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Principal-Agent Problem in Technology Projects on Kickstarter:
an Exploratory Case Study

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Contents

1 Executive Summary

I conducted an exploratory research of the little understood principal-agent interaction in a reward-based crowdfunding environment. A broad-stroke exploratory research like this is unavoidably limited in the extent to which any of the findings can be generalised beyond individual cases.

I attempt to mitigate this by complementing a netnographic approach with a sentiment analysis classifier programme that I have developed. This holistic approach allowed me to gain deep insight into the mechanisms that allow the principal-agent problem on Kickstarter to be resolved successfully despite lack of rigid legislative regulation.

I find that backers on Kickstarter possess sufficient tools to minimise information asymmetry and thus, the principal-agent problem.

I further discover that formations of backers are comprised of two distinct groups – a small vocal and a much larger silent one, with the latter adjusting to the opinions of the former in the short term. I also find that the crowdfunding platform plays a limited, yet important role in resolving the principal-agent tensions.

Finally, I find evidence that formations of backers that surround Kickstarter projects are fluid in their structure, exhibiting under different conditions features of both communities and publics.

2 Acknowledgements

This thesis is written in collaboration with the FOCUS (Future-Oriented Corporate Solutions) programme as a part of my Master of Science in Economics and Business Administration at the Norwegian School of Economics and Business Administration (NHH).

My journey in the field of crowdfunding has started with exploring Kickstarter platform on the dawn of its existence within the scope of the Social Media Marketing course at Norwegian School of Economics. The innovative approach to fundraising which Kickstarter popularised has captured my attention and eventually led me to writing this thesis.

I would like thank my supervisor, Professor Ingeborg Astrid Kleppe for being extremely helpful and responsive during the process of writing this thesis. Prof. Kleppe was always available to answer my questions, provided constructive and useful feedback. Our discussions greatly contributed to improvement of this work.

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3 Introduction

3.1 Research Question

The research idea for this thesis was born when I juxtaposed the explosive success of crowdfunding platforms with the long-established consensus in economic literature that in a 'many principals' – 'many agents' an intermediary must exist that both bears the monitoring costs and enforces fulfilment of principal-agent contracts (Diamond, 1984).

Crowdfunding, paradoxically, has proven time and again that such an open platform with little to no obligations binding the agents can indeed exist and even flourish.

The runaway success of Kickstarter is a particularly interesting example. For reasons not fully explored in current literature, the principal-agent problem on Kickstarter seems to be dealt with very efficiently, as mere nine percent of funded Kickstarter projects fail to satisfy backers in the post-campaign period (E. R. Mollick, 2015).

Hence, the research question: *how is the principal-agent problem resolved in reward-based crowdfunding?*

Both different crowdfunding platforms and different types of creative projects impose different conditions on the principal-agent relationship between the participants in the crowdfunding process. Hence, I restrict my investigation to only one platform – namely, Kickstarter, and one campaign category – hardware technology projects.

3.2 Crowdfunding

Notwithstanding the fact that research in crowdfunding is young several definitions of the phenomenon have emerged in the past five years; these are well summarized in the paper by (Bouncken, Komorek, & Kraus, 2015). For the purpose of this Master's thesis I have chosen one of the earliest and succinct definitions presented by (Belleflamme, Lambert, & Schwienbacher, 2010):

> *Crowdfunding involves an open call, essentially through the Internet, for the provision of financial resources either in form of donation or in exchange for some form of reward and/or voting rights.*

Although the idea of collecting funds in small pieces is old, what distinguishes crowdfunding is the fact that it is a web 2.0 phenomenon and rapid growth of internet accessibility has dramatically contributed to the swift development of crowdfunding (Leimeister, 2012).

3.2.1 Crowdfunding Actors and Models

Crowdfunding is regarded as a two-sided market with a subsidy-side represented by investors (crowdfunder, backer) and money-side being the fundraiser. The third player worth noticing is the intermediary platform (e.g. Indiegogo, Kickstarter) which sets the rules and frames the fundraising campaign and charges fundraisers while investors may provide capital through platform without any additional fees (Giudici, Nava, Rossi Lamastra, & Verecondo, 2012).

Intermediaries follow different investment models. Kickstarter platform, for example, utilizes all-or-nothing investment model, where the fundraiser only receives the amount if a previously defined threshold of investment is met, unlike the keep-what-you-get model, which is less restrictive and allows the fundraiser to receive everything regardless of the fact whether the funding goal was met. These three kinds of actors form the core of crowdfunding.

Scholars have developed the following typology of crowdfunding models with respect to the motives of investors: donation-based, lending-based, equity and reward-based crowdfunding (Pierrakis & Collins, 2013). For example, in the donation model the aim of the funder is purely philanthropic, while in the lending model the main goal of the resource provider is financial return. The focus of this thesis, however, is reward crowdfunding in which investor contribution takes form of a donation and/or pre-purchase of a product. Here rewarding takes both material (investor receives products early on, before market entrance) and immaterial form (the name of the investor will appear in the funded project via acknowledgements) (Bouncken et al., 2015).

Crowdfunders are given the option to choose between different types of rewards which increase in value with the amount of money pledged (Giudici et al., 2012). Interestingly, along with receiving necessary financial resources and getting public feedback, fundraisers have often mentioned little formal obligation as one of the key motivations for engaging with crowdfunding. One may assume that for the same reason crowdfunding platforms might be attracting opportunistic economic agents.

3.2.2 A Note on Terminology

Terms *project creator*, or simply *creator* refer to the crowdfunding agents, i.e. organisations or private persons that initiate campaigns on Kickstarter in order to solicit funds for realising their project.

Terms *backer, project contributor,* and *project supporter* are used interchangeably throughout this thesis to denote the crowdfunding principal, i.e. a person who pledges any amount of money to a project during its fundraising campaign duration.

Finally, the term *superbacker* is used to indicate a Kickstarter user that has "supported more than 25 projects with pledges of at least $10 in the past year" (Kickstarter, 2016).

3.3 Structure of the Paper

I first provide a broad theoretical background necessary to frame my research appropriately. I draw on a number of theories that I expected to contribute to my understanding of the community dynamics that allow backers to efficiently identify opportunistic projects.

I then discuss methods used in this thesis. I use a combination of an ethnographic research method and computer-assisted sentiment analysis tool, which I have developed for this paper. I guide the reader through the process of creating this tool and explain its value in exploratory research.

I later use this hybrid methodology to analyse two Kickstarter projects, providing both a bird's eye overview of community dynamics and a detailed look at particular narratives developed throughout the comments sections of the two projects.

Drawing on insight gained through the analysis of these two cases, as well as a small number of other projects, I generalise results of my investigation and present theoretical implications of my findings.

4 Theoretical Background

In this section I detail theoretical perspectives used in this thesis and provide a brief overview of some of the studies relevant to my research question. While the agency theory is the core theoretical framework I employ, I also draw on scientific explorations of such phenomena as wisdom of crowds and brand communities.

4.1 Principal-Agent Problem

Agency theory was developed during the 1970s, originating from information economics, a branch of economic research that explores processing and conveyance of information by markets and other institutions (Eisenhardt, 1989; Stiglitz, 2008). Agency theory quickly attracted scholars from a wide array of disciplines, ranging from economics, accounting, and marketing to sociology, political science, and organizational behaviour and soon after its inception became one of the most prominent and rapidly evolving fields of socio-economic study (Eisenhardt, 1989; Macho-Stadler & Pérez-Castrillo, 2012).

At the core of the agency theory lies the *agency* (or *principal-agent*) *relationship*, wherein one party, the principal, delegates completion of a certain task to the other party, the agent (Eisenhardt, 1989). Jensen and Meckling (1976) in their seminal paper define an agency relationship as

> "a contract under which one or more persons (the principal(s)) engage another person (the agent) to perform some service on their behalf which involves delegating some decision making authority to the agent."

One of the reasons the principal-agent relationship attracts attention of quite so many researchers is its omnipresence (Ross, 1973). Indeed, most of us encounter its various forms on a daily basis. A shareholder delegates running a business to a manager; an employee is tasked with completing a certain set of tasks on behalf of her employer; a client hires a lawyer for the latter to manage the former's legal affairs; a doctor is called upon to cure a patient in a timely and efficient fashion. Investor, by the transfer of capital, delegates to the investee creation of profit (Rees, 1985).

The relationship between a contributor to a crowdfunding campaign and the creator of that campaign is no different. By pledging a certain amount of money to a project, the user of a crowdfunding platform becomes a principal that delegates to the campaign starter, who thus becomes an agent, creation and delivery of a reward corresponding to the amount pledged by the backer.

In each of the examples described above, the principal-agent relationship has the potential to be beneficial for both parties involved, but can also be troublesome: an employee might shirk her duties, a doctor might prescribe inefficient medications to increase the number of visits a patient has to make to the clinic. Likewise, a project creator on a crowdfunding platform might gather funds for producing a new children's toy or a movie and spend acquired money to buy a new house. All these scenarios are possible because of the *principal-agent problem* that haunts any relationship which involves delegated choice (Rees, 1985).

The *principal-agent problem*, first termed as such by Ross (1973), is central to the agency theory and follows from two properties of the principal-agent relationship: *information asymmetry* and *conflict of interest*.

The concept of *information asymmetry* is used to describe a setting in which one party in a transaction or a relationship has more or better relevant information than another party (Stiglitz, 1989). In principal-agent terms this usually means that the agent has superior information about her own ability to perform a task, amount of effort needed to complete it, truthfulness of any assertions she makes to the principal and so on. An important property of information asymmetry is that eliminating it, i.e. identifying agent's divergence from actions that are in principal's best interests, is often difficult or costly (expensive, time-consuming or otherwise) for the principal (Macho-Stadler & Pérez-Castrillo, 2012).

The term *conflict of interest* refers to the assumption made in the agency theory that, since both the principal and the agent seek to maximize their own utility, ultimately their goals might be different. Therefore, the agent can be motivated to deviate from behaviour that is in the best interests of the principal to satisfy her own needs (Jensen & Meckling, 1976).

Having tasked the agent with making a delegated choice, the principal then observes the outcome, which is a function of agent's effort and noise – all exogenous factors beyond agent's control that affect the outcome (Tabarrok & Cowen, 2015). Existence of noise introduces yet another layer of complexity to the principal-agent relationship: an outcome unsatisfactory to the principal may be a result of agent's deliberate choice to serve her own interests to the detriment of the interests of the principal or a consequence of exogenous factors hindering agent's ability to perform a task, but in the presence of information asymmetry the principal cannot easily distinguish between the two possibilities.

It is this setting — a contract between a principal delegating a task to an agent with superior information and ulterior motives in a context where unknown and uncontrollable factors may influence agent's performance — that gives birth to the fascinating principal-agent problem.

4.1.1 Mitigating the Principal-Agent Problem

Existence of the principal-agent problem is conditional on simultaneous satisfaction of assumptions of information asymmetry and conflict of interest. Therefore, liquidating or minimizing any one of these properties of the principal-agent relationship will naturally result in mitigation or vanishing of the principal-agent problem. Indeed, if the agent and the principal have access to the same information about the agent, said agent will be find it difficult to deviate from prescribed behaviour. If, on the other hand, one is able to ensure that the interests of the agent and the principal are in harmony with each other, agent maximising her own utility will simultaneously maximise utility of the principal.

However, in the real world complete liquidation of either information asymmetry or conflict of interest is next to impossible, which is why practical solutions usually contain recommendations for combating both undesirable properties of principal-agent relationships (Mahaney & Lederer, 2003).

4.1.1.1 Minimising Information Asymmetry

One way of dealing with the principal-agent problem is reducing information asymmetry. Two relevant mechanisms have been suggested: *monitoring* and *signalling*.

Monitoring refers to any activities that the principal might undertake in order to gain previously inaccessible information about the agent and her behaviour (Tabarrok & Cowen, 2015). For example, one study discovered that requiring police officers to wear body cameras can greatly decrease the number of complaints against law enforcers (Ariel, Farrar, & Sutherland, 2015). Hence, a government (the principal) can implement obligatory body cameras as a means of monitoring activities of police officers (the agents tasked with enforcing the law on behalf of the government), therefore making suboptimal behaviour less likely to occur. However, monitoring entails monitoring costs, which, depending on the activity to be monitored, can be prohibitively high.

Signalling, in the context of agency theory, refers to provision by the agent of a believable indication of her type despite the presence of information asymmetry (Spence, 1973, 2002). One classic example of signalling considers a simple job market. An employer want to hire smart employees, but knowledge of the true type ('smart' or 'normal') is private to each job seeker. Hence, there is information asymmetry between the principal and the potential agents. However, a job seeker can prove that their type is 'smart' by completing a college degree, given that acquiring this degree is prohibitively difficult for a job seeker of the 'normal' type. A college degree then becomes a way for the agent (job seeker) to reliably signal their type to the principal (employer).

Agent may also signal their diligence via reputation. However, reputation mechanisms are only relevant for markets with repeated interaction between actors (Tabarrok & Cowen, 2015).

4.1.1.2 Minimising Conflict of Interest

Alternative method of mitigating the principal-agent problem is designing a contract between the principal and the agent in such a way that the agent has incentive to choose actions that maximise the payoffs of the principal (Prendergast, 1999; Stiglitz, 1989). Research of the role of incentives in principal-agent relationships comprises a big part of literature on agency theory (Stiglitz, 1989).

While the exact measures vary depending on the circumstances, the general principle is as follows. By default, the payoffs of the principal and the agent are different. If instead a contract between the principal and the agent is designed in such a way that their payoffs are correlated as much as possible, the agent will have no incentive to deviate from the actions that are optimal for the principal. This is because, given close enough correlation between payoffs of the two parties, the same behaviour by the agent will be maximising utility of the agent and the principal (Stiglitz, 1989).

Contracts designed in such a way are known as outcome-based. A widely known example of an outcome-based contract in the context of a firm is profit-sharing. Profit sharing refers to employee remuneration schemes which include a variable bonus element directly tied to the firm's stock performance. The intuition behind profit sharing is that an employee whose payoff depends on the performance of the firm has more incentive to act in a way that is optimal for the employer than an employee with a fixed wage (Prendergast, 1999).

It is important to note that, within the realm of reward-based crowdfunding, the platforms are responsible for defining the contract between the principals and the agents and backers themselves do not have the power to optimise these contracts at will.

4.1.2 Principal-Agent Problem in Crowdfunding

A qualitative study by Moritz , Block, and Lutz (2015) explored information asymmetries between principals and agents in equity-based crowdfunding. After analysing interviews with both investors and entrepreneurs that utilised an equity crowdfunding platform, as well as with platform operators and professional investors, authors conclude that ventures' pseudo-personal communication with investors and their perceived openness reduced *perceived* information asymmetries.

Frydrych, Bock, Kinder, and Koeck (2014) identified "legitimising signals" that allow agents in reward-based crowdfunding to acquire legitimacy in the eyes of potential backers. The authors discover that relatable story, modest funding target, and short campaign duration all signal legitimacy to backers.

Agrawal, Catalini, and Goldfarb (2013) highlighted the information asymmetry problem in non-equity crowdfunding concerning the feasibility of a project and creator's ability to realise said project. They argued that information asymmetries amplify three disincentives to invest that potential project supporters face: creator incompetence, fraud, and inherent early-stage project risk. This information asymmetry may lead to market failure, as, without having sufficient information about creator's ability and motivation, backers on a crowdfunding platform might discount their valuation of a project, incentivising diligent creators to seek funding elsewhere. The researchers further described four mechanisms through which the reward-based crowdfunding market is prevented from failing: reputation signaling by creators, rules and regulations, crowd due diligence, and provision point mechanism, i.e. making funds transfer to creators conditional on reaching a predefined funding level.

In another paper, a theory of reward-based crowdfunding was proposed (Strausz, 2016). Its author argued that by removing the financial intermediary between a consumer and an entrepreneur, reward-based crowdfunding achieves improved market efficiency despite significant moral hazard on behalf of project creators.

Belleflamme, Lambert, and Schwienbacher (2014) posited that information asymmetry, which arises in crowdfunding due to project creator having superior information about the product quality, favours profit-sharing schemes. As discussed previously, profit sharing can potentially align personal interests of an agent with those of a principal, thus minimising conflict of interests and mitigating the principal-agent problem.

In conclusion, while crowdfunding is gaining more and more attention from academia, state-of-the-art research related to agency theory in crowdfunding does not provide conclusive explanation of how actors in *reward-based crowdfunding* are able to resolve the principal-agent problem. As to reputation mechanisms, these are only relevant for markets with repeated interactions. While it is not unheard of for a creator to launch subsequent projects after a successful campaign and rely on the established reputation to attract backers (see: Pebble), the majority of creators on Kickstarter do not start another campaign even after a successful first one.

It is therefore ambiguous whether the backers in reward-based crowdfunding possess any useful tools for dealing with the principal-agent problem, as reduction in *perceived* information asymmetry does not necessarily result in actual symmetrization of information, while outcome-based contracts, such as profit-sharing schemes, are unavailable for users of popular reward-based crowdfunding platforms.

4.2 Wisdom and Madness of Crowds

A question quite possibly as old as civilisation itself: who is smarter – individuals or groups? Is a crowd better or worse at estimations, predictions, judgements, and decision making than a single expert? Throughout history diametrically opposite opinions had been expressed on this matter, best illustrated, perhaps, by the juxtaposition of standpoints of Mackay (of XIXth century) and Surowiecki (of the third millennium).

In his widely cited 1841 book "Extraordinary Popular Delusions and the Madness of Crowds", Mackay presented a comprehensive collection of historical examples that he used to show how large groups of people are incapable of critical thinking and rationality and often exhibit mob behaviour. "Men, it has been well said, think in herds; it will be seen that they go mad in herds, while they only recover their senses slowly, one by one", he postulated, exemplifying the folly of crowds by the famous Holland tulip frenzy, witch-hunts, and crusades (Mackay, 2012).

A contrasting vision was presented more than a century and a half later in "The Wisdom of Crowds" by Surowiecki (2004). In this book, Surowiecki argued that 'collective intelligence' of a large number of individuals making decisions or evaluations independently of each other is often able to produce better decisions or predictions than those made even by individual experts in their respective fields.

The term 'wisdom of crowds' is often used to denote the higher accuracy of statistical aggregates of opinions compared to individual, even expert, opinions, as mathematical averaging allows one to remove the noise added by cognitive biases, such as anchoring or over-confidence, that will unavoidably be present in individual predictions and decisions (Budescu & Chen, 2014).

As more and more social interactions are being shifted into online space, the notion of wisdom born from the collective decision-making of the crowds is gaining considerable support by recent studies of crowd behaviour on various online platforms. Wisdom of crowds has been shown to be performing on par or even better than expert evaluation in many areas, including creative industries, where individual expert assessment is traditionally held in high esteem and thought of as often different from (and even potentially superior to) that of the masses (E. Mollick & Nanda, 2015).

4.2.1 Rational and Irrational Herding

Relevant to this thesis is confrontation between proponents of *rational* and *irrational herding* – echo of the larger 'wisdom or madness of crowds' debate discussed above.

Irrational herding refers to individuals in a crowd blindly and passively mimicking decisions made by others (Simonsohn & Ariely, 2008; Zhang & Liu, 2012). Several authors claimed that this self-enforcing behaviour serves as the guiding principle for large groups of economic actors in many situations where information about optimal actions is not readily available, resulting in lower payoffs for the decision makers (Ariely & Simonson, 2003; Shiller, 2015; Simonsohn & Ariely, 2008).

The concept of rational herding, on the other hand, is built on the assumption that decision makers in a crowd might forgo their own information about the market and instead rely on observational learning to guide their behaviour if they believe that other market participants might have received better private information about the market.

Zhang and Liu (2012) analysed lending-based crowdfunding platforms (microloan markets) and concluded that individual principals (lenders) are able to rationally infer trustworthiness of individual agents (borrowers) from decisions made by other lenders.

Another study found that individual members of lending-based peer-to-peer crowdfunding platforms use strategic herding that affects bidders positively (Herzenstein, Dholakia, & Andrews, 2011).

Kim and Viswanathan (2014) analysed funding decisions made on Appbackr – an equity crowdfunding platform for mobile applications. The researchers demonstrated how early commitment to a project of investors with expertise in app development causes rational herding to occur, where the crowd of investors interprets decisions made by experts among the crowd as a signal of project's potential.

4.3 Brand Communities and Brand Publics

In their influential paper Muniz and O'Guinn (2001) introduced the idea of a *brand community* – "a specialized, non-geographically bound community, based on a structured set of social relations among admirers of a brand." Based on analysis of communities that evolved around three major brands (Macintosh, Ford Bronco, and Saab), the authors assert that brand communities possess three essential characteristics of a community: shared conciousness, rituals and traditions, and a sense of moral responsibility to the community as a whole as well as its individual members.

In a paper by Arvidsson and Caliandro (2016), relevance of the concept of brand communities is being disputed. The authors of the paper posit that what was previously thought of as the *brand communities* might in fact be *brand publics* – formations whose members do not necessarily interact with each other, but simply share an interest in a particular brand.

Distinct from both *crowds* and *communities*, *publics* arise when crowds are given a prolonged focus and are aggregated around a medium (e.g. newspaper) or a mediated event (Arvidsson & Caliandro, 2016; Papacharissi, 2015).

It is possible that formations of backers spawning around crowdfunding projects resemble aggregations that are built around brands. Understanding which concept, of community or of public, is better suited for crowdfunding, is relevant to the research question, as it may have implications on our insight into the way project supporters deal with the principal-agent problem.

5 Methods

In this thesis I have used a combination of research methods. I analyse the basic dynamics of trust that backers express towards different projects using qualitative technique – netnography, and a machine learning-based approach called sentiment analysis to provide both deep insights into the principal-agent communication and a bird's eye view.

This holistic approach allows me to triangulate the true phenomena, as both in-depth investigation and a more general overview have their drawbacks that will be discussed later on.

5.1 Netnography

First method used in this paper is netnography, a version of ethnographic research method modified by Kozinets to better fit the needs of researchers of online communities (Kozinets, 2002 and 2010). Netnography consists of six distinct subsequent stages. During the first step, the researcher must develop a plan for the forthcoming study; on the second stage they establish an entre by collecting enough information about the community and research phenomenon and identifying research question; during the third stage data collection is conducted via direct copying of online messages of said community members and observation of the latters interaction. The fourth step implies analysis and interpretation of gathered data, inventing a classification system and contextualizing obtained information. Compliance with ethical standards is ensured on the fifth step. Finally, during the sixth step the researcher reports on the studys findings and subsequent insights.

In the approach for netnographic fieldwork Kozinets propose the following guidelines for the choice of the online community and entre part: (a) relevant, they relate to your research focus and question(s), (b) active, they have recent and regular communications, (c) interactive, they have a flow of communications between participants, (d) substantial, they have a critical mass of communicators and an energetic feel, (e) heterogeneous, they have a number of different participants, and (f) data-rich, offering more detailed or descriptive rich data.

Netnography is participant-observation type of research, hence the data can take three forms: (a) data, that researcher directly collects, (b) data, which is generated through the capture of online community events and interactions; and (c) data, that the researcher sketches as field notes. Consequently, data collection becomes direct copy from the communication of online community members and observation of their behaviour along with their interactions and main events.

I have collected data from the comments sections of various projects on Kickstarter.com using a web-crawling programme I had developed for that purpose (see Appendix B). All user names in the collected data were replaced with pseudonyms in order to ensure anonymity of informants.

5.2 Sentiment Analysis

5.2.1 Introduction to Sentiment Analysis

Sentiment analysis is a fast-growing branch of natural language processing – a field of computer science (more specifically, artificial intelligence, computational linguistics, and data mining) that uses machine learning methods to allow for interaction between computers and human languages (El-Din, 2016; Medhat, Hassan, & Korashy, 2014).

Sentiment analysis, also known as opinion mining and subjectivity analysis, is concerned with the computational study, identification, and extraction of opinions, sentiments, and subjectivity found in human-language text and speech (Pang & Lee, 2008; Taboada, Brooke, Tofiloski, Voll, & Stede, 2011; Liu & Zhang, 2012).

Most existing sentiment analysis tools focus on classifying sentiments as either positive or negative, often with the inclusion of a neutral class (Laryea, Choi, Jung, Lee, & Cho, 2015). However, there do exist "beyond polarity" solutions that attempt to look at finer distinctions and more subtle emotional states and types of opinions and intents, e.g. sadness, anger, whether a comment contains advice etc. (Laryea et al., 2015; Grimes, 2010).

Two sources of data for opinion mining prevalent in current research seem to be microblogs such as Twitter (Pak & Paroubek, 2010), and review aggregation websites ((Pang, Lee, & Vaithyanathan, 2012), as both provide abundance of text rich in subjectivity. Limit of 140 characters per post on Twitter forces users to get straight to the point, likely increasing expressiveness of their writing, while reviews published on websites such as Amazon or Rotten Tomatoes are highly subjective by their very nature, seeing as their primary function is explaining the opinion of their author and, often, influence decisions of other users. For similar reason, Facebook closely follows as another important source for many researchers working in the field of sentiment analysis (Feldman, 2013).

5.2.1.1 Sentiment Analysis Applications

Applications of sentiment analysis are numerous. It is used widely in business and government intelligence, on review aggregation websites, as a component of various systems, such as recommendation engines or automatic text summarization, as well as in many disciplines other than computer science that have recently shown an increased interest in opinion mining and analysis of sentiment, such as sociology, political science, and even finance (Pang & Lee, 2008). Indeed, in theory, possible applications of sentiment analysis are almost limitless, as subjectivity is inherent to almost any human interaction (Liu, 2012).

Many large businesses, including Google, Microsoft, Hewlett-Packard, and SAS, have produced in-house opinion mining solutions (Liu, 2012). Such software and its numerous alternatives developed and maintained by text-analytics start-ups, are capable of completing a wide array of tasks. Some solutions specialise in automatic reviews summarization (e.g. Google Product Search, Yandex.Market), others allow a company to track reputation of its brand through social media in real time (Feldman, 2013). Many firms employ sentiment analysis tools for evaluating customer satisfaction with a product or service by assessing the ratio of positive to negative comments about said product or service (or even their individual features) present in social media, blogs, and discussion forums.

Several of the last presidential elections in the US (O'Connor, Balasubramanyan, Routledge, & Smith, 2010; Wang, Can, Kazemzadeh, Bar, & Narayanan, 2012) and numerous European countries (Ceron, Curini, Iacus, & Porro, 2014; Tumasjan, Sprenger, Sandner, & Welpe, 2010) have been extensively analysed with the use of sentiment analysis tools to try to predict elections outcomes based on people's opinions expressed on Twitter. Elsewhere in academia, sentiment analysis of text from Twitter and movie reviews is often used to predict box office revenues (Asur & Huberman, 2010; Joshi, Das, Gimpel, & Smith, 2010; Sadikov, Parameswaran, & Venetis, 2009; Zhuang, Jing, & Zhu, 2006). Movie reviews seem to be a particularly popular source of data for sentiment analysis, as by 2012 there have been 100 papers published that were using the same movie review dataset introduced in 2002 by Pang, Lee, and Vaithyanathan (Pang et al., 2012). Numerous researchers and start-ups have also applied opinion mining to the domain of financial markets, using sentiment extracted from social media and blogosphere to predict stock prices (Bar-Haim, Dinur, Feldman, Fresko, & Goldstein, 2011; Bollen, Mao, & Zeng, 2011; Feldman, 2013).

As shown through the above examples, sentiment analysis has become an important tool used by businesses, governments, and academics alike, with interest in the topic growing steadily – and rapidly – for the last decade (Google, 2016). Its diverse applications indicate that sentiment analysis is a flexible tool that can be tailored to assist a researcher in practically any task that benefits from one's ability to identify subjectivity in large amount of human-generated text.

It comes as no surprise, then, that sentiment analysis can become a powerful instrument for analysing online interactions in reward-based crowdfunding – interactions inherently both rich in sentiment and abundant in quantity.

In the following subsection I describe in detail six steps of the development process of the sentiment classifier that I created for this thesis: from identifying the purpose of sentiment analysis application to creating a training set and choosing specifications of the final classifier model.

The classifier program was written in Python 3 with the use of Natural Language Toolkit library.

5.2.2 Developing a Sentiment Analysis Model

5.2.2.1 Purpose

Solely relying on netnography as a research method was problematic due to the fact that most of the projects that promised rich insight into the principal-agent dynamics had spawned massive discussions, often containing several thousands of comments in their respective comment sections.

One problem stemming from this abundance of comments is that it was impossible to carry out even a cursory inspection of the insurmountable body of textual data to which dozens of thousands of comments across all of the inspected projects had amounted.

Another issue is that, having applied netnographic analysis to select few comments, however rich they may be, we would still be extremely limited in our understanding of how representative these comments are of the general attitude of the community towards any given topic.

Integration of sentiment analysis into the research design of this thesis alleviated both of these problems to an extent. An algorithm was developed that is able to distinguish between doubtful and trusting comments in the designated discussion section on the project's Kickstarter page. By leaving the task of basic sentiment identification to a computer-executed algorithm and only looking at the visual representation of dynamics of trustful and doubtful comments, I was able to identify potential areas of interest without the need to actually read each of the postings, therefore addressing the first issue.

Second problem was mitigated by the fact that, with inclusion of sentiment analysis, I was able to associate any comment analysed through netnographic methods with a diagram illustrating dynamics of trusting and doubtful comments. Combination of an in-depth analysis of individual comments and a chronological bird's eye view on the attitude that a community formed around a project had at any given point in time allowed me, with some degree of confidence, to extrapolate general behavioural trends from the level of individual comments. In other words, upon locating a particularly insightful comment in an 'eventful' period of the discussion revolving around a project, I was able to expect said comment to be representative of the opinion the community at large expressed in that period and not a singular expression of mistrust or assurance.

Sections that follow explain in detail the model specification of the sentiment classifier.

5.2.2.2 Choice of an Approach to Sentiment Analysis

Modern sentiment analysis techniques can be broadly categorized into two approaches: *lexicon-based* and *machine learning* algorithms (Medhat et al., 2014).

Lexicon-based class of algorithms incorporates a number of relatively simple computationally, yet sometimes effective sentiment analysis techniques that all involve use of sentiment *lexicons* or *corpora*. A lexicon is typically created by manually determining a set of keywords that are associated with a certain emotion or opinion. A developer of a sentiment lexicon simply writes down words that she *thinks* are likely to indicate a certain sentiment.

For example, if one were to create a lexicon for classifying input as positive or negative, words such as *enjoyable*, *amazing*, or *superb* could be added to the lexicon as instances of positive keywords and words such as *ghastly*, *disgusting*, or *horrendous* – as examples of negative ones. Often a lexicon obtained in this way is then enhanced by addition of synonyms and antonyms of each of its keywords automatically retrieved from services such as Word Net (Feldman, 2013). As an alternative to developing a new sentiment lexicon, one may instead choose from a selection of existing ones readily available online (Schneider, 2016).

After a new lexicon is completed or an existing one chosen, the model is ready for classification. An input (e.g. a blog post, a tweet, a product review) is then processed by a feature extractor – an algorithm that splits an instance of text into singular words. These individual words obtained from an input text are called *features*, or a *bag of words*.

These features are then fed into the scoring function, which simply counts the number of features that are among the positive and negative keywords in the lexicon, thus obtaining positive and negative scores. The latter score is subtracted from the former, resulting in the final score, which determines the sentiment of the input and the label that should be attached to it (positive for positive value of the final score, negative for negative score, and neutral if the two scores cancel each other out). Visualisation of a general lexicon-based classification algorithm is presented in Figure 1.

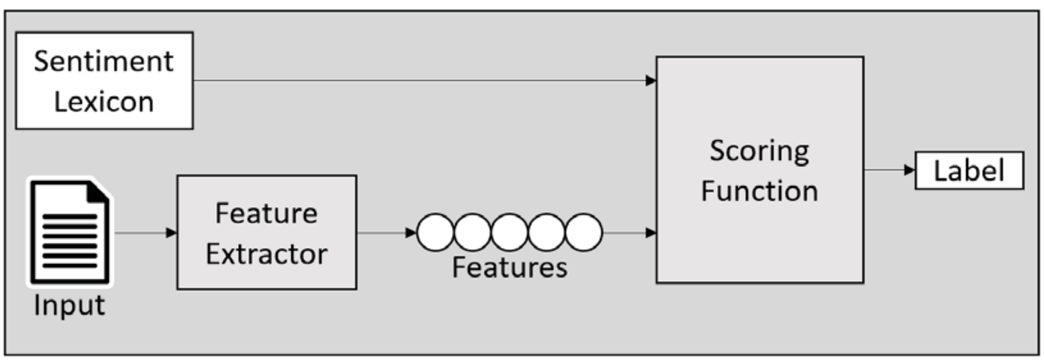

Figure 1: Lexicon-Based Classification Algorithm [Source: own composition]

Machine learning algorithms present an alternative to the lexicon-based approach. Instead of relying on an arbitrary list of words one assumes are likely to appear in an instance of text with a certain sentiment, these algorithms employ supervised machine learning techniques to develop ability to identify sentiment of a new input based on their preceding training on a set of inputs manually classified by a human.

Supervised classification occurs in two subsequent stages: training phase and prediction phase. Preceding both of these phases is the process of creating a training set for the classifier model. For this purpose developer extracts a sufficiently large body of text instances (posts, comments, reviews etc.) similar to that on which the classifier algorithm is expected to be used afterwards. Depending on this data and purpose of the research, a number of classes are identified (for example, positive, neutral, and negative) across which text inputs will need to be distributed. The developer of the model then manually assigns each of the text instances in the training set to one of the previously identified classes. Thus a training set is created, consisting of a preferably large number of text instances each with a label assigning them to one of the classes.

During the training phase, a feature extractor algorithm each separates each instance of text into individual *n-gram features*, which are then fed into the machine learning algorithm alongside the label assigned by a human to the text instance from which the feature came.

N-gram features are features that consist of N items. Given that the minimum unit of analysis is a word, a unigram is a single-word feature; a bigram is a feature consisting of two consecutive words; a trigram is a separate feature that includes three successive words and so on. In Table 1 below you can see all uni-, bi-, and trigrams for the text instance "Sphinx of black quartz".

Unigrams	**Bigrams**	**Trigrams**
sphinx	sphinx of	sphinx of black
of	of black	of black quartz
black	black quartz	
quartz		

Table 1: Ngrams for the phrase "Sphinx of black quartz".

Once features extracted from the training set along with their corresponding class labels are fed into the machine learning algorithm, it begins training a classifier model. After this process is complete, the prediction phase starts. The classifier is given new inputs that undergo the same feature extraction process and assigns labels to these new text instance. Refer to Figure 2 for a visual representation of the supervised machine learning classification process.

Lexicon-based approach has several shortcomings which make it a poor fit for our purpose. First, it is based on the assumption that the sentiment of a subjective expression can be identified based on the polarity of the words used in it, which, due to complexity of human languages, is not always the case (Musto, Semeraro, & Polignano, 2014).

Second, choosing keywords to be included in a sentiment lexicon is not a simple and

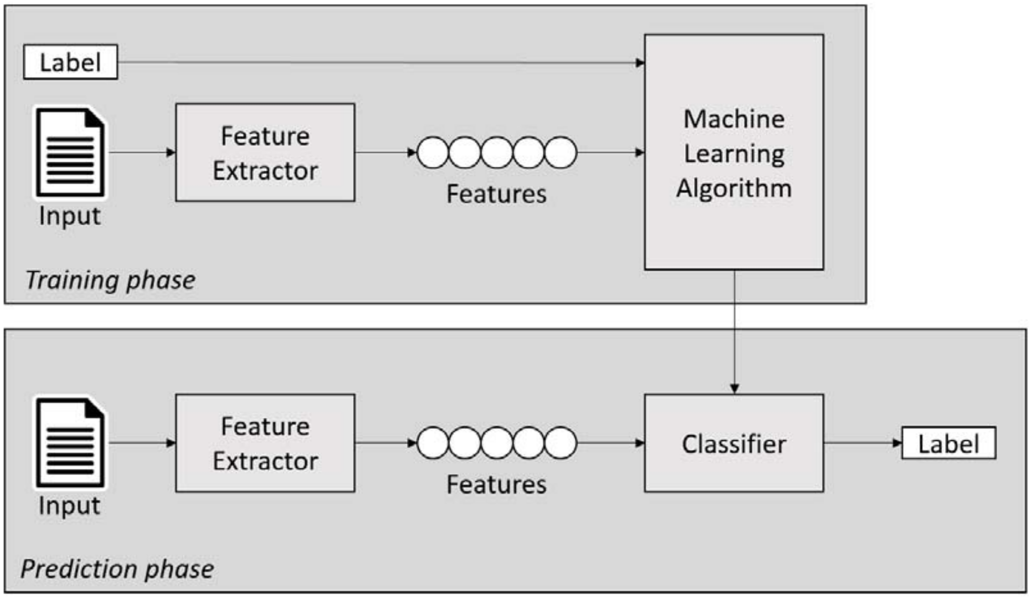

Figure 2: Supervised Classification Algorithm [Adopted from nltk.org]

straightforward job. In fact, as the results of an experiment described in (Pang, Lee, & Vaithyanathan, 2002) demonstrate, humans are not very good at predicting what words are likely to appear in a positive or negative expression. In this experiment, two subjects were tasked with independently creating a list of words that, in their opinion, are strongly associated with either positive or negative emotions. The two resulting lexicons were then put to the test of identifying sentiment expressed in movie reviews and pitted against a statistics-based approach. Accuracy of the latter was higher than that of both human-created lexicons, and the statistics-based classification revealed some unexpected keywords with high predictive power, e.g. the word 'still' that, unintuitively, was highly associated with a positive sentiment. If creating an accurate lexicon of positive and negative sentiment is already hard to achieve, choosing keyword for determining more subtle types of subjectivity, such as trust or doubt, must be an even more difficult task.

In addition, it is possible that some terminology and commonly used language on Kickstarter, especially in a niche such as technology projects, differ from those in other online communities in subtle ways that escape a cursory human inspection, further decreasing the the likelihood that a lexicon-based approach will yield satisfactory results for the task at hand.

Supervised machine learning approach addresses many of the concerns discussed above and was therefore preferred in this thesis. The following section describes further narrowing down of the supervised learning approach to a concrete algorithm as well provides a summary of model specification used in the final version of the classifier.

5.2.2.3 Defining Classes and Developing Training Corpus

Since I was interested in backers' ability to critically assess projects and identify irresponsible creators, I chose to investigate the sentiment dimension of trust. The intuition behind this was that both periods when a lot of doubt is expressed in the comments section and stretches of time where trusting comments appear frequently present eventful periods in which backers collectively utilise whichever tools are available for them in mitigating the principal-agent problem.

Three classes of comments were identified: *trusting, doubtful,* and *neutral.* Definitions of the three classes along with examples from the training corpus are presented in Table 2.

Having defined these three classes, I have created a training dataset by manually classifying 682 backers' comments in two Kickstarter projects: Rock Smartwatch and LMCable, both of which had spawned lively discussions, garnering both critical and supportive backers, before being suspended by Kickstarter just a few days prior to the end of their respective campaigns.

Comments in each of the three classes were randomly shuffled and divided into two parts. First part, amounting to 70% of the collected 682 comments, was used for preliminary training of classifiers with different specifications, while the remaining 30% were used for testing predictive accuracy of each classifier. Once the optimal classifier specification was chosen, this model was trained on all 682 comments, thus forming the final classifier.

5.2.2.4 Identifying Suitable Supervised Learning Classifier Algorithms

Four types of supervised learning classifier classes were initially considered for use in this thesis: Naive Bayes, Maximum Entropy, Decision Trees, and Support Vector Machines. Implementation of the latter, despite it being a relatively popular and efficient method, was not attempted, as Support Vector Machines is an inherently two-class classifier and workarounds available for its conversion to a multiclass classifier are often inelegant (Schütze, 2008). Likewise, the Decision Trees classifier from consideration, as it was rarely used in similar tasks by previous research, although proving quite efficient in other

Class	Definition	Example
Trusting	Commenter explicitly or implicitly expresses her or his certainty in project's feasibility, project creator's honesty and/or intentions to realise the project.	I am a big supporter of new innovative things and small business start-ups. I am backer and wish you all the success. Just remember there are people that are not satisfied with whatever life they are living and will always try to derail you of your path. Stay strong, positive and good luck.
Doubtful	Commenter expresses lack of confidence in any of the following: project's feasibility, project creator's honesty, project creator's intention to realise the project.	I asked like 4 questions and i got 1 answer only. Sorry to say but i read the back comments and yeah, alot of questions were answered with no definite answer. Dont get me wrong, I really wanted this project. Although it seems like all these information are only sugar coated. Nice to have but all the misleading information makes it scary to get one. Sorry
Neutral	Commenter does not address directly or implicitly any of the following: project's feasibility, project creator's honesty, project creator's intention to realise the project.	Please make all those reviews about this watch on the first page linkable. I do not want to search for them.

Table 2: Class definitions

areas, such as part-of-speech tagging (Schrauwen, 2010). The two classifier algorithms evaluated further were therefore Naive Bayes and Maximum Entropy.

Naive Bayes classifier operates under the assumption of conditional independence. That is, the probability of one feature belonging to a certain class is independent from the probability of any of the other words belonging to the same class (Schrauwen, 2010). While this assumption is not representative of the real world, the simplification it provides often allows to solve classification problems with sufficiently high accuracy.

Maximum Entropy classifier operates by iteratively mapping pairs of features and their respective class labels to a vector. Increasing number of iterations over which Maximum Entropy classifier is trained often improves its accuracy, but might result in overfitting, i.e. classifying based on idiosyncrasies inherent to the training corpus and not present outside of it.

Unlike Naive Bayes, Maximum Entropy classifier does not assume that features are conditionally independent of each other. While in theory it should make Maximum Entropy classifier more robust, there is no rule of thumb that would dictate choosing one over the other, and directly comparing classifiers trained via each of these algorithms is advisable to determine the optimal one.

5.2.2.5 Input Pre-processing, Classifier Model Specifications

Before training a classifier, an algorithm must be defined for pre-processing inputs that one wishes to classify. Instances of text that serve as inputs can be stripped of punctuation, URLs, usernames, and hashtags. In addition, it is often advisable to omit the so-called *stop-words* – certain words lacking sentiment that are therefore unlikely to point the classifier towards any class, e.g. ”do”, ”has”, ”end”, ”next” etc. A modified version of a stop-word list available at lextek.com (Lextek-International, 2000) was employed in this thesis. While stop-words normally improve accuracy of classifiers trained on single-word features, bigram-trained models sometimes benefit from inclusion of the stop-words into the list of features. For the sake of reliability, most models, including some unigram ones, were tested both with and without stop-words.

Altogether, four variables in the classifier model specification were available for tweaking: learning algorithm (Naive Bayes or Maximum Entropy), n-grams (unigrams or bigrams), omission or inclusion of stop-words, and, for the Maximum Entropy classifier, number of iterations over which it was being trained. By mixing and matching different values of these four variables, I specified six Naive Bayes and nine Maximum Entropy classifier models, 15 in total. These 15 models were trained on 70% of the available training corpus of 682 comments, with remaining 30% reserved Accuracy achieved for each specification is presented in Table 3.

5.2.2.6 Evaluating The Classifiers

Having obtained estimates of accuracy of the trained classifiers, we now need a criterion to judge them against. Is an average accuracy of 63.43% sufficient or do these models need further improvement to be meaningful? If accuracy of any or all of them is indeed acceptable, should the model with the highest accuracy estimate be chosen? Before answering any of these questions, it is important to note that there is no universal metric for determining whether any given classifier model is sufficiently precise at guessing the sentiment. However, there is a ’rule of thumb’ approach, often utilized both within and beyond the field of sentiment analysis, that allows to weed out impractically imprecise classifiers (Lusa et al., 2010; Maas et al., 2011; Nadeau, Sabourin, De Koninck, Matwin,

Algorithm	N-grams	Stopwords	No. of iterations	Accuracy
Naive Bayes	Unigrams	Omitted	N/A	66.49%
Naive Bayes	Unigrams	Included	N/A	62.63%
Naive Bayes	Bigrams	Omitted	N/A	60.91%
Naive Bayes	Bigrams	Included	N/A	59.89%
Naive Bayes	Uni- & bigrams	Omitted	N/A	64.97%
Naive Bayes	Uni- & bigrams	Included	N/A	63.95%
Maximum Entropy	Unigrams	Omitted	10	57.57%
Maximum Entropy	Unigrams	Omitted	20	64.65%
Maximum Entropy	Unigrams	Omitted	100	63.64%
Maximum Entropy	Unigrams	Included	100	63.12%
Maximum Entropy	Bigrams	Omitted	100	63.45%
Maximum Entropy	Bigrams	Included	100	63.91%
Maximum Entropy	Uni- & bigrams	Omitted	100	63.64%
Maximum Entropy	Uni- & bigrams	Included	100	63.82%
Maximum Entropy	Unigrams	Omitted	250	70.56%

Table 3: Accuracy tests

& Turney, 2006; Narr, Hulfenhaus, & Albayrak, 2012).

The minimum criterion is the *guessing*, or *random-choice, baseline*, which is equal to *100%/k*, where k is the number of classes in the dataset. Guessing baseline is the accuracy that would be achieved, on average, by randomly guessing sentiment of each comment. With three classes present, the guessing baseline equals 33.33%. Most models outperform this threshold by approximately 30%.

For imbalanced training sets, such as the one used in this paper, a stricter approach is available. *Majority class rule* takes into account the bias towards the majority class in the dataset and dictates comparison between a classifier's accuracy and accuracy that would be achieved by assigning label of the class prevalent in the *training* set to every *test* comment. Neutral is the majority class in the dataset employed, with approximately 49% comments assigned to it, hence the majority class rule dictates that an accuracy higher than 49% must be achieved for the classifier model to be able to provide any meaningful results. Once again, every tested model passes this test, outperforming the majority class prediction by 14.43% on average.

To further put things into perspective, another important observation has to be made:

even humans cannot identify sentiment with a 100% accuracy. In fact, a 2005 University of Pittsburgh study had compared sentiments ascribed to the same 447 subjective expressions by two human interpreters and found that they only agreed on an expression's sentiment 82% of the cases (Wilson, Wiebe, & Hoffmann, 2005).

To reiterate, every classifier specification passed the guessing baseline and satisfied the majority class rule and, since sentiment analysis is used in this thesis in conjunction with manual in-depth netnographic analysis, was deemed satisfactory for the purpose of this study. However, upon closer inspection it was discovered that most of the Maximum Entropy classifiers heavily overemphasise neutral and doubtful classes, assigning almost all trusting comments to one of the other two classes. Naive Bayes classifiers were not subject to this bias, hence, despite impressive 70.56% accuracy of 250-iteration Maximum Entropy classifier, Naive Bayes unigram model with stop-words omitted was chosen for subsequent analysis, as it achieved accuracy of 66.49%, highest in its class.

Table 4 lists some of the features final model uses for classifying new inputs. According to the classifier, the word "believe", for example, is 17 times as likely to appear in a trusting comment than in a neutral one – something a human would likely predict. Another unsurprising feature by which classifier is guided is the word "fake", which is nearly 14 times as likely to be present in a doubtful comment than it is in a neutral one. Something much less obvious, though quite understandable in hindsight, is the high predictive value of the feature "pictures" – classifier expects a comment containing this word to be doubtful.

Feature	**Likelihood Ratio**	
features	trusting : neutral	20.2 : 1.0
believe	trusting : neutral	17.1 : 1.0
doesn	trusting : neutral	14.0 : 1.0
protect	trusting : neutral	14.0 : 1.0
company	trusting : neutral	14.0 : 1.0
help	trusting : neutral	14.0 : 1.0
looking	trusting : neutral	14.0 : 1.0
fake	doubtful : neutral	13.9 : 1.0
love	trusting : neutral	12.1 : 1.0
pictures	doubtful : neutral	11.4 : 1.0
glad	trusting : doubtful	11.0 : 1.0
luck	trusting : doubtful	11.0 : 1.0
life	trusting : neutral	10.9 : 1.0
truth	trusting : neutral	10.9 : 1.0
game	trusting : neutral	10.9 : 1.0

Table 4: Most Informative Features

5.2.3 Methodological Contribution

Although the sentiment classifier developed in this thesis is utilizing rather basic classification techniques and is trained on a training size quite limited in size, I believe that it contributes to the existing body of research in two ways.

First, there is little literature seeking to apply sentiment analysis and similar methods to crowdfunding and this paper presents one of the few attempts to utilise the untapped potential of crowdfunding platforms that are heavily underused as a source of rich textual data for sentiment analysis compared to Twitter, Facebook, or movie reviews. Research that I was able to find focuses on predictors of campaign success and chiefly analyses *project creators'* communication through project description and/or updates (Greenberg, Pardo, Hariharan, & Gerber, 2013; Mitra & Gilbert, 2014; Xu et al., 2014).

Meanwhile, sentiment analysis implementation in this paper intended to aid in distinguishing mechanisms that prevent majority of irresponsible agents from receiving funding. What is more, I focus on *backers'* communication instead of looking solely at text generated by *creators*.

Second, I have not been able to find a sentiment analysis model or a dataset developed for distinguishing between trusting and mistrustful instances of text. While the dataset developed for this thesis undoubtedly requires further work, it provides a starting point for classifiers that are able to identify sentiment across the 'trust-doubt' dimension.

6 Data Analysis

6.1 Preamble: Structure and Rules of a Kickstarter campaign

This is an opportune moment for a brief overview of how a Kickstarter project's page is structured and what rules Kickstarter has put in place for the creators, both in form of advice and more restrictive obligations. These rules define the 'playing field' for all creators and shape creator-backer communication. Therefore, a description of Kickstarter's guidelines for campaigners adds context necessary for understanding the principal-agent dynamics present on the crowdfunding platform.

6.2 Campaign page structure

The basic dynamic of the intercourse between the agent and the principals on crowdfunding websites consists of three main building blocks that correspond to three of the sections of a project's campaign hub: 'Campaign'('Story' on Indiegogo) page and 'Updates' and 'Comments' sections. This dynamic can be described as follows.

The agent first creates a *campaign page*, which contains a promotional video and multitude of textual and visual information describing, in as much or as little detail as the creators see fit, the project's essence, team and inspirations behind it, current stage of development, timeline of planned post-campaign activities leading to the launch of the product or service and delivery of rewards to backers, and current and future risks and challenges that creators are or will likely be facing. The project's campaign page is the first element of the two-sided communication flow between the agents and the principals. It is this web page that first presents the project to curious Internet surfers, but also the one to which backers will be returning during and long after the campaign. It is the ultimate source of all factual information about the project, as it contains all technical details, team members' credentials, claims of any patents, achieved results, arrangements with subcontractors and so on.

After the campaign page is published, prospective backers (members of the Kickstarter community at first, but a broader audience of Internet-users later, if the project gets enough traction) start discovering the project and may choose to contribute to it, thus engaging in a principal-agent relationship with the entity behind the project. The more engaged and/or generally more sociable backers then post comments that might be directed at their peers or the project creators, and the latter are free to communicate back using the same *comments section*. Backers often leave comments to make inquiries about a particular side of the project that was poorly (either purposefully or unintentionally) communicated on the campaign page, express their excitement about the project, declare their intention to spread the word about the campaign, propose a modification of the product or service in question, or raise a concern about the project. Creators, then, use the comment section to address the questions raised by the backers, thank them for their engagement, or discuss proposed changes. The *comments section* is the second element of the communication flow and also where most of the interaction – discussion or even collaboration – between the agent and the principals occurs in reward-based crowdfunding.

Finally, creators will usually post periodic updates in the designated *updates section* – texts of normally greater length than a comment that, naturally, provide an update on the project's development, but also seek to answer questions and worries that are being raised by the backers most often and, hopefully, put an end to backers' doubts.

6.2.1 Key Kickstarter Terms of Use

As the platform is viewed as one of the core players in crowdfunding, it is essential for the purpose of this thesis to look into terms of use of Kickstarter in more detail. One of the first things the backer would find is the responsibility of the Kickstarter in deciding which projects may or may not be published. The platform positions itself as one that encourages unique and innovative projects, and does not allow for prohibited items and items for which the project owner does not hold copyright for (unless the permission by third party is granted). Kickstarter reserves the right to reject, cancel, interrupt, remove, or suspend any project at any time and for any reason.

Second set of rules is dedicated to Kickstarters role in communication between backer and the project owner. The platform does not evaluate a project's claims or performance, resolve disputes, or offer refunds, leaving to backers decide what is worth funding. Kickstarter is emphasizing its role as a base for communication and actively recommends to both: backers and fundraisers to read the comments other people leave, as this will allow to the former to make sure the project is trustworthy, and for the latter reading backers comments and actively communicating with them will show openness and reliability.

Since Kickstarter is based on all-or-nothing funding system, no backer is charged until a project meets its funding goal and the funding period ends. Such investment model allows backers to evaluate a project fully through communication with each other and the project creator, and also gives Kickstarter team some time to look into any concerns raised by backers. Backers may report opportunistic project-creator, if enough backers report a project Kickstarter will take action either in form of warning or it can lead to revoking certain privileges or accounts entirely. It is important to note that Kickstarter does not dig in the technological or performance part of the project, it just controls whether a project is published in accordance with guidelines set up by the platform.

A note relevant for analysing hardware technology projects: in May 2012, Kickstarter expanded its guidelines for Technology project by requiring creators to include in a project description a manufacturing plan, a functional prototype, and details about creators' relevant experience (Kickstarter, 2012).

6.3 Case 1: iFind

Table 5 summarizes some key introductory facts about the campaign and contains a breakdown for various metrics of the discussion that developed in the 'Comments' section of iFind campaign page. Some of this data will come in handy later on, while other metrics can serve us as the point of entry to an understanding of this project's fate and backers' role in it.

As one would expect, people that participate in the discussion of the project comprise a small vocal minority of backers – 300 people, only three percent out of almost ten thousand users who were willing to entrust iFind with their money. However, we must bear in mind that members of this relatively small, more intimate gathering within the otherwise shapeless throng of backers, these 300 Spartans of crowdfunding, if you will, are likely capable of exerting influence on creators, the platform itself, and the silent majority of backers.

Superbackers – users that are more heavily invested in crowdfunding activities than an average backer – are not very talkative in iFind's comment section, having posted, on average, both fewer and shorter comments than other backers. Perhaps, superbackers are often more trusting and/or risk-seeking people that are willing to invest more money into crowdfunding projects, but do not assess their feasibility as thoroughly as others.

Meanwhile, iFind's creators have posted more than one fifth of all the comments,

Project Introduction

Title: iFind - The World's First Battery-Free Item Locating Tag
Launch date: May 16, 2014
Product description: A small device intended to be attached to a personal item (e.g. keychain, wallet, bag) and paired with a smartphone via Bluetooth. Upon losing connection to the tag, the smartphone notifies the user that the item is out of range. When within range, a request can be sent to the tag to initiate an alarm to help identify the item's exact location.
Unique selling point(s): Patent-pending technology that allows the tag to operate indefinitely without the battery being charged or replaced by the user (necessary electric charge is harvested from energy contained in FM, Wi-Fi, and other radio waves)
Outcome: Campaign suspended by Kickstarter on June 26th (4 days before the end of the campaign)

Financial Metrics

Funding goal: $25 thousand
Funding by the cancellation date: $546,852
Average Pledge Per Backer: $56

Comments Metrics

Number of backers: 9,771
Number of comments: 2,672
Backers active in the comments section: 304 (3.11% of total number of backers)
Active superbackers: 19 (6.25% of total number of active backers)
Comments by superbackers: 109 (5.17% of total number of backers' comments)
Average comment length: backers – 342 characters, superbackers – 319 characters **
Comments by creator: 564 out of 2672 (21.1%)
Average creator's comment length: 127 characters

Note: Difference in mean comment length significant at: *** – 99.5% confidence level, ** – 95% confidence level, * – 90% confidence level

Table 5: iFind Campaign Summary

though their comments tended to be almost three times as short as the ones left by backers.

Essence of opportunistic behaviour

The claim iFind campaign starters made was *unscientific* – a reasonably sized Bluetooth beacon would not be able to harvest sufficient energy from surrounding radio waves (Mathieu, 2014; Ciuffo, 2014; Aplin, 2014).

6.3.1 Trust dynamics

Overview of changes in proportion of trusting and doubtful attitudes among backers that were vocal in the comment section of iFind's campaign is presented in Figure 3 below.

Let me first take a moment to explain the structure of data presentation in the diagram. As you can see, the graph features two vertical axes. The one on the left corresponds to the share of polar (either trusting or doubtful) comments. A value of 1.0 along that axis must be interpreted as 100% of backers' comments posted on that day having a trusting sentiment. A value of -1.0, on the other hand, means that all comments posted by backers' on that day were doubtful of the project.

Against the secondary vertical exis I have plotted the total number of comments posted by backers in any given day. In addition to potentially giving us insight on its own, this data series serves as a reliability test for the comments polarity. Since the classifier programmed and trained in the previous section has an accuracy of 66.49%, one must be interpreting percentages of polar comments carefully in order to avoid drawing conclusions from what could be an error made by the classifier. The larger the total number of comments posted on a certain day, the more trustworthy are estimates of polarity provided by the classifier. Cross-referencing the share of polar comments with the total number of comments posted should therefore give us a certain peace of mind.

Let us now proceed to interpreting the diagram. Looking at the number of daily comments posted by backers, we can easily spot the campaign's 'pulse' – the flow of liveliness of the discussion around the project. It starts on a high note: on the very first day of the campaign there have been more than 50 comments posted, with backers' interest fluctuating up and down in a couple of weeks that followed.

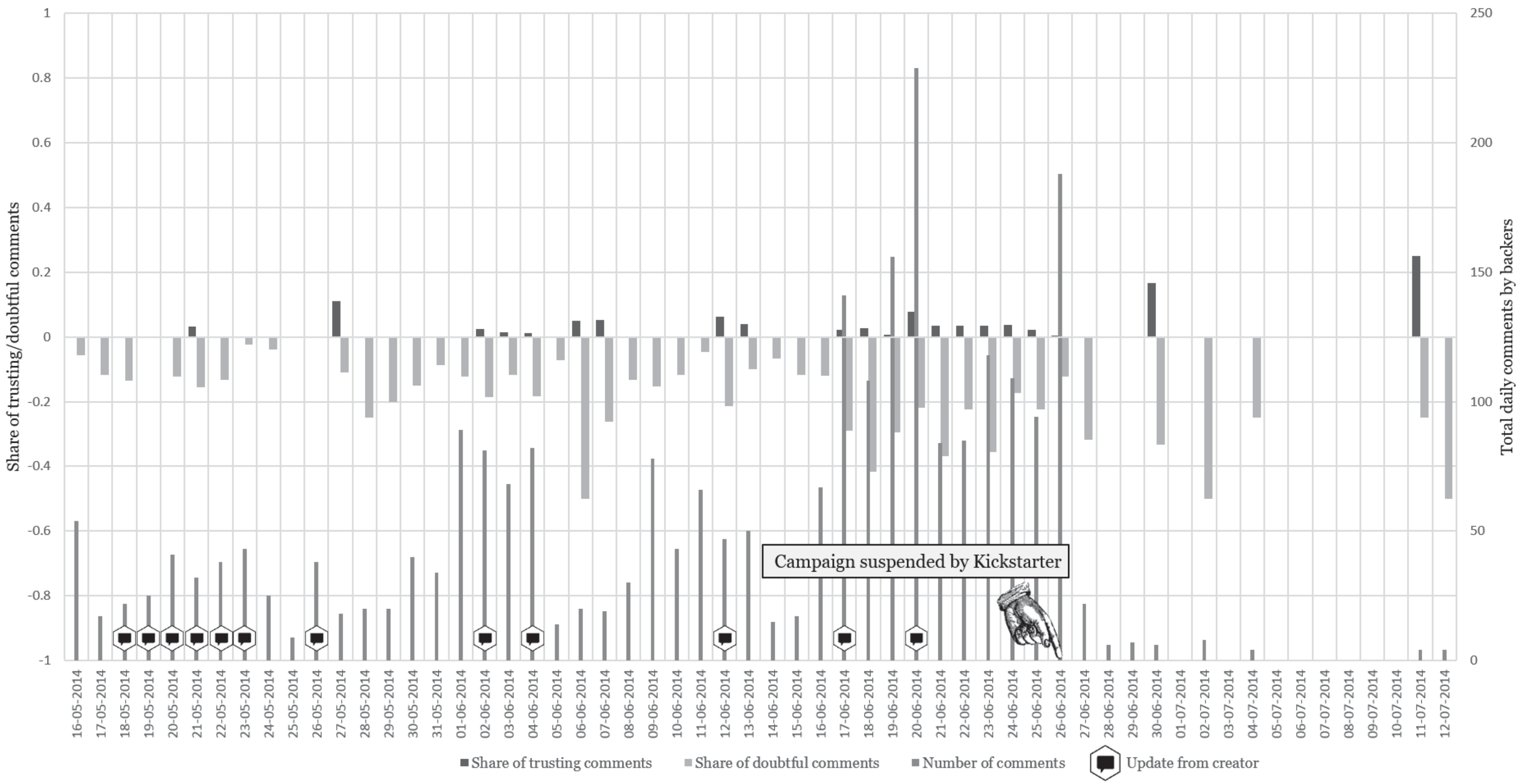

Figure 3: Trust/Doubt dynamics in iFind campaign

One burst of activity lasted from 1st till 4th of June, with around 70-80 comments posted daily. A brief hiatus in the discussion was followed by another, slightly less evident, spike during June 9th – 13th. The final spike, the most significant and prolonged of the three, started around 16th and lasted until 26th of June when the campaign was shut down by Kickstarter. More than a hundred comments were posted on most days during this final spike. Notice also that there is a wave-like property to the spikes, with gradual build-ups and sharp slumps in backers' discussion.

As to the dynamics of trust in the comments section, one thing that is bound to draw attention of an observer is that only a handful of people ever explicitly expressed their faith in iFind. Backers' discussion of iFind had a distinct tinge of suspicion throughout, with around 15% of the comments on most days being doubtful of iFind team's proposition. Could it be that this is representative of Kickstarter community's attitude at large and not specific to this particular campaign? The vocal minority (mere 3.11% of backers in case of iFind) might be fundamentally different from the rest of supporters; their higher engagement might be always followed by more thorough examination of the project and a more critical attitude.

I assumed that comments posted in the first few days of the campaign must be particularly important, as they likely set the tone for the discussion that follows and introduce some of its key participants.

Diving into the comments section proper, we can see that a lot of backers were either intrigued or confused (and often – both) by iFind's unique selling point – ability to operate indefinitely without ever being charged by the user. This confusion, which has quickly become a major theme of discussion, was caused by lack of clearly communicated factual information about the technology behind iFind's miraculous battery-free operation. The creators explained away this secrecy as a measure necessary to protect their pending patent.

The comment section was immediately overflown with people curious to know specifics of the operation of the device. While not overtly doubtful, these comments expressed backers' desire to understand precisely how iFind will behave in a day-to-day use. What EM waves will be able to charge the device? How long can it function in an environment with low or no presence of radio waves? – such questions did not doubt either creator's intentions or even feasibility of the product, but were intended to help backers decide whether iFind was suitable for them.

Figure 4 contains a comment representative of the general attitude of backer towards iFind at this point (kindly refer to Appendix D for the full list of rich comments in this campaign).

Figure 4: Comment 1

By: Don On: 16.05.2014
Nice.[1] **I never knew that one would have enough energy in energy harvesting circuits to drive a BLE radio!!!**[2] Does the app show available charge in the finder? How long can the finder work if I put it inside an anti-em static bag ? what is the charge decay rate? So I can't use this in my RFID blocking wallet then ? **Since you say you don't have battery I am assuming you have a ultra capacitor or super capacitor?**[3] Would it charge if I put it on a Qi charger plate? What will happen ? **What is the broadcast rate of the BLE signal?**[4] How loud is the beep in dB?

[1] Approval
[2] Surprised at feasibility
[3, 4] Request for clarification of a feature

However, it only took a couple of days before the trustworthiness of the project was first called into question. Author of the comment in Figure 5 questions trustworthiness of the project by pointing out that very little personal information has been made available by the creators.

Figure 5: iFind Comment 2

By: Robert On: 18.05.2014
love the idea and concept[1] of this project, **but some of this stuff seems a little too good to be true**[2]. the whole **concept of this item not using batteries is not explained, except for "patent pending."the actual insides of the product are not shown**[3] whatsoever. **i need a little more bona fide before i fully commit**[4] to a project, **especially considering this is your first kickstarter, with no previous history in the community. the actual creators faces/names are not even shown on their own website**[5]. **just seems a little too good to be true**[6].

[1] Approval
[2, 6] Doubt, caution, suspicion
[3] Referring to campaign description/creator's comments
[4] Request for a feature clarification; request for a prototype demonstration
[5] Creators' credentials

Over the course of the next two weeks several other backers similarly expressed their concern based on various reasons. Some were asking for more personal information;

others were pointing out that iFind's decision to launch a Kickstarter campaign makes no business sense, since the technology they claim to have mastered would be a breakthrough in consumer electronics and the team behind iFind would have more lucrative options of financing.

While infrequent at first, questions posed in these doubtful comments were not satisfactory answered by the creators, who refused to give any specific figures regarding their technology. This lead to more persistent demands of a prototype demonstration and/or a detailed report on specifications of the device. These demands peaked in intensity around May 28, when the creators announced that they are working on a technical report and intend to post it as an update.

The technical report was published on June 2 and produced twofold reaction from the backers. One part of the community, seemingly comprised of the more tech-savvy backers, or *experts* in terminology of Kim and Viswanathan (2014), analysed the data in the report and concluded that the device is not feasible. The other part was satisfied that the creators responded to community's request for technical information, evidently interpreting the very fact that a report was published as a signal of creator's legitimacy. The division that occurred in the community is illustrated by comments in Figures 6 and 7 respectively.

The difference in reaction to the report led to a disunity among backers, but also resulted in more backers communicating directly between each other instead of addressing the creator. It seems that this shift increased investigative power of the community of backers, and on June 3 one of the backers announced that they have reported the project to Kickstarter, substantiating this move by lack of a prototype demonstration and apparent technological infeasibility of iFind.

Several days after the technical report had been published, most of the vocal backers seem to have become sceptical of the project at this point, the only variable is their emotional state, which ranges from infuriated to sarcastic to level-headed. Backers in this last category, while not hopeful about the project's feasibility, are still willing to give WeTag team benefit of the doubt, since at this point creators still have nearly a month to provide necessary evidence of a working prototype and there is nothing stopping backers from cancelling their pledges closer to the end of the campaign.

As more and more backers became convinced that the project is infeasible, pressure kept growing on the creators to convince the Kickstarter community otherwise. In an attempt to do so, creators published their second technical report on June 17. Looking

Figure 6: iFind Comment 3

By: Huckleberry On: 02.06.2014
Hi All, **Thanks for publishing the technical info!**[1] The efficiency and usage costs are reasonable, however **theres a fatal problem with the assumption in Figure 1**[2]: Note that when the input power is around +10dBm, which is typical for home WiFi A very strong wifi signal is about -60dBm (5 bars) and a weak one is -110dBm (1 bar.) Your +10dBm assumption is more than *a million* times stronger than a real signal giving 5 bars! **Ive been a radio-frequency engineer for 23 years**[3], but dont take my word for this. Heres a good **writeup explaining real signal strength: http://note19.com/2010/07/04/mapping-cellular-signal-strength-to-5-bars/**[4] The second paragraph is key to understanding the massive problem here. Bottom Line **The Tag as described will never come close to working off wifi signals**[5]. Real, credible home wifi strength is more than a million times weaker than The +10dBm assumption in the WeTag tech docs. There's plenty of sources that confirm real-world signal strengths. The Tag will require a battery or some other substantial source of replaceable power to actually work. Wifi devices need those sophisticated antennas and high gain amplifiers for a reason... (2 bars is a *millionth* of a *millionth* of a watt!)

[1] Referring to campaign description and creators' comments
[2, 5] Technical feasibility
[3] Expertise of individual backers
[4] Technology standards specifications

Figure 7: iFind Comment 4

By: Don On: 02.06.2014
This is good!!! Ask for data and make fun of it when they provide it. **Remember that it's a work in progress.**[1] It's easy to find holes. **I urge each one of you to start a campaign and do something useful instead of critiquing others works.**[2] Being an armchair anything is easy!

[1] Faith
[2] Inter-backer communication

at the diagram, we can see that this report caused massive outrage from the backers: both the number of comments and share of doubtful comments increased dramatically and remained at these abnormally high levels until the campaign was shut down by Kickstarter.

More and more backers were calling upon other contributors to report the project to

Figure 8: iFind Comment 5

By: MrRobot On: 17.06.2014
"@All - Y'know what,[1] we need to do something about this[2] crap[3]. It's NOT enough that the small minority of backers who follow this thread pull their money. How many people pledged money and won't be reading this - at least until it's too late, the money's in their account and the excuses start flowing. NO WAY! ENOUGH. You, fellow backer, are here because you believe in helping to launch new ideas, from sincere entrepreneurs who want to try to do something meaningful. They deserve our help. This so-called project is another example of scammers increasingly feeding on KS; there can be little doubt about that. Re-read the posts below and see if you don't agree. PULLING YOUR OWN MONEY IS NOT ENOUGH [...] REPORT THIS PROJECT TO KS. [...]

[1] Inter-backer communication
[2] Sense of moral responsibility to Kickstarter community
[3] Offensive language

Kickstarter, clearly showing a desire to protect members of the community from what was likely to be fraud.

Whatever sentiment backers active in the comments section expressed, it the voice of a small minority of backers. I use daily net contributions to the project as a proxy for the opinion of the silent majority of backers. The diagram in Figure 9 presents a comparison between the trust that vocal and silent backers have showed iFind at different stages of its campaign.

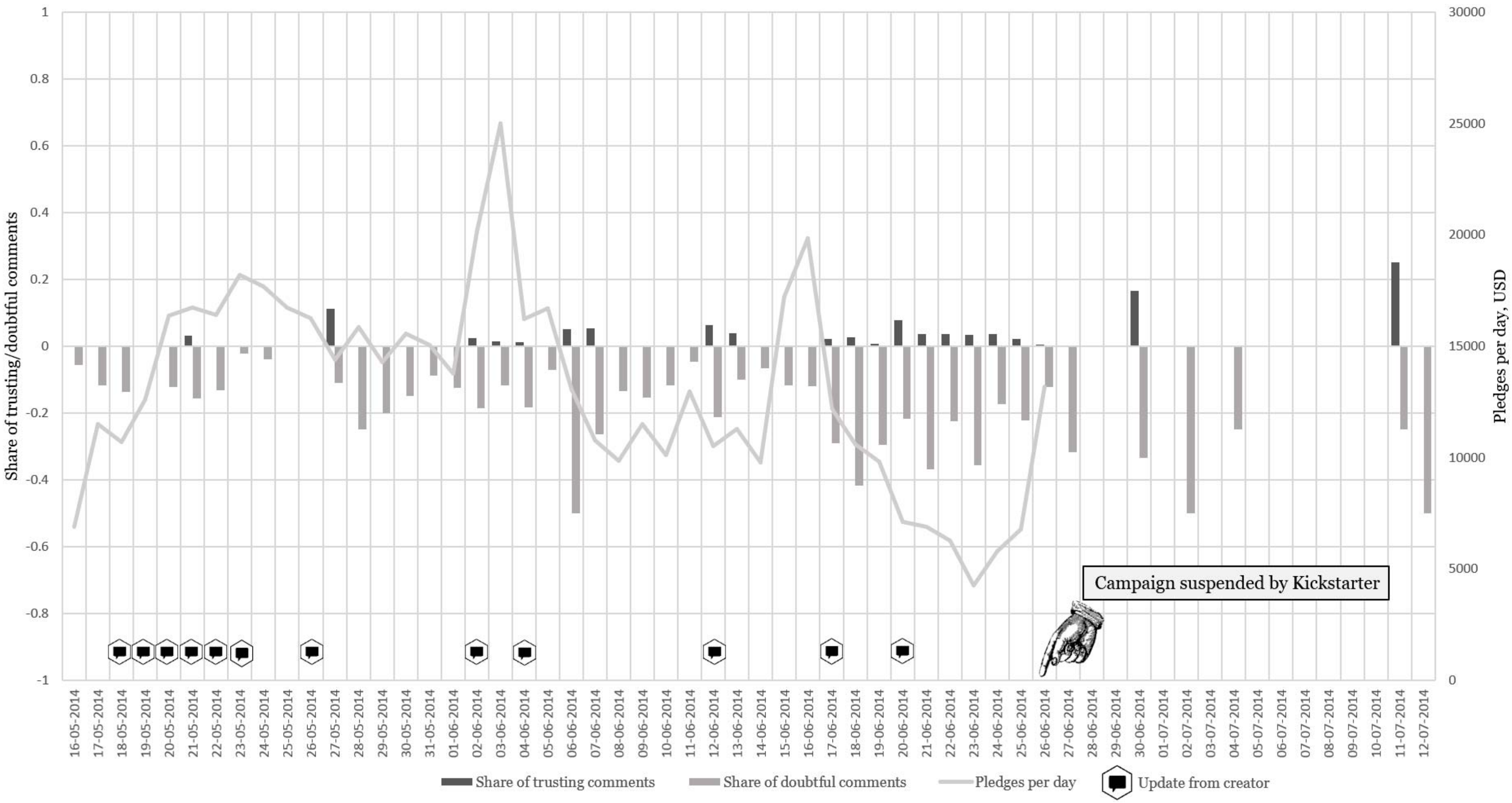

Figure 9: Comparison of trust dynamics between 'vocal minority' and 'silent majority' in iFind campaign

What can we learn from this graph? Kuppuswamy and Bayus (2015) established that the pattern of a Kickstarter project support throughout its funding cycle is typically U-shaped, with more backers contributing to the project in the first and last days of a campaign than in the middle period. This is in contrast with the daily pledges data for iFind campaign presented in Figure 9, which forms a pattern quite distinct from a U-shape.

A possible explanation for this inconsistency is that the silent majority of the backers goes beyond observing **funding decisions** made by earlier backers (Zhang & Liu, 2012), but also attempts to infer a project's trustworthiness from the **communication of current backers** that takes place in the comments sections of a project's home page.

Naturally, were such mechanism indeed at play, the more controversy and doubts a project would spawn, the more pronounced would be the effect of vocal backers' attitude towards a project on the funding decisions of potential contributors who have just discovered said project.

An eyeball test of Figure 9 does not contradict this hypothesis: spikes in the percentage of doubtful comments posted on any given day seem to be accompanied by sudden plunges in the amount pledged to the project on the same and next day. The assumed effect is particularly apparent on June 6 and June 17.

However, it seems that the effect of spikes in doubts expressed by the vocal backers on funding decisions of the silent majority is short-lived, which is likely explained by the fact that most of the potential contributors do not thoroughly analyse the comments section and only check a few newest posts.

6.4 Case 2: StoneTether

Project Introduction

Title: StoneTether - The Smallest Tracking Device at Long Range
Launch date: November 3, 2014
Product description: (same as iFind) A small device intended to be attached to a personal item (e.g. keychain, wallet, bag) and paired with a smartphone via Bluetooth. Upon losing connection to the tag, the smartphone notifies the user that the item is out of range. When within range, a request can be sent to the tag to initiate an alarm to help identify the item's exact location.
Unique selling point(s): Proprietary technology for long-range (150m) Bluetooth connection
Outcome: Project successfully funded on December 13 2014; in an update posted in August 2016 creators announced that they have run out of funds and will not be able to deliver rewards to any of the backers.

Financial Metrics

Funding goal: $15 thousand
Funding by the end of campaign: $366,199
Average Pledge Per Backer: $53

Comments Metrics
(campaign period only)

Number of backers: 6,927
Number of comments: 1811
Backers active in the comments section: 1333 (19.24% of total number of backers)
Active superbackers: 65 (4.88% out of total number of active backers)
Comments by superbackers: 106 out of 1732 (6.12%)
Average comment length: backers – 108 characters, superbackers – 161 characters ***
Comments by creator: 79 (4.36% of total number of comments)
Average creator's comment length: 539 characters

Comments Metrics *(total)*

Number of comments: 4071
Backers active in the comments section: 1709 (24.67% of total number of backers)
Active superbackers: 90 (5.27% out of total number of active backers)
Comments by superbackers: 568 out of 3964 (14.33%)
Average comment length: backers – 186 characters, superbackers – 342 characters ***
Comments by creator: 107 out of 4071 (2.63%)
Average creator's comment length: 552 characters

Note: Difference in mean comment length significant at: *** – 99.5% confidence level, ** – 95% confidence level, * – 90% confidence level

Table 6: StoneTether Campaign Summary

StoneTether is, in many respects, very similar to iFind: the product's functionality is all but identical (iFind highlights battery-free operation; StoneTether places emphasis on an unusually long range), its campaign was launched within the same year and had a comparable funding goal. As will become clear from further investigation, StoneTether's creators also were dishonest, yet, despite all these similarities, this campaign flew under the radar of both backers and the platform, raising 24 times its funding goal and still failing to deliver a single reward.

Since StoneTether campaign was successfully funded, I added to Table 6 separate sections for comment metrics based on the discussion during the campaign period and the entire comment section. It is interesting to note that more than 50% of the comments have been posted in the post-campaign period.

Having observed backer behaviour in iFind campaign, I was surprised to discover that a much higher percentage of StoneTether backers involved in the discussion: approximately 19% of users that contributed to the project posted at least one comment during the campaign period. If we include post-campaign discussion as well, this percentage rises to nearly 25%.

Superbackers comprise around 5% of vocal backers that express their opinions in the comment section – a value similar to what we have observed in the case of iFind. However, there is a peculiarity in post-campaign behaviour of superbackers: if during StoneTether's campaign the amount of comments posted by superbackers was proportionate to the share of superbackers among all vocal participants, after the campaign concluded, superbackers started participating in the discussion considerably more actively, posting approximately 14% of all comments. It is also worth noting that the average length of a backer's comment increased almost by a factor of two in the post-campaign period.

Essence of opportunistic behaviour

Similar to the first case, supposed creators of StoneTether made an *unscientific* claim – Bluetooth modules installed in the current generation of smartphones would not be able to communicate with another Bluetooth device over 150m range, which was the key selling point of the product (TexasInstruments, 2015).

6.4.1 Trust dynamics

Changes in abundance of trusting and doubtful comments throughout StoneTether's 40-day campaign are plotted in Figure 11.

The pulse of comments activity familiar to us from observations made about Case 1 is present in StoneTether's comments section as well. It has several peaks centred around the updates posted by the creator, with the highest peak occurring in the last days of the campaign.

However, this is where similarities between the two campaigns end. We can immediately notice how vastly different is the emotional background of StoneTether's comments section from that of iFind. Where the latter featured a ceaseless grumble of an incredulous crowd with several outbursts of outright mistrust, the former only shows a couple of barely noticeable exclamations of distrust among an otherwise perfectly calm sea of comments. Only towards the last days of the campaign did the share of doubting comments posted in a given day reach 20%, gradually fading back to around five percent in a matter of a few days. Interestingly enough, there were almost no trusting comments posted in this period either.

Surprisingly, within the very first couple of days, one backer displayed a critical thinking approach similar to that of "investigators" in iFind's comment section (see Figure 10).

Figure 10: StoneTether Comment 1

By: Frank On: 04.11.2014
@Creator. **Can you explain**[1] to us **technically**[2], however by antenna and a special firmware, you can achieve 500 feet range and in between houses and walls? Most bluetooth tracker can't even work with 20 meters in between wall. So, **how can an in-built antenna improve it?**[3]

[1] Request for clarification of a feature
[2] Technical feasibility
[3] Doubt, caution, suspicion

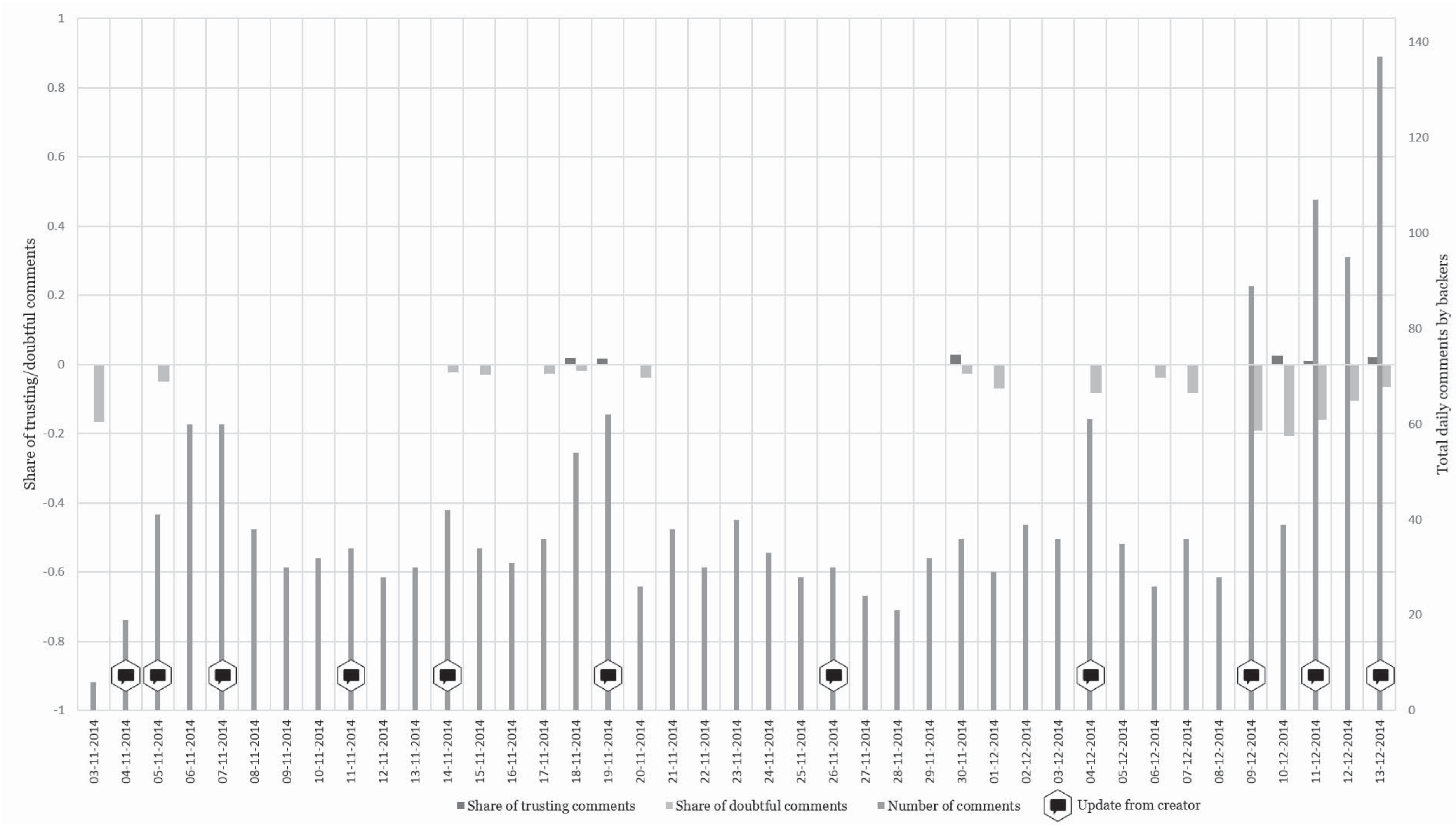

Figure 11: Trust/Doubt dynamics in StoneTether, campaign only

However, this comment is by no means representative of the average frame of mind expressed in the comments section of StoneTether's campaign. Hardly anyone but "Frank" was even mildly suspicious of the product – but, as we know from Figure 11, not a lot of people were expressing their faith in StoneTether's success either. Instead, an average comment of a StoneTether backer throughout the entire campaign period looked like the one presented in Figure 12.

Figure 12: StoneTether Comment 2

By: Ghost On: 04.11.2014
Backed and shared[1] on my Facebook!

[1] Uninsightful

These extremely short exclamations were occasionally accompanied by a question about available colours or a wish of good luck, but in most of the cases only included this information.

This is because in the description of the campaign creators of StoneTether indicated that any backer who will share the link to the campaign on Facebook or Twitter and leave a note saying so in the comment section will be eligible for a bonus free StoneTether device.

Understandably, a lot of backers, in an attempt to maximise their payoffs, gladly accepted this offer, flooding the comments section with identical notifications of them having shared the link to the campaign on social media.

In this torrent of uniform comments more critical ones appeared very rarely, but consistently. They were ignored or answered evasively by the creators, but, if during iFind's campaign this immediately prompted a lively discussion among backers, there is very little indication of inter-backer communication during StoneTether's campaign. The likely reason for this is simple: critically minded backers could not 'hear' each other through the noise of comments with notifications.

It seems that creators of StoneTether, either purposefully or unwittingly, disrupted backers' ability to discuss the project's feasibility, creators' credentials etc. And indeed, if we look at the trust dynamics in the post-campaign period in Figure 13, the difference is quite obvious.

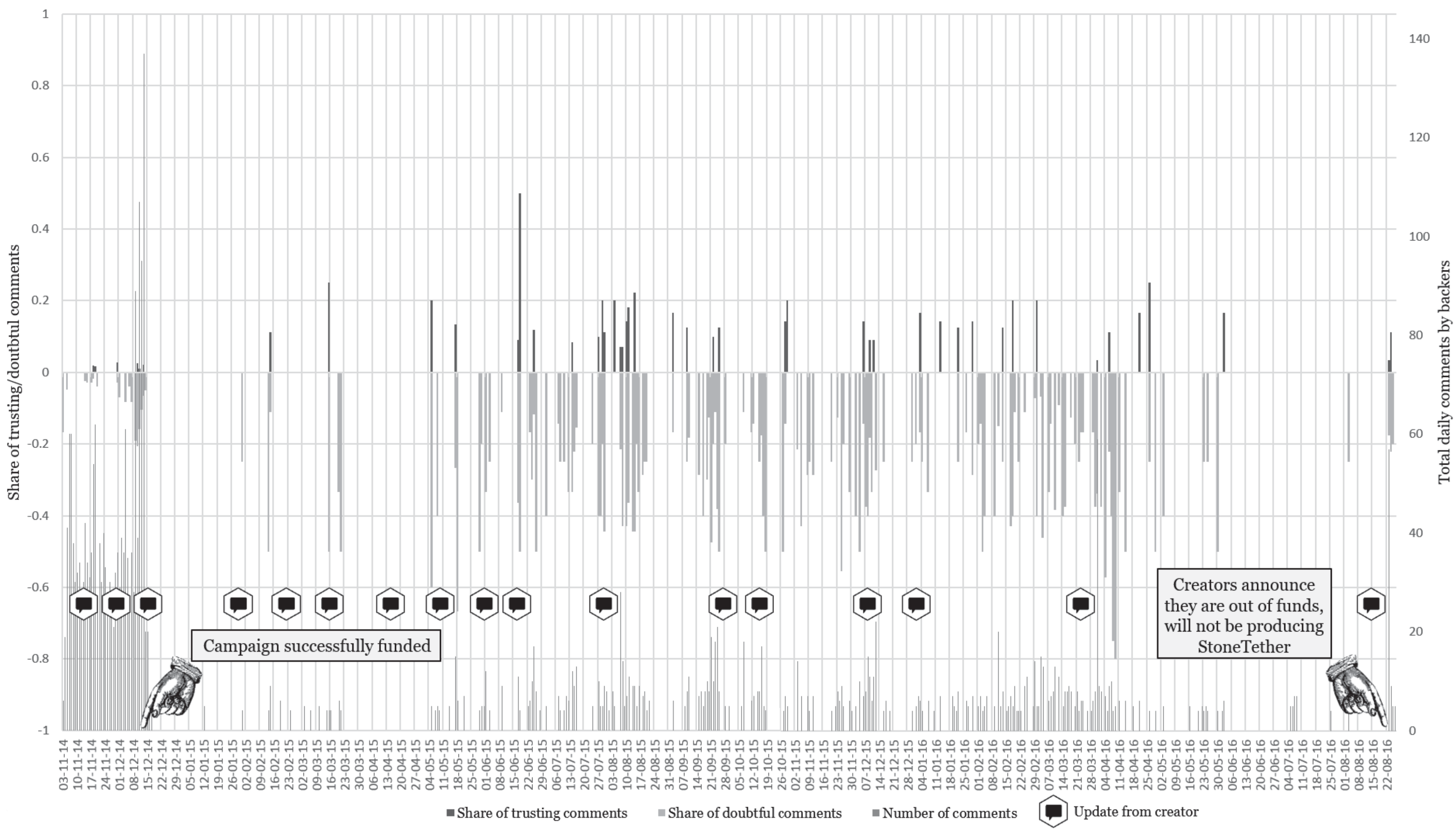

Figure 13: Trust/Doubt dynamics in StoneTether, entire timeline

Activity in the comments section disappears almost completely soon after the conclusion of the fundraising campaign, but re-emerges after each update posted by creators every one or two months. Once yet another update is posted, vocal backers react to it in the comments section and, this time not burdened by the daunting task of looking through hundreds of identical comments, they are able to discuss their concerns about the creator with each other.

Team behind StoneTether estimated the delivery dates to be April – May 2015, but, as the deadline approached, backed out of that promise. This is not unusual even for crowdfunding projects whose creators are diligent and successful in the long term.

With 'noisy' uninsightful comments out of the way, the intensity of trust sentiments expressed in the spikes of discussion around the updates increased dramatically. In Figure 13 we can observe that trusting comments comprised around 10 – 15 % of the total amount of daily posts on numerous occasions. However, much more sizeable is increase in doubtful comments: according to the classifier, there are more than two weeks-worth of days when 50% or more of the comments posted were casting a shadow of suspicion on StoneTether's feasibility and its creators intentions to deliver a product.

Looking through the comments, I noticed that a lot of the doubting ones had a tonality different from that found in iFind. Specifically, sceptical backers of StoneTether often complained not about a newly posted update, but instead mourned their past commitment to the project. In other words, they often used past tense, as, having discussed everything among themselves, they now realised how suspicious StoneTether's proposition looked from the very start. This tonality is illustrated by the comment in Figure 14.

I explain this use of past tense in the following way. After being able to communicate via the comments section, sceptical backers realised that their combined intelligence and expertise would have allowed them to unearth the true nature of the project before the end of the campaign, but they were unable to do so due to the comment section being littered with notifications like the one seen in Figure 12. This attitude persisted until the end of the campaign.

Finally, let us inspect Figure 15 to try to understand the relationship between dynamics of daily net pledges and trusting and doubtful sentiments expressed throughout the campaign period.

Figure 14: StoneTether Comment 3

By: Xavier On: 05.05.2015

Guys,[1] face it, **you've all been had**[2]. For me, it's fortunately just a dollar. For most, it will be a lot more. **They have yet to show one single piece of electronics**[3]. The only "prove" they showed you in the past few months were pictures of a couple of 3D printed housings. They kept you all on a string with beta testers, NDA's, etc. That's just buying time. Also, they provided offer over offer to get more money in their pocket: free devices for sharing their page, 20% off offers for pre-orders (prepaid of course) that got extended over and over again. Looks can be deceiving, but it sure looks like they're cashing, big time! The longer you all wait, the less chance there is to ever see any of your money back. Really, **this project has had all the characteristics of a fraudulent project from the get-go**[4]. Loads of people backed out at the last moment, as did I (well, save a single dollar). I'll keep following it and **really hope I'm wrong**[5]. Good luck!

[1] Inter-backer communication
[2, 4] Past mistakes
[3] Suspicion, caution, doubt
[5] Benefit of the doubt

While discussing the previous case, I have proposed that polarity across the sentiment dimension of trust might have a short-term effect on the funding decisions of the 'silent majority' of the backers. The inflow of funding for StoneTether does not contradict this supposition: the overwhelming neutrality of comments during the fundraising period is matched with a relatively stable funding trend: after the initial surge, daily net pledges amounts kept fluctuating around the $7000–8000 mark until the last days of the campaign, where, in agreement with evidence from (Kuppuswamy & Bayus, 2015).

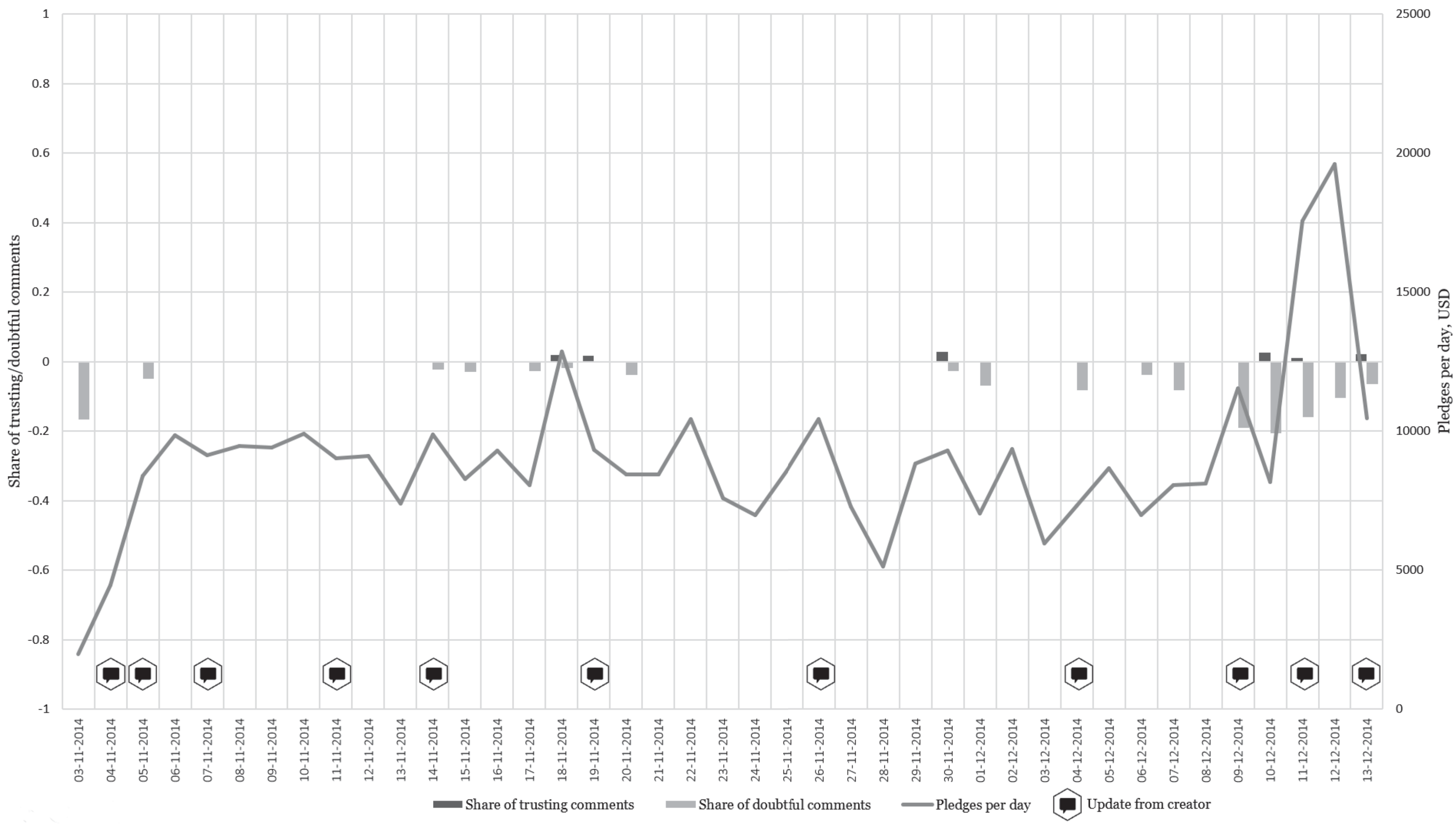

Figure 15: Comparison of trust dynamics between 'vocal minority' and 'silent majority' in StoneTether campaign

7 Findings and discussion

In this section I link observations made during work on this thesis with theories specified in Section 4.

7.1 Monitoring by backers

Out of all the codes devised during examination of the discussions in the comments sections, 15 have been of particular value for answering the research question of this paper. I attempted to decode observations containing these codes to ”decipher [their] core meaning” (Saldaña, 2015) and consolidate this meaning by gradually moving to higher levels of abstraction – first to categories and then to theoretical constructs.

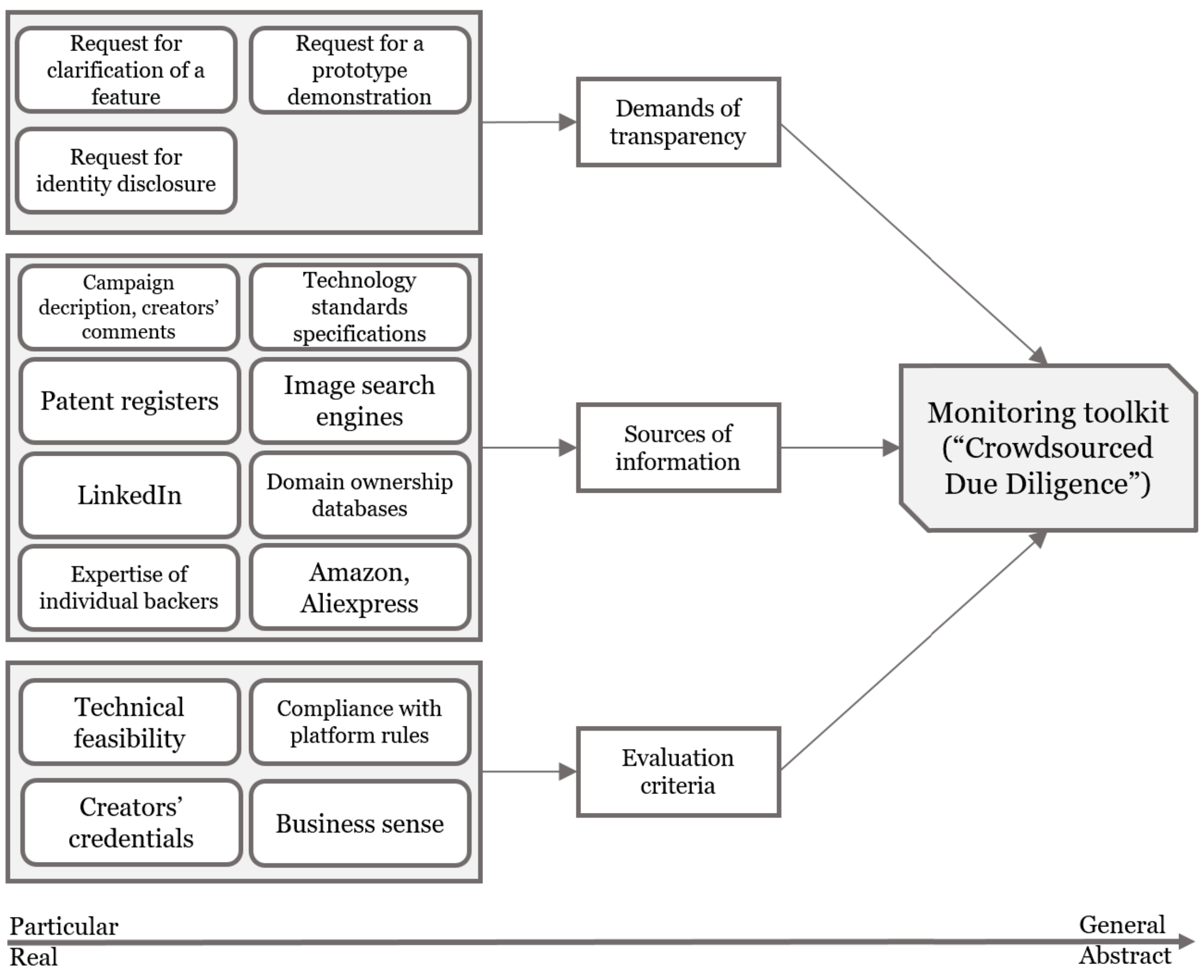

Figure 16: From codes to theory

The vocal minority of the crowdfunding community seems to be able to often identify irresponsible projects due to interaction of three elements: demand of transparency, information sources, and interpretative lenses. Elusive explanation of underlying technology of a product will prompt backers to request detailed technical explanation and/or video demonstrating a working prototype.

This creates pressure on secretive creators to share more information about their project or be considered untrustworthy. Any such new piece of information is then cross-referenced by the community with expert knowledge of individual backers and/or relevant information obtainable through Internet. All the while the project as a whole is being analysed by the backers through the prism of one or all of the following: technical prowess, sound business model, creators' track record, and compliance with Kickstarter guidelines for new projects.

7.2 Wisdom of the Crowd or Responsibility of the Platform?

7.2.1 Dynamics within the Crowd

I found evidence that the 'crowd' that is the formation of backers emerging around a particular project is by no means homogeneous. Instead, it seems to feature two distinct and somewhat disconnected groups: the silent majority and the vocal minority of backers. These two groups are fundamentally different in the degree of their involvement in a project.

The vocal minority are the backers that participate in the discussion that occurs in the comments section of hardware crowdfunding projects. They are often willing to make considerable effort in order to understand the science behind a product. This does not necessarily occurs due to their desire to conduct a 'crowdsourced due diligence' – sometimes they seem to be simply curious-minded and only later, not having received a satisfactory response from the creator, start questioning feasibility of the project.

The silent minority are all other backers – around 80–90%, based on the data collected – that support a project, but do not leave any comments on the project's webpage.

I have studied changes occurring over time in the attitude of the vocal minority based on the amount of trusting and doubtful comments they post. I have also tried to investigate similar changes in the attitude of the silent majority. This was not a trivial task, as these 'silent' backers do not leave a textual trace behind. I used the net amount of pledges in any given day as a proxy for opinion of silent majority towards a project.

Based on these two dynamics, I conclude that the silent majority of the backers employ heuristics of rational herding in their funding decisions. In addition to inferring a project's legitimacy from prior funding decisions made by other backers, backers of hardware projects on Kickstarter also seem to scan the comments section of a project for signs of project's trustworthiness.

However, their depth of scanning is fairly limited: I have observed that net amount of money pledged per day decreases if the share of doubting comments posted in the last one to two days is large. I have not been able to identify such response to less recent doubtful comments.

By collectively brainstorming and pooling their competences doubting backers might be able to achieve synergies that make assessing a project's trustworthiness easier. By joining forces and recruiting more backers into the doubting group they increase their chances of gaining critical mass required for a platform or, potentially, an outside regulator to take action.

7.2.2 Role of the Platform

I conclude that the role of the platform is two-fold. First, as I previously indicated, response of the majority of the backers to suspicion expressed by the active minority in the comments seems to be short-term. This means that often signals of danger sent by the active backers will not be able to prevent a project from getting funded, if these signals get pushed back by new comments that are not as doubtful.

Therefore, the platform has to provide a lever that active backers can use to influence the outcome of the campaign beside the comments section. The ability of any backer to report a project on Kickstarter seems to effectively serve just that purpose, increasing the chances that a successful collective investigative effort by the active minority of backers will prevent opportunistic projects from receiving funding.

Second, backers' ability to have meaningful interaction between each other seems to be integral to successfully conducting "crowdsourced due diligence". As the case of StoneTether indicates, when efficient inter-backer communication is hampered (e.g. when an overwhelming amount of uninsightful comments drowns out critical discussion or makes it impossible in the first place), backers may be unable to efficiently eliminate information asymmetry.

7.3 Publics and communities

Drawing an analogy between established brands and startups that launch campaigns on reward-based crowdfunding platforms, one could take interest in understanding which concept is more closely related to formations of backers around crowdfunding projects. Could it be that on Kickstarter not communities are built, but 'project publics', shapeless masses of backers that have little to no interest in interacting between each other?

Analysis of comments posted by backers in the discussion sections of Kickstarter projects suggests that aggregations of people around crowdfunding projects share qualities that are prescribed to communities (Muniz & O'guinn, 2001) and publics (Arvidsson & Caliandro, 2016).

Much like publics, formations of backers do not spawn spontaneously, but emerge around media devices – comment sections on Kickstarter – and events – crowdfunding campaigns and updates posted by creators. I found that, chronologically, updates posted during and especially after crowdfunding campaign are often surrounded by 'islands' of backers activity. When no communication is seen from the creator's side, activity in the backers formation diminishes or even comes to a full stop.

However, I also discovered that, like communities, crowdfunding aggregations of backers are, under certain conditions, highly interactive and exhibit a strong sense of moral responsibility to each other and Kickstarter user base in its entirety.

I further assume, based on my findings, that the structure of the formations of backers is fluid and can dynamically shift between the state resembling that of a public and the state closer to that of a community (or any intermediary positions along that axis).

These shifts, I hypothesise, occur as a response to the behaviour of the creator and the communication environment that surrounds backers. I assume that the interaction between backers strengthens as the amount of signs that a project is opportunistic grows larger. Based on the projects I reviewed, I posit that once a backer starts doubting a project's feasibility or creators' diligence, she starts looking for like-minded contributors in the comments section.

When there is little indication that the creator is opportunistic, backer formations show little inter-member communication. Instead, most backers directly address the creator with wishes of good luck, questions, suggestions for improvement of the product, and even friendly banter.

Likewise, when inter-backer communication is impossible or difficult (as, I have shown, it was in the case of StoneTether), backer formations resemble publics.

Yet, given enough evidence that the creator is opportunistic, backer formations rapidly develop inter-member connections, shifting their focus from outwards (on the creator) to inwards (on other backers). In this state, backers also exhibit a pronounced sense of responsibility for fellow backers.

7.4 Strategic Implications

It is likely that Kickstarter would not be able to significantly increase its proactive policing efforts via stricter moderation of projects that are admitted to the platform. First, it is likely not viable financially, as monitoring is often costly (Tabarrok & Cowen, 2015; Stiglitz, 2008). Second, in a way, it would go against the very principle of openness to innovation the platform was designed around and would likely scare some creators off.

However, backers themselves seem to be able to identify opportunistic creators and communicate their suspicions to Kickstarter, which then only has to deal with a handful of cases reported by multiple backers. Backers only seem to fail at eliminating information asymmetry in the most subtle of cases and when the platform for inter-backer communication is contaminated by an overwhelming amount of homogeneous comments directed at the creator and not at contributing to a meaningful discussion.

I therefore propose that a forum-based structure of the comments section might be a welcome change that addresses this problem. If backers in the comments section of a project were able to either create discussion threads themselves or choose to comment in one of the pre-defined threads, it would arguably make their communication and monitoring/investigative efforts more efficient. This way the possibility of several lines of dialogue interfering with each other to the point where one of the discussions is completely drowned out or prevented from ever fully developing would be near zero, as each topic for discussion would have its own designated place.

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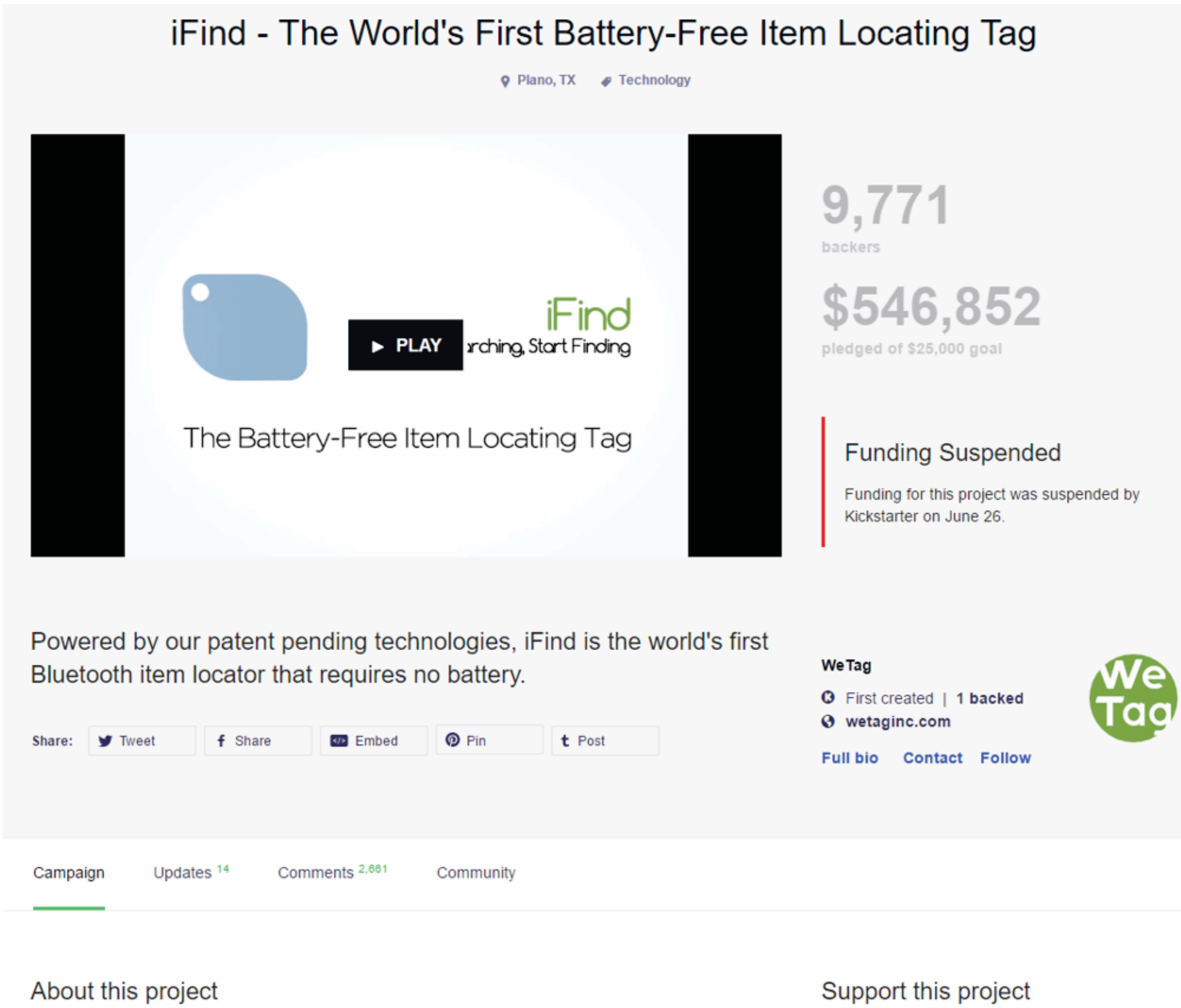
Appendices

A Project's Home Page Structure



[Textual and visual project description] [List of rewards available for backers]

B Web-scraper code

```
from dateutil.parser import parse
import time
from selenium import webdriver
from selenium.common.exceptions import NoSuchElementException  #
    You can't feed the except clause a specific
# exception unless you import it from the library that summons
   it, dummy.
import warnings
with warnings.catch_warnings():  # Oh wow. So this line and the
   next one are a workaround
                                 # just so DeprecationWarning
                                    doesn't appear.
    warnings.filterwarnings("ignore",category=DeprecationWarning
       )
    import xlwt

spreadsheet = input('Name of the .xls spreadsheet: \n')
while True:
    machine = input('d for desktop, l for laptop: \n')
    if machine == 'd':
        workbook = xlwt.Workbook('E:/Dropbox/NHH/Spring 2016/
           Master Thesis/Data/'+spreadsheet+'.xls')
        break
    elif machine == 'l':
        workbook = xlwt.Workbook('D:/Dropbox/NHH/Spring 2016/
           Master Thesis/Data/'+spreadsheet+'.xls')
        break
    else:
        print('Incorrect input, let\'s try again')
        continue
sheet = workbook.add_sheet(str(spreadsheet))

link = input('URL with the comment section for project to be
   inspected: \n')
browser = webdriver.Chrome()
browser.get(str(link))

while True:
    try:
        browser.find_element_by_class_name('older_comments').
           click()
        time.sleep(1)
    except:
        break
```

```
comments = browser.find_elements_by_class_name('clearfix')  # !
    Commonly, a HTML element s class attribute
# has multiple values, like <a href="back.html" class="btn btn-
    default">Cancel</a>. You may only specify ONE
# of them for Selenium

sheet.write(0, 0, "Comment")
sheet.write(0, 1, "Author")
sheet.write(0, 2, "Type of commenter")
sheet.write(0, 3, "No. of projects created")
sheet.write(0, 4, "Superbacker")
sheet.write(0, 5, "Long date")
sheet.write(0, 6, "Short date")

count = 1

for com in comments:
    allTextEls = com.find_elements_by_css_selector("p")
    allText = []
    for i in range(len(allTextEls)):
        allText.append(allTextEls[i].text)
    sheet.write(count, 0, ' '.join(allText))
    sheet.write(count, 1, str(com.find_element_by_class_name("
        author").text))
    try: # Hah, even in line with official Python
        recommendations! (EAFP, aka
        # Easier to ask for forgiveness than permission)
        com.find_element_by_class_name("creator-badge")
        sheet.write(count, 2, "Creator")
        sheet.write(count, 3, 1)
    except NoSuchElementException:
        try:
            com.find_element_by_class_name("repeat-creator-badge
                ")
            sheet.write(count, 2, "Creator")
            sheet.write(
                count, 3, int(
                    ''.join(list(filter(str.isdigit, com.
                        find_element_by_class_name("repeat-
                        creator-badge").text)))
                )  # filters symbols in a string, creates a list
                    of all digits in this string,
                # then joins the list omitting spaces (hence '')
            )
        except NoSuchElementException:
            sheet.write(count, 2, "Backer")
    try:
        com.find_element_by_class_name("superbacker-badge")
```

```
            #superBacker = 1
            sheet.write(count, 4, 1)
        except NoSuchElementException:
            sheet.write(count, 4, 0)

        longDate = parse(com.find_element_by_css_selector("data").
           get_attribute("data-value"))
        sheet.write(count, 5, str(longDate)[:19])
        shortDate = str(longDate).split()[0]
        sheet.write(count, 6, str(shortDate))
        print(count)
        count += 1

#print(count)

browser.close()
if machine == "d":
    workbook.save('E:/Dropbox/NHH/Spring 2016/Master Thesis/Data
       /'+str(spreadsheet)+".xls")
else:
    workbook.save('D:/Dropbox/NHH/Spring 2016/Master Thesis/Data
       /'+str(spreadsheet)+".xls")

#input('Press any button to exit the program ')

# for elem in wait(browser, "span[class='main clearfix p13 m13
    ']"):
#     print(elem)
# datetime.datetime.fromtimestamp(


# //*[@id="comment-12996409"]/div/div[2]/p
# when searching by XPATH: '//div[@class="???"]'
# elem = browser.find_elements_by_css_selector("span[class='main
    clearfix p13 m13']")
# !!! elem = browser.find_elements_by_css_selector("p") -- this
    finds all comments, but also other 'p' elements

# "span[class='main clearfix p13 m13']"
# 'main clearfix p13 m13'
# ".//p[@class='comment-inner']"  # why doesn't it work?
# (see http://stackoverflow.com/questions/14049983/selenium-
    webdriver-finding-an-element-in-a-sub-element)
```

C Classifier Code

```
import pickle
import re
import xlrd
import xlwt
import nltk
import string
from nltk import bigrams


def save_classifier(classifier):
    id = input('Enter ID for the classifier you want to store: ')
    print('.')
    f = open(id+'.pickle', 'wb')
    pickle.dump(classifier, f)
    f.close()


def load_classifier(id):
    f = open(id+'.pickle', 'rb')
    classifier = pickle.load(f)
    f.close()
    return classifier


def save_test_coms(test_coms):
    id = input('Enter ID for the test comments you want to store:
        ')
    print('.')
    f = open(id+'.pickle', 'wb')
    pickle.dump(test_coms, f)
    f.close()


def load_test_coms(id):
    f = open(id+'.pickle', 'rb')
    test_coms = pickle.load(f)
    f.close()
    return test_coms



def getEmptyWordList(SWListFileName):
     emptyWords = []
     # emptyWords.append('URL') # I'm not sure about this one.
     # I think it might be useful to keep track of URLs -- maybe
```

```
        # they are most often used
    # to inform about some shady activities.
    txt = open(SWListFileName, 'r')
    line = txt.readline()
    while line:
        word = line.strip()
        emptyWords.append(word)
        line = txt.readline()
    txt.close()
    return emptyWords


emptyWords = getEmptyWordList('StopWordsEdit2.txt')

shuffleBook = input('Enter shuffle number of the training and
    testing set (X=0...4 in LMC+Rock_upd_X.xlsx): ')
print('.')

bookTrain = xlrd.open_workbook('LMC+Rock_upd_'+shuffleBook+'.
    xlsx')

while True:
    full_test = input('Do you want to train on 70% or 100%?
        (7/1) ')
    if full_test == '7':
        sheetD = bookTrain.sheet_by_index(0)
        break
    elif full_test == '1':
        sheetD = bookTrain.sheet_by_index(4)
        break
    else:
        print('Incorrect input, try again.')

sheet_testD = bookTrain.sheet_by_index(1)


commentsD = []  # (future) feature vector. nested list
comments_testD = []

exclude = set(string.punctuation)

exclude2 = ['0','1','2','3','4','5','6','7','8','9','+','-','=',
    '\'','\"','.',',','!','?','/','\\','*','(',')','[',']',':',';
    ','$','#','&','%','^']


def commProcessor(comment):
    comment = re.sub('((www\.[^\s]+)|(https?://[^\s]+))','URL',
```

```
        comment)  # Convert www.* or https?://* to URL
    comment = re.sub('This comment has been removed by Kickstarter.', '', comment)  # better ignore these altogether
    for char in exclude2:
        comment = comment.replace(char, ' ')
    shortword = re.compile(r'\W*\b\w{1,1}\b')  # This line & the next remove all n-character words (n is specified in the curly brackets)
    comment = shortword.sub(' ', comment)
    comment = re.sub('[\s]+', ' ', comment).lower()  # Removes additional white spaces, enforces lower case
    return comment


def getFeatureVectorU(comm):  # works exactly like nltk.word_tokenize(text), except for the stop words part
    featureVector = []
    words = comm.split()  # split comment into separate words
    for word in words:
        if word not in emptyWords:
            if word.startswith('@'):
                pass
            else:
                featureVector.append(word)
    return featureVector


def getFeatureVectorB(comm):
    featureVector = []
    words = comm.split()  # split comment into separate words
    for word in words:
        if word not in emptyWords:
            if word.startswith('@'):
                pass
            else:
                featureVector.append(word)
    return list(bigrams(featureVector))


def getFeatureVectorC(comm):
    featureVector = []
    words = comm.split()  # split comment into separate words
    for word in words:
        if word not in emptyWords:
            if word.startswith('@'):
                pass
            else:
```

```
                featureVector.append(word)
    bigramFVector = list(bigrams(featureVector))
    finalFVector = featureVector + bigramFVector
    return finalFVector

while True:
    ngram = input('Enter U for unigrams, B for bigrams, C for 
      combo: ').lower()
    print('.')

    if ngram == 'u':
        for row in range(sheetD.nrows):
            comm_textD = sheetD.cell(row,0).value
            sentimentD = sheetD.cell(row,1).value
            formattedCommD = commProcessor(comm_textD)
            featureVectorD = getFeatureVectorU(formattedCommD)
            commentsD.append((featureVectorD, sentimentD))

        for row in range(sheet_testD.nrows):
            comm_text_testD = sheet_testD.cell(row,0).value
            sentiment_testD = sheet_testD.cell(row,1).value
            formattedComm_testD = commProcessor(comm_text_testD)
            featureVector_testD = getFeatureVectorU(
              formattedComm_testD)
            comments_testD.append((featureVector_testD,
              sentiment_testD))
        break

    elif ngram == 'b':
        for row in range(sheetD.nrows):
            comm_textD = sheetD.cell(row,0).value
            sentimentD = sheetD.cell(row,1).value
            formattedCommD = commProcessor(comm_textD)
            featureVectorD = getFeatureVectorB(formattedCommD)
            commentsD.append((featureVectorD, sentimentD))

        for row in range(sheet_testD.nrows):
            comm_text_testD = sheet_testD.cell(row,0).value
            sentiment_testD = sheet_testD.cell(row,1).value
            formattedComm_testD = commProcessor(comm_text_testD)
            featureVector_testD = getFeatureVectorB(
              formattedComm_testD)
            comments_testD.append((featureVector_testD,
              sentiment_testD))
        break

    elif ngram == 'c':
        for row in range(sheetD.nrows):
```

```
            comm_textD = sheetD.cell(row,0).value
            sentimentD = sheetD.cell(row,1).value
            formattedCommD = commProcessor(comm_textD)
            featureVectorD = getFeatureVectorC(formattedCommD)
            commentsD.append((featureVectorD, sentimentD))

        for row in range(sheet_testD.nrows):
            comm_text_testD = sheet_testD.cell(row,0).value
            sentiment_testD = sheet_testD.cell(row,1).value
            formattedComm_testD = commProcessor(comm_text_testD)
            featureVector_testD = getFeatureVectorC(
               formattedComm_testD)
            comments_testD.append((featureVector_testD,
               sentiment_testD))
        break
    else:
        print('Incorrect input, try again.')


featureListD = []
featureList_testD = []

for comment in commentsD:  # feature list for Doubt dimension
    sub_comments = comment[0]
    for word in sub_comments:
       featureListD.append(word)

for comment in comments_testD:  # testing accuracy of Doubt
   dimension
    sub_comments = comment[0]
    for word in sub_comments:
        featureList_testD.append(word)




def extract_featuresD(comment):
    comment_words = set(comment)
    features = {}
    for word in featureListD:
        features[word] = (word in comment_words)
    return features

def extract_features_testD(comment):
    comment_words = set(comment)
    features = {}
    for word in featureList_testD:
        features[word] = (word in comment_words)
```

```
    return features


featureListD = set(featureListD)  # removes featureList duplicates
featureList_testD = set(featureList_testD)




while True:
    current_or_saved_tc = input('Enter C if you want to use current test comments set or L to load a saved one. ').lower()
    print('.')
    if current_or_saved_tc == 'c':
        training_set = nltk.classify.util.apply_features(extract_featuresD, commentsD)
        test_set = nltk.classify.util.apply_features(extract_features_testD, comments_testD)  # for testing accuracy
        offer_to_save_test = input('Do you want to save the test comments? (Y/N) ').lower()
        if offer_to_save_test == 'y':
            save_test_coms(commentsD)
        else:
            print('Current test comments set will not be saved. ')
            print('.')
        break
    elif current_or_saved_tc == 'l':
        tc_id = input('Enter ID of the test comment set that you want to load. ')
        training_set = nltk.classify.util.apply_features(extract_featuresD, commentsD)
        test_set = nltk.classify.util.apply_features(extract_features_testD, load_test_coms(tc_id))  # for testing accuracy
        break
    else:
        print('Incorrect input, try again.')




while True:  # this loop loads or creates a new classifier
    new_or_saved_class = input('Enter N if you want to train a 
```

```
        new classifier or L to load a saved one. ').lower()
    print('.')
    if new_or_saved_class == 'n':
        newClassifierType = input('Enter NB for Naive Bayes or ME for Maximum Entropy. ').lower()
        print('.')
        if newClassifierType == 'nb':
            classifier = nltk.NaiveBayesClassifier.train(training_set)
        elif newClassifierType == 'me':
            iterations = int(input('Specify desired # of iterations: '))
            print('.')
            classifier = nltk.classify.maxent.MaxentClassifier.train(training_set, algorithm='GIS', max_iter=iterations)
        offer_to_save_class = input('Do you want to save the classifier? (Y/N) ').lower()
        print('.')
        if offer_to_save_class == 'y':
            save_classifier(classifier)
        else:
            print('Current classifier will not be saved. ')
        break

    elif new_or_saved_class == 'l':
        loaded_class_id = input('Enter ID of the classifier that you want to load. ')
        classifier = load_classifier(loaded_class_id)
        break

    else:
        print('Incorrect input, try again.')



if new_or_saved_class == 'l':  # prints out accuracy
    print('Accuracy (Doubt dimension, '+loaded_class_id+' type) :', nltk.classify.util.accuracy(classifier, test_set))
else:
    print('Accuracy (Doubt dimension, '+newClassifierType+' type) :', nltk.classify.util.accuracy(classifier, test_set))


try:  # Attempts to print out 15 most informative features, if less are found, raises an exception.
    print(classifier.show_most_informative_features(15))
    print('.')
```

```
        print('.')
        print('.')
    except:
        print('The exception branch was triggered.')
        print('.')
        print('.')
        print('.')


while True:
    offer_to_apply_classifier = input('Do you want to apply
        current classifier? (Y/N) ').lower()
    print('.')
    if offer_to_apply_classifier == 'y':
        bookClassifyname = input('Enter (full) name of the
            workbook with comments to be classified: ')
        bookClassify = xlrd.open_workbook(bookClassifyname)
        sheetToAnalyse = bookClassify.sheet_by_index(0)

        workbookClassifiedname = input('Enter desired name of
            the workbook with classified comments: ')
        workbookClassified = xlwt.Workbook(
            workbookClassifiedname+'.xls')
        sheetClassified = workbookClassified.add_sheet('
            Classified_comments')

        sheetClassified.write(0, 0, "Original comment")
        sheetClassified.write(0, 1, "Processed comment")
        sheetClassified.write(0, 2, "Sentiment (D)")
        sheetClassified.write(0, 3, "Sentiment (E)")
        sheetClassified.write(0, 4, "Superbacker")
        sheetClassified.write(0, 5, "Long date")
        sheetClassified.write(0, 6, "Short date")
      # count = 1
        total_rows = sheetToAnalyse.nrows

        for row in range(sheetToAnalyse.nrows):  # Classifies
            xls/xlsx file and outputs to xls
            if row == 0:  # Skips the header
                continue
            else:
                comm_textToAnalyse = sheetToAnalyse.cell(row, 0)
                    .value
                processedComm = commProcessor(comm_textToAnalyse
                    )
                superBacker = sheetToAnalyse.cell(row, 4).value
                longDate = sheetToAnalyse.cell(row, 5).value
                shortDate = sheetToAnalyse.cell(row, 6).value
```

```
                sheetClassified.write(row, 0, comm_textToAnalyse
                    )
                sheetClassified.write(row, 1, processedComm)
                if ngram == 'u':
                    sheetClassified.write(row, 2, classifier.
                        classify(extract_featuresD(
                        getFeatureVectorU(processedComm))))
                elif ngram == 'b':
                    sheetClassified.write(row, 2, classifier.
                        classify(extract_featuresD(
                        getFeatureVectorB(processedComm))))
                else:
                    sheetClassified.write(row, 2, classifier.
                        classify(extract_featuresD(
                        getFeatureVectorC(processedComm))))
                sheetClassified.write(row, 4, superBacker)
                sheetClassified.write(row, 5, longDate)
                sheetClassified.write(row, 6, shortDate)
                if row % 200 == 0:
                    print(int(row/total_rows*100),'%')

        workbookClassified.save(workbookClassifiedname+'.xls')
        print('Workbook created successfully.')
        print('.')
        print('.')
        print('.')
        input('Press enter to exit.')
        input('One more time just to make sure you\'re not a cat
            :)')
        break

    elif offer_to_apply_classifier == 'n':
        input('Press enter to exit.')
        break

    else:
        print('Incorrect input, try again.')
```

D Encoding of Rich Comments

NB: For a full list of encoded comments kindly follow this link:

http://tinyurl.com/z8a36m4

Figure D.1: iFind Comment 1

By: Patrick On: 16.05.2014
@WeTag **I'm confused**[1] by the lack of specifics over the "no battery" feature. **I understand that you will not detail what's inside and how it exactly work as it's patent pending**[2], **but here are a couple of straightforward questions**[3] that would be interesting to address for backers and their future everyday use of the product: - **Give us one precise example of a suitable source**[4] easily available in everyday life able to charge the iFind. - With this precise source, how long would it take take to charge the "power bank" from 0 to 100% capacity. - Once the "power bank" is at 100%, introducing the device to an hypothetic environment without any "source" available, how long would the device work only using its internal power bank. Thanks!

[1] Confusion
[2] Showing understanding
[3] Wants to compromise
[4] Request for clarification of a feature

Figure D.2: iFind Comment 2

By: Abdul Halim Mat Ali On: 17.05.2014
If this technology is really true[1], I am wondering **why Wetag has not approached** or been approached by the **big Phone manufacturer**[2] companies. Wetag **will definitely make a lot of money producing smart phone batteries rather than using the kickstarter approach**[3].

[1] Doubt, caution, suspicion
[2, 3] Business sense

Figure D.3: iFind Comment 3

By: Krobelius On: 22.05.2014
KS guidelines[1]: "No product simulations" & " Projects must show details (photos, videos, sketches) of their progress so far, along with a prototype demonstrating the product's current functionality" The video seems to feature a simulation. Are the tags shown operational or just plastic models? **No current working prototype is shown.**[2] Please comply with these guidelines.

[1] Compliance with Kickstarter rules
[2] Request for a prototype demonstration

Figure D.4: iFind Comment 4

By: Vladimir On: 24.06.2014
@Dr Paul McArthur, the Creator Just **one more lie on your big stinking pile of lies**[1]. **Update #14 says**[2] "I have not even created a LinkedIn profile". Well Paul, maybe your girlfriend created it but **this is your profile http://www.linkedin.com/in/mcarthurpaul**[3] . Almost everything can be independently verified. **You are obviously hiding much more**[4] than your intellectual property.

[1] Offensive language
[2] Referring to campaign description/creator's comments
[3] Referring to LinkedIn
[4] Doubt, caution, suspicion

Figure D.5: iFind Comment 5

By: Vladimir On: 03.06.2014
"@WeTag Since **your company has no track record**[1], **I would also like to understand the qualifications of your president**[2] - Wanda Klimek. Specifically, what is her education and most recent employer?"

[1] Referring to creators' credentials
[2] Request for identity confirmation

Figure D.6: iFind Comment 6

By: Huckleberry On: 02.06.2014
Hi All, **Thanks for publishing the technical info!**[1] The efficiency and usage costs are reasonable, however **theres a fatal problem with the assumption in Figure 1**[2]: Note that when the input power is around +10dBm, which is typical for home WiFi A very strong wifi signal is about -60dBm (5 bars) and a weak one is -110dBm (1 bar.) Your +10dBm assumption is more than *a million* times stronger than a real signal giving 5 bars! **Ive been a radio-frequency engineer for 23 years**[3], but dont take my word for this. Heres a good **writeup explaining real signal strength: http://note19.com/2010/07/04/mapping-cellular-signal-strength-to-5-bars/**[4] The second paragraph is key to understanding the massive problem here. Bottom Line **The Tag as described will never come close to working off wifi signals**[5]. Real, credible home wifi strength is more than a million times weaker than The +10dBm assumption in the WeTag tech docs. There's plenty of sources that confirm real-world signal strengths. The Tag will require a battery or some other substantial source of replaceable power to actually work. Wifi devices need those sophisticated antennas and high gain amplifiers for a reason... (2 bars is a *millionth* of a *millionth* of a watt!)

[1] Referring to campaign description and creators' comments
[2, 5] Technical feasibility
[3] Expertise of individual backers
[4] Technology standards specifications

Figure D.7: iFind Comment 7

By: Lilu On: 18.06.2014
I have read Hackaday. Drill down to Diego Spinola's comment dated May 22 at 12:22 am. Very interesting background info on the WeTag gang. **Anonymous domain registration**[1], nobody lives in Texas, not really a PhD candidate, no links to any research at all. **Nothing about any of the people listed by WeTag appears to be able to be independently verified**[2].

[1] Referring to domain ownership
[2] Creators' credentials

Figure D.8: iFind Comment 8

By: Schopin On: 19.06.2014

@Len re:[1]"The only item in the public domain is one unrelated patent granted for Paul McArthur." That remark triggered the googler in me. However, it is not true; under that name **Google did find a couple of patents related to locator systems, see: https://www.google.com/search e.g.: http://www.google.com/patents/US6788199**[2] (BTW: **I couldn't find much info on Paul or on his involvement in all the companies mentioned.**[3] Try to Google them yourself. As for the university of Utah I did find references to his name on a patent regarding fluid levels, but not much else). @Yuan Song: You are the creator of the WeTag project on Kickstarter. You are a photographer and I assume also the creator of the pictures on the KS pages as well as the WeTag website (Google couldn't find ObjectBox Studio). **Perhaps you can shed some light by posting a picture of the WeTag team?**[4] A picture of the team is quite normal on KS and I cannot imagine that as a photographer you haven't taken several of them while they were working at the office, building or testing the prototypes; so it must be a small effort to upload some pictures. (BTW. On your personal website your photo's are more revealing and I don't understand the obfuscation of non-sensitive materials in this project) **I really hope this project is real**[5]. **I'm looking forward to clarifications**[6] that will settle my mind."

[1] Inter-backer communication
[2] Referring to a patent register
[3] Creators' credentials
[4] Request for identity confirmation
[5] Faith
[6] Doubt, caution, suspicion

Figure D.9: iFind Comment 9

By: David On: 02.06.2014

Guys can we chill out for a second[1]. There's about a month left of funding and **let's give them some more time to prove to us it works**[2] rather then a bunch of wanna be electrical engineers using generic perfect world equations to prove that this team that has done years of work and research are total wrong and lying. @creator **Still love the look and idea**[3] and **I'm taking your word for it**[4]. **Get us a video of a working prototype**[5] with no editing to show the true abilities of the iFind.

[1] Inter-backer communication
[2] "Benefit of the doubt"
[3] Approval
[4] Faith
[5] Request for a prototype demonstration

Figure D.10: iFind Comment 2

By: Don On: 16.05.2014
Nice.[1] **I never knew that one would have enough energy in energy harvesting circuits to drive a BLE radio!!!**[2] Does the app show available charge in the finder? How long can the finder work if I put it inside an anti-em static bag ? what is the charge decay rate? So I can't use this in my RFID blocking wallet then ? **Since you say you don't have battery I am assuming you have a ultra capacitor or super capacitor?**[3] Would it charge if I put it on a Qi charger plate? What will happen ? **What is the broadcast rate of the BLE signal?**[4] How loud is the beep in dB?

[1] Approval
[2] Surprised at feasibility
[3, 4] Request for clarification of a feature

Figure D.11: iFind Comment 10

By: Brian Bokoske On: 16.05.2014
A quick question - **I'm a little confused**[1] about the ultra low quiescent current mode. **Does the rope mode where the tag tells you if you wander too far away from it**[2] always work or is it disabled when the tag goes into its "sleep mode state?"

[1] Confusion
[2] Request for clarification of a feature

Figure D.12: iFind Comment 11

By: Robert On: 18.05.2014

love the idea and concept[1] of this project, **but some of this stuff seems a little too good to be true**[2]. the whole **concept of this item not using batteries is not explained, except for "patent pending."the actual insides of the product are not shown**[3] whatsoever. **i need a little more bona fide before i fully commit**[4] to a project, **especially considering this is your first kickstarter, with no previous history in the community. the actual creators faces/names are not even shown on their own website**[5]. **just seems a little too good to be true**[6].

[1] Approval
[2, 6] Doubt, caution, suspicion
[3] Referring to campaign description/creator's comments
[4] Request for a feature clarification; request for a prototype demonstration
[5] Creators' credentials

Figure D.13: StoneTether Comment 1

By: Frank On: 04.11.2014

@Creator. **Can you explain**[1] to us **technically**[2], however by antenna and a special firmware, you can achieve 500 feet range and in between houses and walls? Most bluetooth tracker can't even work with 20 meters in between wall. So, **how can an in-built antenna improve it?**[3]

[1] Request for clarification of a feature
[2] Technical feasibility
[3] Doubt, caution, suspicion

Figure D.14: StoneTether Comment 2

By: Ghost On: 04.11.2014

Backed and shared[1] on my Facebook!

[1] Uninsightful

Figure D.15: StoneTether Comment 3

By: Apparition On: 04.11.2014
Great technology![1] **I have backed and shared StoneTether**[2] via Facebook or Twitter

[3] Faith
[2] Uninsightful

Figure D.16: StoneTether Comment 4

By: Quarterback On: 08.08.2015
Alright folks,[1] enough is enough. We're taking action against Del Marth. If Kickstarter won't do anything, I'm sure the State of California will. I've gone ahead and started the process. - I looked up the registration information for Del Marth LLC, and did some additional research: Del Marth LLC - State of California Entity Number 201421210292 Filed: 07/30/2014 - Registrant: **Ehrien Marth 916-543-3735 2159 Red Setter RD Rocklin, CA. (This appears to be a residential address and not a commercial address) Personal Profiles: LinkedIn: https://www.linkedin.com/pub/ehrien-marth/23/621/297** [2] Facebook: https://www.facebook.com/ehrien.marth Twitter: https://twitter.com/ehrienm - Agent for Service of Process: ANTHONY LANGE 9768 Swan Lake DR Granite Bay CA 95746 (Again, residential address and not commercial) Personal Profiles: **LinkedIn: https://www.linkedin.com/pub/anthony-lange/a8/235/b74** [3] E-Mail: anthonywlange@gmail.com (retrieved from http://www.granitebayfc.com/Default.aspx a soccer league in his home town) - I then went ahead and filed a formal complaint with the State of California Department of Justice against Del Marth using this information. You can do the same by visiting: https://oag.ca.gov/contact/consumer-complaint-against-business-or-company - Del Marth has deceived us for too long. They have blatantly stopped communication with us, with the exception of the monthly "updates" which are just recycled content. They have stopped responding to comments. They have shown **no indication that they truly intend to ship out a product to the backers**[4]. There have been cases in the past where I class action lawsuit has forced creators to refund backers, although these guys were smart and hid themselves behind the legal wall of an LLC. **We'll either get the products in our hands, or we'll get refunds - I guarantee it.**[5] I will see this through to the end.

[1] Inter-backer communication
[2, 3] LinkedIn
[4] Suspicion, caution, doubt
[5] Sense of moral responsibility to Kickstarter community

Figure D.17: StoneTether Comment 5

By: Spartacus On: 16.03.2016
EVERYONE[1] **- Please report this to Kickstarter, Facebook, YouTube - Get the 'Click to Pre-order' button removed so other people don't potentially waste their money**[2] - this has been funded many times over and a couple years late. I can't report this to Kickstarter anymore as they have removed the function but everyone else who has not can. Del Marth can't be bothered to update us...

[1] Inter-backer communication
[2] Sense of moral responsibility to Kickstarter community

Figure D.18: StoneTether Comment 6

By: Benjamin On: 23.08.2016
Irrespective of whether or not we believe any of this[1]**, this picture is all wrong**[2]. $115k on app development for a non-existent product? $91k on marketing a product that didn't - and will never - exist. $12k on web development for a website that was rarely updated - and is STILL offering pre-orders on a non-existent product. **I'm no entrepreneur, but even I know that startups need to spend every spare cent on R&D. You are NOTHING without your product and now you are nothing. The web/app/marketing budget should have been closer to $20k.**[3] I won't argue with the patents budget, and I could just about accept the remuneration budget - had a product been forthcoming. So now we know the truth behind your self-promoted Kickstarter prowess. It's just a shame you seem to be lacking the business acumen. At least I know where I stand. Money written off.

[1] Doubt caution, suspicion
[2] Campaign decription, creators comments
[3] Business sense

Figure D.19: StoneTether Comment 7

By: Xavier On: 05.05.2015
Guys,[1] face it, **you've all been had**[2]. For me, it's fortunately just a dollar. For most, it will be a lot more. **They have yet to show one single piece of electronics**[3]. The only "prove" they showed you in the past few months were pictures of a couple of 3D printed housings. They kept you all on a string with beta testers, NDA's, etc. That's just buying time. Also, they provided offer over offer to get more money in their pocket: free devices for sharing their page, 20% off offers for pre-orders (prepaid of course) that got extended over and over again. Looks can be deceiving, but it sure looks like they're cashing, big time! The longer you all wait, the less chance there is to ever see any of your money back. Really, **this project has had all the characteristics of a fraudulent project from the get-go**[4]. Loads of people backed out at the last moment, as did I (well, save a single dollar). I'll keep following it and **really hope I'm wrong**[5]. Good luck!

[1] Inter-backer communication
[2, 4] Past mistakes
[3] Suspicion, caution, doubt
[5] Benefit of the doubt

Figure D.20: Rock Smartwatch Comment 1

By: Watson On: 04.12.2013
So according to your LinkedIn profile[1] and the profile of others in your "team". **You guys have many years of combined expertise in software and engineering. Yet it seems like you can't answer a rudimentary question like amount of RAM, resolution or battery life**[2]. These questions do not require the consul of a lawyer OR engineering guru. **If this watch has been in development since early 2012 as you claim**[3], then YOU as the project creator should have these simple facts at the back of your head. A simple FAQ would have addressed these but as it is, **this now looks like a shoddy fly-by-night project looking at a cashgrab**[4].

[1] LinkedIn
[2] Creators' credentials
[3, 4] Doubt, caution, suspicion

Figure D.21: Rock Smartwatch Comment 2

By: Dandy On: 05.12.2013
Any new backers that don't read down the comment list - read this before backing[1]. **There is evidence that this project might be a scam**[2], and until proven otherwise you should be wary. Also below is a list of the many simple questions we have been waiting days to hear answers to. The watch in this project looks and has same details as the Z3 watch by Uplay. **The creator owns no patents for the watch or the apps despite saying he does on the front page**[3]. The creator has enough of a finished product to quote us ""low prices"" of 100 bucks, but doesn't know how much RAM the watch has, even saying ridiculous things like it having 4 GB RAM. Read through the comments, several backers have worked hard to dig into this project and have found plenty to cause doubt in it's authenticity, but no proof anything Vak says is true. Next time dont take us for idiots !!

[1] Sense of moral responsibility to Kickstarter community
[2] Doubt, caution, suspicion
[3] Creators' credentials