura que aquesta forma col·laborativa de creació de valor emergeix i el sistema econòmic esdevé més complex, apareixen problemes que en redueixen l'eficiència. Alguns dels nous reptes i incerteses que es presenten actualment en l'economia col·laborativa inclouen riscos en la privadesa i en la seguretat, riscos operatius (frau, ciberdelinqüència i interrupcions operatives), fallada de la plataforma, manca de confiança entre els usuaris participants en la transacció fruit de l'asimetria informativa, risc d'impagament, usura, risc financer sistèmic a causa de la liquiditat, i risc creditici causat per la incertesa en el cicle de negoci. A banda de les seves externalitats per als models de negoci tradicionals i per als seus actors històrics, l'economia col·laborativa també planteja un repte al govern pel que fa a la promulgació de noves regles i lleis que regeixin els nous models de negoci , amb la qual cosa interromp els ingressos fiscals durant la seva etapa de creixement.

En aquest treball, l'objectiu és acostar-nos al sistema econòmic col·laboratiu i abordar alguns dels problemes esmentats anteriorment mitjançant la introducció del concepte de coutilitat, que té a veure amb el principi d'autoregulació. Hem considerat casos d'ús específics del model col·laboratiu i hem identificat problemes concrets; a partir d'aquí, hem desenvolupat protocols coútils proveïts de mecanismes d'incentivació per tal d'abordar els problemes subjacents. Més concretament, considerem els models basats en la participació de la gent (micromecenatge i externalització de tasques), i el mercat de préstecs en línia d'igual a igual, i estenem la nostra anàlisi al mercat de comerç electrònic. En aquest tipus de models de negoci, en el qual les plataformes digitals faciliten la col·laboració, cal un principi estàndard que governi els agents egoistes de manera eficient. Per tant, la noció de coutilitat que introduïm en aquest treball és útil per conciliar la llibertat individual i el bé comú de la societat de la informació en la qual s'emmarca l'economia col·laborativa. Per tal de fer front a l'asimetria informativa, i a la desconfiança i als temors inherents al micromecenatge que en resulten, modelem mecanismes potencials d'incentivació que facin el micromecenatge estrictament coútil. Els mecanismes d'incentivació que proposem són la reputació de base comunitària i tècniques criptogràfiques. De la mateixa manera, per al mercat de préstecs en línia entre iguals i per al comerç electrònic, per tal d'abordar el problema de manca de confiança en les transaccions entre els usuaris ens servim d'un protocol de reputació distribuïda basat en el principi de coutilitat. El protocol es fonamenta en la premissa de la confiança transitiva. Aquest mecanisme de reputació és de cost reduït,, anònim en el seu càlcul i robust contra atacs de manipulació indeguda. Aquestes característiques el fan més atractiu per a aquests mercats. En resum, el treball que

presentem contribueix a l'escassa literatura sobre economia col·laborativa i permet de millorar els mètodes convencionals en ús.

Resumen

La economía colaborativa hace referencia a la economía digital del siglo XXI que se basa en la tecnología de la información como principal catalizador. Economía en red, economía de pares o consumo colaborativo son otros de los términos usados frecuentemente para referirse a este modelo de mercado híbrido. Las tecnologías financieras, incluyendo el negocio de las transacciones en redes de pares, el micromecenazgo (o financiación colectiva) y la externalización de tareas (o colaboración abierta distribuida), así como los mercados de innovación y educación, son algunas de las estructuras más comunes de este tipo de economía. Este sistema económico está dando forma a las tendencias actuales en consumo, producción, distribución y, de una forma más generalizada, uso de recursos limitados. Se caracteriza principalmente por la desintermediación del sistema económico centralizado tradicional. Las plataformas digitales que facilitan las transacciones entre pares permiten que funcionen los modelos de negocio de redes de pares que subyacen a este modelo. En la actualidad, estos nuevos modelos colaborativos de negocio representan un importante segmento de la economía mundial y muestran un rápido ritmo de crecimiento y adopción en los diferentes sectores. A medida que esta forma colaborativa de creación de valor emerge y el sistema económico se vuelve más complejo, van apareciendo problemas que dificultan su eficiencia. Algunos de los nuevos desafíos e incertidumbres que se presentan actualmente en la economía colaborativa incluyen riesgos de privacidad y seguridad, riesgos operativos (fraude, ciberdelincuencia e interrupciones operativas), fallo de la plataforma, falta de confianza entre los pares participantes en la transacción como resultado de la asimetría informativa, riesgo de impago, usura, riesgo financiero sistémico debido a la liquidez, y riesgo crediticio dado por la incertidumbre en el ciclo empresarial. Aparte de las externalidades para los modelos de negocio tradicionales y sus actores históricos, este sistema económico también plantea un reto al gobierno en lo tocante a la promulgación de nuevas reglas y leyes que rijan los nuevos modelos de negocio, con lo cual interrumpe los ingresos fiscales en su actual etapa de crecimiento.

En el presente trabajo, el objetivo es acercarnos al sistema económico colaborativo y abordar algunos de los problemas mencionados anteriormente mediante la introducción del concepto de coutilidad, que está relacionado con el principio de autoregulación. Hemos considerado casos de uso específicos de los modelos de negocio colaborativos y hemos identificado problemas concretos; a partir de aquí, hemos desarrollado protocolos coútiles mediante mecanismos de incentivación que puedan abordar los problemas subyacentes. Más concretamente, consideramos los modelos basados en la participación de la gente (micromecenazgo y externalización de tareas) y el mercado de préstamos en línea por pares, y extendemos nuestro análisis al mercado de comercio electrónico. En este tipo de modelos de negocio, donde las plataformas digitales facilitan la colaboración, se necesita un principio estándar que gobierne a los agentes egoístas de manera eficiente. Por lo tanto, la noción de coutilidad que introducimos en este trabajo es útil para conciliar la libertad individual y el bien común de la sociedad de la información en la que se inscribe la economía colaborativa. Con el fin de afrontar la asimetría informativa y la consiguiente desconfianza y temores relacionados con el mercado de financiación colectiva, modelamos esquemas de incentivación que hagan estrictamente coútil el micromecenazgo. Los esquemas de incentivos que proponemos son la reputación de base comunitaria y los mecanismos criptográficos. Del mismo modo, para el mercado de préstamos por pares y el comercio electrónico, con el fin de abordar el problema de la falta de confianza en las transacciones entre los usuarios, usamos un protocolo de reputación distribuida basada en el principio de coutilidad. El mecanismo parte de la premisa clave de la confianza transitiva.

Este mecanismo de reputación es de coste reducido, anónimo en su cálculo y robusto contra ataques de manipulación indebida. Estas características lo hacen más atractivo para estos mercados. En resumen, el trabajo aquí presentado contribuye a la escasa literatura sobre la economía colaborativa y permite mejorar los métodos convencionales en uso.

Chapter 1 INTRODUCTION

1.1 Motivation

Collaborative economy is a new form of economic system that relies on the general economic practices with the information technology as a catalyst. It relies on a hybrid business model of peer-to-peer direct transaction, Hamari, et al. (2015). This economic system is mainly characterized by a technology oriented economic activities of sharing, leasing, swapping, selling and buying, lending, giving and bartering interactions of rational agents. The technology oriented supply-demand facilitation that empowers consumers in the collaborative economy is featured by an abundant liquidity. This economic system unlocks idle capacity and avoids overconsumption underlying the traditional business models which are disintermediated by the customers who directly connect with each other. PricewaterhouseCoopers in 2014 reported that five sectors of the collaborative economy (peer-to-peer financing (P2P lending and crowdfunding), crowdsourcing, P2P homestay networks, ride sharing and music/video streaming) are predicted to generate about $335 billion global revenue by the year 2025.

Unlike the standard centralized economic system, the collaborative economy empowers individual customers to be directly involved in value creation and exchange. Owyang et al. (2013) argue that one of the catalysts arises from the social media, which are supposed to impact the existing communications, marketing and customer care business functions. With a value co-creation principle, this economic system relies on a “win-win” principle in which economic agents interact to maximize their respective utility through a direct involvement in the process of value creation. This win-win scenario is formalized as a notion of "co-utility" in this work and will be presented in the subsequent chapters in detail.

Before we go into further detail and discuss the underlying business models of the collaborative economy (which is at the core of this text), it would be worth fleshing out the trends in the societal structure of this economy. The new phase of societal structure in the informational society in general is categorized into two groups: the *digital natives* (those born in the digital world) and the *digital immigrants* (those who adopted the digital world’s way of life), Prensky (2001). This demographic composition, on the side of market suppliers, has created a tension in the ways incumbent players operate resulting from the competition from the new market entrants. The incumbents are faced with the so called Innovator’s Dilemma in meeting the demand for the diverse societal structure, endangering their existing business lines to the cannibalization risk (Christensen, 2013).

In addition to the disruption in the traditional business models, this trend is supposed to create a tension in the labor market resulting in the substitution of the manually performed tasks to automation. However, scholars in the field argue that the existing trend can co-exist for quite a while until the traditional way of operation fades out and the transformation to the new digital economy is/becomes smooth. According to the Intuit's Future of Accountancy Report (2013), with the demographic shifts from the digital immigrants to the digital natives, irreversible consumer behavior emerges and the transformation of the traditional service sector to the modern digitized service naturally smooths by itself as the millennials hold the market through time and the baby boomers retire. In line to this, Marinc, M. (2015) in analyzing the pace of disruption from the digital wave to the banking industry argued that automatized decision-making in transaction lending techniques cannot make human decision-making based on the soft information present in obsolete banking relationship. The argument is based on the ground that a game of incomplete information, such as a poker game, is much more difficult for computers to master compared to chess, and hence that human decision-making surpasses that of automated actors when it comes to strategic decision-making.

As mentioned above, the existing economic and sociopolitical settings are originating new forms of operations due to the current waves of the internet and digital technologies. As a result, digitization and the advent of the interconnected world with internet as driver are the game changers in the current era of the mesh economy. Information being at the core of this economy, the new informational society has embraced the utilization and manipulation of information in the economic and socio-political activities (including business and marketing activities, education, health service, governance, elections, etc.) through the use of new technologies and the internet. Modification in the business models, change in the customers' preferences and channels of supply and access to the scarce resources at a nearly zero marginal cost (Rifkin, 2014) are some of the specific trends on this regard. Hence, these transformations in the social and economic organization together with the underlying rational human behavior call for a significant work to be done in the current state of the art in capturing the dynamics of this economy.

The existing trends following the new wave of the collaborative economy have a number of features that characterize it, Owyang et al. (2013). Despite its interesting features and potential for further growth, this economic system is prone to security and privacy risks, and the lack of trust between peers of transactional networks limits its efficiency. The lack of trust in peer-to-peers networks refers to the quality and reliability of service obtained in a transaction. In fact, trust is considered to be the 'currency' of the collaborative economy and there is pressing need for standard reputation systems that guarantee such trust. On the other hand, the challenge to the government is noticeable in regulation of the businesses underlying this economic system, which results in disruption of the government revenues and hence another issue with this economic system in its current form. Other issues include disruption to the traditional business models, fear to the incumbent players and business cycle uncertainties with the new business models.

It is clear that the collaborative interaction in this economic system takes place between rational utility maximizing agents. Hence, in this work, in order to conciliate the individual freedom and common good of the collaborative economy, we adopt the concept of co-utility, which refers to the notion of mutually beneficial interaction between self-interested agents. Note that the collaborative economic system mainly relies on mutually beneficial and interdependent value creation process (either goods or services). Hence, the co-utility notion characterizing collaborative protocols that are mutually beneficial for the involved parties is important provided the underlying problems in the practice of this economic system. Here, we mainly focus on the win-win collaborative scenarios under the general umbrella of the notion of co-utility, which we present later in Chapter 4. We focus on some of the collaborative economy business models, specifically the crowd-based business model (crowdfunding and crowdsourcing), the P2P online lending market, and further extend our analysis to the ecommerce market. In each case, we have proposed incentive mechanisms that can tackle the underlying problems of lack of trust between transacting parties and other related problems. Some of the solution concepts we suggested in this regard include reputation mechanisms (for crowdfunding, P2P online lending and e-commerce) and encryption (for the crowdfunding). The detailed analyses and work on these topics are presented in the respective chapters on each case.

1.2 Goals

The main goal of this thesis is to address through the notion of co-utility some of the problems existing in the practice of the business models of the collaborative economy. With the aim of mending the aforementioned fractures in the undertakings of the collaborative economy (more specifically, the security and privacy risks, and lack of trust between the transacting peers), the work focuses on developing co-utile solutions that improve their efficiency. The thesis studies specific use cases and analyzes how to deal with information asymmetries and the resultant problems by introducing incentive schemes and reputation mechanisms whenever needed. This is done by (i) analyzing the collaborative economy use case under consideration in the light of the notion of co-utility, (ii) identifying the main deterrents of co-utility (and, thus, of the success of the underlying system), and (iii) proposing mechanisms that neutralize them (whenever negative utilities to any participating peer arise), thus re-establishing co-utility and ensuring the sustainability of the system. The specific goals of this dissertation work are as follows:

- To adopt the concept of co-utility, which implies a philosophy of economic and social norm that can govern mutually beneficial interaction for the new trends of the sharing economy in a self-enforcing way.
- To provide a co-utility analysis of the collaborative economy with a special focus on the crowd-based business models (crowdfunding and crowdsourcing), the peer-to-peer online lending market, e-commerce and cryptocurrencies, and the application of blockchain technology in the business process.
- To identify the deterrents of efficient collaboration/transaction and the resultant negative utilities to the involved peers in the above stated collaborative economy business models.
- To suppress sub-optimal interactions through self-enforcing mutually beneficial protocols for the business models of the collaborative economy and, hence, foster efficiency. This involves developing, designing and suggesting co-utile solutions that can mend the key underlying problems of the business models of the collaborative economic system. More specifically, community-based reputation mechanism, a decentralized co-utile reputation mechanism and encryption are the main solution concepts introduced into these business models depending on the problem under consideration.

1.3 An overview of this thesis

The remainder of this document is organized as follows.

Chapter 2 presents the general background on the collaborative economy. Further, it identifies issues, such as trust and reputation, that are key to this economic system.

Chapter 3 provides an extensive review of the state of the art of the collaborative economy scenarios studied in this work: crowd-based business models, online lending markets and electronic commerce feedback mechanisms.

Chapter 4 introduces the notion of co-utility, which is the core concept underlying the studies conducted in this work. This chapter provides a formal definition of the concept in terms of game theory and discusses its similarities and differences w.r.t. other related concepts.

Chapter 5 presents the first use case of co-utility amenable games, that is, the crowd-based business model. First, the crowdsourcing market is analyzed by defining the respective utility functions of the players under this market, which show that this market is naturally co-utile. Then, the crowdfunding market is analyzed by identifying its key underlying problems, which are the mistrust and fear effects. Accordingly, due to these underlying problems, the market is not co-utile and an artificial incentive scheme is proposed to make the market co-utile and hence, efficient. The discussion in this chapter is supported through a graphical analysis depicting the mistrust and fear effects in the crowdfunding market. Furthermore, the chapter extends its discussion by forwarding implications to the conventional methods of operation.

Chapter 6 presents an overview of the online lending market and analyzes the underlying problem of mistrust in which we propose a solution to improve its efficiency. Furthermore, an experiment on a simulated platform with data sourced from the Lending Club (one of the well-known P2P lending marketplaces) is used to test the potential of the reputation protocol we introduced to capture the behaviors of borrowers and lenders.

Chapter 7 presents a further use of the decentralized reputation protocol in the electronic commerce market in order to rate buyers and sellers. A detailed analysis of the potentially co-utile nature of the market is presented using the Edgeworth Box, which is commonly used to illustrate a voluntary exchange that represents a win–win situation for the transacting parties.

Chapter 8 highlights the main contributions and lists the publications of this work. It also depicts several lines of future work.

Chapter 2 BACKGROUND

2.1 The collaborative economy: an overview

The collaborative economy (also known as mesh or sharing economy) is a term that refers to a technology-oriented supply-demand facilitation with an on-demand extension of the concept to the production, distribution, and consumption of the previously underutilized resources. By underutilized resources, we mean resources that are not being used to their fullest potential. This has resulted in an efficient utilization of scarce resources, which is the underlying motive of the theory of economics. According to the economic theory, the scarce resources are insufficient productive resources to fulfill the unlimited wants and needs. The collaborative economic system on this regard is a system for the efficient utilization of the scarce human and physical resources through collaborative actions. Even if cooperation, sharing, generosity, individual choice and flexibility are behaviors that have naturally arisen in the course of human history, the current business model predicated on such behaviors takes a more structured form of give and take strategy or simply philanthropy. Information technology and the social media, population growth, growing income disparities, and the increasing global financial, environmental and social crises are some of the driving forces behind this system. The mesh economy takes many varied forms and information technology is playing a key role in enabling most of the sharing ecosystem. Hence, through the collaborative economic setting and with the help of the internet, a means to share and utilize the limited resources in a collaborative way is created. One example of this can be the human capital, which is made easily accessible through the crowdsourcing marketplaces of the collaborative economy business models. In its raw sense, the core principles supposed to govern the system are: collaboration, empowerment, transparency, humanity and altruistic sharing for the common wellbeing. This economic system is characterized by the underlying key economic features of sharing, leasing, swapping, selling and buying, lending, giving and bartering. With these key transactional features, it unlocks the idle capacity in the utilization of the scarce economic resources mainly using, but not limited to, the Internet. Various online platforms enable connections between people, organizations and ideas more efficiently than the traditional ways of communication. This results in new economic, social and financial models that further enhance the sharing economy. Financial technologies, including the business lines of peer-to-peer (P2P) transactions, crowdfunding and crowdsourcing, innovation and educational marketplaces, are some of the common structures of this economy.

The collaborative economy paradigm revolves around the core principles of *collaboration*, *empowerment*, *transparency*, *humanity* and that of altruistic sharing for the common wellbeing, which results in an efficiency with no hyper-consumption. The emergence of irreversible consumer behavior is one of the catalysts for a widespread replication of this system all across the globe. This implies a preference shift of the digital society to a new form of utilization of goods and services. Moreover, the big insights underlying the digital economic system have facilitated (and benefited from) big data processing.. In addition, the uberification of services across different sectors of the digital economy following Uber’s business model of app-enabled mobile services has greatly facilitated the instant access to economic resources.

Rifkin (2014) argues that there is a paradox in the capitalist system and that the invisible hand that has been responsible for the capitalism's success has led to a new successor paradigm called the collaborative economy. This is presented in his book, which describes what he calls the 'zero marginal cost society'. Yet, some of the new business models we came across with this trend have elements of altruism and interest combined, which has diverted the core principle underlying the sharing economy with a seed of capitalism embodied in it. In line with this, some scholars argue that the collaborative economy, which has initially manifested itself in the form of sharing economy, has more tendency to be a pure capitalism. For example, Preez (2015) in his blog post proposes networks with members' co-ownership rather than the operation in the form of monopolistic platforms like that of Uber. A prominent example of a successful co-ownership model in the empirical world is the John Lewis Partnership one, which is a UK-based retail company co-owned by the employees. For the system not to collapse and destroy itself, the values derived should lay on the principles of mutual help and ethical grounds as well. This calls for the novel concept of *co-utility*, proposed in Domingo-Ferrer et al. (2017) and Domingo-Ferrer et al. (2016), which provides the ground to designing interaction protocols among agents that conciliate their selfish and rational choices with societal welfare. Therefore, we adopt the notion of co-utility with its interesting features of welfare maximization for the collaborative economic setting as presented in the subsequent chapters of this thesis.

This economy is characterized by abundant liquidity. PricewaterhouseCoopers estimated that, by the year 2025, transactions under this economy are expected to generate about $335 billion at a global level. Despite its rich liquidity, the collaborative economy has posed many challenges to the incumbent traditional players of the respective sectors. Some of these challenges include disrupting the incumbent customer base of traditional sectors and, also, making their business models and services obsolete. Furthermore, the service sector of this economy is booming with the catalyzing advancements in the digital technology. In the e-education service provision for example, video conferencing and streaming and online collaboration portals without a need for a face-to-face contact have eased the access for global supplies and demand in the sector. Also in the e-health sector, the traditional business is hard hit by this wave in which remote diagnosis, advertising of drugs and other treatments, and the sharing of patient experience through electronic health records are made easy. The same trend is true in the broadcasting and media sector, where a vast amount of social media networks and user-generated contents is flourishing. On the other way round, with the new business models, new risks to the collaborative economy itself arise. These new models are exposed to new challenges and uncertainties unique to their individual set-up. This is mainly due to the dynamic and hasty evolution of the business models in order to cope with the new regulatory and legal codes and latest technology-based competition from their fellow players.

Furthermore, this economy, being in its infant stage of development, poses a challenge to the government, because it is difficult to enact new rules and regulations coping with the dynamics of the collaborative business models. This will disrupt the government's revenue also with a paramount transformation of the incumbent market players before new rules are enacted. Another important thing to point out in this trend of the new economy is the problem of mistrust between the players within the system itself. This results from the uncertainties and asymmetric information that exist in most of the transactions of the collaborative economy models.

The aim here in general is to foster the application of the "collaborative economy" and its core principles through the imposition of co-utile solutions. This helps guarantee efficient transactions in this economy by suppressing sub-optimal interactions through self-enforcing and mutually beneficial protocols.

2.2 Trust and reputation: currency of the collaborative economy

Trust in the business context refers to the act of value exchange in a fair and equitable way stating the level of confidence an individual agent puts on their business partner. Generally speaking, trust depends on the degree of risk involved in a certain set of transactions. This can be supported by the reputation of the business partner regarding trustworthiness. Accordingly, reputation is one of the highly-valued assets in the current era of the digital economy, and it is considered as the currency of the digital ecosystem, (, and Owyang et al. (2013). In an eBay like online marketplace, sellers' reputation affects the demand for their products and acceptance rate of the BIN price (Buy-it-Now price) offered by them in which case highly reputed sellers have more acceptance by the buyers than the less reputed ones (Anderson et al. 2008). Likewise, buyers' credibility both in their bids and customer loyalty depends on their reputation in the market. Economic theories with a motive to capture the dynamics of trust construction between collaborating agents have suggested a number of game theoretic analyses (e.g. Fudenberg, and Levine, 1992, Friedman and Resnick, 2001 and Dellarocas, 2003).

Reputation games generally fall under the umbrella of repeated game (due to the repeated interactions) and Bayesian game structure, with the information asymmetry and uncertainties underlying this type of interactions. This concept has great importance in today's online marketplaces and the crowd-based business models, where information asymmetry and uncertainties are one of the key problems. Online marketplaces like eBay, Yahoo Auctions, Alibaba Group, Amazon.com, Lending Club, Kickstarter, Prosper Marketplace, etc. suffer from some major issues of trust. These markets are commonly characterized by a repeated transactional interaction between a number of rational long-run (mostly sellers) and short-run players (buyers with mostly one time transaction with a single seller) in a sequence of continuous transactions.

In online communities, giving feedback is commonly on a voluntary basis. Since feedback is privately examined and subjectively valued, it is one of the underprovided economic goods. Provided this, a number of reputation models utilizing game theoretic modeling approaches have been proposed, with an assumption that players types are defined by their past record and, hence, committed to honesty (Stackelberg action) with the expectation of their future reputation. This is a sound theoretical modeling. However, the question on how an efficient reputation mechanism should be designed so that it can clearly depict the real player's type is not addressed. Therefore, there should be an efficient reputation mechanism that can guarantee trust within the market and make it efficient. The literature proves that, in repeated simultaneous or sequential games, a long-run player who is patient takes a Stackelberg action with high probability, see Fudenberg, and Levine (1992). This thus guarantees the proper operation of a reputation game between a long-run and a short-run player (or between both long-run players with less frequent interactions) provided that it is well designed. In line with this, Dellarocas's game-theoretic model shows that, with a reputation effect, honest collaboration is the best strategy for the long-run sellers and short-run buyers in an eBay-like online marketplace setting.

Despite several arguments in the analysis of the dynamics of trust in the online marketplaces, key questions aimed to address the prior objective of efficient market development and design, still remain unanswered. Any protocol designed to guarantee trust in a given transactional network should be able to capture the dynamics in the real individual players' behavior, and must be attack-tolerant in a way that sticks the evolving agents to a given equilibrium outcome. Attacks to be tolerated include whitewashing, identity changes (new pseudonym), fraud, strategic manipulation of reputations, retaliation effects, etc. In order to attain this, the mechanism should be designed in such a way that it optimizes the respective utilities of players. Hence, there is a need for defining case-specific reputation mechanisms and adapting efficient incentive/punishment schemes that commit all the players to collaborating in a self-enforcing and decentralized way.

To sum up, even if the collaborative economy is a promising economic system in an efficient and cost-effective utilization of scarce resources, the effectiveness in its undertakings still are questionable. On this regard, being commonly operated in a form of web-based collaborations, the issue of building trust between the collaborating agents is one of the open areas of research as the collaborative economy grows and expands its applications. In the following chapter, we present the state of the art and review of literature by summarizing the related works that deal with the underlying business models of the collaborative economic system.

Chapter 3 LITERATURE REVIEW

3.1 The crowd-based business model

The literature on the crowdfunding and crowdsourcing markets is in its early stage of development. Relatively little scholarly work is available, even though the turnover of these crowd markets is measured in billions. Yet, some scholars in the fields of economics, entrepreneurial innovation, information marketing, HCI (human–computer interaction) and many others have analyzed this emerging industry.

To start with the crowdfunding market, Mollick (2013) pointed out that, beyond or in addition to fund-raising, crowdfunding is used by entrepreneurs to demonstrate/estimate the demand for a proposed product (hence operating as a signal for the traditional form of funding), to pre-sell and introduce a new product (marketing purposes), to create interest in new projects in their early stages of development, to attract the attention of the media, etc. According to Gerber et al. (2012), requesters/entrepreneurs take part in the crowdfunding market to raise funds, establish relationships, receive validation, replicate successful experiences of others, and/or expand awareness of their work through social media. On the other hand, these authors also identified the motives for funders to participate in this market as seeking rewards, supporting entrepreneurs, or engaging and contributing to a trusting and creative community; they concluded that the weight attached to each of these motives varies across different players. In this regard, Pazowski et al. (2014) also argue the same as the aforementioned scholars and further discuss the disincentives for both entrepreneurs and funders. Along the same line, Lehner (2013) stated that the crowd behaves in unpredictable, chaotic and multifarious manners and reacts in a hyperbolic way to any actions by the funded project.

Hildebrand et al. (2014) found that there exist perverse incentives for the group leaders in peer-to-peer lending systems in which there are rewards for the signaling group leaders. As a result, they suggested that the leader take a significant share of the loan and define the cutoff criterion in effect. According to them, this will lead to lower interest rates and lower rates of default.

Personal networks (involving public figures) and extensive social media networks (Facebook, Twitter, etc.), as well as the quality of the underlying project, have most often been mentioned as key factors to the success of crowdfunded projects.

Lack of coordination between funders is one of the key problems in the crowdfunding effort. Provided a time frame for a project to be funded, an experiment on a simulated donation-based crowdfunding platform by Solomon et al. (2015) indicates that a leadership approach is a better strategy to donate for a project of one's interest (signaling for other potential donors). In contrast, the wait-and-see approach is a better strategy for funders with small payouts and relatively weak preferences (wait and make a small contribution at the end). In addition to this, both intentional and unintentional free riding may occur in the crowdfunding market.

According to Wash and Solomon (2014), crowdfunding entails some element of public good. Clearly, if funds are raised for schooling, healthcare, etc., this is public good in the obvious sense. Yet, a subtler form of public good occurs no matter the nature of the new product being funded, because the funding crowd makes that product available to the market for everyone to use *ex post*.

On the other way round, being an interaction between anonymous players, this business model suffers from the information asymmetry problem. As Wash and Solomon (2014) stated, crowdfunding markets do not guarantee a stable match and there exists mistrust by the funders (whether the entrepreneur is trustworthy), while on the side of the entrepreneur/requester there is a fear of failure and a fear of public disclosure of the project idea and its details (with the subsequent loss of intellectual property). Belleflamme et al. (2013) also identified uncertainties and information asymmetries between the entrepreneur and funders in the pre-ordering and profit sharing forms of crowdfunding. They recommended the formation of strategic ties between the entrepreneur and investors/consumers by creating a sense of belongingness, membership to the community and rights of control and vote. The latter rights can be realized in some cases by involving the crowd in some strategic decisions about the design and nature of the product. Mollick (2013) identifies delay in payment of pre-agreed rewards to the funders and failure because of a fraud or an overambitious project as some other challenging uncertainties in crowdfunding.

Like in crowdfunding, players in crowdsourcing also have heterogeneous motives for participation. Slivkins and Vaughan (2014) identified heterogeneities underlying the crowdsourcing market as: individual task performance levels, relative difficulty in the task, attitude of workers and satisfaction. Consequently, incentive schemes in such markets have a significant effect on the functioning of the peer-to-peer interactions, especially with an anonymous large crowd. Huang et al. (2012) found an adverse effect of increasing rewards on the quality of the solutions produced by the crowd: higher rewards do not guarantee higher quality, because participants may exert more effort in the competition itself than in cooperating to achieve quality. The authors proposed a policy that can induce more participation and higher effort with higher expected payoff. Earlier work by Terwiesch and Xu (2008) presented an analysis of the type of innovative tasks that can be executed through crowdsourcing contests and the associated optimal reward structure. A larger crowd size encompasses diversity and indeed benefits the requester, whereas performance-contingent reward in the market induces more effort. A related work by Anari et al. (2014) stated that the requester derives some utility by hiring the crowd and there is a minimum level of wage each worker wants to earn for getting hired. Yet, there is information asymmetry between the requester and the worker, because the information on the minimum wage the worker wants to get paid is private to the workers. With this underlying asymmetric information and the budget constraint of the requester, they designed a budget-feasible mechanism with a given effort level in order to choose the right set of workers that maximize the requester's utility.

According to Ghosh and McAfee (2012) quality and participation (with an associated cost of effort) are the key issues that arise in the crowdsourcing analysis. They argue that the level of effort an agent chooses to exert depends on the underlying incentives offered. In this regard, they analyzed mechanisms that can incentivize high effort in case entry (that is, joining the effort) is an endogenous strategic choice by the participating crowd. Their analysis of crowdsourcing based on attention rewards shows that when the cost of producing the lowest possible quality content is low, the optimal mechanism displays all but the poorest contribution. In the cases where there is a fixed total reward randomly distributed to the participating crowd, subsidizing entry may improve the expected quality of the average contribution, but not the expected quality of the best contribution.

Reputation schemes in peer-to-peer networks have been a mechanism suggested to stimulate smooth operation of crowdsourcing markets. Extensive works have also been carried out by scholars in different streams on capturing the reputation effect on varied areas. For instance, Zhang et al. (2012) argued that there are intrinsic incentive problems underlying the crowdsourcing market, where all the players (the crowd and requester) are selfish, that is, they strategically optimize their own interest. They propose incentive mechanisms based on social norms by integrating reputation mechanisms that can induce high effort.

On the other hand, according to Slivkins and Vaughan (2014) there exists information asymmetry in the crowdsourcing market and workers and requesters can behave strategically. Accordingly, persistent reputation scores for both workers and requesters will limit spam and induce worker effort, while encouraging requesters to be more considerate. They further argue that the basic models for reputation systems have limitations when applied to crowdsourcing markets (for example, limitations in the domain-specific design goals, reputation designed separately from task assignments, limited information about the players, etc.) and they pointed out that there is a need for defining an optimal reputation mechanism specifically designed for the crowdsourcing market.

3.2 The P2P online lending market

Individual agents engage in a P2P lending market for diverse reasons. For instance, borrowers post loan requests in the online P2P marketplaces to finance various aspects in their lives. Lenders in this market view loans as investments to obtain some returns. Also, lenders may have motivations beyond returns, such as to do social good and help the community (Krumme and Herrero, 2009).

Regulatory frameworks for the P2P lending market vary depending on the country in which they are operating. For instance, in some countries like the US, there is a quota restriction requirement for the maximum amount a lender can invest in a given P2P lending marketplace (Serrano et al, 2015). Other regulatory and policy frameworks in the P2P online lending deal with the minimization of operational risk and customer protection (Milne and Parboteeah, 2016) through segregation of the platform user money, well-ordered platform cessation, default and debt management and transparent and informative lending process. For Funk et al (2015), one of the regulatory requirements to operate a P2P lending market in some countries is partnership operation with the traditional banks in facilitating of the lending process. They stress that external stakeholders like banks and credit agencies are vital in P2P lending marketplaces. On the internal aspect of the P2P lending platforms, they suggest a restructuring of the internal form of the P2P platform itself with a focus on the business models, organizational design and those factors that generate success of P2P platforms. Furthermore, other regulatory policies focus on enhancing competition and ensuring efficiency through a fair access to credit.

Zeng (2013) has presented a detailed analysis of the US and Europe’s legal frameworks concerning P2P lending. Following the 2008 regulations in the US, P2P lending market is made more transparent with the Securities and Exchange Commission (SEC) making updated reports of the P2P companies through its EDGAR system (Electronic Data-Gathering, Analysis, and Retrieval). Further, a secondary market operation for the notes following the regulation enabled the liquidity of the P2P loans. According to Zeng (2013), the major regulatory issues regarding the P2P lending market in the US and Europe are the same. Some of these include the following:

1) Securities law, which requires the SEC registration of P2P platforms, P2P offerings, platform notes, of any P2P transaction broker and investment advisers, and platforms' report to the SEC.
2) Lending laws/lender licensing, usury laws, state licensing requirements, bank secrecy act regulations (that is, requirement of the P2P platforms to verify the true identities of both the lenders and borrowers, e.g., criminals or members of terrorist organizations based on information from federal agencies), report any suspicious account activity, information sharing and anti-money laundering programs, and third party usage of bank charters.
3) Consumer protection laws, lenders/funding banks and P2P lending operators are required to provide sufficient information to the borrowers and investors in a given transaction regarding the loan terms. Further, any form of consumer discrimination is illegal (securing a fair access to credit). Furthermore, the debt collection process should be compliant with the law (for example, collecting a debt in a harassing or abusive way is illegal).

Note that, the above regulation list is in the context of the US law and the SEC considered as the authority. The European system has its own regulatory bodies. One of these bodies of the P2P financing in the UK is the Financial Conduct Authority (FCA).

Rotating Credit Association (RCA), a form of P2P lending commonly practiced in many countries including the US, UK, Asia and Africa, has been controversial due to the usury issues associated with it. This is because RCAs are commonly formed between members with regular contributions to a common pool, which is sequentially distributed to each member. In most cases, this form of lending relies on a social trust and high interest rate that are set (about 30%) to offset potential default. As a result, countries like the US and Canada have usury laws that prevent excessive interest rates on loans (e.g. Revised Code of Washington (RCW) 19.52). This law does not exist in the UK, which has served a tax haven for the US payday lenders in the UK. This is also an indication for some of the problems associated with the global regulatory framework disparities in the P2P lending market.

Many scholars in the field have analyzed this new market in different ways. One of these is Marot (2014), who analyzed the expected returns in the P2P online lending market in connection with the probability of default underlying each loan. Accordingly, he predicted that the risk of default varies with time during the loan period and that there is an increasing risk of default with time, which starts to decline when the loan is close to maturity. According to Emekter et al. (2015), loan grade, debt-to-income ratio, credit score (FICO) and revolving line utilization have a significant effect on the probability of default. In the same line, Funk et al. (2015) have presented a detailed review on the factors that define borrower's probability of successful loan origination (liquidity) and those that determine the probability of successful return to the lender. Here, they identified a generalized category of borrower characteristics as financial, demographic and social characteristics, like friends and group affiliation (see also Lin (2009) for the categorization of borrower characteristics into hard and soft credit information).

The market is prone to the following key problems: liquidity risks, fraud, security and operational risks (dangers of fraud, cybercrime and operational outages), platform failure, risk of default, usury and systemic financial risks due to liquidity and credit risks in the business cycle (Milne and Parboteeah (2016), Zeng (2013), McIntosh (2010), Serrano et al (2015), Zeng (2013), etc.). In order to tackle some of the problems stated here, government regulations, systematic agreements and feedback mechanisms are recommended (Zeng, 2013 and Yang and Lee, 2016). Milne and Parboteeah (2016), on the other hand, believe in developing a reliable business process model that can tackle the underlying problems and industry-wide standardization that help achieve the legal requirements set by the monitoring authority. "In the UK the related initiative (HM Treasury, 2014) is to develop standardized APIs (application programming interfaces) for SME data so that transaction information can be shared by all potential lenders, and not only the bank providing a business with payment and bank account services. This standardization could be a further support for the growth of P2P lending" (Milne and Parboteeah, 2016).

On top of the above-mentioned problems is the information asymmetry underlying the market creating difficulties in the online P2P lending markets' day-to-day transactions (see for e.g. Funk et al (2015), Lin (2009), McIntosh (2010) and Serrano et al (2015)). Accordingly, identifying credible borrower's identity is one of the key factors for the lenders' profitability from this kind of investment. Some scholars in the field, like Serrano et al (2015), argue that P2P lending platforms are responsible for providing accurate information on the borrowers' characteristics in order to foster the efficiency of the lending process. Numerous P2P lending platforms are flourishing in this sector of the financial industry. Hence, increasing the participation rate in these platforms depends on the credibility of the platform itself in addition to the borrowers' characteristics and lenders' herding behaviors. Yang and Lee (2016) identified the following three categories of trust for the credibility of a P2P lending platform.

1) *System-based trust* through service quality (efficient and flexible transactions), information accuracy, security, and systematized contractual terms and conditions, which will also help reduce adverse behaviors arising from the information asymmetry.
2) *Cognitive-based trust* by creating first impressions through awareness, reputation and addressing perceived risk.
3) *Affective-based trust*, for instance, the utilization of social networking, which helps for a long-term strategic alliance in order to build trust and mutuality.

Associated with the information asymmetry in this market, there is a significant mistrust effect that draws back the efficiency of the market. Several types of filtering and reputation methods are at play in the market, including third-party algorithmic investing, basic filtering and community-based reputation. On this regard, Collier and Hampshire (2010) analyzed how structural and behavioral community signals interact with a borrower's signals to the mistrust effect in P2P lending. As a result, they developed a model and theoretical application to community reputation systems by considering a person's social reputation together with an outcome-based reputation, which produces an implied market-related reputation. Hence, social capital, that is, the social network and connections between members that help incorporate the soft credit information about the borrower, is considered as one of the tools to bridge the information gap between borrowers and lenders in this market (Lin, 2009, and Greiner and Wang, 2009). Yet, the effect of social capital in filtering credible borrowers depends on the participants' creditworthiness where an agent can strategically mask itself under the social capital shield whenever a group effect is considered.

Sabater and Sierra (2002), on the other hand, analyzed three dimensions of reputation systems: the individual dimension (based on direct interaction of individuals in the light of outcome-based reputation), the social dimension (extended social interaction: witness, neighborhood and system reputation based on a role played by a target agent) and the ontological dimension (a complex reputation mechanism based on a combination of other related behavioral structures of an individual agent). In addition to these three dimensions, the reputation system they recommend also considers an outcome reputation deviation, where greater variability in rating values implies volatility of the target agent in fulfilling their promises.

3.3 Reputation management in online transactions

In this era of collaborative economy, reputation is a highly-valued asset that can be considered as the currency of peer-to-peer systems (see the speech by Botsman (2012) on the TED Talk). Information asymmetry is one of the underlying factors that call for an efficient reputation mechanism that narrows the information gap between collaborating agents. However, the nature, reliability and the dissemination mechanism of information define the efficiency of a reputation protocol to be adopted for a given network.

In this regard, the literature so far is limited in the sense that the reputation systems used by the authors are not self-enforcing and, in some regard, are partial (either community-based or outcome-based signaling). Chen et al. (2004) compared in their experimental study different reputation mechanisms based on the level of information and self-reporting. Accordingly, they defined a trust value in a range [0, 1], where trust values of 1, 0 and 0.5 represent complete trust, distrust and uncertainty, respectively. Buskens (2002), on the other hand, argues that the number of links in a network explains why agents trust more one network than another, while the number of links of an agent explains why another agent trusts this agent more than the others in the same network. These metrics allow developing a control and learning behavior on the agents that continually interact.

Many other authors have suggested a mechanism for building trust in a given network (ranging from Kamvar et al. (2003), to Collier and Hampshire (2010) and Donato et al. (2007)). More recent work by Domingo-Ferrer et al. (2016b) suggests a distributed and co-utile way of computing the agents' reputation. This mechanism has the attractive properties of being attack-tolerant, anonymous, cost-effective and computed in a self-enforcing decentralized way. The reputation mechanisms currently at play in the market are subject to tampering attacks and can be personalized to the peers own benefit, rather than truthfully reporting on a target agent. Because P2P lending implies the interaction between rational agents, the reputation protocol that operates in the market should be self-enforcing in order to be rationally sustainable; in this way, each agent would have incentives to compute values in such a way that it can truly measure the creditworthiness and honesty of all other agents. Hence, making a reputation protocol self-enforcing and beneficial for all involved agents will guarantee that it is in the best interest of each individual agent in the system to compute another agent's reputation as accurately as possible.

E-commerce is a form of internet-based transaction which employs reputation management for its online transactions. Two of the biggest players in consumer-to-consumer web-based transactions are eBay and Amazon.com. These platforms employ various feedback mechanisms that help build trust between the transacting agents. Yet these reputation mechanisms have their own pitfalls apart from being managed in a centralized way. In the eBay reputation system, there is evidence of correlation between buyer and seller feedback, suggesting that the players reciprocate and retaliate (see Bolton et al. (2013), Cabral (2012) and Resnick and Zeckhauser (2002)). The question is how exactly can an eBay bidder use a seller profile to determine how much to bid for something and whether to bid for it at all? In this sense, Aberer and Despotovic (2004) argue that game-theoretic reputation systems, which give the equilibrium of the feedback game, can help handle the problem of seller identification provided that the players are rational utility-maximizing agents. Yet, this method of modeling is limited in capturing the dynamics of online platforms where there is commonly an interaction of a long-term player (e.g. seller) with multiple short-term players (e.g. buyers) and, due to its practical limitations in capturing the reality on the ground and quantifying players' discount factors and the discounting criteria, it is not standardized.

For this reason, the use of game-theoretic reputational mechanisms in the online marketplaces is not so common. Hence, a co-utile reputation mechanism (Domingo-Ferrer et al., 2016b) helps tackle the limitation underlying the current conventional online reputation mechanisms like that of eBay and that of the game-theoretic reputation models suggested in the literature (see for example Dellarocas, 2003). The game-theoretic model and the conventional reputation computations assume a central authority that is responsible for the aggregation of feedbacks, unlike the above-mentioned co-utile reputation mechanism, which operates in a self-enforcing decentralized way.

Hence, from our discussion above, we see that the digitization of everything in the collaborative economy, including finance, service delivery and goods and services trading, has called upon engineering to cope with the limitations of the traditional economic theory based analysis in capturing the dynamics underlying this trend of the economy. The science of building trust calls for varied insights from computer science, information systems, management science and psychology, beyond the conventional microeconomic and game-theoretic human behavior modeling. In effect, in this work (detailed analysis and modeling presented in Chapter 6 and 7 below), we suggest to use a co-utile extension of the well-known EigenTrust algorithm (a reputation mechanism designed for building trust in the P2P online file sharing system) in the P2P online lending and e-commerce markets, specifically in online consumer-to-consumer marketplaces like eBay.

3.4 Conclusion

This chapter has presented a concrete insight of the related works on the collaborative economy, and more specifically the business models underlying the system. Here, we have mainly focused on the business models of the collaborative economic system, and the basic theoretical underpinnings depicting the main issues of the system in a broader sense. The literature covered in this thesis is far from addressing the main issues arising in the collaborative economy. Some of the issues that are not addressed by the literature are lack of trust between collaborating agents, efficiency, disclosure, and other related issues arising in this economic system. In the following chapter, in order to tackle some of the problems that arise in the operation of this business models, we will introduce the notion of co-utility. By co-utility, we mean a self-enforcing and mutually beneficial interaction between collaborating agents. Detailed analyses and presentations of the concept in the context of the collaborative economic system are given in the subsequent chapters of this thesis.

Chapter 4 CO-UTILITY

4.1 Introduction to co-utility

Co-utility refers to a philosophy of economics and social norm of mutually beneficial interaction. It explains mutuality in the framework of the social rational choice theory. Proportional mutual compensation for the magnitude of a non-unidirectional flow of values between individuals or parties may imply a mutually beneficial give or take, but not necessarily equal. This concept can be viewed as an extension to the utilitarian theory with a basic moral foundation. It is a new concept in which the best way of serving one's own interest is to help in one or more other peers' interest fulfillment. Hence, co-utility promotes the interest of all in maximizing pleasure/satisfaction or minimizing pain/suffering in a harmonious way. In co-utility, the interests of the individual agents in their interaction can be symmetric or not. In the latter case, the agents will still have complementing goals.

Co-utility, a notion firstly coined by Domingo-Ferrer et al. (2016) and further discussed in Domingo-Ferrer et al. (2017), can be applied to many P2P interactions in the information society (e.g., content distribution, anonymous queries and data anonymization- see: Domingo-Ferrer and Megías (2016), Domingo-Ferrer et al. (2017), Soria-Comas and Domingo-Ferrer (2015)) and in the physical world (e.g. ridesharing, Sánchez et al., 2016).

In game-theoretic terms, a protocol is a sequence of actions chosen by players in a game. A protocol for a peer-to-peer online lending market, for example, refers to the sequence of interactions between borrowers and lenders within the set of rules of a given marketplace and business model, provided their respective individual strategic behaviors. If the game is a market, a business model or a specific behavior of the market players could be viewed as a protocol. Given a game presented in extensive form (a tree where: nodes are the points where decisions are made; each node is labeled with the name of the agent making the decision; outgoing edges in a node represent the available choices (actions) at that node; each leaf node is labeled with the tuple of payoffs players get when that leaf is reached), a protocol is either a path from the root to a leaf or a subtree from the root to several leaves. A protocol for a game guarantees co-utility between the involved agents if it is designed to be self-enforcing and it results in mutually beneficial interaction between the agents.

In Domingo-Ferrer et al. (2017), self-enforcing and co-utile protocols are defined in the following game-theoretic terms:

Def. 1 *(Self-enforcing protocol):* A protocol is self-enforcing if, at each successive node in the protocol path, sticking to the next action prescribed by the protocol (taking the next edge in the path) is an equilibrium of the remaining subgame (the subtree rooted at the current node), that is, a subgame-perfect equilibrium of the game.

Def. 2 (*Co-utile protocol):* A protocol P on a game G is co-utile if it is self-enforcing, the utility derived by each agent participating in P is strictly greater than the utility the agent would derive from not participating, and P is Pareto-optimal (there is no alternative protocol P' on G giving greater utilities to all agents and a strictly greater utility to at least one agent).

Co-utility can naturally arise, or it can be induced through artificial incentives in case a protocol is not naturally co-utile, Domingo-Ferrer, et al. (2016b). Strict co-utility is achieved when a co-utile protocol *P* offers maximum utility to all agents involved in it.

Therefore, with the above definition of co-utility, an outcome for any game is co-utile if and only if it satisfies the following three conditions:

1. It is an equilibrium (it can be Nash equilibrium, a subgame-perfect equilibrium, a reciprocity equilibrium, myopic stability, farsighted stability, etc.),
2. It is Pareto-optimal, and
3. All players obtain strictly greater payoffs by playing the game than by not playing it.

In games that operate sub-optimally, we can achieve better results by changing the rules of the game in order to attain co-utility. However, there are situations in which co-utility fails to hold; this occurs mostly in games that incorporate some element of competition between players. For instance, in negotiations about global warming, suppose there is a protocol that gives maximum utility to one or a group of countries, while moderately benefiting the other countries as well (providing them with positive utility). Due to economic and geopolitical motives, it is unlikely that the countries with a relatively moderate gain will ratify this protocol (e.g., this was the case for the Kyoto Protocol).

Furthermore, it is worth mentioning the following key points about the co-utility theory.

(i) Players involved in any co-utile interaction can either have symmetric or asymmetric goals. For example, in the case of a P2P file sharing network, the goals of all the agents involved in this network are the same. However, if we take a P2P online lending, the goal of a borrower is soliciting finance, while that of a lender is making profit at a given interest rate.

(ii) A proportional flow of values in a co-utile interaction is a necessary condition in order to keep a positive utility for all the agents involved, yet this flow of values need not be equal.

(iii) Co-utility can arise either naturally or artificially through incentive mechanisms. Here, it is important to consider the time at which payoffs to any co-utile games are attained, i.e. immediate or future expected payoffs. This will help capture the dynamics of co-utile interactions between rational agents, especially when designing artificial incentives that will guarantee co-utility in a potentially co-utility amenable game. In some cases, an agent may do a favor to another because the other has favored this agent in the past or is expected to do so in the future. Hence, in addition to spontaneous interactions, a co-utility framework can be designed to consider the dynamics over time.

(iv) As it is specified in the formal definition of co-utility above, a co-utile interaction results in superior payoff over the next best alternative interaction for all agents involved. Hence, the efficiency of any co-utile game can be measured by quantifying the intrinsic efficiency advantage of co-utile interactions over the other option.

(v) The basic requirements for the fulfillment of an efficient co-utile interaction are collaborative demand (ability and willingness of the parties involved in the co-utile game), commitment and trust between involved parties, a defined platform, and a post-transaction positive utility.

4.2 Co-utility amenable games

There are some empirical examples of human interaction in economic, societal and political scenarios that are potentially co-utile; that is, such scenarios are co-utility amenable games, under a game theoretic perspective. Here we point out a few of this co-utility amenable games, which will later be analyzed in depth in separate chapters.

4.2.1 FinTech in a broader view

Financial technology, abbreviated as FinTech, refers to technology-oriented business lines of the digital economy. FinTech companies range from crowdfunding and peer-to-peer lending to algorithmic asset management and facilitation of investments, financial planning and portfolio management and thematic investing, payments, data collection, credit scoring, education lending, digital currency, exchanges, working capital management, cyber security and quantum computing. Lending Club, Kickstarter, Prosper, Betterment, Xoom, 2iQ Research, ZestFinance, Coinbase, SecondMarket, Tesorio, iDGate, Motif Investing, Stripe and Square are some examples of marketplaces in this industry. In addition, already-established IT companies like Facebook Apple Pay, Android Pay and Google Wallet are also actively involved in the money-transfer markets and mobile payments. This wave of technological penetration in the financial industry has created a significant pressure to the incumbent traditional players in the market. The tech startups come up with an improved artificial intelligence, automation, and algorithmic decision-making, cost effective data mining and processing, and a convenient and efficient operational speed capturing the low-end customers' preferences. According to a report by McKinsey and Co. (2015), traditional banks could lose about 60% of retail profit to tech startups.

Unlike the traditional form of business models, each individual user and consumers themselves are co-originators of value in this new system. Hence, we see that there is a space for co-utility underlying these business models. Some real-world examples of the co-utility amenable games from the digital economy business models include crowdsourcing, crowdfunding, P2P online lending, e-commerce, etc. A detailed analysis and discussion of these business models in the light of the co-utility notion will be presented in the following chapters.

4.2.2 e-Commerce

The digital world has become a venue for entertainment, news, shopping and social interaction, easing the way for the current trends of the collaborative economy. Unlike the core principles of traditional business models, the digitized online marketplaces add significant values to the players in terms of interactive and accessible transactions through mobile apps, well-built online marketplaces with large networks of global players, and reduced transaction cost. The global value chains and the easily accessible marketplaces, on the other hand, have facilitated placing online orders from anywhere across the globe. Buyers aim at maximizing their utility from the set of products available in these marketplaces. The existence of large numbers of suppliers and different marketing strategies that fit various customers' preferences and expectations allow the customers to make rational and strategic decisions. Hence, electronic commerce is a potentially co-utility amenable game. However, some practical problems arising in this form of transaction make the market inefficient. This will be addressed later in Chapter 7 of this thesis.

4.2.3 Cryptocurrencies and the blockchain technology

The digital finance innovations known as cryptocurrencies are further examples of co-utility amenable models. They are considered as the virtual game-changers that meet the FinTech business model needs for digital value transfer and exchange. This technology has made possible geographically unbounded, frictionless, secure and cost-effective flows of values across the globe. Cryptocurrencies like Bitcoin (BTC) are peer-to-peer payment systems in which direct transactions between peers are conducted without a central party. Transactions between peers are confirmed by network nodes and recorded in the blockchain (i.e., a public mutually distributed ledger). The blockchain uses cryptology to guarantee trust between transacting peers in a decentralized way. Some traditional banks and financial institutions facing competition from the new FinTech wave are working to use this technology for a cross-border money transfer and trading (e.g. CBA, Australia, which uses the Ripple payments).

Despite their promising features, these decentralized virtual currency systems also have some limitations. Some of these include (1) difficulty in the exchange with other currencies, (2) being a tool for black market operation and tax evasion purposes in some cases, (3) being prone to potential theft attack of private keys, (4) expensive electricity cost for computations and (5) a possible attack by selfish miners/mining pools who could subvert the system for their own benefit (Eyal and Sirer, 2014; Kiayias et al., 2016; Johnson et al., 2014).

In order to characterize the behaviors of miners in the Bitcoin network, we present the model in the following simplistic way. In its current setting, miners are rewarded based on successfully mining a new block (fixed amount of 25BTC ≈12500€ at the current rate of exchange) and an additional 1.33% of the transactions in the added block (Kiayias et al., 2016). Every miner in Bitcoin aims at maximizing the revenue from mining. Hence, the profit function of any miner, m is defined as follows:

$$\pi_m(r, f(\lambda_m), c_m(\lambda_m, t)) = f(\lambda_m).r - c_m(\lambda_m, t), \qquad (4.1)$$

where r is the reward, λ_m is the miner's relative computational power compared to other miners in the network, $f(\lambda_m)$ is a binary function of successfully solving the puzzle on time ($f(\lambda_m) = 1$ if the miner successfully mined a new block in time before other miners given its computational power λ_m,and $f(\lambda_m) = 0$ if the miner fails to successfully mine the new block on time), $c_m(\lambda_m, t)$ is the unit cost of mining a new block, which depends on the investment in the computing resources and also the time devoted to solving the puzzle, t is the opportunity cost of mining any other new block. The miner's total profit that he wants to maximize is the sum of profits from all the new blocks he mined. Thus, the miner's profit maximization problem can be stated as:

$$Max \sum_{i=1}^{n}[f(\lambda_m).r - c_m(\lambda_m, t)], \qquad (4.2)$$

where n is the total number of new blocks mined by miner m.

Given the profit maximization problem stated above, miners in the Bitcoin network use various strategies by investing in expensive computational resources or employing a number of strategic attacks against other competent players in the network. In practice, the Bitcoin mining game is an asymmetric information game. Rational miners in the Bitcoin network decide on the identification of the block to be mined and when to release or withhold the block (Kiayias, et al., 2016; Narayanan, 2015). Due to the information asymmetry underlying the game, there can be a number of selfish mining attacks. A game-theoretic analysis by Kiayias, et al. (2016) shows that, under both asymmetric and complete information of a mining game, miners with relatively smaller computational power will not deviate from the Bitcoin system design, while those with larger computational power will have an incentive to deviate. Eyal and Sirer (2014) also assert this magnitude effect by the colluding selfish miners who can generate unfair revenues. Likewise, Courtois and Bahack (2014) and Narayanan (2015) showed that a selfish mining pool can make a profit by withholding the block to infiltrate other mining pools in the mining network and consequently make unfair returns. On the other hand, Johnson et al. (2014) showed that mining pools with a relatively larger computational power are also exposed to a DDoS attacks by the smaller ones aimed at slowing down and weakening the target pools.

Regardless of all these drawbacks, a cryptocurrency as a medium of exchange is one example of co-utility amenable game in which encrypted currencies are minted by self-interested miners through a mathematical race that protects the blockchain within the network. With a decentralized setting of the network of miners who keep public records, potentially selfish miners can make the system inefficient. Hence, to make the ecosystem more robust and co-utile, further research work is needed to develop incentive schemes that can hinder malicious miners from subverting the system.

Beyond the cryptocurrencies, key features of the blockchain technology that are attractive to the financial institutions and to other transactional networks are: i) it is decentralized; ii) it is secured with cryptographic validation of transactions; iii) it is reasonably efficient; and iv) transaction records are transparent; see for e.g., Mainelli and Milne (2016) and Petrasic and Bornfreund (2016) on the applications of the blockchain technology to transactional record systems and financial services other than the cryptocurrencies, some of which include securities settlement, currency exchange, supply chain management, trade, P2P transfers, asset registration, correspondent banking, regulatory reporting and AML rules. The technology guarantees efficiency in time because it lets all the stakeholders work in a common dataset and the transaction data are efficiently organized. It also allows easy information exchange with a one-time data entry in a distributed way, without a double and separate record of events, which results in a significant reduction in costs of data reconciliation, checks and transfers. Furthermore, the potential of the blockchain technology to support smart contracts makes it attractive to the financial service sector, because it can be extended with additional features that can fit the purpose of the financial service industry; for example, a permissioned blockchain network with centrally assigned transaction validators (see Tolentino, 2016). The technology facilitates a co-utile business process and organization by allowing rational (selfish) players to interact in a self-enforcing and distributed way.

A specific suggestion in this regard can be the potential of the blockchain technology's application to the financial management and administration industry. A trust company acts as a trustee (someone who acts as a custodian for trusts, estate-oriented services such as guardianship, estate settlement, custodial arrangements, asset management, stock transfer, beneficial ownership registration, etc. and provides audit, tax, consulting, bill pay, check writing, enterprise risk and financial advisory services and other related arrangements) to the other customer enterprises in a business-with-business (BwB) like deals (e.g. Deloitte, Northern Trust, Bessemer Trust etc.). One of the key problems underlying this business sector is the lack of trust on the trust companies, which poses a limit on the efficiency of the service delivered by the financial administration and management companies. As a result, there is a need for development of a collaborative system in which all the stakeholders in this market can act towards the value-creation process and hence minimize the mistrust effect underlying the industry.

Therefore, the blockchain technology, with its aforementioned features, can help create an efficient financial service industry integrating the BwB interactions of this type in a transparent and well-organized way. In line with this, there is a need to transform the rigid accounting business models to a further digitalization and automation, and to define new potential market niches. This is because, with the newly emerging business models, the trust companies should cope with the existing technological and socio-economic trends. In this regard, we recommend the use of artificial intelligence in the sector (Baldwin et al., 2006; Liu and Vasarhelyi, 2014) and the employment of co-creative and co-utile value creation mechanisms building a secure network of transactions. The trust in the network of financial services can be built by organizing a common platform that provides security and privacy by default. The business activity logs and financial data of any registered client company in the platform are saved in a common database and a potential registered and authorized trust company can access the client's data, which are secured through data protection techniques. Possible data protection methods are data anonymization/splitting (see Chow et al., 2009, Ricci et al. 2016 and Calviño et al. 2015 on the outsourcing of computation without outsourcing control for sensitive data in the cloud), homomorphic encryption (Naehrig, et al. 2011) or privacy preserving data mining.

4.2.4 Co-utility in public relations and government policy applications

The concept of co-utility is also important in the public relations and interactions of an organization with its customers and all stakeholders. For instance, a fair market price service provision by a supplier, which neither undercuts the supplier's profitability nor passes on unnecessary cost increases to the customers, is mutually beneficial for the sustainability of the suppliers' businesses and for the cost-effective access to the company's services by the customers. Hence, co-utility as a business strategy is also promising for a sustainable profitability of the business while benefiting the customers. One example of this can be a business strategy followed by Mars, Inc., an American global manufacturer of confectionery, pet food, chocolate, candy and other food products. In 1998, when Russia defaulted on its foreign debt, in order to keep their customer base in this country, the company designed a lifeline offer of a product without payment until it was resold, which halted bankruptcy and allowed continuing their operations even during this uncertain time.

In a more general and aggregate sense, the co-utility concept also applies to the two-way democratic communication between the government and its citizens, whose interaction is based on the principles of of mutuality, empathy, trust and solidarity. This communication is done through a two-way symmetrical communication, characterized by negotiation, conflict resolution and respect. One key type of government interaction with the citizens is carried out through national policy development. For example, in the policy of holding inflation low, there exists a dynamic inconsistency arising from people's rational expectation of the expansionary/contractionary monetary policy measures taken by the government in response to a low or high expected inflation (Romer, 2011).

Two of the models proposed under this scenario are the reputation and the delegation model. In the reputation model, policy-makers with more than a 2-period office stay will aim at either wealth maximization or fight inflation, in which people build their expectations based on the past record of policy measures. A policy-maker can "cheat" since people's expectations (and trust) can be affected by the policymaker's decision, which is the unrevealed type of the policy maker. The reputation model implies that uncertainty about the characteristics of policy-makers reduces inflation. If a policy-maker does not cheat, expectations for inflation will be lower. If he cheats, the reputation will be damaged and expectations for inflation will be higher. On the other hand, a model of delegation calls for the assignment of the monetary policy to an independent inflation-averse institution.

The problem with these models lies in their limitation regarding the risk aversion principle, for example, during economic shocks. Having said this, implementation of a stabilization policy is limited in that the underlying assumption of a linear social welfare function is too strong while, on the other hand, monetary policy fluctuations also result in fluctuations in consumption and fluctuation in working hours resulting in disutility of workers. Hence, policy effects with lags, the existing economic state and uncertainty about the future set a limit on the realization of a stabilization policy. As stable economy hosts and pulls healthy investments, collaborative and mutually inclusive acts both by the government and citizens are needed. Hence, the notion of co-utility can play an important role in the interaction between the government and citizens.

4.3 Co-utility: differences and similarities with related concepts

Common utility vs. co-utility: Basically, co-utility deals with the mutual satisfaction of two or more different individuals, while common utility usually refers to the aggregate/total satisfaction of a given group with diverse individuals. In the co-utility analysis, we mainly focus on individual utility maximization, provided that the individual's best rational choice is also the best for some individual other than himself. This makes the interaction (protocol) self-enforcing and mutually beneficial.

Co-utility vs. Pareto efficiency: Pareto optimality[1] is a state of allocation of resources in which it is *impossible* to make any individual better off without making at least one other individual worse off. In other words, it is a state of allocation in which there are no further Pareto improvements. While Pareto optimality is necessary for co-utility, it is not sufficient, unless it is an equilibrium and all players get more from playing than from not playing. Considering a distribution of goods within a system, a co-utile allocation can achieve a socially desirable (equitable) distribution of resources, unlike a mere Pareto optimal allocation, which does not take into account the equality or the overall well-being of the system.

Note that co-utility captures outcomes which are stable and characterized by a win-win framework. Under Pareto optimality, however, any individual/party can do better while others doing worse. To illustrate the differences between both notions, let us consider the dam construction game for irrigation improvement taken from Gauthier (2013).

Game 1: Co-utile and Pareto-optimal outcome

[1]https://en.wikipedia.org/wiki/Pareto_efficiency

Becoming a monopolist over the water supply is the motivation of two farmers F1 and F2. Each farmer gets the highest payoff if the other does not construct a dam, gets a low payoff if neither of them constructs the dam and gets a fair payoff if both construct the dam. Hence, the payoff matrix is as follows:

		F2	
		Build	Do not Build
F1	Build	(3/4,3/4)	(1,0)
	Do not Build	(0,1)	(1/4,1/4)

From the above table, we see that one of the Pareto-optimal outcomes of the game is the joint dam construction (i.e., neither of the farmers can get a better payoff than their joint dam building without one of them getting a worse payoff by not building the dam). In addition, this outcome is Nash equilibrium of the game. Therefore, the outcome (Build, Build) with payoffs (3/4, 3/4) is a co-utile outcome. On the other hand, outcomes (Do not Build, Build) and (Build, Do not Build) are Pareto-optimal, but not a Nash equilibrium of the game and hence not co-utile.

Game 2: Strictly co-utile and Pareto-optimal outcome

If we change the game by considering a case in which the farmers are better off by helping each other to build the dam (for example because together they can build a larger dam than individually), then each one can attain the highest payoff by jointly building the dam. Therefore, the *strictly* co-utile outcome for this game is the joint building of the dam, which is both a Nash equilibrium and Pareto-optimal. Unlike in the previous case, there is no alternative outcome that can make either of the two better off than this.

		F2	
		Build	Do not Build
F1	Build	(1,1)	(3/4,0)
	Do not Build	(0,3/4)	(1/4,1/4)

Game 3: Investment game with a mistrust effect: not co-utile

Furthermore, an equilibrium outcome, which is not Pareto-optimal, is not a co-utile outcome. Consider a one investor-one entrepreneur investment game with a *mistrust effect*. There are three different scenarios: the investor does not trust the entrepreneur and he will not invest in that project, or the investor trusts the entrepreneur and the entrepreneur betrays him, or the investor trusts the entrepreneur and the entrepreneur rewards the investor on his investment. Let the payoffs (in thousand units) to each be as follows:

		Entrepreneur	
		Reward	Betray
Investor	Trust	(10,10)	(0,20)
	Do not Trust	(6,4)	(6,4)

The Nash equilibrium in this investment game is the (Do not Trust, Betray) outcome, which implies that no project financing takes place and, furthermore, it is not a Pareto-optimal solution of the game. As a result, based on the definition of co-utility, this investment game with a mistrust effect is not co-utile, even if there are other Pareto-optimal solutions that are not equilibria of the game. Another simple example of this can be the Prisoners' Dilemma game.

Co-utility vs. reciprocity: The theory of reciprocity (mainly positive reciprocity), based on experimental evidence of behavioral kindness, assumes that players are kind, and predicts a different equilibrium from that of Nash (Falk et al., 2006). It mainly refers to rewarding kind/positive actions with another kind/positive response, which might not necessarily be proportional. For example, a smiling waiter getting tipped by a customer for the friendly service, rewards/donation-based crowdfunding by accompanying small gifts/rewards of various types to backers, free samples of some products offered by supermarkets, etc. A selfish behavior can predict a Nash equilibrium, but this equilibrium may not encompass other forms of equilibrium that can arise in real life; the players can be not only selfish, but also kind, and may display kind intentions that lead to different types of equilibrium, which can be captured through the notion of reciprocity equilibrium. Therefore, as co-utility can rest on various forms of equilibria, a direct connection can be designed between the theory of reciprocity and the notion of co-utility, in which the reciprocity equilibrium in a reciprocal interaction can be co-utile as long as the outcome fulfills the conditions of Pareto optimality and strictly larger payoff, as compared to not playing the reciprocal game. There can also be negative reciprocity (a simple example can be insulting one another), which is more associated with adverse co-utility.

Co-utility vs. hybridity: Hybridity basically refers to a mixture of two or more different courses of things/actions. Hybridity is defined as "heterogeneous arrangements, characterized by mixtures of pure and incongruous origins, (ideal) types, 'cultures', 'co-ordination mechanisms', 'rationalities', or 'action logics'' (Brandsen et al. 2005, pp. 750). The concept, for example, captures the ideal situation between: profit and non-profit orientation of some organizations, public and private goods (through relational goods), market versus civil society versus state, etc. (Brozek, 2009; Bruni and Zamagni, 2007). The intuition behind this is that utility in this case is not only profit-driven; or the essential fact that humans are neither *homo oeconomicus,* who maximizes utility, nor *homo collectivus,* whose attitude is defined by his membership of a collective, but rather *homo reciprocans,* who can act out of pure kindness. This implies that the equilibrium that arises from a hybrid environment is not only derived from the selfish nature of the players. Co-utility can also rest on such hybrid equilibrium, as long as the equilibrium through a hybrid act is Pareto-optimal and the payoffs of the players through a hybrid act are strictly greater than any other way (for example, pure profit motive or pure non-profit orientation).

4.4. Conclusion

In this chapter, we have presented a detailed overview and introduction of the notion of co-utility, which refers to mutually beneficial and self-enforcing interaction between self-interested agents. A formal definition of co-utility in game-theoretic terms has been given and it has been illustrated on real-world games. Further, we have identified differences and similarities between co-utility and the concepts of Pareto optimality, reciprocity and hybridity. With these discussions showing a clear picture of the concept, in Chapters 5, 6 and 7 that follow, we will introduce the notion in the collaborative economy business models. The aim of doing so is to foster the application of co-utile models and core principles to several potential areas.

Chapter 5 A CO-UTILITY APPROACH TO THE MESH ECONOMY: THE CROWD-BASED BUSINESS MODEL

5.1 Introduction

In this chapter, we analyze the mesh economy (also known as collaborative or sharing economy) in the light of the co-utility notion. As discussed in the previous chapter, the core idea behind this novel concept is to design interaction protocols among agents that conciliate their selfish and rational choices with societal welfare. Specifically, we investigate potential co-utility amenable cases in the collaborative economy: crowdfunding and crowdsourcing. This is the first analysis of these business models within the framework of co-utility and it aims at opening new ways of analyzing various interactions between different agents having diverse interests and complementary goals.

Our main contributions are as follows. Given a market that operates sub-optimally (mainly due to heterogeneity of interests), we model incentive mechanisms that keep the business models of the collaborative economy stable in an efficient way. On this regard, we focus on the games that are potentially co-utile by taking the crowd-based business model. In particular, we show that the crowdsourcing market is co-utile by incorporating basic definitions for the respective utility functions of the participating agents: worker and requester. On the other hand, our analysis of the crowdfunding industry also yields possible solutions that can make the investment crowdfunding market strictly co-utile, that is, that all agents maximize their respective utility.

The rest of this chapter is organized as follows. Section 5.2 presents the conceptual framework with a general view of the collaborative economy and a basic description of crowdfunding and crowdsourcing. Section 5.3 presents case studies focused on crowdsourcing and crowdfunding as co-utility amenable games. For crowdsourcing, we show why the market is co-utile. For crowdfunding, we give a detailed analysis. Furthermore, simplified graphical analyses depicting the *mistrust* and *fear effects* in the crowdfunding industry for investors and entrepreneurs, respectively, are presented in this section together with the proposed incentive mechanisms. Section 5.4 discusses the implications in two well-known crowdfunding platforms. Finally, Section 5.5 summarizes the conclusions of this work and indicates some directions for further work.

5.2 Background

5.2.1 Crowdsourcing

Crowdsourcing means outsourcing a task to an anonymous group of self-interested individuals by means of an open call to the crowd offering rewards for work. It is one of the outcomes of the collaborative economy made possible by the catalyst role of information technology. The crowdsourced tasks can be as diverse as: image annotation, data labeling for machine learning systems, English proofreading, language translation, consumer surveys, rating search engine results, spam detection, product reviews, article reviews, etc.

The crowdsourcing activity may be launched through an offline campaign with self-interested part-time workers or most commonly through online platforms. The accompanying rewards for the participant may take the form of monetary rewards by the task generator (pay-on-task or contest/prize) or in the form of attention rewards for the so-called user-generated content (UGC) based sites. Here, we should take into account that in this model the transaction takes place directly between the two market players (the crowd and requester/task assigner) on a two-sided marketplace platform. CrowdFlower, Mechanical Turk, Innocentive (open innovation problem solving), Presans (connect and solve R&D problems), Ideake (collaborative crowdsourcing), Innovation-community.de (community of innovators, creators, designers and thinkers) and Challenge.gov (crowdsourcing for government problems) are some examples of crowdsourcing platforms.

5.2.2 Crowdfunding

A growing number of individuals motivated by profit, philanthropy or any other reasons are engaged in the crowdfunding industry. This industry is experiencing a fast growth, as indicated in a recent report[2]. A wide range of online third-party market platforms link entrepreneurs, investors and philanthropists to facilitate investing in social enterprises. Currently, there are a number of diverse crowdfunding platforms with different application areas and methods of funding. These include Kickstarter, Sellaband, AngelList, Betterplace, JumpStart Africa, VereinRespekt.net, c-crowd, Seedups, Thundafund, Prosper, Funding Circle, Lending Club, etc.

Crowdfunding is shaping the collaborative economy by creating a financial market that operates as an accelerating catalyst for a wide range of investor-entrepreneur relations. Crowdfunding can generally take the form of investment crowdfunding (which can follow debt-based, equity-based, profit-sharing or hybrid models) or donation crowdfunding, also known as reward-based crowdfunding (see Belleflamme et al. (2014), Mollick (2013) and Wash and Solomon (2014)). In reward-based crowdfunding, the crowd collaboratively donates, pre-purchases products or buys unique expertise experiences in return for a defined set of products or rewards. In equity crowdfunding, several types of capital and creative projects are sold to a crowd of potential shareholders in the form of equity; in contrast, in debt crowdfunding, the crowd investors finance the debt and receive a debt instrument that pays interest in return. Note that equity-based crowdfunding is one of the potentially co-utile markets in the crowdfunding industry, because it is mutually beneficial both for the entrepreneur, who gets new financing sources, and the investor backing this entrepreneur, who earns more by being a stakeholder of a potentially growing startup company.

Investment crowdfunding, however, is still in its infancy: it only accounts for a small share of the total crowdfunding industry and its legalization and formalization are still in progress. In late 2012, President Obama signed the JOBS Act, which legalized equity financing through crowdfunding as seed money to the startups, in an initiative to seek new routes that stimulate the economy[3].

Crowdfunding can be promoted through an open call on one's webpage[4], by posting a notice in a public place, or through organized crowdfunding platforms. According to Greenberg et al. (2013), crowdfunding platforms have the property of supporting the exchange of all six resources described by resource exchange theory: love, status, information, money, goods and services.

[2] http://research.crowdsourcing.org/2013cf-crowdfunding-industry-report
[3] https://www.masscatalyst.com/news/what-is-title-iii-equity-crowdfunding
[4] For example, the movie "Hotel Desire" which raised €170.000 in 80 days at its own website http://hotel-desire.com

The fund-raising projects from the general public through the online platforms commonly rely on two basic models or a mixture of them. One of these models is All or Nothing (a.k.a. return rule method): when the fund-raising period is over, money is only collected from the contributors if a pre-determined minimum amount of money has been pledged; if the target amount is not reached, no money is collected. This method is better for projects whose success critically depends on a certain minimum budget (Wash and Solomon, 2014). The other model is the so called Keep it All (a.k.a. direct method), where all the funds collected over that specified fund-raising period are handed over to the requester (entrepreneur), whether the target amount is reached or not. This second model is convenient for continuous projects in which any amount of funds raised can still be used to keep the project in progress. The bounty model, in which a reward is raised for the entrepreneur completing a certain task, can be viewed as having some elements of the previous two models. According to Wash and Solomon (2014), the All or Nothing method in the donation-based crowdfunding increases the donors' willingness to donate; further, it leads them to donate according to their preferences rather than rely on the projects that signal high funding preference by other funders; however, it disincentivizes coordination. On the other hand, according to the same authors, the Keep it All mechanism encourages coordination, with a less efficient outcome.

5.3 Demonstrative examples of co-utility amenable games

In the case studies that follow, we model crowdsourcing and crowdfunding as co-utile protocols in the crowd-based market/game. More specifically, we show that crowdsourcing is naturally co-utile and we examine to what extent crowdfunding can be made co-utile through artificial incentive mechanisms.

Note that some authors consider crowdfunding a special case of the "parent notion" crowdsourcing (for example, Schwienbacher and Larralde, 2012). However, there is a clear-cut distinction between the two business models, even though they have the general public sourcing in common. According to Brabham (2013), "crowdfunding describes a *funding model* for financing projects and ideas through general public participation in soliciting funds, hile crowdsourcing is a distributed *problem-solving and production model* to leverage the collective intelligence of online communities to serve specific organizational goals".

5.3.1 Case study I: crowdsourcing

The crowdsourcing market is a co-utility amenable game, in which both agents benefit by collaborating for their own best interest. In the process of crowdsourcing, a requester (a.k.a. employer or company) has a problem/task, the requester broadcasts the problem, and the solvers/workers from the crowd submit solutions/complete the task. Then the company rewards workers with a standard basic task-based pay (or more generally, incentive). Since the requester and the crowd of workers profit mutually (Brabham, 2013), the system is co-utile.

Here, it is worth noting that in this market there is usually a platform/two-sided marketplace that acts as a catalyst third party in return for reasonable service fees (see Figure 5.1). Therefore, even though the basic transaction takes place directly between the two players as in a P2P system, strictly speaking it is not a P2P system.

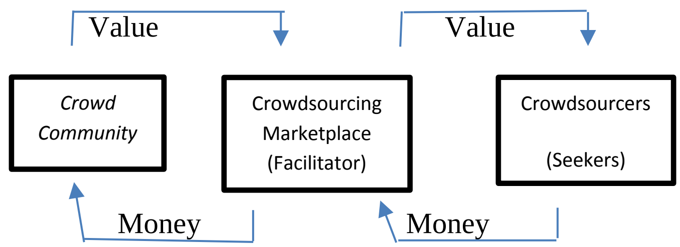

Fig 5.1: The crowdsourcing value chain

Given a crowdsourcing platform and a vector U of agent utility functions, there exists a co-utile protocol with respect to U, which is mutually beneficial for worker and requester irrespective of their individual interest. Co-utility in this market is viable provided that the goals of requester and worker are complementary and the qualification type of the worker matches the task. Based on this specification, we define the respective utility function for each agent as follows.

i) Worker's utility function

The utility worker i gets by performing task $\mathcal{T}$ through crowdsourcing is given by

$$u_i(\mathcal{T}, e) = f_i(\mathcal{T})[\alpha_i r_i(e) - c_i(\mathcal{T}, e)], \qquad (5.1)$$

where:

The actions available to the worker are to participate or not to participate;

$f_i(\mathcal{T})$ is a binary function that specifies whether or not task $\mathcal{T}$ matches worker i's interest and qualifications (ability);

$f_i(\mathcal{T}) = 0$ means worker i is not interested or not qualified to perform the task;

$f_i(\mathcal{T}) = 1$ means worker i is qualified and willing to exert effort towards this specific task;

e is the level of effort required to perform the task; $r_i(e)$ is the expected reward to worker i for effort e; α_i is a weight variable reflecting how much the individual values the reward; $c_i(\mathcal{T}, e)$is the task-specific cost of effort to worker i (it can take the form of time devoted to reading, understanding and performing the task, expenses incurred to perform the task, etc.).

From the above utility function, if $f_i(\mathcal{T})$ is zero, worker i will not exert effort to perform this task; however, he values the reward associated with the task. Since he does not participate in the sourcing, he derives no utility with regard to this task. On the other hand, if $f_i(\mathcal{T})$=1, worker i obtains some return which will lead him to derive utility or disutility depending on his expected return, on how he values the associated return and other underlying factors. The participation decision of an individual entails a trade-off between labor-leisure choices (neoclassical model of labor supply). Hence, there should be a reasonable incentive scheme influencing the worker's participation. In this setup, we assume that $c(\mathcal{T}, 0) = 0$, implying that, if no effort is exerted, there is no cost for the worker. Given the utility function and the rationality assumption, worker i participates in the crowdsourcing market if $u_i(\mathcal{T}, e) > 0$ and $u_i(\mathcal{T}, e) > u_i(l)$, where l stands for leisure; otherwise he refuses the offer and does not participate.

ii) Requester's utility function

Consider the monetary reward-based crowdsourcing. The goal of the requester is to maximize her expected utility, $Max\ u(\pi)$. That is, she wants to maximize the value she receives from the completed work minus the payments made.

In order to form the utility function of the requester and for the sake of simplicity, we assume that: all requesters have identical utility and production functions; the output is a function of only labor, and rewards are identical. We further assume that the cost and amount of effort exerted by the crowd workers are unknown to the requester. A requester who wants a task $\mathcal{T}$ to be performed has the choice between sending an online request to the anonymous crowd and relying on an off-line traditional employee. Thus, the available actions for the requester are to request the crowd or not to request (and rely on a traditional employee). The utility function of requester j can be formulated as

$$u_j = u_j(\mathrm{y}, \mathrm{w_j}, \mathrm{Crd}, \mu_j, \mathcal{T}) = \alpha_j(\mathrm{y} - \mathrm{w_j}\mathrm{Crd}\text{-}\mu_j(\mathcal{T})), \qquad (5.2)$$

where

α_j is a weight variable reflecting how much the requester values the overall gain from the output;

$\mu(\mathcal{T})$ is the minimum threshold she expects to gain from the task accomplishment;

y stands for the total output by the crowdworkers;

Crd stands for the crowd labor supply;

w_j is the per task pay offered by requester j.

Note that, when a worker who exerts low effort (shirks) is hired, requester j's cost includes both wage and disutility from hiring a shirking individual. Hence, we assume that the utility function u_j accounts for the posteriorly disclosed behavior of the individual reflected by the quality or quantity of the output produced.

A rational requester who wants a task $\mathcal{T}$ to be performed will post the task to the anonymous crowd only if $u_j(\mathrm{y}, \mathrm{w_j}, \mathrm{Crd}, \mu_j, \mathcal{T}) > 0$.

Therefore, based on the utility functions we defined above and the incentive scheme underlying the market, we see that both agents (worker and requester) maximize their respective utilities by taking part in this market. Since this does not depend on the private types of the agents, we can say that strict co-utility is achieved.

5.3.2 Case study II: investment crowdfunding

Investment crowdfunding can follow debt-based, equity-based, profit-sharing or hybrid models. It is one of the examples of a potentially co-utile market, in which two or more agents with different motivations interact. The case we analyze here in detail is a specific type of investment crowdfunding, debt-based crowdfunding, which can be extended to equity crowdfunding through convertible notes. Like in crowdsourcing, anonymity in the crowd and asymmetric information between the crowd and the entrepreneur are key features in this industry. As stated by Romer (2011), such asymmetric information between the two dealers can distort investment choices, more than would be the case for decisions based on only interest rates or profits. In this market, both agents (funder and entrepreneur) are rational and take part in the market to optimize their respective expected utility ("profit").

Investment crowdfunding is in its infancy and it represents only a very small share of the total crowdfunding volume. In addition to the legal constraints imposed to the market, other factors (including mistrust and fear of disclosure, as described above) deter individual players from taking part in such form of investment. These factors still keep drawing the market back, despite the approvals and legislations enhancing such open funding. For this reason, a co-utile protocol, whereby both agents mutually benefit and derive their optimal utility, would be very useful. In this sense, we aim at neutralizing the potentially deterring factors through incentive mechanisms in order to ensure the co-utility of the protocol.

To analyze the market and model the respective utility functions for investor and entrepreneur, we take into account the investment decision model under financial market imperfection with asymmetric information. Unlike Romer (2011), who modeled the traditional form of investment, we also consider here a case in which the crowd investor may end up with negative returns (loss of the principal invested plus verification costs) which is an extreme scenario in case the crowdfunded project fails or happens to be a fraud.

i) Problem Formulation

Assume that an entrepreneur has a creative project to be posted on one of the online platforms for crowdfunding. Let us further consider the following assumptions:

1. Being the owner of the project, the entrepreneur has much more information about her investment project (return, actual output, risk, actions of the entrepreneur, etc.) than the potential crowd investors.
2. The investor incurs a verification cost α to gather enough information on the project details to make an investment decision; this verification cost is assumed to be compensated by the entrepreneur (see Romer, 2011).
3. The project financing wholly relies on crowdfunding (as a special case of Romer's financial markets imperfections analysis, we here assume the entrepreneur's wealth invested in this project is zero) and has an expected output of γ, which might be different from the actual output, y.
4. There is large number of crowd investors and there exists competition among them.
5. The investors are risk-averse and their investment decision takes into account the risk-free rate, r_f, and the random return on the risky asset, r. So we implicitly assume the risk premium is within the random rate of return, that is $r = r_f + \mathrm{k}$, where $\mathrm{k} > 0$ represents the credit spread for the risk-averse investors in order to induce investment. This gives them the choice between investing in a safe asset and undertaking the project investment. Hence, at equilibrium, the expected rate of return on their investment to the project must be r.

6. Entrepreneurs in online platforms also are risk-averse towards publicizing creative project ideas/products to the anonymous crowd for fear of being copied.

Assumptions 5 and 6 imply the type of players (entrepreneur and investor) in the market. Given the pre-stated assumptions, the investor i's and the entrepreneur j's expected return will respectively be

$$E(R_i) = (1+r)C_i + \alpha_i, \qquad (5.3)$$

$$E(R_j) = \gamma - [(1+r)C + \alpha], \quad (5.4)$$

where C is the total invested amount (by all investors), C_i is the amount invested by individual investor i, α is the total verification cost (by all investors), and α_i is the verification cost incurred by investor i, with $\alpha_i \geq 0$.

The entrepreneur becomes indebted to reward the expected return to the investors. Hence, the entrepreneur's optimal strategy is the one that minimizes the verification cost, given their respective basic returns, at some critical level of debt to the entrepreneur, D. Assume that returns are uniformly distributed and the maximum possible level of output is γ*. Given the agreed upon amount of return D, the entrepreneur is indebted to satisfy that amount without any verification cost by the crowd and takes the surplus with probability:

$$\pi = (\gamma^* - \mathrm{D})/\gamma^*. \qquad (5.5)$$

Unlike the traditional form of investment, this form of investment may end up with zero return and, hence, loss to investors even if they pay the verification costα with probability $(1-\pi)$.

ii) Crowd Investor's Funding Decision

The expected net return to the investor (crowd) under this debt contract with the competition and risk of project failure assumptions will be a function of *D* given as:

$$E(R_i) = \pi x_i D + (1-\pi)[-(1+r)C_i - \alpha_i], \qquad (5.6)$$

where x_i is the proportion of investor i's investment to the project, $\sum_{i=1}^{n} x_i = 1$ and $D_i = x_i D$. By substituting Expression (5.5) into Equation (5.6), differentiating with respect to *D* and equating the result to 0, we get that the net return R_i is optimal for $D = \frac{\gamma* - (1+r)C_i - \alpha_i}{2x_i}$. The investment decision of the crowd depends on the expected net return of the project, $E(R_i)$. Therefore, investor i takes part in the crowdfunding of the project if and only if the required net return, $(1+r_f)C_i$, is not more than the optimal expected net return, R_i*, (i.e. $(1+r_f)C_i \leq R_i^*$). This implies that, in order for her to invest in the project, her return for investing in that project should, at least, match the return of investing in a safe asset. Otherwise, if the latter return is greater than R_i*, she does not take part in the project at any interest rate, *r*.[5] Note that this also implies that the risk premium offered by the projects should be substantial enough, depending on the market, to surpass the minimum required level of return which could be attained by investing in a safer asset. Furthermore, it is limited to the extent in which it can offer optimal

[5] This is a so-called credit rationing scenario (see Romer 2011, who presented the analysis for the traditional investment financing with risk neutral investors).

return to the individual investors. Also, the unobserved risk premium induced in the random interest rate offered by varied projects to be crowd financed should minimally be bound to the market optimal level of return.

The actions available to a potential investor i are to invest or not to invest. The utility function of an individual who might potentially take part in the crowdfunding can be formulated as a function of return $u_i = u(R_i)$, where $R_i = \pi x_i \mathrm{D} - (1 - \pi)[(1 + \mathrm{r})\mathrm{C}_i + \alpha_i]$ is the return on investment.

Given the debt contract, $D,$ and x_i, if the probability that the project pays the expected return is close enough to one and, hence, $R_i > 0$, then the underlying investment decision depends on the utility a potential investor might derive from this level of return, given the required rate of return. Consider a risk-averse crowd investor who decides whether to invest in this project or not with imperfect information. Assuming a classical negative exponential utility function, her utility of return can be presented as:

$$u(R_i) = -e^{-\beta_i R_i}, \qquad (5.7)$$

where $\beta_i > 0$ is the risk aversion factor for investor i (we assume that investors have different risk aversion based on their level of information, experience with such investment, invested amount, income, etc.).

Hence, for $R_i > 0$, we have $u'(R_i) = \beta_i e^{-\beta_i R_i} > 0$ and $u''(R_i) = -\beta_i{}^2 e^{-\beta_i R_i} < 0$, where $u'(R_i)$ and $u''(R_i)$ are the first and second derivatives of the utility function w.r.t. return, respectively; thus, the properties of non-satiation and risk aversion are satisfied. Furthermore, this utility function exhibits a property of constant absolute risk aversion and invariant risk in absolute money terms (Cvitanic and Zapatero,2004).

The investor, who is maximizing her expected utility of return, invests in the project if she derives positive utility from the funding ($u_i > 0$), and $u(R_i{}^*) \geq u_i((1 + r_f)C_i))$. That is, if the utility she derives by investing in that project is, at least, as high as the utility she would obtain with a safe asset. With the above formulation, if $\pi \approx 1, E(R_i) \approx x_i D$, then $u(R_i) \approx -e^{-\beta_i x_i D}$, and at the optimal return, $R_i{}^*, u(R_i{}^*) = -e^{-\beta_i \frac{\gamma * -(1+r)C_i - \alpha_i}{2}}$. If $\frac{\gamma * -(1+r)C_i - \alpha_i}{2} \geq (1 + r_f)C_i$, then $-e^{-\beta_i \frac{\gamma * -(1+r)C_i - \alpha_i}{2}} \geq -e^{-\beta_i (1+r_f)C_i}$, by the non-satiation assumption on the utility function, where $u(m+1) > u(m)$, for any money return, m . Therefore, keeping all other factors constant, a risk-averse investor takes part in the crowd investment at the optimal debt contract when deriving higher utility as compared to a safe asset. If $R_i{}^*(D) < (1 + r_f)C_i$, say $(1 + r_f)C_i/2$, then $-e^{-\beta_i(1+r_f)C_i/2} < -e^{-\beta_i(1+r_f)C_i}$ for $\forall r_f \in (0,1)$ and $C_i > 0$. Hence, the individual i does not invest (i.e., does not take part in the crowdfunding) since she derives less utility than by investing at any interest rate r.

Another interesting scenario is the case in which the investor might end up with negative returns, $R_i < 0$, in case of fraud or failure of the project. A risk-averse investor also tries to avoid this scenario in her investment decision, reflected in the *mistrust effect*, which we will discuss later in this chapter.

iii) Entrepreneur's Investment Decision

Suppose that, if the project idea is sold to some buyer, it can be valued at a value V, and, if the project idea cannot be transferred to any buyer, then V will be zero. The entrepreneur has a choice to either run the project through crowdfunding with a net expected return of $\gamma - [(1 + r)C + \alpha]$ or refrain from resorting to crowdfunding. Here, to avoid complications with more options of traditional investment, we assume that, if the project is profitable to run, the entrepreneur prefers to run the project through online funding. This may be in order to access a large number of investors or for any other reason like demonstrating the demand for a proposed product, creating interest in new projects in the early stages of development, attracting the attention of the media, marketing strategy, establishing relationships, receiving validation, replicating successful experiences of others through feedback, expanding awareness of work through social media, etc. (see Mollick, 2013, and Gerber et al., 2012).

The available actions for the entrepreneur j are to request crowdfunding or to refrain from doing so. Hence, the entrepreneur broadcasts the project for public funding if the net return $\gamma - [(1 + r)\, C + \alpha] > V$ given that $(1 + r_f)C \leq R^*$ from the investors' point of view.

Due to the *disclosure fear effect* that we will later discuss, the entrepreneur is also risk-averse towards her project being funded through the anonymous crowd. Therefore, assuming our previous risk-averse investor's classical negative exponential utility function, the entrepreneur's utility function can be formulated as:

$$u_j(C, r, \gamma, V) = -e^{-\beta(\gamma - (1 + r)C - \alpha - V)}, \qquad (5.8)$$

where $V \geq 0$ and $\beta > 0$ is a risk aversion coefficient for the entrepreneur.

A rational entrepreneur broadcasts her project to the crowd if the utility derived from this project is positive, and $u_j(C, r, \gamma, V) \geq u_j(V)$. That is, the entrepreneur goes for crowdfunding for her project if the utility she derives by running the project through seed money financing from an anonymous crowd is, at least, as high as the market value of her project idea, *V*, when sold to some buyer. More generally, the investor solicits finance through a crowdfunding if the expected return paid to the outside investors does not result in credit rationing and if the expected net returns to her are higher than what she can earn by refraining from running the project (opportunity cost of investment).

iv) Disutility: The Fear and Mistrust Effects in the Investment Crowdfunding Market

From the discussion above, we see that, to make crowdfunding co-utile, we must deal with negative utilities that deter an individual investor or entrepreneur from taking part in this market. Apart from the net return based investment decisions illustrated in the formulation above, some other factors might discourage the participation of an agent.

One of the main deterring factors is *mistrust by funders* regarding possible frauds. Funders want to be sure that their investment goes to the right project and they want to be guaranteed the promised return. As Lehner (2013) pointed out, the utility functions of equity investors in crowdfunded ventures may differ from those of traditional for-profit investors. From the entrepreneur's point of view, *fear of failure, imitation or plagiarism with full content disclosure* (loss of intellectual property) are deterring factors for crowdfunded ventures. This element of fear on the side of the entrepreneurs affects the extent they could freely signal quality and preparedness of their project idea to the general public. As a result, the entrepreneur faces a trade-off between a need of raising capital and a threat of their idea being copied by other market participants (Pazowski et al. 2014).

In order to capture the effects arising from the above disutilities, let us formalize the utilities of investors and entrepreneurs taking them into account.

The utility function for crowd investor i, u_i, accounting for the mistrust effect, assuming a negative exponential utility function, is redefined as:

$$u_i(R, \Gamma) = \begin{cases} -e^{-\beta_i \Gamma R} \text{for } \Gamma \neq 0, \\ 0 \qquad\qquad \text{for } \Gamma = 0, \end{cases} \qquad (5.9)$$

where Γ is the variable for trust taking values in the interval between $[0,1]$, where the boundaries are defined as 1 (if the potential crowd of investors completely trusts the entrepreneur to reward the expected return) and 0 (if the potential crowd investors does not trust the entrepreneur at all). Hence, with no trust in a given project (case $\Gamma = 0$), a potential investor does not take part in the crowdfunding of the project, because she derives no utility from it.

Likewise, the utility function for entrepreneur, j, accounting for the *fear of disclosure effect* is redefined as:

$$u_j(C, r, \gamma, V, \mathcal{F}) = \begin{cases} -e^{-\beta\mathcal{F}(\gamma-(1+r)C-\alpha-V)} \text{ for } \mathcal{F} \neq 0, \\ 0, \qquad\qquad\qquad\qquad \text{for } \mathcal{F} = 0, \end{cases} \qquad (5.10)$$

where $\mathcal{F}$stands for the no-fear of content disclosure (loss of intellectual property or being copied), and it takes values between $[0,1]$, where $\mathcal{F}$ is1 if the entrepreneur can broadcast her project content with no fear of being copied by others and no other project-related fear (e.g. failure), and 0 if the entrepreneur is in complete fear of broadcasting her project content (there is no utility for her in broadcasting the project).

v) Graphical Analysis Depicting the Mistrust and Fear Effects

This section presents the *fear* and *mistrust effects* in the investment decision of the investor and entrepreneur using graphical presentation. The graphs in the Figure 5.2 below are based on Equation (6.6) above. For simplicity of presentation and without loss of generality, we normalized the parameters that do only affect the scale of investment to a constant value. We also calibrated the discount factor, *r*, to be 6.5% (see pp. 953-954 of Taylor and Woodford, 1999). The analysis is done on an artificial platform with a uniformly distributed range of values for the principal amount invested by each individual crowd investor (ranging between \$100 and \$131 with a 0.5 step) and potential output of projects (ranging between -\$8000 and \$8000).

Figure 5.2 graphically presents the investment decisions of an individual investor at the optimal debt contract and a given probability of success of the project. As it can be seen from the figure, the investment decision of an individual investor depends on the threshold level (that is, the required rate of return). Hence, as it is also discussed in Section ii above (crowd investor's funding decision), the collaboration in crowdfunding takes place above the red plane representing the accrued amount at the risk-free rate of return, *ceteris paribus*. Note that, given the monotonocity assumption of the utility function with respect to wealth, the same logic holds as for the return to investment; the plot in the figure directly presents the return as a decision criterion for the sake of simplicity and without loss of generality.

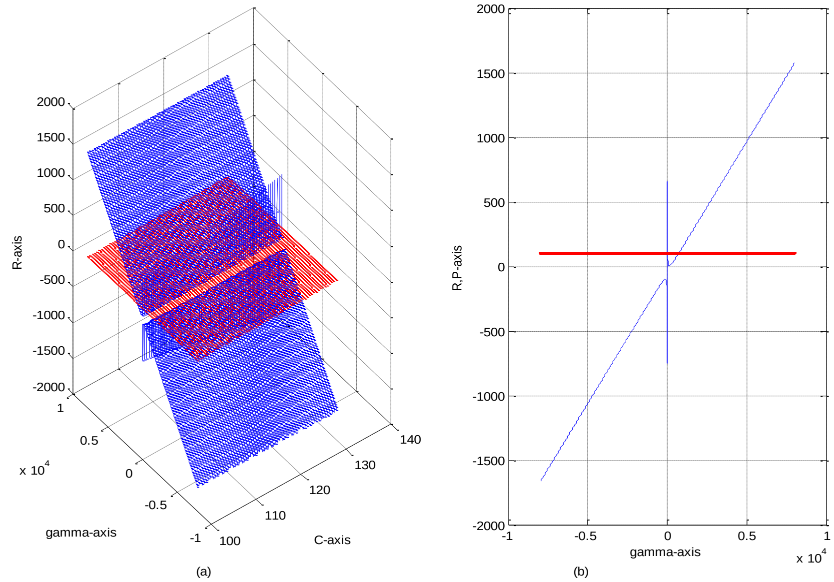

Fig 5.2: Investment decision by an investor relative to the required rate of return: (a) Return on the Z-axis, total output (gamma) on the Y-axis, and principal ($\boldsymbol{C}$) on the X-axis; (b) Return on the Y-axis and output on the X-axis.

Furthermore, we have seen that factors other than return can affect the investment decision of an individual investor in crowdfunding. Therefore, in the following graphical analysis, we present the effect of mistrust in the investment decision of the individual investor accounting for the negative exponential utility function given in Equation (6.9) above. Here again, we calibrated the coefficient of risk aversion, β, to be 1, which is also common in a set of macroeconomic, microeconomic and asset pricing evidences and we used a simple interest rate of 6.5% as in the previous case. As discussed before, we took continuous values for the variable trust, $\Gamma \in [0,1]$, to show how the utility of the individual investor evolves with the increased credibility of the project.

From Figure 5.3, we can see that, with a larger level of output, γ, and a higher credibility of the project, the individual investor's utility increases, while this is not true if the project has larger output and low credibility. Hence, above the minimum required return with perfect trust close to 1, the utility of the individual investor will be the highest possible one under this condition, and collaboration in the crowdfunding takes place with full credibility. On the other hand, with low trust, sufficiently close to 0, the credibility of the project fails and even above the threshold line (red plane) no collaboration in the crowdfunding takes place (to the left of the yellow plane in this specific case).

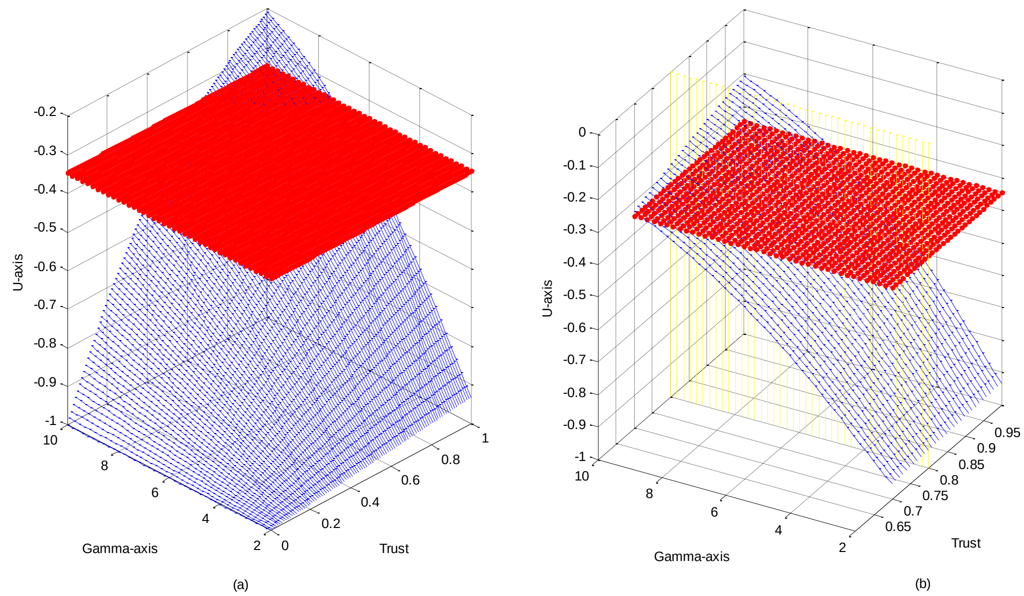

Fig 5.3: Mistrust effect in the investment decision of crowdfunding: utility on the Z-axis, total output (gamma) on the Y-axis, and trust on the X-axis

As it can be seen from Figure 5.4 below, collaboration in the crowdfunding business on the side of the entrepreneur takes place above the threshold level $u(V)$, the utility derived from the market value of the project if transferred/sold to some buyer. The analysis is based on Equation (5.10). Again, we took $\beta = 1$ and $r = 0.065$ for the same reasons mentioned above. Graph (a) in the figure is simulated under the condition of fixed optimal market value, while graph (b) is simulated for a range of output values depicting the same reality. Graph (b) depicts that the entrepreneur is willing to broadcast her project above a standard no-fear level ($\mathcal{F} \geq 0.5$ to the right of the yellow plane in this specific case, where the utility is relatively higher). On the other hand, she will not broadcast her project for crowdfunding if her no-fear level in broadcasting the project is poor ($\mathcal{F} < 0.5$ in this specific case), that is, if her fear of disclosure is high. This high-fear region is depicted with the part of the graph below the threshold $u(V)$ (red plane) and to the left of the yellow plane.

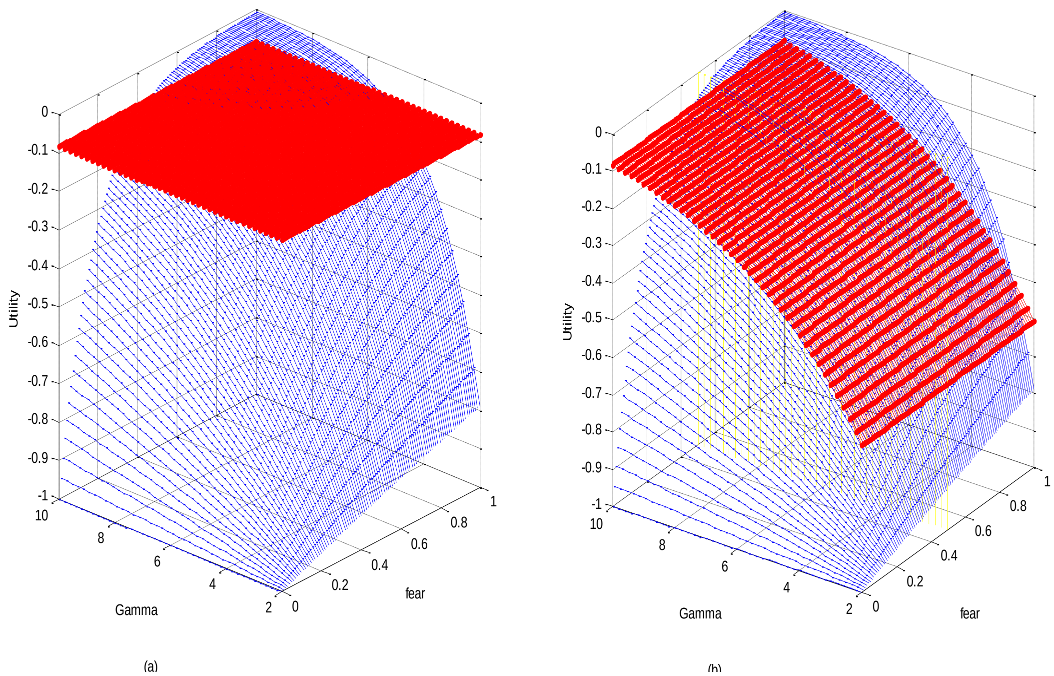

Fig 5.4: Fear effect on the entrepreneur's choice of the type of project funding: Utility on the Z-axis, total output (gamma) on the Y-axis, and no-fear on the X-axis

For clarity of presentation, the graphs for the investor and entrepreneur are presented separately in Figures 5.3 and 5.4, respectively. Having a closer look at these graphs together, we can see that there is a Pareto-optimal point at which strict co-utility is attained in the given range of values in the graphs. Here, the graphs on the left of the respective figures show that the partial derivatives of the utility function with respect to total output (gamma), trust and no-fear are positive over the range of values under consideration[6]. Hence, the utility is increasing in all the variables (gamma, trust, and no-fear), which implies that at the maximal point of output, trust and no-fear indicate a maximum point of utility at $\gamma = 10$, $\Gamma = 1$ and $\mathcal{F} = 1$ for both the investor and entrepreneur. Therefore, all the points above the red planes in both graphs are points of collaboration. Inversely, all collaboration taking place below these planes are not co-utile. The only co-utile point of collaboration is the Pareto-optimal point at which the optimal level of no-fear and trust is attained, and this point lies above the threshold level at which the return-based investment decision takes place.

vi) Proposed Mechanisms to Keep the Investment Crowdfunding Market Strictly Co-utile

As presented in Game 3 of Section 4.3, for an investment game with a mistrust effect, such a disutility leads a potentially co-utile market to a non-co-utile outcome. To keep the investment crowdfunding market strictly co-utile, we provide the following solutions that neutralize the disutility arising from mistrust by investors and fear of intellectual property loss or other project-related fear by the entrepreneur.

[6] It is trivial from Equations (9) and (10).

Firstly, the entrepreneur should be guaranteed protection for her intellectual property that does not depend on any legal common framework accepted by all investors (protection should be self-enforcing if we want to achieve co-utility). To do so, any individual entrepreneur, before publicly broadcasting her idea, should encrypt it and secure the private key with a decentralized timestamp[7], where an individual hash tag is generated for each project description in a common basket for all the projects running on a specific platform. Hence, in case of any claim, she can decrypt the document and claim ownership. Secondly, in addition to the previous artificial incentive to mitigate the entrepreneur's fear of intellectual property loss, we introduce a reputation mechanism to rate entrepreneurs and mitigate mistrust by investors.

Individuals taking part in this market are rational and investors can diversify the risk by investing in more than one project. Mollick (2013), in his analysis of the crowdfunding industry, has found evidence that funders respond to signals about the quality and creditworthiness of the project, regardless of their expectations for financial return. Signaling can be through peer ratings, where the probability of failure from the past record and poor quality or an infeasible project can be revealed and publicly displayed based on these general public ratings. Such a public rating also allows for experts within the crowd to evaluate the project idea.

Moreover, as Wash and Solomon (2014) stated, individual project funders complement each other because no individual funder can finance the project alone. Thus, each funder prefers to contribute to projects that are promisingly financed by others, so that the project receives enough funds to succeed. Likewise, investments in crowdfunded startups do not rely wholly on one individual investor's contribution, but on an aggregate contribution by the entire crowd. Therefore, we also argue that equity investments by the crowd complement each other. This implies that there is a need for collaboration between the agents (either between the investors themselves, or between entrepreneurs, or between investors and entrepreneurs). Hence, in our setting, we consider the interdependent utility of the community by maintaining the resource flow within the community with the reputation mechanism.

Furthermore, we assume that an individual can form a team and be a head of her team. Hence, in this setting we introduce a team player, where there will be varied teams of different nature and interests within the market. An entrepreneur can broadcast her project idea individually or join a team for a signaling effect. Any individual investor who is interested in any of the teams will join the team to avoid the risk of failure with a membership fee that is proportional to her individual investment capacity. An entrepreneur who wants a signaling effect from such team leaders pays a stimulation fee for the signaling effect of the head and the fee is paid in two rounds: first, before the signal, and second, after a successful campaign with the signaling effect. This will allow for a detailed and closer look at the feasibility of the project by a second party who plays a signaling role. The key role of the head in this transaction is to bear the risk of failure, with an insider's view assumption, through signaling for a potentially promising project. The head issues protection notes to the members in that it guarantees potential investors (team members who are supposed to pay continual membership fee) to be paid some percentage of their invested amount as compensation in case of failure of a wrongly signaled project. Furthermore, the signaling also has a spillover effect for other potential investors who are not members of the team.

In the deal between the entrepreneur and the head, the entrepreneur provides the head with additional convincing information on her project far more detailed than the information disseminated to the general

[7] Refer to the decentralized timestamp mechanisms in crypto currencies like Bitcoin.

public. In order to avoid the project idea being leaked or overtaken by the head, the entrepreneur provides a redacted document, with key content being reasonably suppressed. We further assume that there will be a defined time frame within the platform in which it is expected to raise the funds for the project. Hence, assuming the debt contract as discussed above, when the project is broadcast for crowdfunding, the head pledges some amount of money which will be issued in the form of convertible notes as early as possible to signal the trustworthiness and value of the project. In doing so, she takes into account the net gain she draws from the investment. Her return from the signaling investment depends on the level of risk she takes, which in turn depends on the level of creditworthiness of the project provided the level of generalized information in the redacted document and other detailed information, including the personnel qualifications and general public rating.

Note that the head derives an informational advantage over the general public from directly observing the redacted project idea and other more detailed information. A rational head aims at maximizing her gain by minimizing the possible risk due to the failure of the project. The protection note issued is some percentage of the purchased share. Hence, the possible loss by the investor who is a member of the team in case of failure of the project will be reduced to the interest, the unrecovered proportion of the loan and the time value of money. Therefore, when responding to the signaling effect of the head, investors should take into account the possible scenarios in which the entrepreneur really signals a potentially promising project.

If a potential investor would like to convert her invested amount C into a share, the outstanding balance of the loan is automatically converted to equity at a discount rate *d*. In this case, she will have a greater share amount of $\frac{\mathrm{d\,C}}{p-dp}$ over a new individual investing the same amount of money at price *p* at the valuation of a later funding round, in addition to the expected return on equity. For example, suppose an investor invested €21,000 in a project start-up using a convertible note with a discount rate *d*=15%. Let the stock price, *p*, at the valuation of the later funding round be €7 per share. Then, at the valuation of a later funding period, she will have a total of 3529.4 shares weighing to unrealized return amount, $(\frac{\mathrm{C}}{p-dp})p$, of €24705.8 at €7 per share. However, a new investor of the same amount of investment will have a total of 3,000 shares at the valuation of the later funding round.

The expected total return to the head will be the principal C_h (where C_h is the invested amount by the head), the interest on the invested amount, the service charge for membership to the group β_i, the stimulation fee for the signaling effect and the risk taken by the head (in two forms, fixed rate of pre-payment, $\beta_{s,}$ followed by upon fulfillment fee which is some percentage of the pledged amount by the head, η, and total money for the protection note, γ, with the probability of success $1-\pi$) or incur loss with probability of failure, π.

Mathematically, the return is

$$\beta_i + \beta_s + (1-\pi)\left[\gamma + C_h(1+r) + \eta + \frac{d\,C}{p-dp}\right] + (\pi)[-\gamma - C_h(1+r)]\,. \qquad (5.11)$$

As long as the project to invest in is successful through the signaling effect, all the parties (investor, head, and entrepreneur) benefit. Furthermore, in order to avoid false signals from their investment decisions, there should be a clear-cut criterion which filters reasonable signaling with a sufficiently large share of investment by the head (commonly referred to as *sufficient skin in the game*).

In case of systematic signaling to a potentially failing project, a total sum of membership fees and equivalent compensation for upon-success return, over her initial signaling investment, C_h, to the head, $\beta_i + \beta_s + (1-\pi)\left[\gamma + \theta + \frac{d\,C_h}{p-dp}\right]$ should outweigh the potential loss, where $\theta = C_h r + \eta$ is some percentage of the total loan pledged by the head. Here, the likelihood of failure of the project is assumed known by the head with an insider's view assumption, while it is unrevealed to the other investors. A potential investor incurs loss by investing in an unsuccessful project with probability of failure π, if the net return in a simplified form is negative, that is, $(1-\pi)[C_h(1+r) + \frac{d\,C_h}{p-dp}] - C_h < 0$. This is a sufficient condition for a project that fails to reward the investors for sure. In other words, for any project with negative return, the head systematically signals only if the potential gain upon her initial investment level C_h and signaling service fees is greater than the loss incurred.

That is, a rational head maximizing her net gain takes the risk and signals the project if the potential net gain from signaling is greater than the net loss she might incur by signaling this project, i.e.

$$\beta_i + \beta_s + (1-\pi)[\gamma + \theta + \frac{dC_h}{p-dp}] > (1-\pi)[C_h(1+r) + \frac{dC_h}{p-dp}] - C_h. \qquad (5.12)$$

Solving for C_h,

$$\beta_i + \beta_s + (1-\pi)[\gamma + \theta] > -C_h[\pi(1+r) - r]\,. \qquad (5.13)$$

Note that from the above equation, in case of failure of the project, $(1-\pi)[C_h(1+r) + \frac{d\,C_h(1+r)}{p-dp}] - C_h$ is negative. Hence, provided that $C_h > 0$, then $\pi(1+r) - r > 0$ for any project resulting in loss to potential investors, that is, $\forall \pi > \frac{r}{1+r}$.

Therefore,

$$C_h < \frac{\beta_i + \beta_s + (1-\pi)(\theta+\gamma)}{\pi(1+r) - r}\,. \qquad (5.14)$$

Hence, given the probability of failure for the project, π, a profit maximizing head signals the project if and only if the required signaling amount she is supposed to lend is less than her upper optimal boundary of share, $\frac{\beta_i + \beta_s + (1-\pi)(\theta+\gamma)}{\pi(1+r) - r}$.

For example, when the head knows that the project is not promising, $\pi = 1$, then $C_h < \beta_i + \beta_s$, to at least help issue the protection note and gain from the service charge for both the stimulation and service charge to the mass investor in her team. Note that the above equation holds under the assumption that there is some fear of failure of the project, that is, the probability of failure cannot be zero.

Suppose the membership fee β_i is 1% (i.e. a proportion of the potential investment capacity of the individual, allowing for proportional contribution by each member). In addition to the membership fee, the entrepreneur rewards the head with a stimulation fee β_s of 2% of the expected amount of total crowdfunds for the project. Suppose the protection note issued to this specific project costs the head 0.5%

of the total protection note issued in the group. The entrepreneur offers interest rate r of 12%, including the risk premium. Consider a project with a probability of failure 0.5 upon the public rating and let the head's overall expected gain on her loan θ (including the interest and ex-post stimulation fee) be 10% of her total transaction during the process. Then, given this set of information, $C_h < 0.1875$; i.e, the upper bound to her possible signaling investment of this project should be less than 18.75% of the total funds requested by the entrepreneur for the project in which an ordinary investor would incur loss with the stated probability of failure and an insider's view. Hence, given the provided rate of return by the entrepreneur and a conversion discount of the convertible note into a shared stock relative to the next fixed priced round, there will be a higher probability of loss to a regular investor following the signaling effect of the head with less than 18.75% of investment participation out of the total amount requested for the start-up financing. Therefore, based on this criterion, potential investors can filter reasonable signals on investment projects they are interested to invest in, regardless of the unrevealed type of the other parties involved.

While Hildebrand et al. (2014) have applied such a cut-off criterion for the peer-to-peer lending system, we propose here an extension that: i) neutralizes the disutility arising from the mistrust effect in the market and ii) considers convertible notes for debt crowdfunding in a more general sense. Also, unlike Gintis (2009) who proved that there exists a truthful signaling equilibrium using own capital as a signaling device for producers with sufficient capital, the case we presented here is different. Because self-financing capacity is rare in most crowdfunding situations, we propose a second-party (head of team) signaling.

Therefore, with the mechanisms we propose in this chapter to neutralize the fear of disclosure and mistrust effects, the investment crowdfunding market is strictly co-utile to all agents involved, which enhances the crowd-based start-up financing efficiency.

To sum up, given the online platforms facilitating the investment crowdfunding industry, and the artificial incentives we propose, there exists a co-utile protocol with regard to the respective utility functions of the agents which is optimal at a predefined optimal debt contract through the convertible note.

5.4 Discussion and implications

As discussed above, the market inefficiency arising from the *fear* and *mistrust effects*, in addition to the asymmetric information, limits the applicability of crowd-based financing. "Building a crowdfunding ecosystem depends on key enablers to build trust" (a quote from the World Bank's article, 2013). The model we present for crowdfunding implies that, under the return-based investment decision, collaboration in the market takes place as long as the optimal net return R_i^* is not less than the required net return ($(1 + r_f)C_i$). However, with the mistrust and fear effects in the market, co-utile collaboration takes place at the Pareto-optimal point at which the optimal level of no-fear and trust is attained ($\Gamma = 1$ and $\mathcal{F} = 1$), and this point lies above the threshold level at which the return-based investment decision takes place. Hence, such market inefficiencies also reduce investment at a given interest rate, and they are among the most important factors affecting the broader applicability of this business model. Studies show that there exists a significant variation in the success rate of projects being financed across different crowdfunding platforms (Jeffries, 2013, and Lau, 2013). These success rate variations across project types and platforms are also related to the *fear* and *mistrust effect* issues raised in this chapter.

Along the variation within and across the platforms, we can draw repercussions for the behaviors of investors and entrepreneurs in the crowdfunding ecosystem. For instance, a significantly visible difference between Kickstarter and Indiegogo is that the former is focused on specific project categories and geographical settings, and has more restrictions on the types of projects and incentive schemes offered by individual projects. As of January 2016, Kickstarter is open for worldwide backers, while it is limited to the projects from the US, UK, Canada, Australia, New Zealand, Netherlands, Denmark, Ireland, Norway, Sweden, Spain, France, Germany, Austria, Italy, Belgium, Luxemburg and Switzerland. Moreover, the funding model that it follows is the "all-or-nothing" method, which has the effect of increasing the donors' willingness to donate and leads them to donating according to their preferences (*self-capacity signaling of projects*) and hence builds trust. However, this method disincentivizes coordination (Wash and Solomon, 2014); the reputation mechanism we suggest in this chapter can be used to handle such a coordination problem. Hence, in addition to the project qualities and other platform-related marketing packages, we are inclined to say that the relative credibility (the higher trust to the entrepreneurs on this platform coming from the platform's setup itself) and the focus group targeting of the platform have contributed for a relatively higher success rate of projects running campaigns through this platform. This credibility has also something to do with the reduction in the fear of failure effect; hence, more projects come upfront for soliciting finance from the crowd.

On the other hand, Indiegogo encompasses more types of projects and a relatively wider geographical coverage. Furthermore, the funding model it follows is more flexible and also encompasses the "keep-it-all" method (in addition to the "all-or-nothing" method), which encourages coordination with a less efficient outcome than the "all-or-nothing" method (Wash and Solomon, 2014). A study conducted by Cumming et al. (2014) on the mixed funding model used by Indigogo since 2011 provides sample evidence that projects using the "all-or-nothing" method have more average completion rate and more attraction of investors than projects using the "keep-it-all" method. Here again, this has implications for the *mistrust effect* underlying the "keep-it-all" mechanism.

Despite the traditional investment (see Romer (2011) for analysis of the imperfections of financial markets), crowd-based project financing most commonly does not rely on the entrepreneur's wealth, in which we have also assumed that the entrepreneur's wealth invested in a project is zero. Hence, whether a project on a crowdfunding platform is funded or not depends only on the potential output, but not on the financial base of the entrepreneur. Additional catalysts could be the product type and novelty, the ability to run a successful campaign, incentive schemes including the risk premium and product offer, and the like. This implies that the effect of shocks that may occur outside the financial system is low: any outside shock affecting the entrepreneur's wealth will not have any implied effect on the project's output. Crowdfunding also allows for any individual entrepreneur to get financing from the crowd regardless of the individuals' wealth. In this regard, even though the efficiency of this business model has not been tested over the long run, its potential survival rate in any business cycle will be relatively high, unlike the traditional funding model.

Besides, the funding success rate of new projects owned by previously successful entrepreneurs is high, which implies a *reputation effect*. For example, this rate is reported to nearly double that of the overall site average in Kickstarter -see Table 5.1 below-. Based on the analysis offered in this chapter, if the reputation of the entrepreneur is high (e.g., because he has a long record of successful projects), then even low returns can be co-utile for the investors. An additional factor here can also be the experience acquired in the previously run campaigns (this builds the trust on the side of investors and somehow tackles the fear effect on the side of the entrepreneur).

Table 5.1: Success rate of entrepreneurs' first projects compared to that of subsequent ones by category in Kickstarter, March 24, 2015

Category	**First projects**	**Second or later projects**	**Increase in success rate**
Games	26%	56%	116%
Technology	21%	36%	75%
Crafts	23%	40%	73%
Design	31%	50%	60%
Publishing	29%	41%	41%
Comics	45%	62%	39%
Fashion	24%	33%	35%
Food	28%	35%	26%
Photography	30%	36%	21%
Journalism	25%	30%	20%
Art	42%	50%	18%
Dance	64%	75%	16%
Theater	61%	67%	9%
Music	53%	57%	9%
Film & Video	39%	41%	6%

Source: Kickstarter's statistics page

5.6 Conclusion

The current collaborative commons paradigm has laid foundation in various economic activities. Information technology plays a significant catalyst role in the ensuing collaborative economy. With the heterogeneity of interacting individual agents, there is a need for conciliating individual rational choices and the common good in a way that helps the system operate smoothly. Along this line, this chapter has proposed to leverage a novel concept called co-utility in which an agent in the system chooses to serve another agent's complementing goal for her own best interest.

We have shown that two well-known business models of the collaborative economy, crowdsourcing and investment crowdfunding, can be made co-utile. We have demonstrated that crowdsourcing is strictly co-utile in a natural way (without additional artificial incentives). For debt crowdfunding, we have added artificial incentives to the market in order to neutralize the potential deterring factors that arise in practice, thereby achieving strict co-utility. The simulation result depicting the *trust effect* in the investment decision of investors shows that, given the required rate of return, the threshold over which collaboration in crowdfunding takes place depends on the credibility of the project. Likewise, entrepreneurs will be willing to broadcast their project for crowdfunding above a confidence level guaranteeing a return that outweighs the expected loss due to the risk of undue disclosure (*fear of disclosure*). This implies that receiving small contributions can be co-utile only if the fear of disclosure is very low, sufficiently below the value of the threshold compensation. The incentive schemes proposed in this chapter to neutralize the disclosure fear and trust effects arising in the market are: a reputation mechanism with a signaling effect on the general public and, more specifically, through the head of a special interest group issuing a protection note to the members; and encryption of publicly posted projects with decentralized time stamps guaranteeing self-enforcing intellectual property protection.

To summarize, the analysis presented in this chapter results in several key consequences. First, collaboration is always rationally sustainable, as long as the system is co-utile. Specifically, if the types of players are such that the entrepreneur has no fear of disclosure and the investor has no fear of loss, then co-utility exists as long as the expected return is non-zero; however, only donation-based crowdfunding campaigns are likely to fit this (risk-neutral) case. For the investment crowdfunding, co-utility can be achieved provided that efficiency is guaranteed through incentive schemes like the ones introduced in this chapter.

Yet we can specify an intermediate playing field of cases in which some types of projects guarantee a safer transaction either to the entrepreneur or the investor or both. Concretely, if the type of the entrepreneur involves fear of disclosure, there is co-utility for the entrepreneur only if the investment by the investor is higher than a threshold representing the expected loss when the investor leaks the idea. This means that receiving small contributions can be co-utile only if the fear of disclosure is very low, say, if the entrepreneur feels no one other than himself can successfully carry out the project. For example, projects that are more artistic/skill-oriented suffer less from fear of disclosure than projects consisting of developing a mass produced/digital item (that can be copied). Likewise, projects with better potential expertise suffer less from fear of failure and, therefore, are more trusted by potential investors (especially if the entrepreneur offers defined reward guarantees, like perceptible prototypes presented during campaigns). In addition, those projects with a focus group targeting (i.e., where the investor targets and defines interest groups like the ones we see in Kickstarter) tend to have a better success rate. Moreover, projects owned by previously successful entrepreneurs will have higher success rate, which implies a *reputation effect*: if the entrepreneur's reputation is high (see the discussion in Section 6 about Kickstarter), even low returns can be co-utile. Projects with timely issues and special orientation to a focus group also tend to enjoy higher trust, attracting sympathetic investors; in this category, we can mention green start-ups, medical solutions or projects with a social dimension (say, assistive technologies for the elderly), etc.

As illustrated in the graphical analysis part, all possible favorable crowdfunding market conditions (including the potential profitability, optimal rate of return, risk premium and all other related market incentives) relative to the next best alternative investment choices will lead to collaboration in the market. However, not all collaboration taking place under these conditions is co-utile. The only co-utile point of collaboration is the Pareto-optimal point at which the optimal level of no-fear and trust is attained, and this point lies above the threshold level at which the return-based investment decision takes place. However, some projects fail to meet their aim, even if they promise sufficient reward and incentive schemes. One of the reasons behind this can be the campaigning method they follow. In Section 5.4, we have seen that projects using the "keep-it-all" method for their campaign have relatively higher risk of being fraud and, consequently, have higher mistrust effect than the ones using the "all-or-nothing" method. Hence, reputation mechanisms, like the one we propose in this chapter, can mitigate this effect.

From a more general perspective, we can conclude that all co-utile outcomes are Pareto-optimal; but not all Pareto-optimal outcomes are co-utile. Moreover, reciprocity and hybridity are compatible with co-utility, as long as the outcomes fulfill the conditions of Pareto optimality and provide strictly larger payoffs compared to not playing the reciprocity/hybridity game. Finally, the *mistrust effect* on the side of investors and the *fear of disclosure effect* on the side of the entrepreneur may turn a potentially co-utile market into a non-co-utile one. This implies that, beyond the expected returns, these two factors (fear and trust) have substantial effects on the debt financing market of start-ups, as it can be expected in a financial market with imperfect information.

Chapter 6 DECENTRALIZED CO-UTILE REPUTATION FOR P2P ONLINE LENDING MARKET

6.1 Introduction

Peer-to-peer lending (P2P lending) is the practice of lending money between peers (individuals or businesses) through online marketplaces by a direct transaction between the borrowers and the lenders. The platforms that facilitate this practice operate, in return, for a service charge they receive from the customers, by rendering services of match-making and credit checking. Some examples of such online marketplaces include Lending Club (world's largest P2P online lending platform), Prosper Marketplace, Funding Circle, Zopa, SoFi, Comunitae, RateSetter, and ThinCats. There also are some non-profit global Person-to-person microlending platforms such as Kiva and Zidisha (unlike Kiva, Zidisha involves no local intermediaries in its global operations).

P2P lending commonly follows the installment loan type, in which loans are repaid in periodic installments (usually monthly ones) that include the principal and the interest. These loans can be unsecured or secured and, normally, do not have government insurance protection, being operated based on a private deal. Some platforms (e.g. Zopa and RateSetter in the UK) offer protection funds.

Peer-to-peer online lending is a co-utility amenable game. That is, borrowers and lenders in this market engage in this transaction for the mutual benefits of getting a loan and the associated reward, respectively. Peer-to-peer lending marketplaces provide services matching potential investors with borrowers on on-line platforms, thereby serving borrowers' and lenders' interests. Unlike the classical setting in which lenders determine the loan rate through bidding for prices, nowadays rates are assigned centrally by the platforms based on the credit score of the borrowers (for example, see Prosper Rating). Non-qualifying borrowers are filtered out from the market and loan notes that satisfy the credit grade standard of the platforms are approved for credit listing. In most cases, about 90% of loan applications are filtered out of the market (for example, Lending Club and Prosper). These platforms use loan approval credit and pricing models for assigning rates to the applications based on their level of risk. Yet, some of the models applied by Lending Club and Prosper have raised legal issues because their current loan ratings were claimed to violate the state interest rate caps in the US (Scully 2015)

Another form of P2P lending is the non-profit lending market (e.g. Kiva and Zidisha). The interaction in this type of global-level P2P lending networks is co-utile: a chain of interaction between the P2P microfinance website, local microfinance institutions (MFIs), borrowers and the non-profit humanitarian lenders is formed in a mutually beneficial way. Here, the MFIs get capital at a near zero cost, the MFI borrowers are linked to the potential lenders through the global lending website, and the non-profit global lending site links lenders to the MFI borrowers. Note also that the probability of default and the level of information asymmetry is larger in the non-profit lending markets. Kiva uses a multi-tiered system of credit scoring to rate the local microfinance institution (MFIs). By examining Kiva's internal monitoring system and considering the strategic incentives created by MFIs, McIntosh (2010) showed that, if a borrower on Kiva's listing defaults, it is highly probable that the MFI (who receives capital from Kiva at a 0 interest rate) will cover the repayment in order to keep its Kiva score high. Consequently, Kiva's reputation scheme does not directly ensure the underlying reliability of the end users. Hence, unlike the successful rating of institutions, the rating mechanism employed in this platform is far from being accurate for the individual borrowers. This and other related factors make the non-profit P2P lending different from the individual peers' level analysis of the profit-oriented P2P lending market we present in this chapter.

Since the operations managed by humans are carried out through an online interface, the P2P lending ecosystem encompasses both technical and human factors. The underlying rational human behaviors (both on the side of borrowers and of lenders), which autonomously interact through the facilitation of the technical e-business system, define the efficiency of the market. The problems arising from the human and technical factors can easily make the system a complex and hard one to control. It is also worth noting that the human factors play a prominent role, and the way a technical algorithm responds to manage such factors accordingly is one of the key indices of the efficiency of the system.

The market is prone to a mistrust problem between the borrowers and the potential lenders. In practice, the platforms make loan grading/rating to identify loans based on their level of risk. Moreover, there are third-party platforms (platforms with an automated investing tool), like LendingRobot and BlueVestment (for Lending Club), LendingMemo, etc., that thicken the P2P lending market layer with the addition of middle-ground players. Such platforms cause the market to deviate from its original peer-to-peer nature. These third parties use automated algorithms that can filter out the credibility of the loans in the platform in return for the service charge they receive, hence, replacing the basic individual-level manual filtering mechanism. By doing so, they indirectly signal those loans with higher potential return and hence, they discard the potentially defaulting loans. Filtering in peer-to-peer lending (financial arbitrage) means choosing the loans that have historically performed better than others, even if they had exactly the same loan grade Cunningham (2015).

A number of reputation mechanisms have been applied to the internet-based business models. Some of these include consumer and agency-based ratings, like those of eBay, and community-based reputation mechanisms in which groups of special interest signal the creditworthiness of an individual project or loan request in the crowd-based business models (Turi et al. (2016) and Collier and Hampshire (2010)). Moreover, loans are also filtered based on their characteristics, which depict their historic performance relative to the other loans of the same grade. However, these mechanisms are managed mostly centrally and, whenever handled in a distributed way, they lack a self-enforcing nature; as a result, they are exposed to tampering attacks and have the potential of being manipulated to one peer's interest. To mitigate these issues, and mainly to tackle the problem of mistrust underlying the P2P lending market, we propose a novel way of computing the borrower's reputation in a decentralized way, accounting for all underlying loan characteristics and past records of transaction. This mechanism will make the computation self-enforcing and beneficial for all involved agents (co-utile, see Domingo-Ferrer et al., 2016).

This chapter presents an analysis of the online peer-to-peer lending market to determine the extent to which it satisfies co-utility (mutually beneficial and self-enforcing interaction between agents). As discussed in Section 4.2.1, the market is an example of a co-utility amenable game, despite its key challenges of misevaluation of loans and lack of trust between the borrowers and the potential lenders.

6.2 Contribution and plan of this chapter

As we have mentioned above (and further discussed in Section 3.2 of this thesis), one of the key challenges currently underlying the market is the lack of trust by the lenders. This factor displays the inefficiency of the market, which has room for improvement both for lenders and borrowers. As Krumme and Herrero (2009) argued, the long-term sustainability of the P2P online lending network depends on the reconciliation of risk and expected rewards. Consequently, this calls for an efficient reputation mechanism that guarantees expected reward and trust in the system. One of the research questions to be addressed in this analysis is: how do the global reputation scores interact with a latent individual borrower's behavior and associated type of a loan originated by her? Answering this through an efficient reputation protocol will help minimize the lender's risk in connection to a given transaction under consideration.

Furthermore, individual investors in the conventional P2P lending markets today face stiff competition from the institutional investors that can relatively better sink the potential risks with the economies of scale at an institutional level. Moreover, unlike the private investors who are seldom financial experts, the institutional investors have their own credit algorithms that help them evaluate loan pricings (e.g., TruSight by the Ranger Capital Group). For instance, in the US, there are many financial institutions that invest in the P2P lending marketplaces (Milne and Parboteeah, 2016). In this setting, it is clear that the forerunning P2P lending marketplaces will through time be monopolized/taken over by institutional investors, whereby the capitalist system will prevail, rather than being replaced by the collaborative economy. Hence, by focusing on the original form of the P2P lending between private lenders and borrowers, we aim at building a protocol that guarantees the efficiency of the system in a purely peer-to-peer and distributed way without institution-based competitions and interferences. The reputation mechanism we propose helps the private lenders make informed decisions and, more generally, to build an active trust-oriented collaborative P2P society. This is in line with harnessing the abundant liquidity of the zero marginal cost collaborative economy through consumer-to-consumer direct interactions (Rifkin 2014).

In the internet era, where markets can operate at a global level, no common legal framework can be enforced in an efficient way. Hence, there should be a mechanism to develop self-enforcing rules that can harmonize the needs of various rational agents and keep their interaction smooth and efficient. These rules should also be developed in a way that is mutually beneficial to the agents involved (see the definition for the *co-utile* protocol). Neither the existing reputation models (including community-based reputation mechanisms, which are not actually at play nowadays due to centralized rating and loan valuation by individual platforms) nor the filtering mechanisms (both basic and third-party algorithmic investing tools) in the P2P online lending market are co-utile, which makes it difficult for the market to operate in a purely peer-to-peer way. This is because, in its current form, the P2P lending market still needs a centralized authority (the P2P lending platform) or an external agency to enforce trust between the transacting peers; besides, these trust-building mechanisms are not efficient by themselves (Emekter et al., 2015; Serrano et al., (2015).

To tackle this issue in this chapter, we propose incorporating a distributed co-utile reputation mechanism into the P2P lending ecosystem and designing a way to measure and evaluate the peers' reputation in this market in order to build trust. Note that risk perceptions are commonly presented in terms of the interest rate outcome following the platforms' individual loan rating (see the loan grade/rating of the individual platforms and also Collier and Hampshire (2010)). Yet, in our case, we also aim at taking into account the underlying loan characteristics defining the loan types (this will be discussed in depth in Section 6.6). Another research question is to define the rating mechanism based on the individual loan characteristics by considering them in the calculation of the agents' reputation scores. The reputation protocol should be designed to operate in a decentralized way; this avoids depending on central authorities/agencies that may bias the reputation calculation in their own interest (and, thus, hamper the co-utility of the system). Our goal in this work is to take a stride towards associating an agents' local reputation (sourced from direct individual transactions) in the P2P lending marketplaces with her global reputation (target agent's final reputation score based on aggregation of a set of local reputation scores).

This chapter is organized as follows. In Section 6.3, we present a brief overview of the peer-to-peer marketplaces and thereby discuss the co-utile nature of the market. In Section 6.4, we discuss the negative utilities arising in the P2P lending market. In Section 6.5, we introduce a decentralized and co-utile reputation protocol. In Section 6.6, we apply this mechanism to the online peer-to-peer lending marketplaces by modeling the local and global reputation for the borrowers in a way that takes into account the loan characteristics in addition to the outcome of the transactions. In Section 6.7, an empirical analysis is made based on experiments on a simulated platform fed with data from a sample P2P lending platform (Lending Club). Section 6.8 contains conclusions and future work directions.

6.3 Co-utility in the P2P online lending market

As it was mentioned above, our focus is on the purely profit-oriented P2P lending market. In the subsections that follow, rather than performing the usual general analysis of any lending market, we consider two different scenarios (a case in which lenders cannot borrow and a case in which reinvestment is possible) in order to analyze the market in a broader and practically meaningful way. Hence, the definitions of the respective utility functions for borrowers and lenders are based on these two different scenarios.

In order to characterize the behavior of borrowers and lenders in this market, we assume that:

i. There is asymmetric information (Funk et al., 2015; Lin, 2009; McIntosh, 2010; Serrano et al. 2015).
ii. The P2P online lending market is perfectly competitive with a large number of borrowers and lenders.
iii. Lenders are risk-averse and borrowers are risk-neutral. Hence, a borrower's utility function is weakly concave in that she can be risk-neutral (or risk-averse in some exceptional cases with lower impatience to borrow). On the other hand, lenders who invest in the loan notes of anonymous borrowers have strictly concave utility function (strictly risk-averse).
iv. Lenders and borrowers are expected to be utility maximizers, with strictly increasing preferences.
v. The income of the borrower and the loan amount originated are exogenously defined, and strategic default is an endogenous factor depending on the loan type.
vi. There is a visible deterministic functional relationship between the loan type (based on the level of risk) and the interest rate assigned to it, which is trivial from the intrinsic quality of the loan.

With these assumptions in mind let us analyze a borrower's and a lender's behavior in this market, for each of the two above-mentioned cases.

6.3.1 Case 1: lender cannot borrow

This is a unidirectional investment scenario in which loans are originated only by potential lenders. In this case, lending and borrowing tasks are performed by two disjoint groups (borrowers and lenders).

a) *Borrower*

We assume that there are no constraints on the payment profile and, as stated above, borrowers are risk-neutral. This means that they will only be concerned by the origination of the loan at any cost, given the level of urgency of the need for loan financing. Based on the formula for calculation of present value of annuities, the present value of a loan amount l_0 with future annuity payments, P, is given by $a_{n|i} = \frac{1-(1+i)^{-n}}{i}$, where n is the number of terms of the loan (commonly 3-5 years terms in online P2P lending market) and i is the per period random interest rate, accounting for risk premium. This accounts for the time value of money (interest rate), and the future value and the present value are linear in the amount of payments of the loan. The present value of monthly payments of P is: $PV(P|i,n) = P \times a_{n|i}$. From this follows that the payoff to the borrower after the origination of the loan is the net gain over the loan term discounted to present value. Hence, the borrower's net gain from the loan origination, Π_b, is:

$$\Pi_b = l_0 - P\,\frac{1-(1+i)^{-n}}{i}. \quad (6.1)$$

The borrower is expected to be a utility maximizer. Her utility is a function of the difference between the loan amount and loan repayments in the first period and discounted future payments for the term of the loan, given her current income. Therefore, the utility of the borrower depends on the borrower's residual income after the loan repayment discounted to its present value over the term of the loan at a presumed level of impatience:

$$U_b = U\left(y + \sigma(t)\left(l_0 - P\,\frac{1-(1+i)^{-n}}{i}\right)\right) \quad , \qquad (6.2)$$

where l_0 is the loan amount at origination, and $\sigma(t)\epsilon[0,1]$ is an exogenously defined weight parameter representing the level of impatience of the borrower to get the loan. It measures the urgency on the demand for loan at a given time t. The higher $\sigma(t)$, the more patient the borrower is. The more patient the borrower is over her current financial need, the more she can wait before borrowing.

The optimal decision by a rational borrower takes place at the maximum point of utility. Note that the borrower's utility is subject to the constraint of lenders' optimal profit, $\Pi^*_{l\,l}$ where $\Pi^*_l = 0$ for a perfectly competitive market with a large number of borrowers and lenders, see Leece (2008).

b) *Lender*

Risk diversification through investment portfolio is common in P2P online lending. For lending as an investment, preferences on loan notes depend on the respective expected return from each loan. Hence, a rational investor composes her portfolio of investment with loan notes that can guarantee optimal expected return. From the portfolio of investment, our focus is on the individual interaction of a lender with each individual borrower, provided that there is a diverse probability of default across the borrowers. Investment on an individual note depends on the expected return for that note.

Payments are based on the loan function for the term of the loan. The market interaction between a large number of borrowers and lenders defines the optimal interest rate for different loan type categories. Edelstein et al. (2003) argue that the volatility in the interest rate, the covariation among market interest rate, the borrower's collateral and income, the loan term, and the risk preference of borrowers and lenders determine the optimal loan interest rate contracts. The lender's profit is the difference between the cost of funds and loan repayments by the borrowers. Krumme and Herrero (2009) predicted that lenders in the P2P market fail to maximize the expected payoff, where there is sub-optimal behavior by lenders because of the investment preference for riskier and highly defaulting loans. They argued that a lender investing in a higher credit grade scoring has greater expected payoff than one investing in a lower grade, as there is a high rate of default associated with a low loan grade.

With a large number of lenders, the loan market is competitive and there is a minimum non-zero spread between the contract and market interest rate below which no lending occurs. The lender's utility depends on the net lending profit. The lender's total return on the loan amount l_0 is equal to $(1 + \mathrm{i})l_0$, where i is the nominal interest rate of the loan contract. The associated cost of funds to the borrower (with the time value of money) over the term of the loan is given by $(1 + \mathrm{r})l_0$, where r is the real market interest rate. Hence, the net gain to the lender is $(\mathrm{i} - \mathrm{r})l_0$.

A Von Neumann-Morgenstern expected utility function for the lender is

$$u_l = \sum_{n=1}^{n} u[(i - r)l_0\gamma(t)p(t)], \qquad (6.3)$$

where $\gamma(t)$ is the proportion of the loan paid at time t over the loan period n and $p(t)$ is the probability of default at time t. The lender estimates the probability of default based on the observable borrower attributes that generally depict the borrower's creditworthiness based on past record of a given characteristics (McIntosh, 2010).

Theoretically, given a loan term distribution function $F(t)$ (commonly known as lifetime distribution function in survival analysis), for a loan term t, and the probability density function $f(t)$, the rate of default for a loan is given by $p(t) = \frac{f(t)}{1-F(t)}, F(t) < 1$; where, $p(t)dt$ represents the instantaneous risk a borrower will default in the time interval $(t, t + dt)$. To compute the probability of default, $p(t)$, for any loan type τ, we can simply take the ratio between the number n of defaulting loans of characteristics τ, and the total number N of type τ loans listed in the marketplace. The default rate of a loan grade g at time t is $p_{t,s} = \frac{\text{number of defaults in grade } g \text{ at time } t}{\text{total number of loans in loan grade} g \text{ at time } t}$.

However, as Marot (2016) noted, this computation is prone to statistical noise, where it results in unexplained variation in the overall loans under consideration (for example, exceptional intrinsic loan characteristics, other than the one under consideration, or sub-grades). As the probabilities of default are correlated with varied loan characteristics, unlike Marot who considered only the loan grade, this computation takes into account all possible loan characteristics that could define the rate of default for each loan. In addition, the noise arising from the aggregation of the general sample can be smoothed through *linear* or *nonparametric graduation* noise elimination technique (Wang, 2005). Hence, the smoothed default estimate of a loan at age t after its origination is a weighted average of the default rate, where weights are defined by the smoothing technique and adjusted locally at each age of the loan t:

$\hat{p}(t) = \sum_{i=1}^{n} c_i(t)p_i$, where $c_i(t)$ is the weight and $\sum_{i=1}^{n} c_i(t) = 1$, at each time t.

Since a default to a loan can happen at any time during the loan period, we can group loans into time interval categories under their respective loan term. Such grouping helps identify the point at which loans fail to pay back and hence capture the dynamics in the probability of default over the loan period. However, the grouping can result in a biased estimate of the default rate, mainly at the closer end of the loan period (inconsistency at larger t). Hence, in order to have an unbiased estimate of the default rate, we transform $\hat{p}(t)$ as recommended by Wang (2005). The transformed rate of default estimate will be: $\varphi(\hat{p}(t)) = -\log(1 - \hat{p}(t))$.

Given a twice-differentiable Bernoulli utility function, $u(x)$, for the money return, x, of the amount invested on a safe asset (which could alternatively be invested in a riskier asset, i.e. P2P lending), a Von Neumann-Morgenstern expected utility function $U(f(l_0))$ for the lender can be redefined as

$$U(f(l_0)) = \int u(x)df(x), \qquad (6.4)$$

where $f(l_0)$ is the distribution of monetary payoffs of the loan. The investment decision of the lender depends on the certainty equivalence condition[8] $c(f(l_0), u)$: the amount of money for which the lender is indifferent between investing in a risky P2P online lending market and the certain amount she could rather gain by investing in another safe asset (e.g., in a government bond); that is, $c(f(l_0), u) = \int u(x)df(x)$.

Note that the lender aims at maximizing the profit, which is the sum of profits from the loan origination to all potential borrowers from her portfolio of investment across the notes. The lending rate across the notes can differ depending on the level of riskiness of the target borrower. Provided this, the lender's profit maximization problem can be given as a function of the probability p_i of repayment of each borrower, the interest rate r_i and the size k_i of each note in the portfolio composition:

$$Max \sum_{i=1}^{n} [p_i k_i (1 + r_i) - k_i], \quad (6.5)$$

where n is the number of notes in the portfolio of investment of the lender. The lender invests in the notes with positive expected profits, and the lowest-profit note that the lender choses to invest in is the break-even-note with the probability $p_i = \frac{1}{1+r_i}$ from Equation (6.5). Keeping all other factors constant, from the lending market equilibrium, we can see that the lender choses to invest in the notes of a P2P lending market if the return rates are high enough to compensate the loss, i.e., $\frac{dp_i}{dr_i} = -1 < 0$, which implies that, the higher the interest rates, the more likely the lender will be willing to invest in the risky notes. However, the valuation of the loans in the conventional P2P lending markets is questionable. In this regard, Emekter et al. (2015) argue that the higher interest rates charged on riskier loans at the Lending Club are not enough to offset the associated incremental risk due to default by comparing the theoretical

[8] For details on the concepts of certainty equivalence and probability premium, refer to Mas-Colell (1995).

interest rate with the actual one set for the loans at the Lending Club. In line with this, Iyer et al. (2009) contend that the borrower's creditworthiness depends on factors other than the platforms' rating and argue that about 28% of the interest spread between the highest credit grade (AA) and that of the lowest grade (HR) in the Prosper marketplace is due to the other borrower characteristics. Likewise, the loan grades in the Lending Club accurately predicted about 60% to 80% of the loans' probability of default (Serrano et al., 2015). Yet, the remaining inaccuracy with the predictive power of the loan grades calls for a more robust technique that could handle the potential credit risks underlying the market and hence keep the accuracy of the lenders' expected profit.

6.3.2 Case 2: lending with reinvestable borrowing

Another scenario to be considered is one in which reinvestment is possible. That is, lenders can also borrow from others to reinvest in the same market. Here, the lender is assumed to rely on short-term loans for extending long-term loans to her borrowers. In this case, individual lenders mimic banks in that they rely on borrowing in addition to their own capital to make loans for profit. Thus, we take into account making profit through arbitrage opportunities in the market, which we call *P2P loan carry trade*.

Def. 3 *(P2P loan carry trade)*: This is an investment technique seeking profit from the spread in interest rates in reinvestable borrowing of the online P2P lending market.

Given the associated risk of loss, the profit margin from the arbitrage is the net gain to an individual lender who borrows for reinvestment.

Consider an individual lender in P2P loan carry trade that has an initial investable capital K and lends an amount L at a random interest rate. The lender also borrows from the P2P lending market in order to cover the loans not financed by her own capital K. That is, she invests on notes with a relatively low market rate r' expecting to make profit from the reinvestment. By assumption (ii) stated at the beginning of the section, the P2P online lending market is perfectly competitive, which implies that lenders are price takers. Hence, lenders maximize profit by choosing how much they would like to lend and the loan type, based on their risk preference by taking the lending rates as given. Following the banker's profit maximization problem by Carlin and Soskice (2014), we can define the profit maximization problem of the lender with reinvestable borrowing in the P2P online lending as maximizing the difference Π_l between the total return on the loans and the total funding cost:

$$\Pi_l = \frac{rL - r'(L-K)}{K} - \frac{\delta^2(\Pi)}{2\beta}\left(\frac{L}{K}\right)^2, \qquad (6.6)$$

where $\delta^2(\Pi)$ is the variance of the return on the loans by measuring the probability of default across the loans in her portfolio of investment (riskiness measure for the portfolio composition). Lenders are profit-oriented and hence rational, so we can assume that $r > r'$. The term $\frac{\delta^2(\Pi)}{2\beta}\left(\frac{L}{K}\right)^2$ in Equation (6.6) represents the total risk with this investment as a product of the risk on the loans, $\delta^2(\Pi)$, and lenders leverage, $\left(\frac{L}{K}\right)^2$, weighted by the coefficient of risk aversion of the lender, β. Thus, the more risk-tolerant the lender is, the higher her return. A rational profit-maximizing lender invests on the optimal portfolio composition by choosing loan amounts that can maximize profits. Therefore, by differentiating Equation

(6.6) above with respect to the loan amount L, equating the differential to zero and solving for L, we get that the optimal loan amount is $L^* = \frac{\beta K}{\delta^2(\Pi)}(r - r')$. Hence, a profit-maximizing lender's leverage, $l = \frac{L}{K}$, is optimal at $l^* = \frac{\beta}{\delta^2(\Pi)}(r - r')$.

Given the profit function from the loan carry trade, the utility function of the lender with a borrow-to-lend scenario is:

$$u_l(\Pi_l) = u(\frac{rL - r\prime(L-K)}{K} - \frac{\delta^2(\Pi)}{2\beta}\left(\frac{L}{K}\right)^2). \qquad (6.7)$$

As we can see from the above formulation under two different scenarios (Sections 6.3.1 and 6.3.2), one in which the lender can only be a lender and another scenario in which the lender can also be a borrower, rational players engage in the market to maximize their respective financial goals. As long as their respective goals are met, there is a self-enforcing mutually beneficial interaction between the borrowers and lenders in the market. Hence, from this follows that, given a P2P online lending platform and a vector U of lenders' and borrowers' utility functions, there exists a co-utile protocol with respect to U, which is mutually beneficial for lenders and borrowers and reasonably pulls both players to the system. Thus, P2P online lending is a co-utility amenable game.

6.4 Negative utilities in the P2P online lending market

Despite the potentially co-utile nature of the market, some practical problems arising in it entail disutility for the players involved, thereby reducing the potentially attainable maximum level of utility. Generally speaking, two main practical problems arise: *financial arbitrage*, resulting from imperfect rating of loans, and *mistrust effect*, resulting from asymmetric information in the market.

Utility maximization is the motivation of both lenders and borrowers in P2P lending. An individual borrower in a P2P online lending market gets the highest payoff if potential lenders can offer the required loan at an optimal rate of return to the borrower. A borrower gets the lowest payoff if either she does not request the loan or there is no potential lender who is willing to finance the requested loan. On the other hand, a lender in this market gets the highest payoff if she invests in loan notes that can generate an optimal rate of return, given a required rate of return relative to investing in an alternative safe asset. The lender gets the lowest payoff if there is a high probability of default by the borrowers. Hence, we can see that both borrowers and lenders are at an optimal state if they are both involved in the market and the transaction takes place at an optimal rate of return, provided that all other effects arising from practical problems in the market are kept constant. However, this outcome does not guarantee Pareto-optimality under a *mistrust effect* (fear of default by the borrowers) and lenders will prefer to abstain from financing loan requests and shift to rather safe assets. Hence, even if participation in the P2P online lending market at an optimal rate of return is the equilibrium of this game under perfect information, in practice there is no co-utile collaboration due to the underlying *mistrust effect*. In order to elaborate this, consider a binary trust game presented in Figure 6.1. A lender (A) and borrower (B) have $10 each. A's decision to lend money to B depends on her trust level on B, and B's decision to payback depends on her trustworthiness.

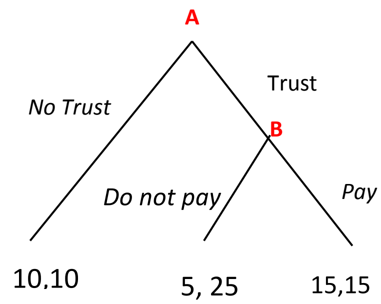

Figure 6.1: A binary trust game

The Nash equilibrium of this game is the 'do not trust' for the lender. Note that, the borrower defaults if the lender trusts. The desired response of the game (15, 15) gives both the borrower and lender higher pay-off than the equilibrium, yet lower than the borrower's highest pay-off. With the mistrust effect in this game, the payoff to both will be (10, 10); no flow of money. With full trust, any return for the borrower greater or equal than \$10 implies a Pareto optimal situation in which none of both agents could be made better off without making the other worse off. Hence, based on Definition 2, this game is not co-utile.

To introduce co-utility in the above game, an efficient and self-enforcing mechanism is needed that generates trust between agents. Such a mechanism should be able to neutralize the negative utilities arising from the practical problems mentioned in this section. To this end, we leverage in this chapter a novel decentralized co-utile reputation mechanism that is cost-effective, anonymous and attack-tolerant. Such a mechanism builds trust among peers. Beyond reducing the mistrust effect, reputation allows squeezing the financial arbitrage opportunities. This is because reputation can lead to an efficient valuation of loans based on their underlying characteristics.

6.5 A Co-utile decentralized reputation system

In Domingo-Ferrer et al. (2016b), the authors propose a co-utile (and, thus, self-enforcing) reputation management protocol for P2P scenarios. Thanks to its fully decentralized nature, it does not rely on a central authority to compute reputations. A central authority is problematic for at least two reasons: i) possible biases in the reputation calculation introduced by the authority for its own benefit (which would break co-utility); and ii) privacy issues caused by the systematic compilation of agents' opinions and reputations by a sole central entity. Beyond avoiding a central authority, the protocol also presents several other features that makes it interesting for P2P lending, such as:

- *Anonymity*: being fully distributed, the protocol relies on agents' collaboration in order to compute reputations. However, agents remain anonymous to each other during the calculation process, which prevents them from colluding in order to distort a target agent's reputation in their own benefit.
- *Low overhead*: even though a distributed protocol usually requires more information exchanges than a centralized one, the protocol limits the number of messages and communication

interactions needed to compute reputations. Moreover, the reputation calculation can be done in parallel and without interfering with the main purpose of the P2P network.

- *Proper management of new agents*: newcomers do not gain any reputation benefit and, hence, agents cannot expect to neutralize a bad reputation by taking a new identity (which in turn disincentivizes bad behaviors).
- *Attack tolerance*: the protocol is also robust against a number of tampering attacks, both targeted at increasing the agents' own reputation and at decreasing the reputation of others. In fact, agents trying to tamper with reputations can be easily detected by others (and punished by lowering their reputations).

i. Local reputation

The protocol calculates reputations based on the well-known EigenTrust model (Kamvar et al., 2003), which distinguishes between local and global agent reputations. Local reputation refers to the reputation score (trust) of an individual target agent, j, computed by another agent, i, who had a direct transaction with j. The local reputation is defined as the summation of payoffs (reward/loss) resulting from the set of transactions, Y_{ij}, of i with j:

$$s_{ij} = \sum_{y_{ij} \in Y_{ij}} payoff_i(y_{ij}). \qquad (6.8)$$

ii. Global reputation

The global reputation of an agent, j, is the aggregation of each local reputation value s_{ij} computed by the agents who directly interacted with j. In order to compute this value, first, each local reputation value is normalized to a value between [0, 1], denoted by c_{ij}, as follows:

$$c_{ij} = \frac{\max(s_{ij},0)}{\sum_j \max(s_{ij},0)}. \qquad (6.9)$$

The normalization results in positive values for well-behaving agents and zero for both bad-behaving agents and newcomers. Hence, this prevents agents from whitewashing a bad reputation (i.e., to operate under a new pseudonym or start all over), and rather provides an incentive for building and maintaining one's own reputation. The normalization also guarantees that all agents contribute equally to the computation of global reputations, regardless of the number of transactions.

To compute global reputation values, the normalized local reputation values are aggregated based on the notion of transitive trust (Kamvar et al., 2003), which generates a unique global trust value for each agent in the system. By transitive trust, we mean that, if agent i trusts any other agent j, then she trusts all other agents trusted by j. Therefore, the global reputation value of agent k, g_{ik}, is computed by taking the local reputation values of k from other agents j who have directly interacted with an agent k, and weighting the values with the respective local reputation value agent i has assigned to agents j. Hence, the estimated global reputation of k, is given by$\hat{g}_{ik} = \sum_j c_{ij} c_{jk}$.

Moreover, to avoid selfish tampering, the global reputation of each agent k is computed by one or several other agents (called score managers of k) on behalf of k. If the score manager knows c_{ij} for the whole network, the entries generate a matrix of local reputation values, $C = \{c_{ij}\}$. The matrix construction assigns zero entries to those agents with no interaction. Consider the vector $\bar{c}_i = (c_{i1}, ..., c_{in})^T$. Then, every agent i can compute $g_i^m = (C^T)^m \bar{c}_i$ for $m = 1,2, ...$ If C is irreducible and aperiodic, as m grows,

g_i^m converges to a vector g that is identical no matter which agent computes it. This vector is the left eigenvector of C and its components are the global reputations of agents.

The *co-utile decentralized reputation protocol* proposed in Domingo-Ferrer et al. (2016b) implements the distributed reputation calculation depicted above in the following way:

a) Score managers that compute the global reputation of individual agents are defined according to a distributed hash table (DHT) associated with the network topology, which maps each agent to a set of several score managers. The system works in such a way that every agent i is a score manager of another set of agents (daughter agents, D_i, w.r.t this score manager), and has its own score manager itself, thus fairly balancing the load of reputation calculations.

b) Computation of the global reputation for an agent, k (a daughter agent of agent i) is based on the local reputation of k w.r.t. the set of agents, J, with whom agent k had direct interaction, weighted by the reputation of these agents w.r.t. their score managers. This guarantees that the computation is handled in a distributed way without any individual agent's direct influence. Note that the local reputation of an agent $j \in J$ with respect to agent i is $c_{ij} = 0$ for $j \notin A_i$, where A_i is the set of agents with whom an agent i had direct interaction.

The protocol is co-utile, in that it is self-enforcing since all agents interacting in the network obtain the best outcome they can get (i.e., to have their reputation fairly computed) and obtain no benefits of deviating from the protocol (because they cannot influence their own reputation calculation by subverting the protocol).

6.6 A decentralized co-utile reputation model for the P2P marketplace

As discussed in Section 6.4, the co-utile nature of a P2P online lending market relies on the condition that agents trust each other. This calls for an efficient reputation mechanism that can neutralize potentially arising negative utilities due to the *mistrust effect*. A decentralized co-utile reputation system for the P2P online lending market is defined as an electronic system using a distributed chain of computation that signals the creditworthiness of a given borrower for a potential transaction to be handled by a specific platform. This is done by formally embedding the actual performance or reputation effects into the information system of the P2P marketplace. We develop a technology implementing a co-utile protocol that provides a purely electronic reputation that can minimize the actual financial costs (because transactions are better guaranteed).

Based on the calculation of local and global reputation values, we can build a trust-oriented and *strictly peer-to-peer* lending market, in contrast to the current P2P lending market, which needs a middle layer and hence is not strictly P2P. The system is set in such a way to encompass the type of loans and underlying behaviors of the participating agents.

The co-utile nature of the above-described reputation protocol applied to P2P lending lies in the mutual benefit of agents computing the reputation, that is, the lenders: if borrowers can also lend, then all agents are interested in the availability of a reliable reputation to assess the loan risk; if borrowers cannot lend, then lenders are only interested in computing reliable reputations, and mutual benefit holds between lenders. Co-utility, and in particular the self-enforcing nature of the protocol, ensures correct computation of reputations by lenders, with no incentive to deviate.

Furthermore, the key characterizing features of the co-utile reputation system depicted above have a significant potential for improving the efficiency of the P2P online lending market. For instance, the decentralized nature of the protocol assures the operation of the market without central authorities. This is a very important advantage when extending the operation of P2P lending practices beyond geographic boundaries where there is no common legal framework that binds individuals across the globe to specific rules. In addition, decentralization eliminates third-party platforms acting as intermediaries and hence reduces operational costs. Furthermore, the self-enforcing property of the reputation protocol ensures correct computation of reputations, with no incentive to deviate.

On the other hand, the proper management of new agents embodied in the co-utile reputation protocol can be useful in guaranteeing differentiation of existing players from new entrants, which will also solve one of the underlying problems in community-based lending. In this regard, one of the prominent examples can be the problem underlying the community-based reputation mechanism (Hildebrand et al., 2014; Collier and Hampshire, 2010) in which communities signal the creditworthiness of an individual member agent. A finding by Krumme and Herrero (2009) shows one of the drawbacks underlying the community-based reputation, where the lenders' preference pattern with regard to credit grade remains unchanged across community groups with different reputation and, hence, there is no identification effect of the community-based reputation when combined with the credit grading effect. Such reputation mechanism has a problem with the management of new entrants because if a previously existing community has poor loans, it would be easier to start all over with a new community of no history. A specific case is a seller with a poor rating in eBay: he will be rationally interested in whitewashing his reputation by mutating into a new seller with a new pseudonym. The adaptation of the above-described decentralized co-utile reputation protocol to the P2P online lending market promises to deter whitewashing and improve the efficiency of the system.

In this section, we describe the adaptation of the protocol to the P2P lending market by taking into account the loan characteristics and by defining how local reputations can be computed to capture the outcomes of a lending interaction. Then, we show how (global) reputation values can be used in the market for decision making.

We consider the calculation of local agent reputations in two different scenarios: one in which the lender cannot borrow and a second scenario in which reinvestment of borrowed money is possible.

6.6.1 Local reputation of a borrower in P2P marketplaces

The local reputation of a borrower is the trust in an individual borrower, j, computed by lenders, $i \in I$, who had a direct transaction with borrower j. Following the construction of the local reputation discussed in Section 6.5 above, the local reputation of a target borrower j, with respect to an individual lender i who had a direct set of transactions, Y_{ij}, with j is defined as the summation of the payoffs that lender i has obtained from this set of transactions. The payoffs here measure the net return an individual investor gets by investing in a given loan. Hence, redefining Equation (6.8) for the P2P lending case, the local reputation of an individual borrower with a loan type τ can be defined as the summation of the utilities derived from a set of transactions by an individual investor i with the target borrower j of loan type τ, weighted by the conditional probability of default, $\mathrm{p(t)}_j^\tau$ .That is,

$$S_{ij} = \sum_{y \in Yij} u(x)_{iy}, \qquad (6.10)$$

where $u(x)_{iy}$ is the utility of investor i in the transaction y from the set of transactions Y_{ij}, performed with a borrower j. It measures the degree of satisfaction/dissatisfaction obtained after the analysis of the transaction outcome. For uniformity of the analysis of the various satisfaction measures, we bound the range of values of this utility function in between [-1, +1]. Hence, agents give values close to -1 to defaulters and agents give values close to +1 to reflect satisfaction (honesty of the target agent). With this in mind, we define $u(x)$ by a function that goes toward -1 for negative x values (loss) and toward +1 for positive x values (gain):

$$u(x)_{iy} = 1 - {}^{2}\!/_{(1 + \exp(x))}, \qquad (6.11)$$

where x is the net return on investment, $x = (1 - \mathrm{p(t)}_j^\tau)c_i(1 + r) - \mathrm{p(t)}_j^\tau c_i$, such that c_i is the initial investment and r is the random interest rate, including the risk premium, and $\mathrm{p(t)}_j^\tau$ is the conditional probability of default for the borrower j at time t over the loan period T, and it depends on the loan characteristics τ. For example, a borrower with a loan purpose for a vacation and another one with a medical purpose might have a different default rate, even if they belong to the same loan grade, *ceteris paribus*.

Taking this into account, in order to further define the probability function, we use Cox's proportional hazards model (David, 1972). Applications predicting how much a given loan will return before reaching maturity have been presented in an article by Marot (2014) for loan filtering purpose. By defining the loan characteristics for each type of loan, Marot showed the probability of default over time for loans that will default.

Usually, in the P2P marketplaces there is a fixed amount of monthly payments (installments) to repay a loan (principal and interests). Even if loans have different terms and time horizons, a default can happen at any point, either at the initiation or at maturity, sometimes after partial payment. Note that this can also extend beyond the maturity time, in the case of delayed payments.

Applying Cox's proportional hazard model, the probability of default of a loan with characteristics X at a given time t is given as:

$$p(t)_j = p(t)_0 e^{\beta X}, \qquad (6.12)$$

where $p(t)_0$ is the baseline hazard function implying the risk of default for the loans whose covariates X (filtering characteristic variables) are all assumed to be zero. It shows the probability of default of a hypothetically average loan, without any loan characteristic effect. On the other hand, the effect parameters show how the probability of default varies depending on loan characteristic covariates X. The model implies that the covariates play a multiplying effect on the baseline hazard function in defining the creditworthiness of the loan. In order to account for indices other than the credit grade offered by the platforms, we included a set of loan characteristics that can potentially define the loan type and, hence, its credibility. The main characteristics of the loan that can be drawn from the available set of data provided on the credit details of the borrowers on the platforms include: Rating/Grade[9](Rt), commonly based on Credit Score (for e.g. FICO score); Debt-to-Income Ratio (D/M); Credit Lines (Cr); Number of Delinquencies (NoD); Inquiries in the Past 6 Months ($NoI6$); Home Ownership (mortgage, none, own) (HoS); Loan Purpose (car, credit card, debt consolidation, education, home improvement, major purchases, medical, small business, vacation) (Lpr); Number of Public Records ($NoPr$); Borrower's Age (active, on retirement) (age); State/Region (S); and Term of the Loan (t). We drop the loan characteristics variables of Loan Amount and Length of Employment as they are proved to have no significant effect in defining the probability of default (Serrano et al., 2015).

In order to see the variation in the probability of default with the loan purpose, consider Figure 6.2 below. The figure depicts the variation in the probability of default with survival function for loan purposes sourced from Serrano et al. (2015) based on data from Lending Club for the years between 2008 and 2014. From the figure, the survival curve for the loan purpose 'wedding' has a higher survival rate (less risky) than the other loan purposes under consideration, while the loan originated with a 'small business' purpose has the lowest survival rate (higher probability of default). The other loan characteristics variables also have a similar variation in defining the probability of default of a borrower.

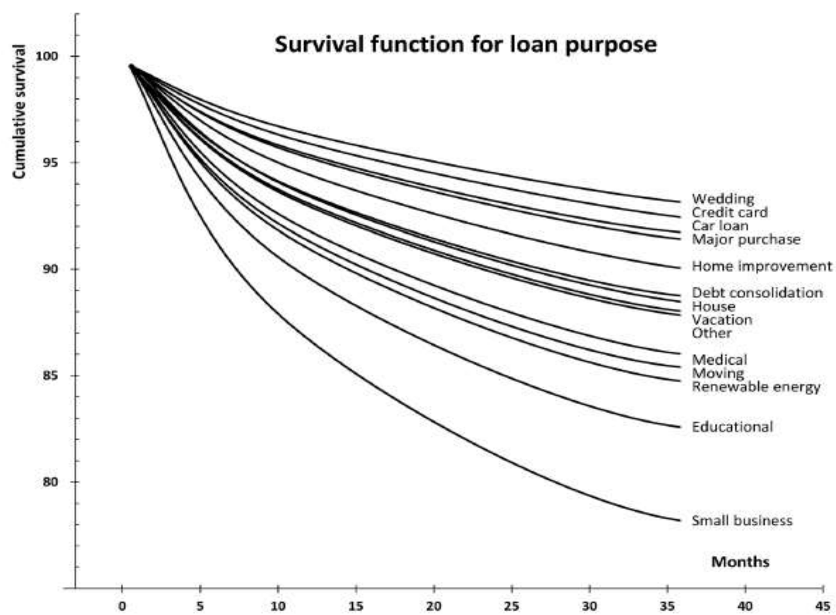

Figure 6.2: Survival function for loan purposes of sample loans in the Lending Club between the years 2008 and 2014 (Serrano et al., 2015)

This set of loan characteristic indices is used by individual investors in basic filtering and third-party automated algorithmic investment filtering. The set of covariates characterizing the underlying characteristics of a loan are defined on the above common basic and algorithmic filtering inputs: $X = \{Rt, D/M, Cr, NoD, NoI6, HoS, Lpr, NoPr, Age, S, t\}$. The conditional probability estimate in Equation (6.12) is used for the estimation of the expected return in Equation (6.11).

[9]Lending Club assigns loan grades ranging from A(safest) to G(riskiest) and Prosper assigns grades from AA (safest) to HR (high risk).

This mechanism leads the investors into investing in the loans of good reputation (which also takes into account the loan characteristics), upon preferred risk tolerance.

6.6.2 Global reputation of a borrower in P2P marketplaces

The global reputation is the overall reputation score of a borrower based on the local reputations obtained from a set of transactions she undertook with a set of lenders in the market. This score, if available, is the one used as an immediate reference for the future credible potential transaction. The global reputation of a borrower j is based on aggregation of each normalized local reputation value s_{ij} computed by the lenders i who directly interacted with j. Hence, based on the preceding discussion in Section 6.5, the normalization for the reputation value of the borrower in the P2P lending market follows Equation (6.8), where the local reputation takes a positive value for a potentially non-defaulting borrower, and takes a zero value for a defaulter or a newcomer to the market with no reputation. New entrants can be filtered out with the underlying zero reputation score and loans with higher risk that are already priced at a higher interest rate. This implies that, in order for a borrower to obtain a trusted loan (in favorable conditions), she should have a positive normalized reputation value from her local transaction score.

By using the transitive trust assumption, the global reputation value of borrower k, $g_{ik} = \sum_j c_{ij} c_{jk}$, follows the computation procedure stated in Section 6.5 above, where $S_{ij} = \sum_{y \in Yij} u(x)_{iy}$, from Equation (6.10) above and c_{jk} is the normalized local reputation value of borrower k w.r.t. j. A matrix of local reputation values, C, will have zero entries for those borrowers and lenders with no interaction. A lender, who is a score manager of a set of borrowers, can compute the global reputation, $\hat{g}_i$, which is the left principal eigenvector of the matrix C (see the discussion under Section 6.5 and Kamvar et al. (2003) for details on the computation mechanism).

The decentralized computation of the reputation is done by score managers, that are defined for each borrower using a distributed hash table (DHT) (see Section 6.5 above and Domingo-Ferrer et al. (2016b)). A score manager computes the borrower's global reputation based on the local reputation fetched from the set of direct transactions by the borrower. The electronic system must publicly maintain the computed reputation score of each agent within the market and is continually updated with upcoming transactions (reputation scores can be updated on a daily or a weekly basis). Once the global reputation for each agent in the market is computed in a decentralized way, transactions are more predictable to a rational investor. Before deciding to lend money to a borrower k, a potential lender i asks the reputation system for the global reputation of k, or directly refers to the local reputation i gave to k if a transaction took place between the two in the past. In some cases, where there is a direct transaction record between i and k, the investor i might realize a variation between the global reputation score and that of the local reputation record she has about k. In this case, she compares the two and takes the one with a lower value for further investment decisions regarding k. The normalized local reputation score identifies if a borrower k is credible (positive reputation values) or if she is a defaulting type or just a borrower with a first-time loan request in this market (zero reputation value). In addition, the global reputation score reveals the borrower's creditworthiness based on her weighted local reputation scores.

A simplified computation of a reputation score for a lending transaction is presented in Fig. 6.3 in which a score manager i computes the global reputation score of a single borrower k. The figure depicts a graph with local-trust-value weighted nodes of a network of interaction of peer k. The computation of k´s global reputation by a single score manager, SM_k is based on their network of interaction.

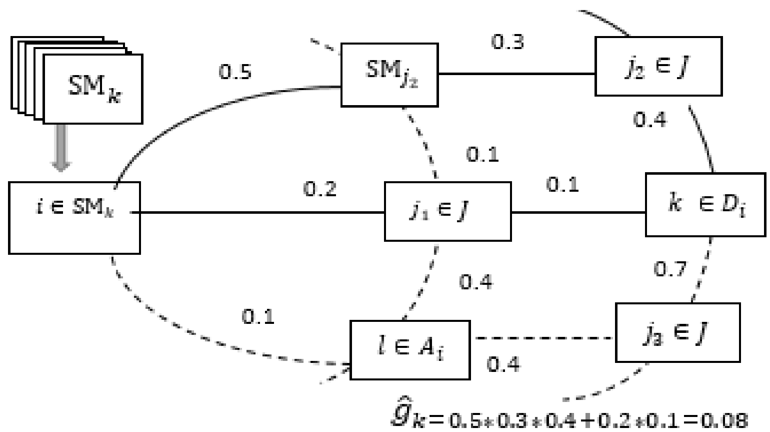

Figure 6.3: Co-utile reputation calculation ($\mathbf{SM}_{\boldsymbol{k}}$ and $\mathbf{SM}_{\boldsymbol{j_2}}$ are the score managers of k and $\boldsymbol{j_2}$ respectively).

One important note is that the system works in different ways for the two main lending market scenarios discussed in Section 6.3 above. With the key underlying problem of *mistrust* in the market, it matters whether lenders can borrow or not:

- *Lenders can borrow*. In this case, the *mistrust effect* is multidirectional in that any potential lender can be in the position of a borrower. This clearly makes a difference in the assignment of the global reputation values, because the incentive to rate individual borrowers by being a score manager depends on the existence of a potential lending transaction between the score manager and the borrower. To use the transitive trust assumption, the local reputation assigned by a lender needs to be weighted by the reputation the lender earns as a borrower.
- *Lenders cannot borrow*. In this case, the lender relies only on its own capital for investment in the market. The lenders' aim is to define the credibility of borrowers in the market, and the *mistrust effect* is unidirectional: lenders mistrust borrowers. If the lender cannot be a borrower, then the local reputation she assigns is weighted by the lender's initial reputation. This initial reputation is set to a small positive value, to avert the problem of zero reputation for a lender that earns no reputation as a borrower. Only lenders act as score managers and their motivation to do so is to be able to come up with reliable reputations to minimize the lending risk.

Allowing lenders to borrow further increases the flow and the potential re-use of money in the market. That is, a chain of interlinked interactions increases the velocity of the money in the system, resulting in more frequent transactions between agents in the market. The reinvestment possibility will also enhance the computation of global reputations with more frequent transactions and more involved agents (every agent is a potential lender and hence can contribute to computing reputations).

Figure 6.4 depicts the workflow of the decentralized reputation protocol when applied to the online P2P lending market. In the figure, consider that a potential lender, A, in an online lending market, wants to invest in the loan requests of borrower, B. We now comment on the various steps of Figure 6.4:

1. B is a registered borrower in a platform.

2. A set of lenders, J, who had past transactions with borrower B, gives local reputation scores to B.
3. The reputation system in the platform assigns a global reputation score for each member based on a decentralized co-utile reputation protocol. Hence, the score manager of B queries the set J and computes the global reputation of B based on the transitive trust assumption.
4. A potential lender A queries the global reputation system for the reputation scores of his target notes, in order to make an investment decision on her preferred loan note out of the entire return rate category based on her risk preference.
5. In addition to checking the global reputation score of B, according to the implementation rules of the protocol, if investor A has already interacted with borrower B and, thus, has calculated a local reputation value, then A can make her investment decision by directly referring to B's local reputation. Here, self-experience is considered a good reference point. However, local and global reputation values may not always be the same, since global reputation is a weighted sum of all the local reputations of borrower B. In that case, it is better for A to take both valuations into account and make the investment decision based on the comparison of these values (with a negative bias, taking the one with the lower reputation value).
6. The potential transaction takes place between lender A and borrower B, based on B's reputation.

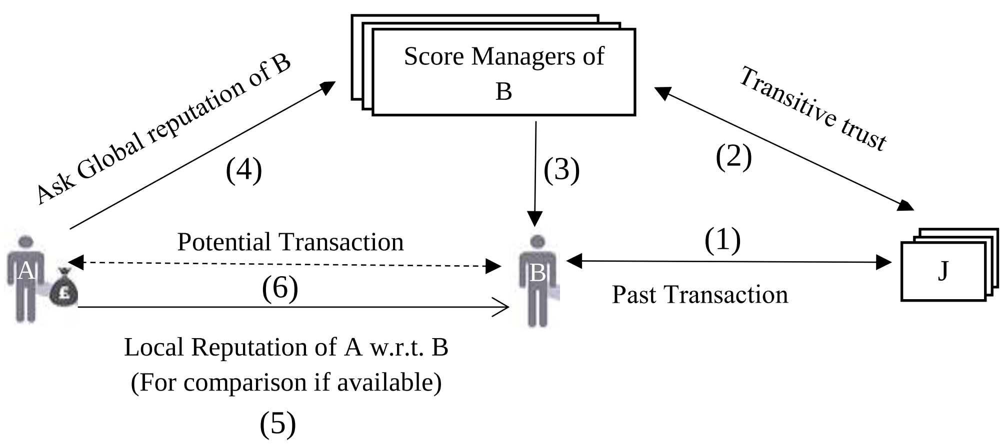

Figure 6.4: Workflow of the decentralized co-utile reputation system for P2P lending

Note that the diagram in Figure 6.3 is drawn under the assumption of non-diversified investment (for simplicity of presentation), whereas investors can have a portfolio of diversified investment.

The application of the reputation protocol to the P2P lending market makes the latter strictly co-utile by neutralizing the negative utilities discussed in Section 6.4. With a perfect trust and exact valuation of notes in the market, participation in the P2P online lending market offers the highest possible reward. The reason is that investment in a P2P online lending market generates better rewards than the traditional banking market, because: (i) many loans that would not have been approved by traditional banks are listed for financing in these marketplaces with relatively higher rates of return; and (ii) the reputation protocol can help identify the creditworthiness of the individual borrower (which helps exploit all potential loan listings) so that investing in that borrower's note is better for a rational utility-maximizing lender. Moreover, there is no way for the lender to get a better payoff, without getting the borrower worse off (maybe through increased rate of return or refusal to finance). In the same way, it is not possible for the borrower to get a better payoff, without a decrease in the lender's payoff (maybe through defaulting or imposition of a lower rate of return).

6.7 Empirical work

To evaluate the effect of reputation management on P2P lending, where investment decisions are made merely based on the platform-based filtering, we took a sample network of 200 lenders and borrowers. During each round of transactions, we assumed that each borrower could borrow at most once, while each lender could invest in as many notes as she could afford and was willing to invest in this market.

The data for this analysis was sourced from the Lending Club Statistics, where a random sample of 200 loans with an average probability of default of 0.085 was taken. Note that this simulation is a simplistic presentation of the scenario and the probabilities were drawn on a random basis, and did not take into account the underlying loan characteristics. Here, we used a right-skewed beta distribution (in order to get normally distributed values in the range between 0 and 1), where the mean of the beta distribution was given by $1/(1+\frac{\beta}{\alpha})$. Hence, given an average probability of default of 0.085, with $\alpha = 5$ and, hence, $\beta = 53.824$, the beta distribution generated random probability values of interest with an average probability of default as in the sample data. The minimum and maximum loan amount in this sample were \$1,000 and \$35,000, respectively, with an average loan request amount of \$15,095.75. The loans were composed of either 36 or 60 terms.

The goal of this computation is to derive the global reputation of borrowers based on the payoff which lenders derive from each of them and individual successive lending transactions. By using Equation (6.11) above, we computed the utility derived from investing in this P2P lending network and, based on this, the local reputation of each individual borrower and lender (for those borrowers who also borrow for re-investment purpose). The utility values computed based on this formula were used to calculate the respective local reputation score of each borrower in the market.

The size of the network was 200, with 100 lenders and 100 borrowers, and we set a fixed positive reputation score of 0.01 for the lenders. Note that, based on the EigenTrust rule of computation, entries in the normalized local reputation for those agents with no interaction (borrower-to-borrower here) were set to zero. In the first iteration, we took an initial reputation vector of size 200 with 0.01 entries for the lenders and 0 entries for the borrowers (which accounts for the reputations prior to these transactions) and this vector was multiplied by the transpose of the local reputation score matrix. The successive global reputation score was based on each preceding global reputation. We repeated this step until the factor between the successive global reputation scores of each borrower was less than 10^{-5} (i.e. $\delta_i < error$). The computation is simulated for two main lending market scenarios:

- *Lenders cannot borrow*. Based on the underlying pre-trusted peer assumption of the reputation protocol, the initial reputation for lenders is set to a small positive value (0.01), to avert the problem of zero reputation for a lender that earns no reputation as a borrower.

- *Lenders can borrow*. In this case, the *mistrust effect* is multidirectional in that any potential lender can be in the position of a borrower. To use the transitive trust assumption, the local reputation assigned by a lender needs to be weighted by the reputation the lender earns as a borrower.

Furthermore, in order to see the evolution of global reputation in the long term, we considered further computations with more than one transaction. For instance, a randomly selected borrower with a probability of default of 0.01 (which is internally perceived by the borrower and is fixed for each transaction) implies that this borrower will default at least once in 100 repeated transactions. The reputation protocol should be able to capture the behavior of this borrower by refining the computation according to the type of borrower in each lending transaction. Hence, to this end, we repeated transactions 100 times. The results are presented in Figs. 6.5 and 6.6, respectively for pure lenders and for lenders that can borrow.

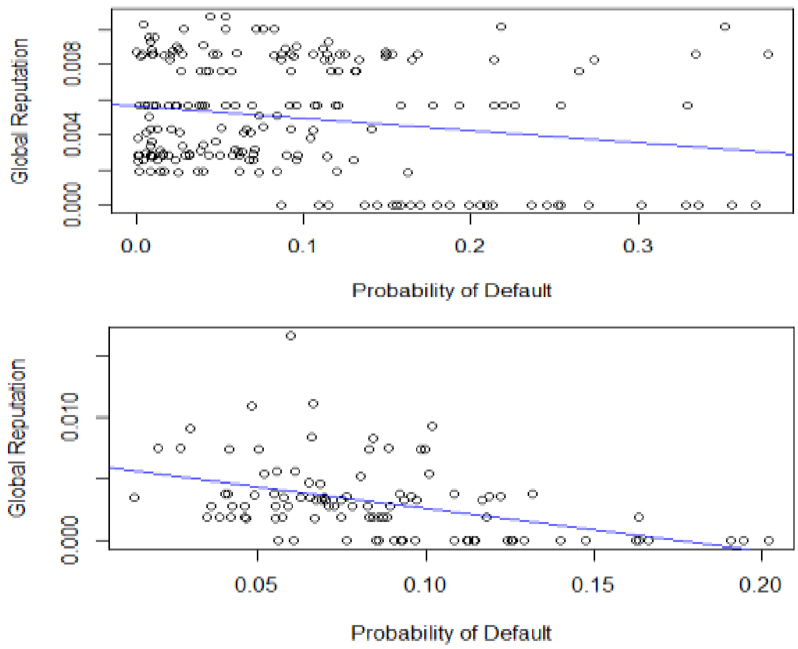

Figure 6.5. Global reputation scores vs. probability of default for pure borrowers; after the 1st transaction (upper) and after 100 successive transactions (lower). Pearson's product-moment correlation: -0.17 (upper) and -0.45 (lower).

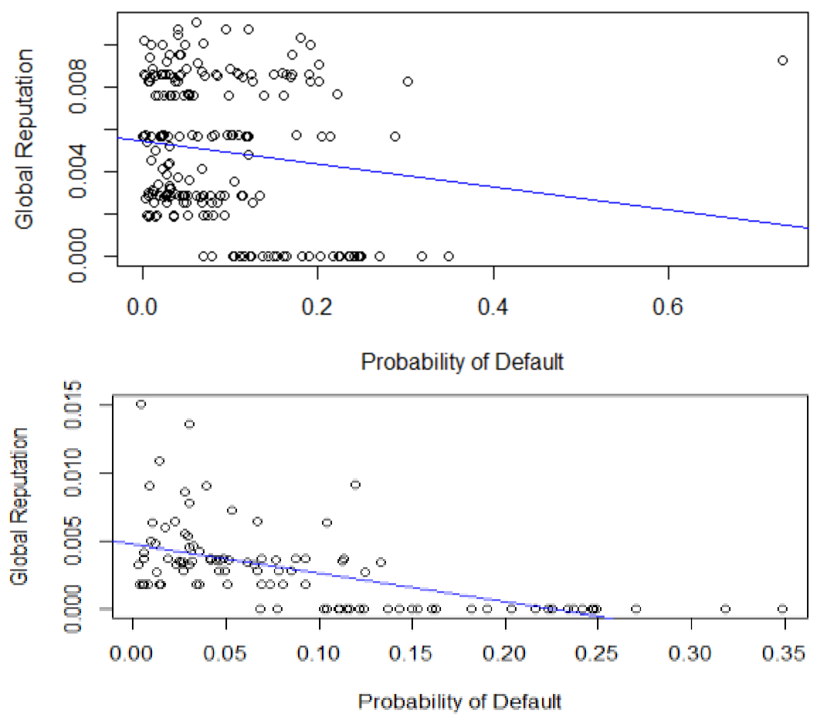

Figure 6.6. Global reputation vs. probability of default with reinvestment; after 1st transaction (upper) and after 100 successive transactions (lower). Pearson's product-moment correlation: -0.14 (upper) and -0.56 (lower).

The reputation mechanism identified ill-behaved borrowers by assigning low global reputation scores as the computation gets refined in successive iterations. Hence, with repeated transactions over time, the global reputations will be highly correlated with the probability of default. The fitted line in the figures depicts a negative correlation between reputation and probability of default of the borrowers, *ceteris paribus*. The Pearson's correlation test for the plots above shows that there is a statistically significant negative correlation between the global reputation and probability of default, with an increasingly strong correlation through successively repeated transactions of 100 times. Fig. 6.5 shows a downhill linear relationship between the global reputation and the probability of default that is stronger after 100 transactions (-0.45 correlation coefficient) as reputations build up through successive transactions. Fig. 6.6 shows analogous results for the reinvestment case. Therefore, by examining global reputations in the long term, lenders can filter borrowers according to their probability of default.

6.7.1 Filtering credible borrowers

In order to collaborate with the loan request of borrowers in the network, lenders filter loans based on a minimum global reputation score according to their risk preference. Here, a quite important thing to consider is the question of how the system acts with the minimum threshold of global reputations set by the potential lenders for any collaborative decision. With the assumption of pre-trusted peers underlying this reputation protocol, borrowers with reinvestment motive tend to have relatively higher reputation scores than pure borrowers. Besides, there also is a spillover effect of the borrowers' credibility on the reputation of those lenders who partially rely on the capital sourced from this network. Hence, the more risk-averse the lenders in the network, the higher the minimum threshold of global reputation, and as a result, the higher the number of loan requests to be filtered out. Kamvar et al. (2003) propose two different filtering mechanisms for the reputation of agents. These are the deterministic and probabilistic approaches. The first refers to a fixed reputation score as a threshold filtering mechanism, while in the latter case, peers select agents with varied global reputation scores based on distributions instead of fixed reputation scores.

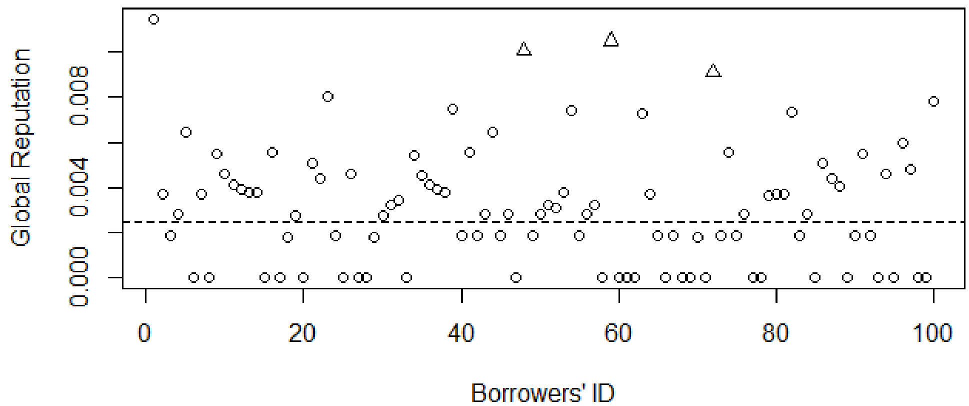

Figure 6.7 Global reputation scores of each borrower in the network: deterministic vs. probabilistic loan filtering

In Fig. 6.7 above, the horizontal dashed line represents the threshold global reputation ($\bar{g_i}$=0.0025) based on a deterministic approach. This approach requires a standardized level of global reputation, which every borrower needs to minimally attain accounting for all loan characteristics. The extreme case is to pick a borrower with the highest reputation score. If a probabilistic algorithm is employed, given a vector of global reputations $g = \{g_1, g_1, .. g_n\}$, a potential lender chooses an honest borrower i (with g_i>0) with probability $\frac{g_i}{\sum_{j=0}^{n} g_j}$ and chooses a dishonest borrower j (with g_j=0) with a fixed probability 0.1 (thereby fairly accounting for newcomers, see Kamvar, et al. (2003)).

Presented in a simplistic way, in Fig. 6.7 the triangular points in the plot represent the three consecutively selected borrowers with high reputation based on the $\frac{g_i}{\sum_{j=0}^{n} g_j}$ condition, where $\sum_{j=0}^{n} g_j = 1$. Borrowers with larger reputation score g_i have a higher chance of being selected as compared to borrowers with low g_i.

Since P2P loans have no collateral, we assume that the *reputation capital* (reputation of the borrower) is an intangible collateral of this transaction. Borrower k defaults if the value of defaulting, $v^d(l_i, \bar{g}, g_k)$, is greater than the value of paying back, $v^p(R) = l_i(1 + r)$. Her gain from the default is the loan amount originated, given an initial presumed small positive reputation of the system, $\bar{g}$. Yet, with the current transaction's default, she will also lose her reputation g_k. Hence, $v^d(l_i, \bar{g}, g_k, f_o) = l_i - f_o - \bar{g} - g_k$, where f_o is the origination fee (commonly 5% of the loan). This also implies that the reputation gain punishes an intention to default. In order to standardize the computation together with the global reputation scores, the loan amount and return to the lender are normalized between 0 and 1. Therefore, given the global reputation scores, a potential lender will reject the loan request by borrower k if $v^d(l_i, \bar{g}, g_k) > v^p(R)$. Figure 6.8 below presents the borrowers filtered out (rejected) based on their global reputation. The extreme default values (black) above the return value curve (gray) depict the borrowers with default value higher than payback value (that are hence filtered out).

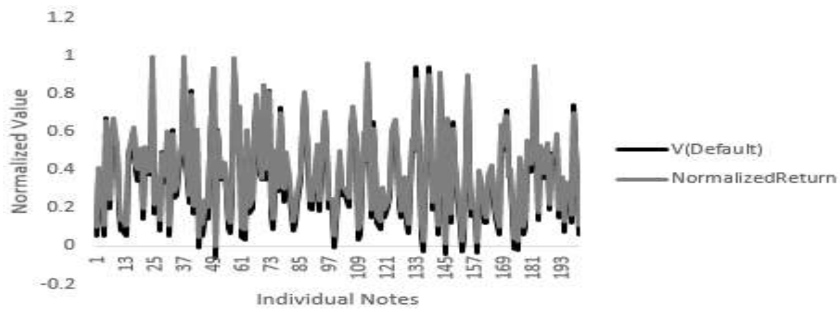

Figure 6.8: Borrowers filtered based on global reputation scores

Consider an individual lender who wants to invest her $10,000 in this P2P lending market. Commonly, investors in the P2P lending market can minimize risk of loss by diversifying their investment across different loans at the same time. For example, in Lending Club individual lenders can diversify their portfolio composition by investing in portions of loans (notes), minimum of $25 each. Hence, let us assume that a hypothetical portfolio of this lender is composed of 100 randomly selected notes of 36 months term from the above-mentioned network. She invests $100 uniformly in each note, at different interest rates based on the loan grades. Ten of these notes defaulted before maturity (5 of them defaulted after 5 months payment, and one in the 15th month). For simplicity of presentation and without loss of generality, we assume that her investment is one-time and that no re-investment is made till all the notes reach maturity. This portfolio composition based on platform-based filtering and random selection (based on a deterministic reputation approach) generates her an average monthly interest of $72.59. She can filter notes of her preference by either replacing the notes of lower reputation score from the bigger network, or just filtering out the existing portfolio composition without replacement, which will reduce the number of notes in which she invests. Here, we will consider the filtered portfolio composition without replacement in order to make a comparison within the same set of notes of the previous portfolio composition. If the lender filters out the notes with global reputation score of less than 0.005 (which also includes the borrowers with a previous default record, without replacement), the average interest she receives each month increases to $78.15. Hence, unlike the existing filtering mechanism, the filter based on the reputation mechanism we stated here results in a greater and more secured return to this lender. Figure 6.9 below presents the monthly interest paid to the lender across the 3 years (36 months), both for the random and reputation-based lending.

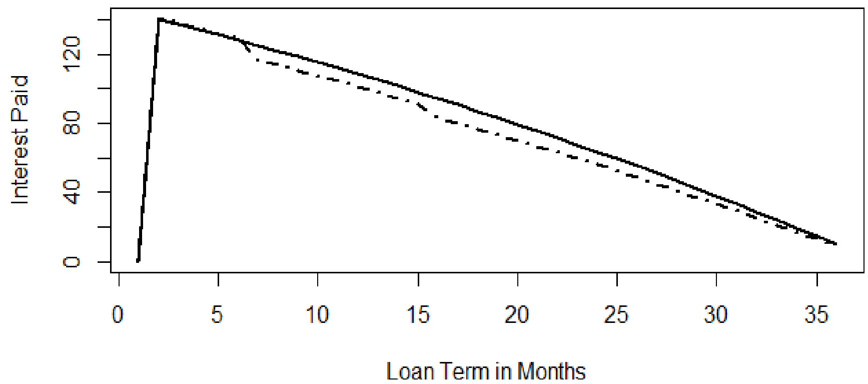

Figure 6.9: Interest paid on notes selected on a random basis (dashed line) vs. note filtering based on a global reputation score (solid line)

However, reputation is valuable only in repeated interactions. Therefore, in order for reputation to be used as an intangible capital, we formulate a repeated game where the borrower in each period $t = 0, 1, 2, ...$, has a strategy $s_t = \{pay, default\}$ to choose on the loan she took. Assume that the borrower's type in the cold start, without any reputation effect, is not observable by the lenders in the network. Provided her credit score and loan grade, the loans to this borrower are set at a random rate r. The type of the borrower s_t is privately known only to her. Lenders in the network choose in each period t whether to invest in the loan listings of this borrower or not. Let $\delta \epsilon (0,1)$ be the discount factor. Lenders who have invested in this borrower's loan in period t learn the borrower's type. Unlike in a static one-shot game, in case of repeated transactions with future reputation effect, the borrower will choose to pay her current debts within this lending network. In this setting, potential lenders invest in this borrower's loan listings and set their expectation of trust based on the borrower's reputation. The borrower's reputation at t depends on her past record of transactions. At $t = 0$, lenders expect the borrower to be trustworthy based on the loan grade or other pre-transaction factors. Yet, at $t > 0$, lenders trust the borrower only if she has not defaulted at all prior periods. If the borrower has defaulted at some period t, then lenders do not trust this borrower anymore and will not be willing to invest on a loan l_t higher than 0.

The strategy of the borrower follows: at $t = 0$ borrower takes out a loan $l_t > 0$ and pays back the debt at a rate r according to the loan contract. The borrower keeps on being honest and pays back the loan if she has been honest in all the previous periods. If the borrower never deviates, then her discounted payoff from Equation (6.1) is $\sum_{T=0}^{\infty} \delta_t l_t - P\frac{1-(1+i)^{-n}}{i} = \frac{l_t - P.\frac{1-(1+i)^{-n}}{i}}{1-\delta}$. After any deviation, she defaults and gets loan amount $l_t = 0$ in any future loan listings. Hence, the borrower's payoffs after any deviation are $l_t > 0$ in the period of default and zero ever after. In any case of default, the borrower's discounted payoff is l_t. As a result, default is not profitable if $\frac{l_t - P\frac{1-(1+i)^{-n}}{i}}{1-\delta} > l_t$. If the inequality holds, future loan originations are more valuable than short-term gain from default. This occurs when the borrower's discount rate δ and $l_t - P\frac{1-(1+i)^{-n}}{i}$ are relatively high and when the borrower's reputation matters in the lenders' investment decisions, which is the case in online P2P lending with asymmetric information. With the repeated game setting presented here, the conditions for which the value of reputation outweighs the value of defection hold for the P2P lending with the reputation effect which can be scored with the co-utile distributed reputation mechanism presented in this chapter.

6.8 Conclusion

The peer-to-peer online lending market is an example of a co-utility amenable game. However, this market suffers from the lack of trust (*mistrust effect*) hindering its potential to be strictly co-utile. In this chapter, we have shown how to apply a decentralized co-utile reputation system to this market in order to neutralize this problem. The reputation system is co-utile (and hence rationally sustainable) and it allows P2P online lending to operate efficiently. In order to adapt the protocol to this market, we have characterized the behaviors of borrowers and lenders according to their preferences for their respective utility maximization. We have considered two different scenarios: a case where lenders cannot borrow and a case in which reinvestment is possible. In addition, we have also taken into account for the loan characteristics variables other than common loan grading standards. In order to define the conditional probability of default based on these loan characteristic variables, we have used Cox's proportional hazard model (David, 1972), which is then leveraged to compute the local reputation of the borrower. From local reputations, the computation of the global reputation follows based on the assumption of transitive trust.

In this co-utile protocol, rational peers cooperate to compute each other's reputation scores. Reputation scores of borrowers are computed based on the outcome of direct transactions. Then, the reputation mechanism helps filter credible borrowers based on their respective reputation scores. By using an experiment on a simulated platform with a randomly selected sample of loans from Lending Club, we show that this protocol can improve the efficiency of the P2P online lending market by filtering out defaulting borrowers. Moreover, the results show that there is a negative correlation between the probability of default and the global reputation of the borrowers, which implies that the protocol helps accurately identify each borrower's type.

The decentralized co-utile reputation protocol has interesting features that make it novel to define the identity of individual borrowers for a potential transaction in the P2P online lending market. The first and most important feature is that it is handled in a decentralized way. This is fundamental in such a global market where no common legal framework applies efficiently. Other relevant features are that the reputation protocol is self-enforcing, attack-tolerant, cost-effective, and anonymously computed. Also relevant is that whitewashing reputations is discouraged. All in all, the application of this protocol improves the efficiency of the market and makes it strictly co-utile.

Chapter 7 A CO-UTILE DISTRIBUTED REPUTATION MECHANISM FOR E-COMMERCE

7.1 Introduction

Feedback systems in e-commerce marketplaces are crucial to tackle information asymmetry and the underlying market-related risks. An efficient reputation mechanism allows sorting out malicious buyers/bidders within the transactional network, by imposing buyer requirements in the marketplace to those with policy violations, retaliation feedback motive, unpaid items (after placing a winning bid or purchase order) or fraudulent payments. On the other hand, buyers that are being positively reputed can be identified and may benefit from loyalty programs and rewards. On the other hand, a buyer with a negative reputation can find limits on account privileges; such privileges in eBay, for example, include eBay Money Back Guarantee, discount and reward offers, gift cards and coupons, and non-cash eBay Bucks customer rewards program (greater or equal to $5 in the form of an eBay Bucks Certificate to qualifying buyers). The reputation mechanism should be designed in such a way that it clearly identifies loyal customers in the transactional network with these incentive schemes under consideration, whereas negative ratings result in a limit on these privileges or overall buying activity, and account suspension in the extreme case.

On the other side, selling performance measures can be used to rate the reputation scores of the sellers in the transactional network. These measures include defect rate (item description accuracy), late shipment rate (item delivery), shipping and handling charges, communication and cases closed without seller resolution. Therefore, there is a need for reputation protocols that can be all inclusive and distributed so that all involved in the network rate each other in a rationally self-enforcing way.

Like in the P2P online lending market, lack of trust between transacting agents is one of the problems hindering the efficiency of the e-commerce market. This mainly arises due to asymmetric information between the transacting parties, buyers and seller, which is a most common situation in the internet-based transactions. In this chapter, we present an extension of the well-known EigenTrust algorithm (applied to the P2P online lending market in the previous chapter) under a co-utile protocol; we also apply this new protocol to e-commerce, specifically to online consumer-to-consumer marketplaces like eBay, in which goods and service are traded.

The remainder of the chapter analyzes the e-commerce market, under the general umbrella of the co-utility notion. First, we assess the common feedback mechanism applied in this type of marketplaces. Further, by outlining the disutilities arising in e-commerce transactions, we leverage the reputation protocol to neutralize the potentially arising negative utility due to the lack of trust between transacting parties.

7.2 Co-utility in e-commerce: benefits to the buyer and sellers

As we have pointed out in Section 4.2.2, e-commerce is one example of co-utility amenable game. In e-commerce, voluntary exchanges between transacting parties takes place through the internet. In the economic theory, the Edgeworth box with the indifference curves for the trading parties is used for illustrating a voluntary exchange that represents a win–win situation of the transacting parties (Schotter

2008). This is a handy tool to elaborate the co-utile nature of the electronic transactions taking place in online marketplaces like eBay or Amazon.com.

Consider two consumers, i and j, who have two goods, X and Y, respectively. These consumers can engage in an exchange trade depending on their demand for the goods in the market. Given indifference curves of each consumer presented in the Edgeworth box of Fig. 7.1, their preference for any kind of the goods motivates a transaction deal between the two. Hence, at any point where the marginal rates of substitution differ between the two consumers, a mutually beneficial transaction is attainable (the gray region). Given an initial possible transaction point P_1, both i and j are better off with any transaction deal that leads them to a Pareto-optimal point P_2 within the mutually beneficial region. P_2 is a point at which the marginal rates of substitution between the two goods of consumers i and j are equal, which corresponds to a co-utile transaction. This can be achieved all through the contract curve in which the tangency between the indifference curves is attained. Unlike the initial point, any movement outside the contract curve, for example point P_3, will not be beneficial for at least one of them.

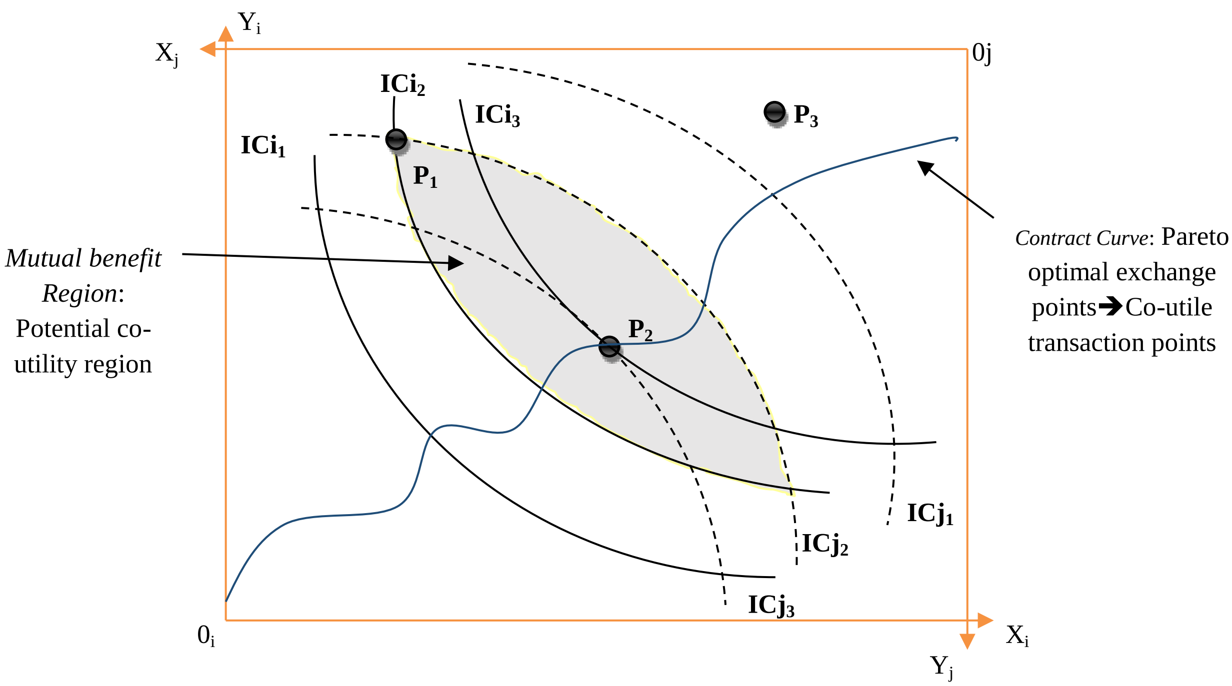

Figure 7.1: Edgeworth box depicting a potential co-utile exchange between transacting agents

This situation is empirically proved by the growing number of consumer-to-consumer (C2C) e-commerce markets like those in eBay. Voluntary exchanges taking place in this market are self-enforcing and are governed by the win–win rule. The main role of these marketplaces is that they facilitate cost-effective[10] ways for parties (sellers and buyers) with different marginal rates of substitution to connect them and make transaction deals. The transaction between the buyers and the sellers takes place depending on the scale of preferences (depicted through indifference curves) between the money spent and item purchased. As it is illustrated through the Edgeworth box diagram, transaction deals between self-interested agents in the mutually beneficial region will contribute to their combined welfare. Hence, this proves that the C2C-based e-commerce transactions are co-utility amenable games. For example, in eBay, sellers place online

[10] The zero marginal cost society of the collaborative economy (Rifkin, 2014).

auctions with possible reserve price of their choice and Buy-it-Now options. A reserve price is the price below which a seller will not sell the item, which is commonly not observable to the buyers, except for the signal that the listing is with an unmet reserve price. Accordingly, having a look at the existing listings, the customers make self-fulfilling[11] decisions on whether to take part in this transaction and in which way.

7.3 Reputation as a trust building tool in the online marketplaces

Consider the following Vickrey auction game between an eBay seller and a winning buyer. Note that buyers compete and bid according to a private valuation of the product. The set of available actions of the winning bidder is either pay or do not pay. The seller, upon receipt of the payment, has the choice to either send the item or to keep it (cheat). Let the payoff matrix for this game be given as:

Buyer/Seller	Send	Keep
Pay	(1,1)	(-2,2)
Don't Pay	(2,-2)	(-1,-1)

The Nash equilibrium of this game (Don't Pay, Keep) implies that the deal collapses due to the mistrust effects on both player sides. Apart from the payment failures, in eBay-like marketplaces, a seller with a default record commonly receives less or no bids on its listings. The prominent assumption in this analysis is that the players' types are identified by their record of past transactions..Therefore, if this stage game is repeated in a sequence of transactions, no transaction deal will take place between these two rational utility and profit maximizing players in the long run. This is because, in expectation of default by the seller depicted in the initial stage game, all other buyers do not bid or make low valuations for this seller's listings. As a result, with future reputation effect, a long-run player (seller) would prefer to be credible both in its product specification and delivery. In this case, the player is identified with the commitment type of players, commonly referred to as “irrational” players.

One of the game-theoretic approaches other than the Nash Equilibrium that captures this type of interaction is the Stackelberg action, which results in an outcome that commits the seller to being honest at any cost in fear of reputation loss (see Section 2.2). With this in mind, both the buyer and seller in the above game will choose the action (Pay, Send) in the current stage game with the expectation of future positive reputation and long-run pay-off. Therefore, when the reputation effect comes into play, the socially suboptimal equilibrium does not hold anymore, and that is what keeps the existing online marketplaces going on empirically. Yet, this way of analysis does not guarantee optimal return to the seller with strategic behavior underlying the short-term buyers.

The subjective nature of feedbacks is commonly avoided by a scoring method based on a set of values for a random variable representing the feedback (e.g., eBay feedback score and the detailed seller ratings). Another method suggested is clustering and filtering the feedback scores according to their common features in order to capture the heterogeneities among individual raters (e.g. Amazon feedback and ratings). Yet collusive behavior, Sybil attacks and biased ratings deviate online ratings. As a result, the

[11] Note that bidding a true value is a dominant strategy in the second price sealed bid (Vickrey 1961).

reputation score aggregation mechanism for the online markets is an open research question. Moreover, cross-validating malicious reporting and whether enough amount of feedback is solicited depend on the underlying incentive scheme under the feedback mechanism.

7.4 An overview to the eBay feedback method

Founded in 1995, eBay is one of the online marketplaces headquartered in San Jose, California operating as an online auction and shopping website in the global ecommerce ecosystem. As of the year 2016, the company has 164 million active registered users according to the Statista. eBay employs two main feedback mechanisms to bridge the gap resulting from the information asymmetry and to build trust between transacting individuals in the network. These are the *Feedback score* (FS) and the *Detailed seller rating* (DSR) The FS method uses an aggregation of positive, negative or neutral rating values for sellers, and positive rating values for buyers which later are aggregated to compute each individual seller's/buyer's reputation from the transaction records every week. On the other hand, DSR is used as a descriptive index of individual seller's reputation which can take values from 1 star (lowest) to 5 star (highest); the average ratings are computed every 12 months for each seller with a minimum of 5 rating records for the months under consideration.

Star	Color	Number of ratings
	Yellow	10 to 49
	Blue	50 to 99
	Turquoise	100 to 499
	Purple	500 to 999
	Red	1,000 to 4,999
	Green	5,000 to 9,999
	Yellow shooting star	10,000 to 24,999
	Turquoise shooting star	25,000 to 49,999
	Purple shooting star	50,000 to 99,999
	Red shooting star	100,000 to 499,999
	Green shooting star	500,000 to 999,999
	Silver shooting star	1,000,000 or more (Wow!)

Figure 7.2: The eBay Stars and their ratings

In the eBay rating scheme, the feedback score is positively correlated with the number of positive ratings indicated by the color of the star from yellow star (for aggregated score of 10-59) up to a silver shooting star (for an aggregated score greater than 1 million). Yet, as the feedback score is an aggregation of all the negative, positive and neutral scores a player has in the market, this way of rating can be biased by the size of the player’s transactional network. For instance, consider that two different sellers *A* and *B* have transactional networks of sizes 1,000 and 100,000, respectively. Assume that from all the transaction records, each has 10% negative ratings and 90% positive ratings. According to eBay's feedback computation, even if both sellers have a proportional record of feedback, seller A will be a purple start, while seller B will be a purple shooting star due to the scale effect (see Figure 7.2). The other limitation of this method of computation is that it takes a long time to update, as it aggregates every week's transaction record regardless of the number of transactions in that specific week. Hence, this reputation mechanism fails to capture the real transactional behavior of the players in the market.

7.5 Designing an online market trust system through a co-utile reputation mechanism

7.5.1 An incentive compatible co-utile reputation mechanism

Given the strategic nature of feedback giving, in which users may retaliate and reciprocate, we propose a co-utile reputation mechanism as an alternative to the sequential method in eBay or the ones suggested in the literature, such as the simultaneous or blind feedback giving method proposed by Bolton et al. (2013). As introduced in Section 6.5, the mechanism we use computes the global reputation of a user according to the normalized weighted local reputation scores given by her peers. In Turi et al. (2016), we argue that the reciprocity equilibrium can lead to a co-utile outcome for positive reciprocity, provided that the outcome is Pareto-optimal and results in strictly greater payoff to the players. Therefore, a reciprocal feedback can be a co-utile feedback. Yet, favoring one or another in a reciprocal setting might lead to a biased reputation system at an aggregate level. Hence, the aggregation mechanism should be designed in such a way that it weights each individual transaction in the network.

In game-theoretic reputation models, the feedback aggregation strategy depicts the behavior of the players in the selection of equilibria (Aberer and Despotovic, 2004). Hence, the aim of a reputation system designer in a game-theoretic reputation modeling to draw a feedback aggregation strategy that results in a single socially desirable equilibrium from the set of available equilibria. Some of the conventional aggregation strategies used by the existing online marketplaces include summation of all the rating scores (all the negative, positive and neutral scores), an average of the total feedback score in a given period of time, or the percentage of positive reviews from the total reviews. With the co-utile reputation mechanism, the designing mechanism is within the underlying assumption that the aggregated global reputation is derived from the normalized local reputations computed in a self-enforcing way. Therefore, along with its other interesting features, this makes the co-utile reputation mechanism a viable complement to build fairly organized and efficient online market places.

Some of the common problems in online markets are that they are global in nature and, hence, it is difficult to enact global standard rules and regulations and, as a result, it is hard to make efficient contractual agreements. Additional problems are information asymmetry, and the difficulty of identifying possibly unstable pseudonym operation (frequent name changes). *Zero marginal cost pseudonyms* (i.e. a strategic new account creation with no associated cost) complicate transactions in the online marketplaces. Friedman and Resnick (2001) proposed two mechanisms to cope with this problem: (1) cryptographic verification of unique identities of the members with a protocol that uses blind signatures and (2) a transactional network structure with unprofitable exit and re-entry setting through a new entry fee (or implicit cost of an initial reputation building) that offsets the gain from any potential exit and re-entry. The co-utile reputation mechanism we propose employs the second mechanism by setting zero reputation scores for all new and malicious players with an intention to disincentivize whitewashing.

Setting zero reputation (the worst possible reputation) to new entrants in online marketplaces is proved to be the most reasonable mechanism to punish malicious players re-entering the market with a new pseudonym (see also Dellarocas, 2003b).

7.5.2 Decentralized co-utile reputation computation

Consumer/producer surplus is the term used in economic theory to refer to the quantitative measure of the gain of a buyer/seller for a certain transaction. This notion can be used to capture the utility derived from a certain transaction while computing the general welfare of the system. A reputation score of an individual peer (buyer/seller) within the transactional network has two forms: local and global reputation.

The computation of the local reputation follows the definition under Section 6.5 replicated for the buyers and sellers in the e-commerce. Provided that customer experiences can help build trust in a given seller, these can be used to compute the seller's reputation if the aggregation from a set of different transactions is done in an efficient and fair way. Hence, the local reputation of an individual seller j is the summation of the utilities derived by buyer i from a set Y_{ij}:

$$S_{ij} = \sum_{y \in Yij} U_{iy}, \qquad (7.1)$$

where U_{iy} is the utility of buyer i in the transaction y from the set of transactions Y_{ij}, performed with a seller j. This measures the degree of satisfaction/dissatisfaction obtained after the analysis of the transaction outcome. For simplicity of presentation, we analyze the auction-style listings with a Buy-it-Now (BIN) price, which will also depict the fixed price listing's customer behavior if the item is purchased at the BIN price. The buyer makes a strategic decision on whether to buy at a fixed price or bid based on the expected utility derived under the two cases, and the participation and buy threshold of the item (see Wang and Srinivasan (2008) for the details on this). In either case, for this analysis, we are mainly interested in the ex-post transaction utility derived in a given transaction. The buyer has quasilinear utility depicting the difference between the bidder's surplus over her valuation (v_{iy}) and the transaction costs:.

$$U_{iy}^{bidder} = \mathrm{v}_{\mathrm{iy}} - \mathrm{p}_w - c_{iy}; \qquad (7.2)$$

where p_w is the actual price paid by the winner (the second highest bid in an eBay like second-price sealed bid auction) and c_i is the transaction cost. The latter cost includes the transaction risk and market uncertainties for buyer i accounting for auction duration, shipping time, effort to bid, opportunity cost, low product quality, additional costs with miss-specified or over-specified product, counterfeit goods, branding uncertainty, security issues over unsecured web pages (for e.g. phishing by fraudulent scammers) or a fraud transaction deal (no product delivery). Note that the buyer's valuation is unobserved and hence, for simplicity of the analysis, we assume that customers' valuations are uniformly distributed in the interval [0, 1] following Wang and Srinivasan (2008). In an auction-format listing, an opening bid amount set by the seller defines the participation threshold for the bid. For consistency with the value computation, p_w is a random value in the interval $[p_o, \mathrm{v}_{\mathrm{iy}}]$, where p_o is the opening bid amount. If $\mathrm{v}_{\mathrm{iy}} = p_o$, a customer wins the bid only if she is the only bidder provided that there is no reserve price. In eBay, the reserve price is set to be higher than the opening bid and, if the bid does not reach the reserve price, there is no sale, which costs the seller \$2 or 1% of the reserve price (whichever is higher) for choosing this option. Hence, p_w is set as a random value in the redefined interval of $[p_r, v_{iy}]$, where, p_r is the seller's reserve. If $v_{iy} = p_r$, customer i can win the bid if she is the only bidder with the highest valuation. Note that, if there is only one bidder with $v_i \geq p_r$, the item sells at p_r and, if there is more than one bidder with $v_{iy} > p_r$, the item sells at the second highest valuation.

If there is a Buy-it-Now option in the listing (greater than or equal to 30% of the opening bid price in the eBay auction-format listings, which is neither the minimum reserve nor a maximum price of the item), customers can choose to buy the item right away without waiting for the auction. The utility function of a customer who purchases at the Buy-it-Now (BIN) price, p_{BIN}, is given by:

$$U_{iy}^{buyer} = v_{iy} - p_{BIN} - c_{iy}, \tag{7.3}$$

where p_{BIN} is a random value in the interval $[v_b, v_i]$, given the valuation v_b at which the customer is indifferent between the bid and buy options.

In either case, utility values close to -1 imply dissatisfaction, and values close to +1 reflect satisfaction. With the increase in the transaction cost, the consumer's surplus diminishes, and the customer ends up with dissatisfaction resulting in a lower local reputation score to the seller.

The normalization of the local reputation to aggregate it into the global reputation (see Section 6.5 above) prevents agents from whitewashing a bad reputation (i.e., to operate with a new pseudonym or start all over) and instead creates an incentive for building and maintaining one's own reputation. The normalization also guarantees that all agents contribute equally to the computation of global reputations, regardless of the number of transactions. Note that the aggregation mechanism in eBay's feedback mechanism is biased with the scale effect we mentioned under Section 7.4.

In the same way as the P2P online lending's rating, sellers rate buyers based on the utility they derive from each transaction they perform with the buyers. The local reputation of a buyer i in this case is defined as the summation of the payoffs the seller j gains from the set of transactions where he sold to this buyer: $S_{ji} = \sum_{y \in Yij} U_{jy}$. The seller will not sell at a price less than the production cost. Provided that sellers make a normal profit under a perfectly competitive market, let us assume that the reserve price is equal to the marginal production cost ($p_r = MC$). Then, the utility of the seller from this transaction is the producer's surplus ($p_r - p$) minus the transaction related costs (c_{jy}):

$$U_{jy}^{seller} = (p_r - p) - c_{jy}\ , \tag{7.4}$$

where the actual price, p, is a random value in the interval $[p_r, 1]$ and, again for simplicity of the presentation and without loss of generality, c_{jy} is uniformly distributed in the interval [0,1]. The transaction cost to the seller includes market uncertainty (e.g. exchange rates), false winning bid, the time spent until the auction closes, fraud payments, etc. Hence, as the transaction cost increases, the producer's surplus diminishes and becomes negative for transactions whose cost outweighs the expected producer's surplus. The normalization of the local reputation follows the same formulation as in Section 6.5 augmented for the e-commerce case and accordingly aggregated based on the notion of transitive trust. Hence, the computation of the reputation score for the players (buyers and sellers) in e-commerce can be summarized as follows:

1. Let $j \in S$ be a registered seller in a platform. Let a set of buyers, I, who had past transactions with seller j, give local reputation scores to j. The reputation system in the platform assigns a global reputation score for each member based on a decentralized co-utile reputation protocol. Accordingly, all the sellers in the set S have a listing of their items with the item description, price and their global reputation score computed by the system. Hence, the score manager of j queries the set I and computes the global reputation of j based on the transitive trust assumption that displays in each seller's ($j \in S$) listing.
2. A potential buyer i queries the global reputation system for the reputation scores of seller $j \in S$ selling her preferred item. Upon completion of the transaction, i assigns a local reputation of j that weights j's future global reputation score.
3. In addition to checking the global reputation score of j, according to the implementation rules of the protocol, if buyer i already has a past transaction record with seller j and, thus, has calculated a local reputation value, then j can make her purchase decision by directly referring to j's local reputation. Local and global reputation values may not always be the same, since global reputation is a weighted sum of all the local reputations that seller j has from her total transaction records in the network. In that case, buyer i should consider both valuations and make the purchase decision based on the comparison of these values (with a negative bias, taking the one with the lower reputation value).
4. Buyer i chooses seller j from the set of available suppliers of identical items, S, based on j's reputation.

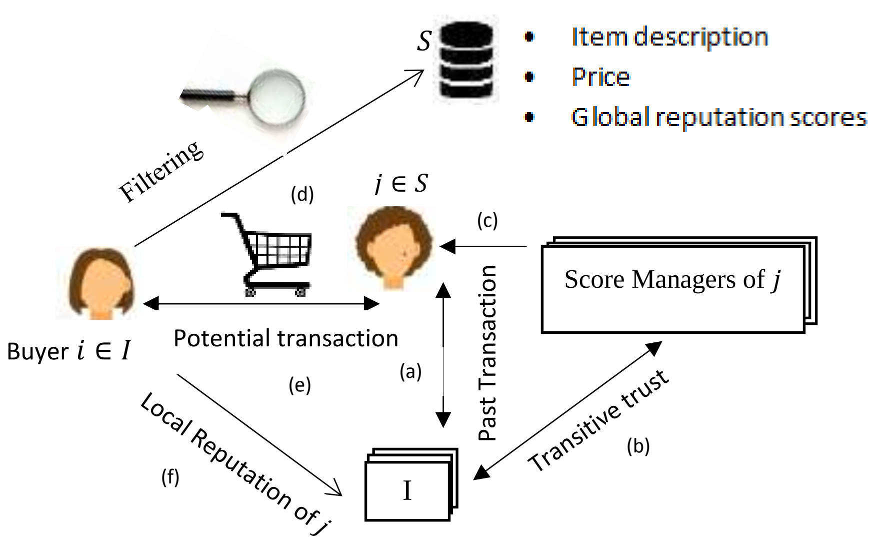

Figure7.3: Workflow of an online transaction with a co-utile reputation mechanism

In addition to its interesting features stated in Section 6.5, this reputation mechanism is robust against common abuses of online rating systems, namely retaliation and reciprocal feedback, unlike the reputation in eBay (Bolton et al. (2013), Cabral (2012) and Resnick and Zeckhauser (2002)).

7.7 Concluding remarks

One of the key problems underlying the electronic commerce market is the lack of trust between transacting agents. This is due to the uncertainties and information asymmetry problems underlying these marketplaces. These problems are similar to the ones we described for the P2P lending market, and therefore they can be addressed in a similar way. In this chapter, we have leveraged a decentralized reputation mechanism that is self-enforcing and co-utile, to make the operation of this market more efficient. In contrast to the game-theoretic reputation model (which assumes long-lived sellers, e.g. Dellarocas (2003)) and the conventional feedback mechanisms implemented in current marketplaces, the co-utile reputation mechanism is efficient and incentive-compatible.

Chapter 8 CONCLUSIONS AND FUTURE WORK

We summarize in this chapter the main contributions of this thesis, we list the publications resulting from this work and we identify issues for future research.

8.1 Contributions

We have discussed and applied the notion of co-utility, a new concept describing self-enforcing and mutually beneficial interactions among self-interested agents, to business models in the collaborative economy.

More specifically, the main contributions of this work are as follows:

- We have analyzed the notion of co-utility under the perspective of the collaborative economy. Specifically, we have discussed the related concepts of reciprocity and hybridity and the compatibility conditions under which these concepts satisfy a co-utile form of interaction. We have also identified co-utility amenable games framed within the collaborative economy, which include crowdsourcing, crowdfunding, cryptocurrencies and P2P online lending.
- We have analyzed the crowd-based business models under a co-utile perspective. In particular, by identifying the key problems underlying the crowdfunding market, we have modeled potential incentive schemes to address the mistrust and fear effects that may prevent crowdfunding from being strictly co-utile. The incentive schemes we propose are community-based reputation and cryptographic mechanisms. By characterizing the project types (i.e. those projects that guarantee a safer transaction either to the entrepreneur or the investor or both) we have elaborated the extent to which a given project is exposed to a given risk level. Furthermore, based on our analysis, we have pointed out implications to improve the conventional methods of operation.
- The peer-to-peer online lending market also suffers from the mistrust effect, which may render it inefficient. In order to tackle this problem, we have leveraged a distributed reputation protocol based on the co-utility principle. In this co-utile protocol, rational peers cooperate to compute each other's reputation scores. Reputation scores of borrowers are computed based on the outcome of direct transactions. Then, the reputation mechanism helps filtering credible borrowers based on their respective reputation scores. By using an experiment on a simulated platform with a randomly selected sample of loans from Lending Club, we have shown that this protocol can improve the efficiency of the P2P online lending market by filtering out defaulting borrowers.
- Finally, we have also applied the decentralized reputation protocol to the electronic commerce market in order to rate buyers and sellers. In addition to being decentralized and anonymous, the reputation mechanism we employ also discourages agents from whitewashing a bad reputation; that is, it deters buyers and sellers from operating under a new pseudonym or start all over, which is one of the common problems in this market. The mechanism does so by assigning the worst possible reputation scores to new market entrants and increasing the reputation costs of exit and re-entry.

8.2 Publications

The lists of publications resulting from the work done in this thesis are the following:

[1] Abeba Nigussie Turi, Josep Domingo-Ferrer, David Sánchez, and Dritan Osmani (2015) "Co-utility: conciliating individual freedom and common good in the crowd based business model". In: *2015 IEEE 12th International Conference on e-Business Engineering (ICEBE)*, pp. 62-67, Beijing, China. Oct. 2015. **CORE ranking: B**.

[2] Abeba Nigussie Turi, Josep Domingo-Ferrer, and David Sánchez (2016) "Filtering P2P Loans based on co-utile reputation". In: *13th International Conference on Applied Computing 2016*, pp. 139-146, Mannheim, Germany. **CORE ranking: C**.

[3] Abeba Nigussie Turi, Josep Domingo-Ferrer, David Sánchez, and Dritan Osmani (2017) "A co-utility approach to the mesh economy: the crowd-based business model". *Review of Managerial Science*. March 2017, Volume 11, Issue 2, pp 411–442. **ISI-JCR Impact Factor: 0.814**.

[4] Abeba Nigussie Turi, Josep Domingo-Ferrer, and David Sánchez (2017). "Problems in the undertakings of the collaborative economy: co-utile solutions". In: J.Domingo-Ferrer and D. Sánchez (eds.) *Co-Utility – Theory and Applications*. Springer, In press.

[5] Abeba Nigussie Turi, Josep Domingo-Ferrer, and David Sánchez (2016) "Decentralized co-utile reputation for P2P online lending market". Submitted to *Mathematics and Financial Economics*. **ISI-JCR Impact Factor: 0.727**.

8.3 Future work

Based on the work developed in this dissertation, we propose the following general list of directions for future work.

- Even if crowdfunding has been a very relevant funding source of the collaborative economy in the recent few years, it has not yet reached maturity and access to the greater share of the global population. Hence, there is still a potential for this industry to increase its current trend of growth to its fullest potential. The crowdfunding platforms facilitate the match between the entrepreneurs, investors and backers (donors), and hence should be designed in such a way that all the players communicate the transactional information and maximize their respective utilities. We have considered uniform distribution of returns and classical negative exponential utility functions for the analysis of equity crowdfunding. In addition, we have taken a reputation-based incentive mechanism, while there might be other possible incentive schemes that can also ensure a safe transaction by changing the rules of the game. Hence, directions for future modeling can be: i) consider other distributions of returns; ii) consider other forms of risk-averse investors' utility functions with modifications of the underlying assumptions; and iii) allow for other possible incentive schemes that can help design a co-utile protocol for the market.
- Our analysis of the crowdfunding market is limited to investment crowdfunding. Other forms of crowdfunding, like donation-based crowdfunding, and other variations of investment crowdfunding other than debt-based one are clearly different and require a different analysis that can capture the motivations of donors and project owners under the general umbrella of co-utility. In addition, redefining the crowd-based business model to fit a variety of project types, as well as flexible applicability under various conditions (mainly in developing countries as an alternative to the existing

microfinance models) can be avenues for further research. There is a need to understand and examine the dynamics of the crowdfunding industry and its potential to be applicable to any type of project financing and attract the largest number of backers/investors. Here, considerations in the design of incentive schemes should be the dynamics of the market with time, factors that affect the success of a given crowdfunding campaign, networking effect, a self-enforcing reputation scheme, the crowdfunding type, project type, type and methods of reward, etc. Incentive design is at the core of the collaborative economy and accounting for the notion of co-utility helps develop an efficient and attractive incentive scheme which accounts for all the stakeholders' utility, and hence is self-enforcing to all involved.

- As discussed in Chapter 2 and further implemented in the subsequent chapters, reputation is the backbone of the collaborative economy, which is in general prone to the information asymmetry risk. However, the co-utile reputation approach presented in this work is purely outcome-based and it does not take into account the individual behaviors beyond the specific transactions, being predicated on past transaction records. Also, our current approach does not leverage any previous reputations available for newcomers (who are assigned zero reputation with the aim of thwarting whitewashing). Therefore, a direction for future work is to take a stride towards merging the outcome-based reputation with the social reputation (using state-of-the-art social media, like Facebook, Twitter, Instagram posts or LinkedIn connections in which a bunch of personal data are available) and with the market-related reputation (such as Amazon or eBay purchases and credit card expenses, or length of phone calls). This will help consider the initial reputation of the target agent's behavior in these social networks and markets other than in the platform under review. As a result, a richer and multi-dimensional understanding of the borrower's foreseeable behavior will be reached. Extending global reputation in this way will also pave the way to new risk assessment methods, not merely reliant on outcome-based reputation (which only considers credit history, credit scores and suchlike). Hence, the next question will be how to best use the data from the social media, other marketplaces and all other information sources for the reputation purpose in the P2P lending market.
- A promising avenue is to seek an aggregated reputation integrating outcome-based, social and market-related reputations with proper weights for each reputation type, under the general umbrella of the decentralized co-utile reputation protocol. For example, for e-commerce, further inclusion of the reputation of the peers (buyers and sellers) prior to the transaction is needed for a fair treatment of new entrants. In this case, unlike the costly exit-and re-entry punishment method employed under the co-utile distributed reputation mechanism, which blindly aggregates all newcomers, the aggregation mechanism calls for the inclusion of the prior reputation of the peers beyond this market. The same reasoning applies to P2P lending. This includes the target peer's economic, commercial and social records beyond this market while properly punishing malicious peers. Such a compounded reputation can clarify the expected behavior of an agent much more accurately. For example, an individual can be reputed loyal if she has good reputation of not defaulting on previous loans, being loyal in social interactions, having a stable income base, having a stable credit card record, not being bankrupt or in a devastated economic condition that would prevent paying back, being careful, etc. Thus, it would be highly interesting to develop such an integrated reputation. Further work to be done in this regard includes experimenting on a simulated platform to evaluate how the market behaves with the dynamics of the system as trust builds with the computation of the reputation scores.
- Another interesting research question regards the yet underexplored potential applications of the blockchain and distributed ledger technology in the business-to-business transactional networks.

Several recent works have come up with the suggestion of using blockchain technology to enhance the efficiency, transparency and trustworthiness of a business process. However, more research is needed to extend the technology with additional features that fit the industry under consideration. Here, a business process design method accounting for the co-utile nature of the system is important. For instance, for the financial administration and management industry, a collaborative setting is needed in which all the stakeholders (accounting professionals, financial analysts, business consultants, legal experts, IT experts, and the client companies of the trust company) can interact through a well-built blockchain technology adopted specifically for this purpose. This will help the industry improve its efficiency and make it co-utile for the stakeholders that co-create the value.

- In general, co-utility based analyses could be extended to other systems in the collaborative economy, albeit case-specific incentive schemes are required that capture the dynamics of each system. For instance, in the games that incorporate some element of competition between the players, changing the rules of the game requires a different analysis. Beyond the collaborative economy, our co-utility based analysis can also be used in scenarios like international environmental agreements, self-enforcing anti-trust cases, trans-boundary water issues, tax policies, etc.

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