ISCTE Business School
Department of Human Resources and Organizational Behavior

Innovation through Technology Adoption in E-commerce Retailing

João Azambuja

Thesis specially presented for the fulfillment of the degree of

Doctor in Management
Specialization in Human Resources and Organizational Behavior

Supervisor:
Professor Ralitza Nikolaeva, Assistant Professor,
Instituto Universitário de Lisboa

Co-supervisor:
Professor Luís Filipe Lages, Full Professor,
Nova School of Business and Economics - Universidade Nova de Lisboa

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Jury:

Professor Ana Passos, Associate Professor,
Instituto Universitário de Lisboa

Professor Marco Visentin, Associate Professor,
University of Bologna

Professor Henrique Manuel Caetano Duarte, Assistant Professor,
Instituto Universitário de Lisboa

Professor Luís Fructuoso Martinez, Assistant Professor,
Nova School of Business and Economics - Universidade Nova de Lisboa

Professor Ralitza Nikolaeva, Assistant Professor,
Instituto Universitário de Lisboa

Professor Luís Filipe Lages, Full Professor,
Nova School of Business and Economics - Universidade Nova de Lisboa

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to my son Diogo, my wife Sónia, and my parents

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Abstract

This thesis focus on the roles of imitation and past performance in technology adoption among a population of firms composed by e-retailers. The first study assesses the motivations behind the adoption of technology. Claiming that the predominant perception about the technology results in different shapes of the effect of prior adopters on the probability of subsequent adoption, it uses the adoption of Facebook from 2006 to 2014 for a panel composed of the largest e-retailers in the United States, to test for evidence of the motivations for the adoption. The results are consistent with social learning. The second study follows the proposal to move from the view of strategy as an antecedent of performance and looks at the impact of changes in performance to changes in strategy. It assesses if changes in performance influence the make (in-house) versus buy (outsourcing) technology sourcing mix among 14 technologies during eight years. It finds that, in the studied sample, strategic changes follow changes in performance. The third study tests if there is evidence about the reasons for adoption, either based on rational assumptions or social pressures for conformity and legitimacy, while using a technology. As perceiving the adoption as an “efficient choice” is expected to result in a larger effort to implement, the adoption by e-retailers of the social media platform Twitter was used to test this claim empirically. There is evidence of the adoption of Twitter being based on social pressures.

Keywords: innovation, technology adoption, e-commerce, imitation, social networks

Resumo

A presente tese estuda a importância da imitação e da performance prévia na adoção de tecnologia numa população de empresas de comercio eletrónico a retalho. O primeiro estudo foca-se sobre as motivações que resultam na adoção de tecnologia. Baseado no pressuposto de que a perceção predominante acerca da tecnologia resulta em diferentes efeitos do número de utilizadores na probabilidade futura de adoção, este estudo testa se este efeito é notório na adoção do Facebook por um painel de 2006 a 2014. Os resultados são consistentes com a lógica de "social learning". O segundo estudo responde à proposta de estudar o impacto das mudanças na estratégia em resultado de mudanças na performance e não apenas encarar a estratégia como um antecedente da performance. É testado se mudanças na performance influenciam o desenvolvimento interno de soluções de tecnologia em vez da sua aquisição, para um grupo de 14 tecnologias durante oito anos. No caso da amostra utilizada, os resultados apontam para a relevância do impacto da performance na definição da estratégia. O terceiro estudo testa se as razões para adoção de tecnologia, baseadas em pressupostos racionais ou na pressão social, são notórias na utilização da mesma. Uma vez que a perceção da adoção como escolha mais eficiente deverá resultar num esforço maior para a sua implementação, as duas perspetivas foram empiricamente testadas na adoção e utilização do Twitter por 1430 empresas de comercio eletrónico. Foram encontrados indícios que sustentam a adoção baseada na pressão social.

Palavras-chave: inovação, adopção de tecnologia, comércio electrónico, imitação, redes sociais

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List of Acronyms and Abbreviations

CLOGLOG complementary log-log

EU Europe

IR Internet Retailer

US United States

ZTNB zero-truncated negative binomial regression model

1. Introduction

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> "I think the high-tech industry is used to developing new things very quickly. It's the Silicon Valley way of doing business: You either move very quickly and you work hard to improve your product technology or you get destroyed by some other company. And so that's the approach that I have. I've been through many company near-death experiences, starting with [software company] Zip2 and then PayPal." Elon Musk in Ward (2012)

1.1. Overview

Innovation is key to thrive and survive in highly competitive sectors. As Elon Musk described, the "silicon valley" mindset that inspires many innovators and entrepreneurs worldwide is based on a fast pace of development and diffusion of new procedures, new technologies, and new approaches. The uncertainty and ambiguity that these agents face, demands that firms monitor and quickly respond to unexpected changes in the environment. The way they react to those changes and strategic moves from their competitors is key for their long run success. There is a long stream of research about the adoption of new technologies. However, new settings and business models continue to challenge decision makers in new and unpredictable ways, having to decide while facing highly uncertain conditions.

Although organizational scholars attend to the diffusion of innovations for decades, it remains an interesting and important topic. This subject is studied within several research traditions about organizations that started by opposing to a view based on economic rationality. One of those topics is imitation. It continues to motivate an ongoing discussion about the phenomenon with several recent studies questioning some of its earlier assumptions (Nikolaeva, 2014). Another one results from the limitations of managers to read and act upon changes in the environment (March, 2006; Lages, Mata and Griffith, 2013). Several studies continue to advocate the need for more studies linking different streams of research and population ecology has a contribution to make. Two literature reviews also urge scholars about the need for more research about imitation (Lieberman and Asaba, 2006; Ordanini, Rubera and DeFillippi, 2008). Some authors argue that, despite their differences, population ecology and neo-institutionalism can be "fruitfully combined" and, therefore "how scholars in both traditions can benefit from a closer relationship" (Haveman and David, 2008: 574). The quantitative analysis prescribed by the ecological perspective can help to assess the magnitude of the phenomenon and neo-institutional perspective may help explain why it may be optimal for some companies to engage in behaviors that are not fully supported by a pure technical rationality. According to Meyer and Rowan (1977: 351):

> "Ceremonial criteria of worth and ceremonially derived production functions are useful to organizations: they legitimate organizations with internal participants, stockholders, the public, and the state, as with the IRS or the SEC. They demonstrate socially the fitness of an organization. The incorporation of structures with high ceremonial value, such as those reflecting the latest expert thinking or those with the most prestige, makes the credit position of an organization more favorable."

Similarly, the perspective of organizational learning is sometimes absent from discussions, which are usually anchored in the technical rationality assumption. Indeed, the impact of performance feedback is generally not considered.

Social networks became the closer link between firms and their customers, as well as the other stakeholders in general. The emergence of social networks with a large adoption between the population followed the expansion of Facebook. Nowadays, building a brand starts by creating an online community. This creates new challenges resulting from the type of communication that Internet provides. The appearance of social media platforms allowed firms to have a closer contact with their customers and stakeholders in a way it was not possible before. The fast diffusion and rhythm of messages creates a sense of urgency in the management of these "forums". Nowadays, content is easily created in few instants and in seconds is available worldwide to a broad audience that immediately starts to respond, providing immediate feedback about what was posted. While this is appealing to the managers of the platform, a mistake can rapidly become viral and get unexpected negative reactions. This fast pace can expose firms to potential social media blunders with unpredictable consequences. The importance of social networks extends to many domains where it assumed a central role as the prime communication forum replacing other features implemented through their website. Firms use social networks to keep an active conversation with all their stakeholders. While this may require new competencies for some firms, e-commerce retailers are used to managing an online presence. They have experience managing distant web communities by the use of forums or by allowing their customers to post reviews to their webpages. Creating content for web viewing is also a competence they already have to create banners, online campaigns, or just displaying their products. According to Lieberman and Asaba (2006) imitation played a role in the e-commerce boom-bust cycle of the beginning of the millennium so it constitutes an interesting sector to revisit focusing on a second wave of adoption triggered by the new role of social networks in contemporary world. The fast pace of e-retailing industry and the characteristics of the technologies that these firms use make it a good candidate for this research.

The reasons behind the adoption of technology can have a large impact in the future of an organization. Indeed,

> "Imitation can spur productive innovation, or it can amplify the errors of early movers. Thus, imitation can lead to large positive or negative outcomes for individual firms and society as a whole. " (Lieberman and Asaba, 2006: 366)

Rather than blindly following a trend, managers are expected to understand the benefits and the risks involved and decide to adopt or not an innovation according to the objectives of the stake-

holders of the firm. The fast pace of technological innovation in some industries has a significant economic and social impact that research is trailing. These changes question previous assumptions and settings in face of major changes in society.

1.2. Literature Gap and Research Question

The critics of the institutional perspective point that there is more to institutional story than just counting the outcomes of the process (Suddaby, 2010). According to this author,

> "Institutional work, of course, is conducted by individuals and it is somewhat surprising to me how individuals often disappear from institutional research. Institutional logics, for example, must have a perceptual component that operates cognitively at the level of individuals." (Suddaby, 2010: 17)

While it is important to bring back cognition to institutional theory, managers do not usually consider to reveal their inner motivations, as the cited author admits. The approach that will be followed is to collect data that helps reveal information about the motivations behind the decisions that, otherwise, would not be possible to gather for a large population of firms. A positivist approach is assumed considering that these elements may be "amenable to objective measurement, even when they are complex and multilayered" (Carroll and Hannan, 2000: 85). On the other hand, firms are not isolated from their peers and apart from other influences from their environment. These interactions should be taken into consideration. As it was noted by Gavetti, Levinthal and Ocasio (2007: 531)

> "Like individuals, organizations are not 'islands' onto themselves. They operate in populations of other organizations and in institutional environments, which provide norms of appropriateness that lie apart from any individual organization."

The approach that will be followed is to focus on a population of firms. The actions of the managers reveal information that would not be possible to accurately collect through a questionnaire because social pressures could prevail and inhibit them to reveal the real motivations.

This thesis focus on two antecedents of technology adoption: isomorphic pressures and past performance. The appearance of new social arenas like the social networks pose new challenges, even for those firms that thrive by competing in this environment, as e-retailers do. Considering that for those firms there is no aversion to online communication or managing distant audiences, these technologies offer a new channel allowing them to be closer to their stakeholders. Social networks

like Facebook and Twitter offer a particularly adequate setting to study imitation and infer about the reasons behind adoption. The messages that are posted in these websites reveal not only the time of adoption but also the time and frequency of content publication. This way, firms disclose information that allows to assess and infer their motivations. Firms engaging in ceremonial adoptions are not expected to behave similarly to the ones that see it as an opportunity. The second antecedent that may play a major role in the decision of technology adoption is past performance. Performance is one of the most immediate feedback channels for all stakeholders about the adequacy of past strategic decisions, and certainly an immediate one for those that do not have access to detailed information, that usually is restricted to managers. Those stakeholders that do not have access to detailed information have to infer from the one that it is public and widely available. This mechanism makes performance an important mechanism in the assessment of the work of the management team. Studying performance only as a dependent variable ignores the importance of the feedback impact of past performance achievements over the cognitive assessment and judgment (Lages *et al.*, 2013). The research question is, therefore, defined as:

What are the roles of imitation and past performance in technology adoption?

1.3. Studies

1.3.1. Study 1 (Chapter 2)

In the first study, the focus will be on the motivations behind the adoption of new technologies, namely if the reasons are related to social learning or to social influence resulting from the moves of players perceived as having superior skills in this type of decisions. As companies present different responses to the same institutional pressures (Kennedy and Fiss, 2009; Nikolaeva, 2014), we will use the observable behavior among a population of firms to evaluate if it is possible to infer the main reason behind adoption. Young (2009) provides a grouping of the diffusion models into three classes, contagion, social influence, and social learning. This study will focus on social influence and social learning. It is claimed that the predominant perception about the technology will result in different shapes of the effect of prior adopters on the probability of subsequent adoption. This study aims to answer the following research question: *Is it possible to empirically distinguish predominant imitation motives within an industry?*

1.3.2. Study 2 (Chapter 3)

The second study will look at technology adoption and the influence of past performance in this decision. Following the work of Lages *et al.* (2013) to move from the view of strategy as an antecedent of performance and look at the impact of performance in strategy, the focus will be on the impact of predominantly using a make (in-house) versus buy (outsourcing) technology sourcing mix. It provides a new approach to the work of Tsai, Raghu and Shao (2013), framing the problem according to a different theoretical perspective. Therefore, studying the reasons for a strategic move can help to understand the reactions of managers when deciding about technology sourcing and the importance of performance feedback in the framing of these decisions. It will be assessed if a change in performance alters the propensity to choose a different make (in-house) versus buy (outsourcing) sourcing mix about technology vendors. This study aims to answer the following research question: *To what extent changes in performance influence changes in strategy?*

1.3.3. Study 3 (Chapter 4)

Finally, the last study focus on the post adoption use of the technologies. Following an extensive list of calls (Kennedy and Fiss, 2009; Nikolaeva, 2014), it will be studied the impact of motivations for adoption in the post adoption period. The reasons for adoption will lead to different efforts to implement it. Perceiving the opportunity for gains is expected to result in a larger effort to implement while following the crowd and adopting as a response to social pressures most probably result in less use of the technologies. This study aims to answer the following research question: *Is there empirical evidence, at the aggregate level, about the rational or social perspectives of innovation adoptions?*

1.4. Structure

This research is organized around the three studies that are summarized in Table 1.1. Every table, figure, equation, hypothesis (H), and estimated model (M) is numbered sequentially and by order of appearance, and starts with the number of the chapter. All bibliographic references and the content of the chapters of the appendix are referenced in the text.

Table 1.1. The three studies of the present thesis.

	Study 1 (Chapter 2)	Study 2 (Chapter 3)	Study 3 (Chapter 4)
Subject	Role of imitation in technology adoption	Changes in strategy resulting from performance feedback	Post adoption behaviors
Theory	Institutional theory, organizational ecology and innovation diffusion	Organizational learning theory	Institutional theory and innovation diffusion
Research Question	Is it possible to empirically distinguish predominant imitation motives within an industry?	To what extent changes in performance influence changes in strategy?	Is there empirical evidence, at the aggregate level, about the rational or social perspectives of innovation adoptions?

2. The Role of Imitation in Social Media Adoption

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> "Failure is OK, many experts tell us, so long as one fails conventionally. 'For most CEOs, only one thing is worse than making a huge strategic mistake: being the only person in the industry to make it': explains McKinsey's Charles Roxburgh. " (Bonabeau, 2004: 47)

2.1. Introduction

The diffusion of new practices is an area with a long tradition in organizational studies with several studies focusing on the relevance of imitation in the adoption process as a response to legitimacy pressures (DiMaggio and Powell, 1983; Kennedy and Fiss, 2009; Nikolaeva, 2014). It was found that decision makers attend to some strategic issues and ignore others based on categorizing them as opportunities or threats (Dutton and Jackson, 1987; Kennedy and Fiss, 2009) and that this individual perception results in different responses to the same phenomenon (George, Chattopadhyay, Sitkin and Barden, 2006). Although imitation was widely studied (Lieberman and Asaba, 2006; Ordanini *et al.*, 2008), it is a ubiquitous phenomenon with companies mimicking their peers in several business decisions. Therefore, it is a key strategic move with a high impact on performance and, ultimately, in the long run survival of the organization.

There is a research stream stating the importance of linking institutional theory with the motivational aspects of innovation diffusion and adoption and suggesting a correspondence with opportunity and threat framing (Nikolaeva, 2014; Kennedy and Fiss, 2009). Starting from these contributions, it is important to define a strategy to operationalize these concepts and test them. Young (2009) groups the diffusion models from economics, marketing and sociology into three broad classes - contagion, social influence, and social learning - with different underlying assumptions. The author formulates the "aggregate dynamics" of each class of models and provides a framework to assess its plausibility against a specific diffusion process. This study aims to use the data from the diffusion of innovation to see if it is possible to empirically distinguish the predominant imitation motives within an industry to have a better understanding of the competitive dynamics influencing the spread of innovations.

It is proposed to further investigate the reasons resulting in imitative behavior by using data from the adoption of a social network, Facebook, by e-commerce retailers in the United States (US). Social media is a major source of information for customers and changed how the companies communicate with them (Michaelidou, Siamagka and Christodoulides, 2011). The adoption of social media is of the utmost importance for e-commerce firms because there is no physical contact of the customers with store employees or other shoppers and because it is a proxy for a plethora of new technologies that will influence this industry (e.g., avatars, recommendation agents or video stream) (Karimov and Brengman, 2011). Some of its characteristics also make it an interesting research setting: even though there are no immediate outlay costs due in the moment of adoption, maintaining an engaged community and avoiding social media blunders requires a considerable investment, namely through monitoring and follow up. In the present case, contagion is not consistent with the nature of adoption, more based on observation then communication between the firms. Having ruled out contagion as it

is not adequate for our case, Young (2009) proposes two types of processes: social learning or social influence. Social learning posits that managers do not blindly react but make an assessment and act on a possible opportunity based on the information generated by prior adopters (Young, 2009). Pressured by the illegitimacy of non-adoption, companies experience what neo-institutional theory designates by mimetic isomorphism. According to the theory of rational decision making, managers "know all possible alternatives and can forecast returns to each alternative, at least as a probability distribution" (Ordanini *et al.*, 2008: 387). If adoption is resulting from the information generated by prior adopters, we expect to observe a slow initial reaction and a late super-exponential growth, because firms are waiting to learn more about the results of others and, just then, decide about its benefits for their own business. Social influence sees adoption as a reaction to the popularity of the innovation. Two theories may help explain the reasons for this type of behavior: information cascades and the theory of bounded rationality. According to information cascades, imitation is seen as a defensive strategy, while the theory of bounded rationality posits that it is based on the limited cognition of individuals (Ordanini *et al.*, 2008). The fear of falling behind or losing legitimacy may result in the probability of adoption increasing as more and more firms adopt according to a pattern that is characterized by an initial and brief exponential growth.

This study makes several contributions to the existing literature. First, this study empirically shows that the predominant framing of about technology adoption can be inferred from aggregate behavior using data from a population of firms. Second, being consistent with the literature on adoption processes we formulate nonlinear hypotheses to test this proposition. According to Pierce and Aguinis (2013: 317), the presumption of linear relationships leads to the proliferation of deficient theories, suggesting that "a paradigmatic shift from linear to curvilinear models is needed to improve management theory and practice, regardless of level of analysis and subfield of study". Third, it provides an empirical test of the adoption of social media by e-retailers using a large panel and eight years of data. Social media is a recent phenomenon and most studies use small or limited datasets that do not allow to infer aggregate behavior. This panel also allows us to answer the call of Lieberman and Asaba (2006), stating the importance of using event history models outside organizational sociology.

2.2. Theory and Hypotheses

2.2.1. Theoretical Background

This research is based on several theoretical foundations. First, it assumes that managers are not unbounded rational so they use heuristics, like imitation, to overcome their cognitive limitations (Simon, 1955). Second, decision makers attend to some strategic issues and ignore others based on categorizing them as opportunities or threats (Dutton and Jackson, 1987; Kennedy and Fiss, 2009; Nikolaeva, 2014), so they can overcome their cognitive limitations. This individual perception results in different responses to the same phenomenon (George *et al.*, 2006). Third, imitation is one of strategies that individuals use to deal with uncertainty. Fourth, the result of decision making at the individual level should be observed at the aggregate level.

Imitation can be defined as a "phenomenon that occurs when one or more decisions made by one or more organizations increases the likelihood that the same choices will also be made by other organizations" (Ordanini *et al.*, 2008; Haunschild and Miner, 1997: 378). Firms may imitate when they introduce new products and processes, adopt new methodologies, change their organizational form, decide about market entry or the timing of investment (Lieberman and Asaba, 2006). DiMaggio and Powell (1983) proposed a discrimination of the isomorphic behavior among firms into coercive, mimetic or normative. This research focuses on mimetic isomorphism: the imitation of other organizations that are considered to be more successful to deal with uncertainty. This behavior can also be seen as a risk reduction strategy used by firms that aim to get legitimacy, but it is different from collusion because it is an *ex-post* decision to copy other players' decisions after they executed them (Ordanini *et al.*, 2008).

Among the initial studies about imitation, DiMaggio and Powell (1983) and Tolbert and Zucker (1983) proposed a dichotomy among early and later adopters. According to DiMaggio and Powell (1983), early adoption is based on a rational perspective and knowledge building while later adoption seeks legitimacy (Lieberman and Asaba, 2006). In the case of Tolbert and Zucker (1983), early adopters seek technical gains while later adopters seek the social benefits of legitimacy. Since these early days, several contributions were made addressing imitation as a strategic response by decision makers. Kennedy and Fiss (2009) and Nikolaeva (2014) provide new frameworks extending the decision framings and motivations that trigger adoption among early and later adopters.

Two important studies, Lieberman and Asaba (2006) and Ordanini *et al.* (2008), reviewed the several theoretical streams on imitation and helped identify common trends. Nikolaeva (2014) suggests that the classifications of Lieberman and Asaba (2006) and Ordanini *et al.* (2008) have a cor-

respondence with opportunity and threat framing, and this paper will follow this view.

Lieberman and Asaba (2006) reject a ritualistic view of imitation and group the main theories into “information based theories” and “rivalry based theories”, two categories that are not mutually exclusive. Information based theories consider that companies follow the ones that are regarded as having “superior” information, framing it as an opportunity. Within information based theories, they consider economic theories like “information cascades” (or social learning) and institutional theory. Rivalry based theories consider imitation as a defense strategy to maintain competitive parity and mitigate rivalry, to neutralize a strategic move from a competitor and maintain the same relative position, corresponding to framing it as a threat. These theories emphasize that these strategies punish deviant behavior promoting homogeneity among competitors, and try to minimize risk by maintaining their relative competitive position. Rivalry based imitation opponents often compete in the same market, have similar size or resources, and operate in a low uncertainty environment. Lieberman and Asaba (2006) point that there are several paths: mimetic, vicarious (e.g., through investing in absorptive capacity) or experiential learning. This study will focus on mimetic isomorphism.

Ordanini *et al.* (2008) proposed to group the several existing streams of research into risk reduction or search for effectiveness. Risk reduction is a response to external factors with firms accepting lower payoffs to reduce the risk exposure, a “taken-for-granted” decision (Haunschild and Miner, 1997). The risk reduction approach is based on framing as a threat. Search for effectiveness aims to reduce the competitive gap to other players, namely the market leaders. This strategy can be seen as pursuing an opportunity. Firms respond heterogeneously to the same institutional pressures (Kennedy and Fiss, 2009; Hillebrand, Nijholt and Nijssen, 2011) so, if there is a predominant framing of imitation, as an opportunity or a threat, this will result in different shapes of the effect of prior adopters on the probability of subsequent adoption.

The study of populations of firms is the focus of organizational ecology. While the current research is focused on technology adoption in neo-institutional perspective rather than on the study of a population of firms, it faces similar challenges so some of the methodologies are also similar to the ones used by organizational ecology and corporate demography. Because organizations are “constructed social entities”, the use of demographic tools used in biological populations has to be adjusted to focus on them (Carroll and Hannan, 2000). In fact, corporate demography has a long tradition of working with population processes. One of them is the theory of density dependence by Hannan and Freeman (1987, 1988). This theory is considered as the “theoretical backbone” when working with single populations (Freeman and Audia, 2006), driving the processes of legitimation and competition. In fact, imitation can be seen as a strategy to gain legitimacy among peer players. According to Greenwood, Oliver, Suddaby and Sahlin Andersson (2008: 3): “because organizations

are expected to behave rationally, Meyer and Rowan proposed that rationalized myths are accepted as prescriptions of appropriate conduct. Organizations conform to them - i.e. become isomorphic with their institutional context - in order to signal their social fitness and gain legitimacy in the eyes of critical constituencies". Legitimation is obtained when the behavior is socially taken-for-granted (Carroll and Hannan, 2000) and managers may adopt it without fully assessing the benefits and costs it brings to their own firm and business model.

2.2.2. Hypotheses Development

Ordanini *et al.* (2008) differentiate two perspectives about imitating behavior: the mimetic logic and the organizational learning perspective. According to the mimetic logic, firms aim to gain legitimacy by following social pressures. According to the organizational learning perspective, firms observe the behavior of other actors and the results they obtain, responding selectively to the ones that seem beneficial to their own objectives. This is consistent with the framework of Nikolaeva (2014) that defines several propositions based on the fact that manager first identify an issue and frame it as an opportunity or a threat and, in a second moment, assess the imitation decision, as an opportunity or a threat, before they decide what to do. So, early adopters tend to base the decision on a "imitate the successful" heuristics and to be early adopters, while later adopters usually follow a "imitate the majority" heuristics and tend to delay adoption.

DiMaggio and Powell (1983) state that mimetic behavior is a taken-for-granted behavior and not a result of a conscious selection process as suggested by Hannan and Freeman (1977). Isomorphic actions may also result from perceived "legitimacy-related loss of control" (George *et al.*, 2006: 365) with firms imitating the most relevant competitors to gain legitimacy and reduce the uncertainty about their environment (Ordanini *et al.*, 2008). Terlaak and Gong (2008) suggest that rivalry pressures result in companies scanning the competitors in their industry about adoption behaviors. According to them, a symbolic adoption is a strategic behavior observed when companies announce the adoption without the intention to engage in the efforts to implement it due to institutional pressures, with research arguing that the adoption tend to occur later rather than earlier.

Based on the sociological literature on innovation, Young (2009) notes that in a social influence process there is a *social threshold* for each individual that will determine his interest in adoption. After the process starts and the number of adopters continues to increase, more and more firms surpass the threshold they need to engage in adoption. According to what was exposed, there is an increasing value of the information generated by previous adoptions. This way most part of the cumulative adoption curve will tend to present a non concave shape. Hence,

Hypothesis 2.1a As the number of prior adopters increases, the probability of subsequent adoption increases at a non-decreasing rate. (H2.1a)

According to organization learning perspective, firms observe and capture the results of the experience of their peers (Levitt and March, 1988). This strategy allows firms to collect the information they need to decide without engaging in an experimentation process (Ordanini *et al.*, 2008). Instead of firms *jumping on the bandwagon*, we expect to observe a slower adoption as different agents have different prior beliefs and levels of information resulting in a high level of heterogeneity (Young, 2009). As time passes and a larger group of competitors adopt the technology, the incremental value provided diminishes. As the technology is widely adopted, the potential competitive gains are lower. According to this, the adoption curve will be characterized by a concave shape, where most of the time we observe an increase at a decreasing rate. Hence,

Hypothesis 2.1b As the number of prior adopters increases, the probability of subsequent adoption increases at a decreasing rate. (H2.1b)

2.3. Data and Methodology

The research hypotheses will be tested in the context of social media adoption by e-commerce retailers in the US. As an important source of information for customers (Michaelidou *et al.*, 2011), social media present firms with a need to decide whether they engage or not in social networking and in what websites to be present.

E-commerce companies largely benefit from using social networks to mitigate time and geographical distance, using it to attract customers and cultivate customer relationships (Michaelidou *et al.*, 2011). In the early days of social media, several websites emerged and it was not clear for the companies which ones they should choose to be present at (Kaplan and Haenlein, 2010). Weinberg

and Pehlivan (2011) distinguish several groups of social media: blogs (e.g., WordPress), communities (e.g., MacRumors), micro-blogs (e.g., Twitter) and social networks (e.g., Facebook). These authors also attribute different marketing objectives to each of these categories, and this may explain that they do not know which ones best serve their own objectives.

Apart from the first days of the Internet, branding is nowadays about building a community and promoting conversations about the brand (Christodoulides, 2009). Companies could follow a strategy of adopting a presence in every one of these platforms, much like they are used to do with top-level domains. However, in this case, it is not just about redirecting the main domain name. It involves an active management and follow up. The adoption of social networks do not require a large initial investment when compared to other technologies like e-commerce (Michaelidou *et al.*, 2011), but maintaining their online presence and avoiding social media blunders can be costly when the effort with the follow-up and management is also included. However, it is one of the most important marketing tools keeping an open and direct channel with their customers and stakeholders.

2.3.1. Data Collection

Among the several social networks, Facebook soon emerged as top player among its peers. Facebook started accepting everyone to join in the last quarter of 2006 (Associated Press, 2014; Facebook Inc., 2016) and in 2010 topped Google as the most visited US web site regarding weekly traffic (Pepitone, 2010). To empirically test our research hypotheses we will study Facebook adoption using a sample of companies consisting of the largest e-retailers in the US, based on e-retail sales, from the Internet Retailer (IR) Top 500 Guide (top500guide.com). This source was already used by other researchers and was considered adequate and reliable (e.g., Chuang, Lu, Peng and Heim, 2014; Griffis, Rao, Goldsby, Voorhees and Iyengar, 2012; Tsai *et al.*, 2013; Karimov and Brengman, 2011).

The data source was composed of the yearly top 500 largest e-commerce companies and was published from 2008 till 2015 based on data from the previous years, including information from 2006 to 2014. The adoption by each company was followed since 2007 based on information manually collected from the retailers' websites and Facebook pages. After aggregating the yearly information regarding each retailer, the sample ended with 799 companies. The data was organized into 9,427 firm-quarter observations resulting in a discrete quarterly longitudinal panel.

However, not all information is available for all the retailers in all the years. This results from combining censored and uncensored observations and from changes observed in the data provided for each company in each of the years. Indeed there are few variables with information for all the

retailers in all years, so to estimate a model with more controls one has to accept a reduction in the sample used. This analysis will proceed with the estimation of two models, a full and a restricted model, to be able to deal with the specifics of the information available in the dataset. Whereas the restricted model uses the information from all the firms, the full model will use information from a subsample composed by 456 companies and 2,840 firm-quarter observations.

2.3.2. Variable Definitions

To estimate the non linear effect of prior adopters of Facebook on the probability of subsequent adoption, the dependent variable was defined as a dummy assuming a value of one when the adoption was observed in the quarter (see Table 2.1 with the variables summary). The information about the time of adoption was collected from the Facebook pages managed by each company based on the date joined or the first manual post published in the timeline.

Table 2.1. Variable definitions.

Variables	Description
Dependent Variable	Dummy variable: one if the firm adopts Facebook during the quarter, zero if not.
Proportion of Adopters	Cumulative number of adopters in the prior quarter over the number of retailers in the particular product category.
Proportion of Adopters sq.	Squared “Proportion of Adopters”.
Web Only	Dummy variable: one if the merchant was a web only player, zero if not (catalog/call center, consumer brand manufacturer, or retail chain).
Age	Yearly age of the firm based on the launch date of the e-commerce operations of retailers as reported by IR and other sources, namely information provided by the firms.
Quarterly Growth of Media Mentions	Count of media mentions of Facebook per quarter provided by Highbeam Research (highbeam.com) (in thousands). [Lagged]
Share of Web Sales in Merchandise Category	Percentage of web sales within the total category sales in IR database. [Lagged]
Product Recommendations	Dummy variable: one if the firm has a product recommendation feature, zero if not. [Lagged]
Blog	Dummy variable: one if the firm has a blog, zero if not. [Lagged]

To capture the effect of prior adopters, the cumulative percentage of adoption within the industry was used as an independent variable. It was computed based on the cumulative number of adopters until the prior quarter over the total number of retailers in the product category of the retailer (information based on the full sample), assuring that it is comparable across product categories. There are 15 categories in the sample - “Apparel/Accessories”, “Automotive Parts/Accessories”, “Books/Music/Video”, “Computers/Electronics”, “Flowers/Gifts”, “Food/Drug”, “Hardware/Home Improvement”, “Health/Beauty”, “Housewares/Home Furnishings”, “Jewelry”, “Mass Merchant”, “Office Supplies”, “Specialty”, “Sporting Goods”, “Toys/Hobbies” (see Table 2.2 for the distribution of merchandise categories within the sample). Another variable that helps to characterize the companies is the type of

Table 2.2. Facebook adoption by retail categories in the full sample.

Merchandise Category	Adopted Facebook						Total		
	No			Yes					
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	5	10.2	2.6	188	25.1	97.4	193	24.2	100.0
Automotive Parts/Accessories	0	0.0	0.0	19	2.5	100.0	19	2.4	100.0
Books/Music/Video	5	10.2	10.2	44	5.9	89.8	49	6.1	100.0
Computers/Electronics	7	14.3	8.4	76	10.1	91.6	83	10.4	100.0
Flowers/Gifts	1	2.0	4.5	21	2.8	95.5	22	2.8	100.0
Food/Drug	4	8.2	10.8	33	4.4	89.2	37	4.6	100.0
Hardware/Home Improvement	5	10.2	10.4	43	5.7	89.6	48	6.0	100.0
Health/Beauty	0	0.0	0.0	43	5.7	100.0	43	5.4	100.0
Housewares/Home Furnishings	7	14.3	9.5	67	8.9	90.5	74	9.3	100.0
Jewelry	1	2.0	4.2	23	3.1	95.8	24	3.0	100.0
Mass Merchant	1	2.0	2.2	44	5.9	97.8	45	5.6	100.0
Office Supplies	4	8.2	15.4	22	2.9	84.6	26	3.3	100.0
Specialty	6	12.2	8.8	62	8.3	91.2	68	8.5	100.0
Sporting Goods	1	2.0	2.4	40	5.3	97.6	41	5.1	100.0
Toys/Hobbies	2	4.1	7.4	25	3.3	92.6	27	3.4	100.0
Total	49	100.0	6.1	750	100.0	93.9	799	100.0	100.0

merchant, whether web only, catalog/call center, consumer brand manufacturer, or retail chain (see Table 2.3 for the distribution of retailers among the merchant types and Table 2.4 for the merchant types within each merchandise category). A dummy variable, “Web Only”, was created to attend to the distinctive characteristics of the web only players.

A control variable that also used was the number of media mentions of Facebook per quarter, “Quarterly Growth of Media Mentions”, compiled by Highbeam Research (highbeam.com). This variable captures the effect of public awareness about the social network. Other variables related to the use of social networks are the dummies “Product Recommendations” and “Blog”. These two variables control for the use of common e-commerce platform functions that enable the firms to interact with their customers as they did before social media.

Two other controls are the ones related to the size and experience of the firm. “Share of Web

Table 2.3. Facebook adoption by merchant type in the full sample.

Merchant Type	Adopted Facebook						Total		
	No			Yes					
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Catalog/Call Center	5	10.2	4.3	111	14.8	95.7	116	14.5	100.0
Consumer Brand Manufacturer	6	12.2	6.1	92	12.3	93.9	98	12.3	100.0
Retail Chain	12	24.5	5.5	205	27.3	94.5	217	27.2	100.0
Web Only	26	53.1	7.1	342	45.6	92.9	368	46.1	100.0
Total	49	100.0	6.1	750	100.0	93.9	799	100.0	100.0

Table 2.4. Merchant type by merchandise category in the full sample.

Merchandise Category	Merchant Type				Total
	Catalog/Call Center Row %	Consumer Brand Manufacturer Row %	Retail Chain Row %	Web Only Row %	Row %
Apparel/Accessories	11.9	23.3	35.2	29.5	100.0
Automotive Parts/Accessories	15.8	0.0	21.1	63.2	100.0
Books/Music/Video	12.2	2.0	22.4	63.3	100.0
Computers/Electronics	13.3	19.3	21.7	45.8	100.0
Flowers/Gifts	22.7	13.6	9.1	54.5	100.0
Food/Drug	21.6	16.2	24.3	37.8	100.0
Hardware/Home Improvement	12.5	2.1	16.7	68.8	100.0
Health/Beauty	9.3	16.3	20.9	53.5	100.0
Housewares/Home Furnishings	21.6	8.1	28.4	41.9	100.0
Jewelry	8.3	12.5	12.5	66.7	100.0
Mass Merchant	17.8	0.0	33.3	48.9	100.0
Office Supplies	3.8	3.8	23.1	69.2	100.0
Specialty	20.6	4.4	20.6	54.4	100.0
Sporting Goods	9.8	9.8	48.8	31.7	100.0
Toys/Hobbies	18.5	7.4	33.3	40.7	100.0
Total	14.5	12.3	27.2	46.1	100.0

Sales in Merchandise Category" accounts for the relative size of the firm when compared to the more closer competitors. "Age" controls for the newness of the firm and other factors like experience that may play a role in the adoption process.

2.3.3. Model Specification

The characteristics of the dataset recommend the use of a discrete-time survival model. These models make possible the estimation through a dichotomous response model after the data is in the form of firm-period and the inclusion of covariates (Rabe-Hesketh and Skrondal, 2012). The dataset that is used follows this format. According to the same authors, the final dataset results from "interval censoring" because even though it happens in continuous time, it only possible to its occurrence in one of the time intervals, and it is of "absorbing" type because it can only happen once for each firm. Allison (1995) prescribes the same approach, attending to three characteristics of the collected data: there are censored and uncensored observations, the data was collected in discrete quarterly intervals and there is no theoretical basis for the shape of the time dependence. According to this specification, time dependence will be modeled through year dummies.

One of the key factors for choosing a logit model over a complementary log-log (CLOGLOG) is the fact that it does not assume proportionality of the hazard functions (Jenkins, 1995). As it is not expected that this assumption is valid in our dataset, we will use the logit model. An example is the case of variable "Blog". To test it, a Cox model was estimated [see Table 2.5] that confirmed what can also be visually assessed (through a plot), pointing to the same result. After the estimation of a Cox model, the proportionality assumption was tested using the Schoenfeld residuals. The results of this test are included at the end of the table. According to this test, there is evidence against the proportional hazards assumption when using some controls.

The empirical tests to the proposed hypothesis will use a panel data logit regression for estimation of the occurrence of the event, the adoption of Facebook. These models are "specified in terms of the discrete-time hazard, defined as the conditional probability that the event occurs at time t, given that it has not yet occurred" (Rabe-Hesketh and Skrondal, 2012: 750). Following Jenkins (1995), the hazard rate is:

$$h_{it} = \Pr\left(T_i = t \mid T_i \geq t; X_{it}\right) \tag{2.1}$$

where X_{it} is a vector of covariates for firm i at time t that may vary with time and T_i is the discrete random variable indicating the occurrence of the event. For the logit model this probability is expressed

Table 2.5. Testing proportionality assumption. Estimation of a Cox model and of the test of proportional-hazards assumption (PA) using the Schoenfeld residuals.

	Coef.	Rob. S.E.	z	P > z
Proportion of Adopters	2.659**	1.256	2.118	0.034
Proportion of Adopters sq.	−1.305	1.334	−0.978	0.328
Blog	0.112	0.107	1.045	0.296
Number of subjects	508			
Number of failures	409			
Number of obs. / Time at Risk	3192			
Log pseudolikelihood	−2188.971			
Chi-squared	10.174			
Prob. > Chi-squared	0.017			
AIC	4383.941			
BIC	4402.146			
PA Chi-squared	7.885			
PA d.f.	3			
PA p	0.048			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

as:

$$h_{it} = \frac{e^{(\alpha_t + \beta' X_{it})}}{1 + e^{(\alpha_t + \beta' X_{it})}} = \frac{1}{1 + e^{-(\alpha_t + \beta' X_{it})}} \tag{2.2}$$

which can be rewritten as:

$$\ln\left(\frac{h_{it}}{1 - h_{it}}\right) = \alpha_t + \beta' X_{it} \tag{2.3}$$

where α_t is the baseline hazard. The model accounts for the dependency resulting from the multiple firm-quarter observations by using the cluster-correlated robust estimate of variance (Froot, 1989; Rogers, 1993; Williams, 2000).

The inclusion of time dummies allows the estimation of the discrete-time survival model through a dichotomous response model without imposing a functional form (Rabe-Hesketh and Skrondal, 2012). However, it is important to make two remarks. First, the goal is not to investigate the shape of the hazard function so it can be any function of time. Second, the use of dummy variables for each year will account for other effects that we cannot measure but that affect all firms. When analyzing datasets with many periods, as it is the case, the inclusion of time dummies for each one

of them results in models with many unknown parameters. The estimation follows Singer and Willett (1993) about how to obtain a more parsimonious representation of time and constrains the quarterly parameters to be equal within each year.

To test if there is evidence of opportunity driven or threat driven adoption, the estimation will take into consideration the mathematical formulation proposed by Young (2009) for the social influence process. According to this model, there is a level of adoption after which the social pressure to adopt will prevail instead of the benefits for the business, that will be assessed through the curvilinear effect of prior adopters on the probability of subsequent adoption. According to H2.1a it is expected to find a linear or convex relationship, while according to H2.1b it should have a concave curve shape. The effect of prior adopters that is reflected in the curvilinearity will be assessed through the cumulative density dependence.

Following the standard approach in research on adoption/new market entry, the density dependence will be modeled by introducing a quadratic term of the independent variable (Dobrev and Gotsopoulos, 2010) representing the prior number of adopters over the number of companies in each merchandise category. As the number of retailers in each merchandise category varies widely in each of the 15 categories used by IR, this approach makes the values comparable across categories.

In the first group of models, the additional control variables were restricted to the ones available for all firms in all periods, so that it is possible to use all the dataset. This model contains the basic structure of the estimation:

$$\begin{aligned}\ln\left(\frac{h_{it}}{1-h_{it}}\right) = \alpha_1 &+ \beta_1 \text{ Proportion Of Adopters }_{it} \\ &+ \beta_2 \text{ Proportion Of Adopters sq. }_{it} \\ &+ \beta_3 \text{ Time Dummy 2008 (Ref.2007) }_{it} \\ &+ \beta_4 \text{ Time Dummy 2009 }_{it} \\ &+ \beta_5 \text{ Time Dummy 2010 }_{it} \\ &+ \beta_6 \text{ Time Dummy 2011 }_{it} \\ &+ \beta_7 \text{ Time Dummy 2012 }_{it} \\ &+ \beta_8 \text{ Time Dummy 2013 }_{it} \\ &+ \beta_9 \text{ Time Dummy 2014 }_{it} \\ &+ \epsilon_{it},\ i = 1, ..., n \end{aligned} \tag{2.4}$$

The estimation was conducted using Stata 14.2 software (StataCorp, 2015b) and the command '`logit`'.

2.4. Results

The quarterly number of retailers adopting Facebook is presented in Figure 2.1. Most of the adoptions occurred between the last quarter of 2007 and the first quarter of 2010. Among the 799 retailers that compose the sample, 750 of them adopted Facebook corresponding to a 93.9% adoption rate [see Figure 2.2 for the evolution of the percentage of adoption among all companies in the sample].

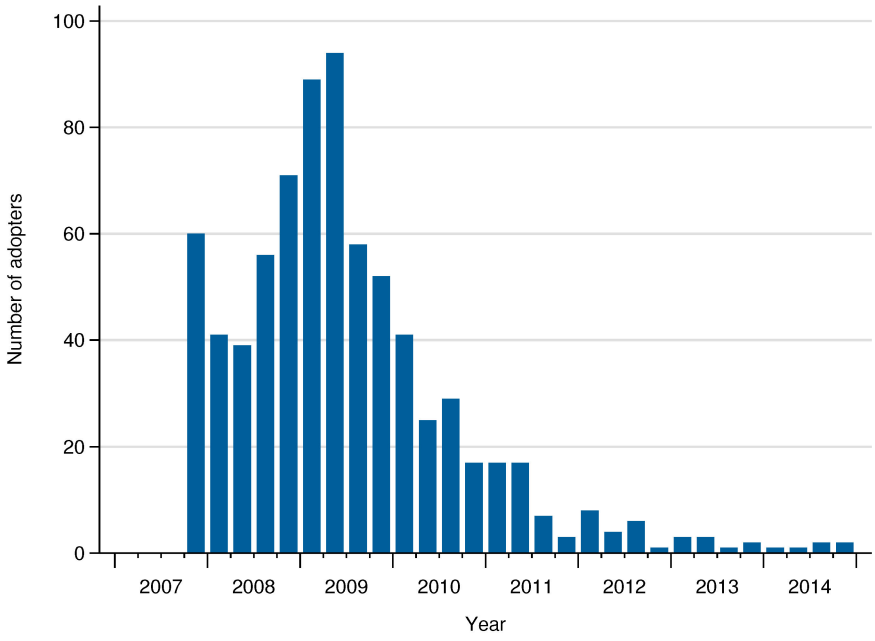


Figure 2.1. Number of e-retailers adopting Facebook in the full sample.

As our methodology is based on the adoption among competitors, it is also relevant to look at the quarterly adoption rates by product categories [see Figure 2.3 and Figure 2.4]. The shape of the adoption graph is similar even though the differences among categories regarding the number of companies. The adoption values vary from the lowest adoption rate of 84.6% - Office Supplies - to 100% adoption rate - “Automotive Parts/Accessories” and “Health/Beauty”.

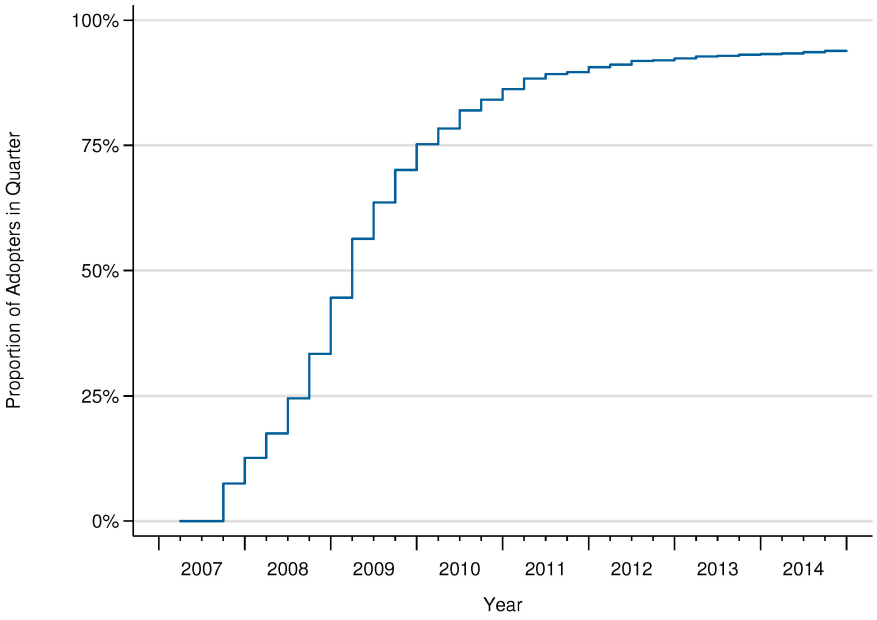


Figure 2.2. Percentage of adoption (non-lagged) in the full sample.



Figure 2.3. Number of e-retailers adopting Facebook by merchandise category.

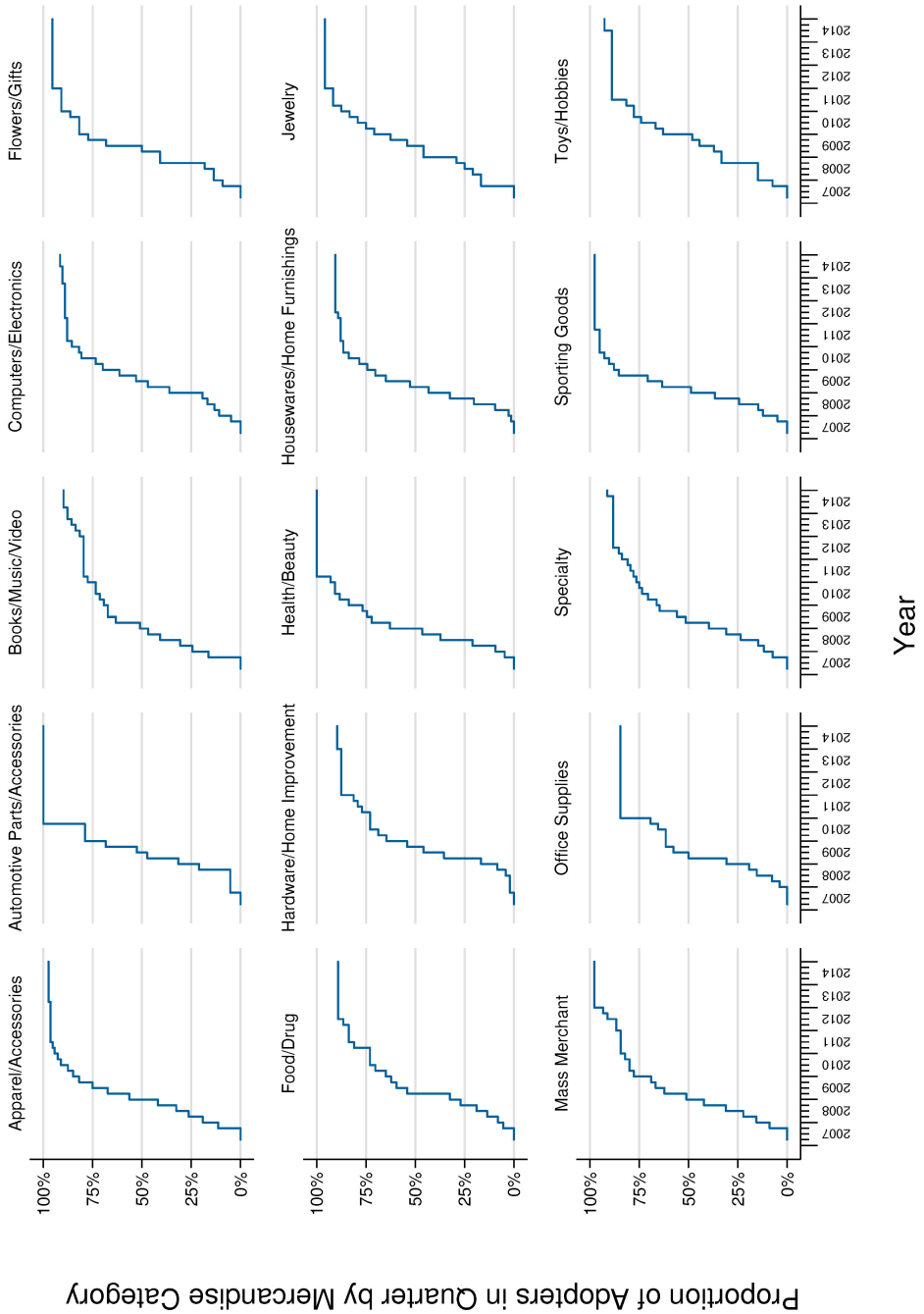


Figure 2.4. Percentage of adoption by merchandise category (non-lagged).

It is also relevant to look to two of the most common problems with survival analysis studies: censoring and truncation. This method is suitable if there is left-truncation and right censoring but nor if there is left-censoring or right-truncation (Rabe-Hesketh and Skrondal, 2012). The follow-up period starts in the beginning of 2007 and ends in the last quarter of 2014. The followup of the firms started before any one of them adopted Facebook so there is no left censoring. However, by the end of the study not all of them had adopted so we have right censoring.

As the information in some of the variables are not available for all the companies we will estimate two groups of models: the first using information available to all the firms but with a restricted set of variables, designated as a "restricted model", and a second type using more variables but with a smaller number of companies (because there are some variables that are not available to all firms in the dataset), designated as "full model". The restricted model regressions consider all the firms in the panel. The information that is used is available for all firms in all years. The descriptive statistics and correlations for the restricted model are shown in Table 2.6 and Table 2.7 while for the full model are presented in Table 2.8 and Table 2.9.

Table 2.6. Summary statistics for the restricted model.

		Mean	St. Dev.	Min.	Max.
Proportion of Adopters	(1)	0.28	0.32	0.00	0.98
Proportion of Adopters sq.	(2)	0.18	0.27	0.00	0.96
Year	(3)	2008.51	1.71	2007.00	2014.00
Web Only	(4)	0.50	0.50	0.00	1.00
Quarterly Perc. Growth of Media Mentions	(5)	648.78	1062.74	−3714.00	4211.00

Table 2.7. Correlation matrix for the restricted model. Correlation table built handling missing values by pairwise deletion.

		(1)	(2)	(3)	(4)	(5)
Proportion of Adopters	(1)	1.00				
Proportion of Adopters sq.	(2)	0.96	1.00			
Year	(3)	0.92	0.92	1.00		
Web Only	(4)	0.09	0.09	0.09	1.00	
Quarterly Perc. Growth of Media Mentions	(5)	0.41	0.36	0.24	0.06	1.00

Table 2.8. Summary statistics for the full model.

		Mean	St. Dev.	Min.	Max.
Proportion of Adopters	(1)	0.36	0.28	0.00	0.98
Proportion of Adopters sq.	(2)	0.21	0.26	0.00	0.96
Web Only	(3)	0.43	0.50	0.00	1.00
Year	(4)	2008.95	1.39	2008.00	2014.00
Quarterly Perc. Growth of Media Mentions	(5)	761.99	1100.16	−3714.00	4211.00
Share of Web Sales in Merchandise Category	(6)	0.03	0.07	0.00	0.64
Product Recommendations	(7)	0.67	0.47	0.00	1.00
Blog	(8)	0.30	0.46	0.00	1.00
Attrition	(9)	0.24	0.43	0.00	1.00

Table 2.9. Correlation matrix for the full model. Correlation table built handling missing values by pairwise deletion.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Proportion of Adopters	(1)	1.00								
Proportion of Adopters sq.	(2)	0.97	1.00							
Web Only	(3)	0.05	0.06	1.00						
Year	(4)	0.85	0.90	0.07	1.00					
Quarterly Perc. Growth of Media Mentions	(5)	0.42	0.38	0.06	0.20	1.00				
Share of Web Sales in Merchandise Category	(6)	0.04	0.05	−0.11	0.10	−0.00	1.00			
Product Recommendations	(7)	−0.07	−0.08	−0.05	−0.10	−0.02	0.02	1.00		
Blog	(8)	0.15	0.16	0.26	0.17	0.06	−0.00	0.12	1.00	
Attrition	(9)	0.28	0.30	0.15	0.29	0.13	−0.12	−0.11	0.03	1.00

In the restricted model (see Table 2.10), with all observations in the sample, we use as regressors the ratio of prior adopters in linear and quadratic form, the year dummies, a dummy if the retailer is a pure web retailer, and the growth of Facebook media mentions. The detailed estimation results are provided in Appendix A - Tables A.1, A.2, and A.3.

Table 2.10. Restricted model estimation. Logit models with cluster-robust standard errors.

	M2.1	M2.2	M2.3
Facebook Adpt.			
Proportion of Adopters	3.690****	3.604****	3.537****
Proportion of Adopters sq.	−2.766***	−2.728***	−2.812***
Year (ref. 2007)			
2008	0.989****	1.002****	1.017****
2009	1.408****	1.459****	1.429****
2010	1.013***	1.102****	1.014***
2011	0.670*	0.762**	0.701*
2012	0.172	0.260	0.286
2013	−0.377	−0.297	−0.063
2014	−0.658	−0.584	−0.448
Web Only		−0.293****	−0.297****
Quarterly Perc. Growth of Media Mentions			0.000*
Constant	−3.956****	−3.832****	−3.855****
Number of obs.	9427	9427	9427
Number of clusters	799	799	799
Log pseudolikelihood	−2374.918	−2368.041	−2366.417
Chi-squared	390.709	394.814	406.629
Prob. > Chi-squared	0.000	0.000	0.000
Pseudo R-squared	0.093	0.095	0.096
AIC	4769.836	4758.081	4756.834
BIC	4841.349	4836.746	4842.650

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

These results provide support for H2.1b. The observed heterogeneity may result from agents waiting to have more information before they decide to adopt. This is an interesting result because the adoption of a social network does not imply a cost. Moreover, managing a social presence also exposes the companies to risks. Some stakeholders may use these platforms to express their opinions, either fair or unfair on their judgments, easily reaching a large percentage of their peers, a very relevant audience for the firm. Since the consequences are not fully predictable, firms are expected to avoid these situations. This may lead firms to wait and have more information before

adoption, ignoring the social pressures to adopt immediately.

An important set of independent variables is composed of the time dummies. They reflect the shape of the adoption curve that we can visually check through Figure 2.1. The probability of adoption is higher during the years from 2008 to 2010 (compared to 2007), period when most firms started their presence.

To test additional covariates, some of them being available only to a smaller group within the sample, a new set of models was estimated, designated by full model estimation, including more variables that control for other effects. Using 456 firms across 2,840 firm-quarter periods, the full model results in Table 2.11 are aligned with the ones from the restricted model with a positive and significant linear term and a negative and significant quadratic term. More details related to the estimation of these models are supplied in Appendix A - Tables A.4, A.5, and A.6. These results also provide evidence of a concave relationship and support for the H2.1b.

Table 2.11. Full model estimation. Logit models with cluster-robust standard errors.

	M2.4	M2.5	M2.6
Facebook Adpt.			
Proportion of Adopters	3.909***	3.864***	3.943***
Proportion of Adopters sq.	−3.532***	−3.491***	−3.569***
Year (ref. 2008)			
2009	0.718****	0.724****	0.706****
2010	0.544*	0.570*	0.533
2011	0.233	0.247	0.201
2012	−0.789	−0.770	−0.832
2013	−0.767	−0.738	−0.759
2014	−0.197	−0.105	−0.177
Web Only	−0.343***	−0.327***	−0.386***
Quarterly Perc. Growth of Media Mentions	−0.000	−0.000	−0.000
Share of Web Sales in Merchandise Category	−0.251	−0.281	−0.316
Product Recommendations		0.255**	0.225*
Blog			0.234*
Constant	−2.653****	−2.835****	−2.861****
Number of obs.	2840	2840	2840
Number of clusters	456	456	456
Log pseudolikelihood	−1069.159	−1067.006	−1065.321
Chi-squared	109.828	112.386	114.677
Prob. > Chi-squared	0.000	0.000	0.000
Pseudo R-squared	0.051	0.053	0.055
AIC	2162.318	2160.011	2158.641
BIC	2233.737	2237.381	2241.963

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

A group of control variables was tested and most of them are significant in the expected direction. A covariate with an unexpected sign is “Web Only”. It was found that e-retailers without a physical presence are less likely to adopt Facebook. It was expected that pure online retailers would be faster to adopt Facebook because of two reasons. First, their expertise in managing online platforms gives them an advantage as they are used to develop and publish online content. Second, an online presence would be a form of shortening the distance to the customers and other stakeholders. However, web only players may be afraid about customers leaving their web site and going to their Facebook page where they are less likely to return and make a purchase. This is an issue that is being addressed from the early days of e-commerce, with the firms being reluctant in providing links to external webpages. According to the variable “Share of Web Sales in Merchandise Category”, firm size was not found to influence the adoption of Facebook. This result is aligned with what was expected as the technology is free as easily available to smaller competitors. It may even be more attractive to firms with smaller advertising budgets because it may well be managed without a large investment. However, introducing the controls for the experience having previously implemented two other technologies, “Product Recommendations” and “Blog”, we find the results consistent with the previous findings. The impact of media stories on the adoption is zero or non-significant. Media is considered be one of the sources of social pressure (Hillebrand *et al.*, 2011), so this is a proxy for the degree of influence of media stories over the firms. This result provides a special contribution to this analysis because it confirms the lack of support for H2.1a.

A final set of models tested the response to the shape of the adoption curve when controlling for several performance measures [see Table 2.12 as well as the detailed results in Appendix A - Tables A.7, A.8, and A.9]. Two new variables were used: “Conversion Rate” and “Monthly Visits”. There is statistical evidence that the effect does not change when controlling for those measures.

Table 2.12. Model estimation controlling for performance. Logit models with cluster-robust standard errors.

	M2.7	M2.8	M2.9
Facebook Adpt.			
Proportion of Adopters	4.048****	3.832****	4.105****
Proportion of Adopters sq.	−3.929***	−3.609***	−3.988***
Year (ref. 2007)			
2008	0.970****	1.004****	0.962****
2009	1.601****	1.619****	1.590****
2010	1.463****	1.402****	1.461****
2011	1.281***	1.140**	1.300***
2012	0.696	0.521	0.725
2013	0.772	0.569	0.769
2014	0.587	1.111*	0.597
Conversion Rate	0.378		0.243
Monthly Visits		−0.000	−0.000
Constant	−3.758****	−3.739****	−3.746****
Number of obs.	5012	5185	5012
Number of clusters	595	610	595
Log pseudolikelihood	−1400.191	−1441.493	−1399.479
Chi-squared	269.683	268.814	270.750
Prob. > Chi-squared	0.000	0.000	0.000
Pseudo R-squared	0.107	0.105	0.108
AIC	2822.382	2904.985	2822.958
BIC	2894.097	2977.074	2901.194

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

2.5. Discussion

It was proposed to empirically test if the reasons for the adoption of a new technology could be observed at the industry level and discriminated as a response to social pressures or the pursuit of what is believed to be an opportunity. Answering to the calls of Lieberman and Asaba (2006) and Ordanini *et al.* (2008) for more empirical research aimed at testing alternative imitation theories, the present study draws conclusions about the main motivations among a population of firms.

2.5.1. Theoretical Implications

According to George *et al.* (2006), the cognition can add a new layer to the study of social pressures among organizations. As organizational actions result from managerial decision making one can expect to see evidence of cognitive framing in aggregate firm behavior. Prior studies argue that opportunity/threat framing may explain different decisions by managers facing the same envi-

ronmental information (Dutton and Jackson, 1987; George *et al.*, 2006; Kennedy and Fiss, 2009; Nikolaeva, 2014).

Two hypotheses were proposed to establish if it is possible to identify the main driver of adoption. The hypotheses are based on the shape of the adoption curve as a sign of the underlying assumptions of the decision-makers. A process fueled by social pressures would result in an adoption curve with a steeper increase. On the other hand, when firms use social learning they may wait before adopting and the timing of adoption will be more heterogeneous. The delay allows them to collect more information about the usefulness of the innovation and the costs of its implementation. The fact that the adoption of this technology does not imply an initial cost strengths the results as the price is not a constraint to firms.

It was found support for the informative value of imitation, consistent with companies viewing adoption as an opportunity. This technology has two characteristics that make it suitable for testing imitating behaviors. First, it is free. Ruling out the immediate cost for adoption makes feasible adopting without using it. If there were high initial costs, there was a higher probability of not adopting if the firms did not considerer to use it. Second, it is widely visible to each company which competitors established a social media presence. Even considering that some companies do not publish links driving customers outside their websites, it is easily discoverable if there is a Facebook page.

The present research aims to make three contributions. First, the main contribution is the inference of the motivations for imitation from the pattern of adoption in the case of social media adoption. A predominant framing can be inferred from the adoption curve based on the reaction from observing prior adopters. Second, the use of non-linear competing hypothesis answers the calls for more precise theories (Edwards and Berry, 2010; Aguinis and Edwards, 2014; Pierce and Aguinis, 2013). Third, while social media is one of the most important marketing tools for firms, there are no studies tracking social media presence among e-retailers. E-commerce retailing companies are used to manage an internet presence and face the challenge of distance, so it is a particularly interesting group to study. The public exposure resulting from adopting a social media website constitutes an interesting characteristic while answering the calls of Lieberman and Asaba (2006) and Ordanini *et al.* (2008). While it is a familiar media, the date of adoption is public, so it does not rely on self-reported information.

2.5.2. Managerial/Practical Implications

One of the challenges that managers face is to determine the benefits of early investment of resources in adopting a new technology or procedure. Within a context of deciding under uncertainty,

the resources they have or the time they can invest in the decision process, this study helps to determine the expected evolution. A deeper understanding of the adoption process and imitation drivers can help managers identify the potential benefits and prevent some of the risks. For firms offering those innovations, a good start is not always a guarantee of good prospects for future years. Alternatively, a slow initial adoption rate it is not a sign that the firm will not be a major player. For the firms providing the technology, it helps to plan for the deployment and how to interpret the market reaction. This way they will be able to respond and act timely to the adoption patterns they face. This is the case if the company is heavily dependent on post adoption services to monetize the platform.

2.5.3. Directions for Future Research

Implementing a new technology does not end with its adoption. Firms have to invest in the development and implementation of new practices to integrate and manage it. In the specific case of social media, companies have to actively engage in managing their presence to be able to fully capture the benefits of adoption and avoid a social media crisis. An interesting contribution would be the study of post adoption behaviors. After the initial adoptions, the effective use will help reveal the reasons behind the decision. This path will be further explored in Chapter 4.

2.6. Conclusion

This study brings together institutional theory and cognition to test the effect of legitimacy pressures on the decision about the diffusion of a new technology. The reasons for adoption can help explaining the role of competitive dynamics on adoption. Based on the views of the process of adoption as resulting from social influence or social learning, two hypothesis were proposed about the shape of the adoption curve. The existence of a social threshold, as it was proposed by Young (2009), will condition the shape of the adoption curve if the process is driven by social influence.

The adoption of a social network constitutes an interesting field to test the reasoning that is predominant among a population of firms. Considering that social networks like Facebook had a rapid adoption among individuals and a very large media coverage, it was chosen as a testing ground for the theoretical hypothesis. It is free, so firms do not have an initial adoption sunk cost, and it the adoption is easily observed and monitored. Taking into consideration that not all firms have the same experience with web communication, a dataset composed of the largest e-retailers in the US was chosen. For each firm, it was determined if they were present in the selected social network and the date of adoption was gathered. By combining information about the e-retailers with information about

the use of Facebook, it was possible to gather a unique dataset and address the hypotheses about adoption curve shape using a discrete time survival model. The estimation was conducted starting from a panel with eight years of information and collecting unique information about the adoption of Facebook.

According to the results and by ruling out social pressures, companies view adoption as the result of social learning, consistent with framing it as an opportunity. This result was obtained when controlling for several characteristics of the firms as well as the increasing media coverage about Facebook during the period.

This result has important scientific and practical implications. The use of non-linear competing hypothesis to infer the reasoning behind the adoption curve provides a framework to study adoption among a population of firms. The use of a social network contributes to the study of a phenomenon that is changing how firms communicate and even reshaping many aspects about how do people consume and share information.

3. Changes in Strategy as a Result of Performance Feedback

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> "Demographic research on transformation reveals that organizations rarely change their fundamental properties quickly when environmental opportunities and constraints change. Such inertia is often viewed, both by participants and academic analysts, as pathological - if only firms and bureaucracies were better managed or better designed, they would be nimbler. No doubt, many organizations do suffer poor management and poor design. However, this does not seem to be the crux of the matter. Even organizations that are hailed as paragons of good management and felicitous design often stumble when conditions change suddenly and unpredictably." (Carroll and Hannan, 2000: 362)

3.1. Introduction

One of the most important decisions about technology sourcing is whether developing the tools in-house (customizing to the specifics of their business and consumer characteristics) or outsourcing this task (by acquiring or developing over pre-existing ones) (Tsai *et al.*, 2013). Tsai *et al.* (2013) focus on the study of the relationship between performance and degree of sourcing using a panel of data with four years of information. However, this type of approach does not account for the dynamic nature of the decision process: if the change in performance from one year to the next is positive, managers will be less likely to change the technology sourcing strategy that they already have in place. While it is very important to acknowledge the expected return of this type of investment, the reasons behind the change are often overlooked.

Organizational learning theory considers that firms base their decisions on the knowledge generated by their previous experiences. As it is expected that the strategies that fail to deliver the expected results are more prone to be abandoned, the experience of decreases in performance should trigger a search for a better solution. This study claims that the change in the in-house/outsourcing strategy mix should, therefore, vary with the comparison of historical performance and achievement of expected results.

E-commerce firms depend on their website to attract and retain customers, so this decision about the sourcing of technology is of the foremost importance. It is a highly competitive sector with a vast array of technology solutions to choose from. These firms have to decide about the vendors they use for a large set of technologies (e.g., “CRM” or “Payment Systems”). These changes are also immediately visible to their competitors defying geographical distance barriers. Moreover, because the website is the main link to the consumer, companies aim to carefully choose the technologies to be able to provide a rewarding experience to their customers and attract visitors. Otherwise, customers can easily move to buy from another competitor. Zeithaml, Parasuraman and Malhotra (2002) state that the development by Bizrate of service quality measures to review and identify strengths and weaknesses of the websites is a signal of the importance that consumers and the industry put on usability. Changes in the technologies supporting some of the features of the website are, therefore, up for change when the results are not up to the expectations of the managers.

This study focuses on the changes of the sourcing mix between external vendors and internal development among e-retailers. To answer this question, a sample of e-retailers from the US was compiled using a panel with eight years of data regarding information about performance and technologies as well as the technology sourcing they were using. Those eight cross-sections resulted in a panel of six years of information with lags.

This study makes four contributions to the literature. The first contribution is the study of the importance of performance feedback as an antecedent of changes in make/buy sourcing decisions. This perspective is often forgotten from the study of these decisions, but it is an important source of information for decision-makers. The second contribution is accounting for the dynamic nature of environments where managers do not look only to the level of performance but value also its changes. The third contribution is the segregation between technologies associated with different processes that respond to different performance metrics. The fourth contribution is the use of a large panel with eight years of rich information about each of the individuals of the dataset.

3.2. Theoretical Background

An important strategic decision when adopting a technology is whether developing the tools in-house or outsourcing. While in-house development allows to fully customize it to the specific needs and characteristics of the firm and its business, outsourcing also has some advantages, like capturing the benefits of the experience and resources of the supplier. Tsai *et al.* (2013) focused on the performance outcome of technology adoption contrasting the *make* versus *buy* strategies. Their analysis is founded on contingency theory and was conducted "by identifying important contingent variables for different contexts and by examining the alignment of internal decisions and external context" (Tsai *et al.*, 2013: 346). However, a fully rational decision is not attainable because the natural limitations to perfect knowledge (Gavetti, Greve, Levinthal and Ocasio, 2012).

March (2006) claims that the complex nature of firms environment challenges the manager's limited capabilities regarding cognition, attention, and memory. He also argues that procedures that result in successes have better chances to survive and to be replicated and are the basis of several theories of feedback-based adaptation over time: experiential learning, learning from others (diffusion, imitation), and variation/selection. According to this view, managers respond to performance feedback with differences in the adopted strategies. Experiential learning theories argue that past positive results using a certain strategy increase the propensity to use the same strategy again (March, 2006). This view is consistent with decision makers' bounded rationality (Simon, 1955; Lant, 1992) and with limitations to the ability to process and react to all available information in a fully rational perspective. Not being able to optimize along all options and considering all scenarios, managers respond to the ones that they can perceive and understand as more probable. As managers are often deeply involved in the decision process and in the monitoring and follow up, these facts are better understood and easily remembered. This perspective is frequently absent from previous con-

tributions. As an example, the study of Tsai *et al.* (2013) does not consider the complexity invoked by March (2006).

According to Levitt and March (1988) and Lant (1992), organizational learning theory considers that firms behavior is based on routines, that their actions are history dependent and that firms are goal directed. They also posit that aspirations are updated according to observed performance. Moreover, favorable and unfavorable feedback has been found to influence the definition of goals by firms (Cyert and March, 1963; Lant, 1992). The propensity to conduct a strategic reorientation was also found to be influenced by past performance (Lant and Milliken, 1992).

As the technologies used closely depend on the markets and products of the company, we expect that firms should react to performance because it is a proxy for the adequacy of the strategy to the market. Positive performance may be seen as a sign of an adequate strategy, with higher results seen as strong evidence of this view.

Tsai *et al.* (2013) discuss the benefits and risks with the decision about the inhouse or external degree of sourcing. Balancing the benefits and risks of this decision takes into consideration the individual advantages of in-house versus external development. These authors observe that in-house development allows the firm to take advantage of the experience of the supplier, reducing the risk, but may imply some disadvantages like the loss of critical skills or some loss of control.

There may also be several different reasons that would explain why this claim may not apply to all cases in the technology sourcing. This can result from technical limitations or licensing terms. First, changes in the size of the company may render the older technologies (e.g., software) inadequate. Second, management goes further in the learning curve while time goes by and may acknowledge that the technology that they are using is not adequate and that they must invest in a new one. However, if there is a strong tendency to follow the logic proposed by the organizational learning theory, these reasons should not prevail over the main effect from changes in performance.

Hence, this paper aims to answer the following question: *to what extent changes in performance influence changes in strategy*?

3.3. Data and Methodology

To test the proposed research question, this study uses a panel composed of e-retailers from US and eight years of data. As the estimation is based on lags, the final dataset will result of information regarding six years each one also considering data from the two preceding years. Restricting data to only one country reduces the potential for differences in reported measures that are used to assess

performance (Katsikeas, Morgan, Leonidou and Hult, 2016), and this study will focus only on US firms.

3.3.1. Data Collection

The dataset is a panel compiled from information based on IR Top 500 Guide (top500guide.com). It is composed by the largest e-retailers in the US based on web sales. This source of data has been previously used by researchers on e-retailing (e.g., Chuang *et al.*, 2014; Griffis *et al.*, 2012; Tsai *et al.*, 2013; Karimov and Brengman, 2011).

The aim is to investigate the impact of changes in performance to changes in the sourcing strategy. This study follows the empirical strategy of Lages *et al.* (2013) that tests the changes in strategy from year $t-1$ to t by looking to the previous changes in performance from year $t-2$ to $t-1$. So for each year, the procedure consists in building a panel with three years of information and using the first two to assess the change in performance and the second and third ones to assess the change in strategy.

Instead of considering only one strategic option for each technology and one three-year panel, the present research looks to changes in make/buy strategy for three indexes based in a total of 14 different technology sourcing decisions and uses a panel with eight years of original data, allowing to build a six period panel with lags from year $t-1$ and $t-2$.

3.3.2. Variable Definitions

Table 3.1 enumerates the variables that are used in the empirical test of the research question. The variables that will be used as dependent variable for each of the three estimations were based on the sourcing strategy of the 14 different technology decisions. The technologies whose vendors were tracked and accounted for were grouped into three distinct sets according to Tsai *et al.* (2013): Logistics & Operations (“Content Deliver”, “Content Management”, “Site Design”, “Web Analytics”, “Web Hosting”, “Web Performance Monitoring”), Marketing (“Affiliate Marketing”, “e-Mail Marketing”, “Search Engine Marketing”), and Sales (“e-Commerce Platform”, “Fulfillment”, “Order Management”, “Rich Media”, “Site Search”). For each the 14 technologies, it was calculated the ratio of the internal over all sources (internal and external) used by each firm in each year. For each of the three groups, it was computed the average of these ratios for each retailer in each year. Finally, the three final variables were compiled based on the changes in each groups ratio from year $t-1$ to t.

Table 3.1. Variable definitions.

Variables	Description
Logistics & Operations Make/Buy Ratio Change	Change in the average logistics & operations ("Content Deliver", "Content Management", "Site Design", "Web Analytics", "Web Hosting", "Web Performance Monitoring") make/buy ratio from year $t-1$ to t.
Marketing Make/Buy Ratio Change	Change in the average marketing ("Affiliate Marketing", "e-Mail Marketing", "Search Engine Marketing") make/buy ratio from year $t-1$ to t.
Sales Make/Buy Ratio Change	Change in the average sales ("e-Commerce Platform", "Fulfillment", "Order Management", "Rich Media", "Site Search") make/buy ratio from year $t-1$ to t.
Web Sales (10^6) Change	Change in web sales from the year $t-2$ to $t-1$.
Web Sales (10^6) Level	Web sales in year $t-2$ (in millions of USD), scaled.
Conversion Rate (10^6) Change	Change in conversion rate from the year $t-2$ to $t-1$.
Conversion Rate (10^6) Level	Conversion rate in year $t-2$ (in millions of USD), scaled.
Average Ticket (USD) Change	Change in average ticket from the year $t-2$ to $t-1$.
Average Ticket (USD) Level	Average ticket in year $t-2$, scaled.
Monthly Visits Change	Change in monthly visits from the year $t-2$ to $t-1$.
Monthly Visits Level	Monthly visits in year $t-2$, scaled.
Monthly Unique Visitors Change	Change in monthly unique visitors from the year $t-2$ to $t-1$.
Monthly Unique Visitors Level	Monthly unique visitors in year $t-2$, scaled.
Year Dummies	Dummy variables controlling for the year.

The main independent variables accounting for performance were based on web sales, conversion rate, average ticket, monthly visits, and monthly unique visitors. As Lages *et al.* (2013), the estimation will account for changes in performance from year $t-2$ to $t-1$ and the level of performance at the year $t-2$. All these metrics account for the specificities of e-retailing business. Based on each retailer' metrics, it was calculated the percentage change from year $t-2$ to $t-1$, designated as "Web Sales Change" in the case of web sales, as well as the level in year $t-2$, designated as "Web Sales Level". The variables accounting for the level were scaled to the interval between zero and one.

An important control is the inclusion of time dummies, built from the variable "Year". These variables account for simultaneous shocks affecting all firms in the dataset in each of the periods. The final dataset has one row for each firm in each year.

3.3.3. Model Specification

The estimation will be conducted by using fixed effects with clustering on the firm unique ID panel variable, resulting in an estimation that is robust to "cross-sectional heteroskedasticity and within-panel (serial) correlation that is asymptotically equivalent to that proposed by (Arellano, 1987)" (StataCorp, 2015a).

The model aims to fit the model (StataCorp, 2015a):

$$y_{it} = \alpha + x_{it}\beta + \nu_i + \epsilon_{it} \tag{3.1}$$

for $i = 1, ..., n$ and, for each i, $t = 1, ..., T$ of which T_i periods were observed. The model runs ordinary least squares from the model:

$$\left(y_{it} - \overline{y}_i + \overline{\overline{y}}\right) = \alpha + \left(x_{it} - \overline{x}_i + \overline{\overline{x}}\right)\beta + \left(\epsilon_{it} - \overline{\epsilon}_i + \overline{\nu}\right) + \overline{\overline{\epsilon}} \tag{3.2}$$

where $\overline{y}_i = \sum_{t=1}^{T_i} y_{it}/T_i$ and $\overline{\overline{y}}_i = \sum_{i=1} \sum_{t=1} y_{it}/(nT_i)$. The estimation uses cluster robust standard errors (Froot, 1989; Rogers, 1993; Williams, 2000) and was conducted using Stata 14.2 software (StataCorp, 2015b) and the command '`xtreg`'.

3.4. Results

The final dataset that was compiled to test the hypothesis has firms that are followed for six years (not including the two initial years that were also collected for generating lags) in their decisions about the sourcing of 14 technologies. This study includes firms from 15 different merchandise categories [see Table 3.2]. Regarding the merchant type, the dataset is very well distributed along the four categories [see Table 3.3].

Table 3.4 presents the count of the number of firms that changed strategy in each of the years observed in the sample. Looking to each one of the tables reporting the distribution of the changes observed in each one of the years [see Tables Table 3.5, Table 3.6, Table 3.7, Table 3.8, Table 3.9, and Table 3.10], it is possible to observe that many firms change the total make/buy ratio, reinforcing the relevance of the study of the reasons for these changes.

Table 3.2. Strategy change events by retail categories in the sample.

Merchandise Category	Total Make/Buy Ratio Change (binary)						Total		
	No Change			Change					
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	221	27.2	62.1	135	24.5	37.9	356	26.1	100.0
Automotive Parts/Accessories	13	1.6	81.3	3	0.5	18.8	16	1.2	100.0
Books/Music/Video	36	4.4	52.9	32	5.8	47.1	68	5.0	100.0
Computers/Electronics	72	8.9	55.4	58	10.5	44.6	130	9.5	100.0
Flowers/Gifts	19	2.3	67.9	9	1.6	32.1	28	2.1	100.0
Food/Drug	41	5.0	68.3	19	3.4	31.7	60	4.4	100.0
Hardware/Home Improvement	22	2.7	53.7	19	3.4	46.3	41	3.0	100.0
Health/Beauty	52	6.4	65.0	28	5.1	35.0	80	5.9	100.0
Housewares/Home Furnishings	85	10.5	63.4	49	8.9	36.6	134	9.8	100.0
Jewelry	17	2.1	51.5	16	2.9	48.5	33	2.4	100.0
Mass Merchant	69	8.5	49.3	71	12.9	50.7	140	10.3	100.0
Office Supplies	26	3.2	56.5	20	3.6	43.5	46	3.4	100.0
Specialty	66	8.1	58.9	46	8.3	41.1	112	8.2	100.0
Sporting Goods	54	6.7	63.5	31	5.6	36.5	85	6.2	100.0
Toys/Hobbies	19	2.3	55.9	15	2.7	44.1	34	2.5	100.0
Total	812	100.0	59.6	551	100.0	40.4	1363	100.0	100.0

Table 3.3. Strategy change events by merchant type in the sample.

Merchant Type	Total Make/Buy Ratio Change (binary)						Total		
	No Change			Change					
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Catalog/Call Center	184	22.7	65.0	99	18.0	35.0	283	20.8	100.0
Consumer Brand Manufacturer	95	11.7	62.9	56	10.2	37.1	151	11.1	100.0
Retail Chain	292	36.0	57.3	218	39.6	42.7	510	37.4	100.0
Web Only	241	29.7	57.5	178	32.3	42.5	419	30.7	100.0
Total	812	100.0	59.6	551	100.0	40.4	1363	100.0	100.0

Table 3.4. Strategy change events by year in the sample.

Year	Total Make/Buy Ratio Change (binary)						Total		
	No Change			Change					
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
2009	141	17.4	61.6	88	16.0	38.4	229	16.8	100.0
2010	128	15.8	56.4	99	18.0	43.6	227	16.7	100.0
2011	158	19.5	70.9	65	11.8	29.1	223	16.4	100.0
2012	155	19.1	67.7	74	13.4	32.3	229	16.8	100.0
2013	77	9.5	34.2	148	26.9	65.8	225	16.5	100.0
2014	153	18.8	66.5	77	14.0	33.5	230	16.9	100.0
Total	812	100.0	59.6	551	100.0	40.4	1363	100.0	100.0

Table 3.5. Strategy change events during 2009 by merchandise category in the sample.

Merchandise Category	Total Make/Buy Ratio Change (binary)								
	No Change			Change			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	40	28.4	69.0	18	20.5	31.0	58	25.3	100.0
Automotive Parts/Accessories	3	2.1	100.0	0	0.0	0.0	3	1.3	100.0
Books/Music/Video	6	4.3	50.0	6	6.8	50.0	12	5.2	100.0
Computers/Electronics	10	7.1	45.5	12	13.6	54.5	22	9.6	100.0
Flowers/Gifts	4	2.8	80.0	1	1.1	20.0	5	2.2	100.0
Food/Drug	5	3.5	50.0	5	5.7	50.0	10	4.4	100.0
Hardware/Home Improvement	4	2.8	57.1	3	3.4	42.9	7	3.1	100.0
Health/Beauty	10	7.1	71.4	4	4.5	28.6	14	6.1	100.0
Housewares/Home Furnishings	16	11.3	66.7	8	9.1	33.3	24	10.5	100.0
Jewelry	4	2.8	80.0	1	1.1	20.0	5	2.2	100.0
Mass Merchant	10	7.1	45.5	12	13.6	54.5	22	9.6	100.0
Office Supplies	7	5.0	87.5	1	1.1	12.5	8	3.5	100.0
Specialty	11	7.8	57.9	8	9.1	42.1	19	8.3	100.0
Sporting Goods	7	5.0	50.0	7	8.0	50.0	14	6.1	100.0
Toys/Hobbies	4	2.8	66.7	2	2.3	33.3	6	2.6	100.0
Total	141	100.0	61.6	88	100.0	38.4	229	100.0	100.0

Table 3.6. Strategy change events during 2010 by merchandise category in the sample.

Merchandise Category	Total Make/Buy Ratio Change (binary)								
	No Change			Change			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	31	24.2	51.7	29	29.3	48.3	60	26.4	100.0
Automotive Parts/Accessories	2	1.6	100.0	0	0.0	0.0	2	0.9	100.0
Books/Music/Video	5	3.9	45.5	6	6.1	54.5	11	4.8	100.0
Computers/Electronics	13	10.2	61.9	8	8.1	38.1	21	9.3	100.0
Flowers/Gifts	3	2.3	60.0	2	2.0	40.0	5	2.2	100.0
Food/Drug	9	7.0	81.8	2	2.0	18.2	11	4.8	100.0
Hardware/Home Improvement	4	3.1	57.1	3	3.0	42.9	7	3.1	100.0
Health/Beauty	10	7.8	71.4	4	4.0	28.6	14	6.2	100.0
Housewares/Home Furnishings	12	9.4	52.2	11	11.1	47.8	23	10.1	100.0
Jewelry	1	0.8	20.0	4	4.0	80.0	5	2.2	100.0
Mass Merchant	14	10.9	58.3	10	10.1	41.7	24	10.6	100.0
Office Supplies	2	1.6	28.6	5	5.1	71.4	7	3.1	100.0
Specialty	9	7.0	50.0	9	9.1	50.0	18	7.9	100.0
Sporting Goods	10	7.8	76.9	3	3.0	23.1	13	5.7	100.0
Toys/Hobbies	3	2.3	50.0	3	3.0	50.0	6	2.6	100.0
Total	128	100.0	56.4	99	100.0	43.6	227	100.0	100.0

Table 3.7. Strategy change events during 2011 by merchandise category in the sample.

Merchandise Category	Total Make/Buy Ratio Change (binary)								
	No Change			Change			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	45	28.5	77.6	13	20.0	22.4	58	26.0	100.0
Automotive Parts/Accessories	3	1.9	100.0	0	0.0	0.0	3	1.3	100.0
Books/Music/Video	7	4.4	70.0	3	4.6	30.0	10	4.5	100.0
Computers/Electronics	15	9.5	68.2	7	10.8	31.8	22	9.9	100.0
Flowers/Gifts	4	2.5	80.0	1	1.5	20.0	5	2.2	100.0
Food/Drug	9	5.7	81.8	2	3.1	18.2	11	4.9	100.0
Hardware/Home Improvement	6	3.8	85.7	1	1.5	14.3	7	3.1	100.0
Health/Beauty	6	3.8	46.2	7	10.8	53.8	13	5.8	100.0
Housewares/Home Furnishings	17	10.8	85.0	3	4.6	15.0	20	9.0	100.0
Jewelry	4	2.5	66.7	2	3.1	33.3	6	2.7	100.0
Mass Merchant	12	7.6	52.2	11	16.9	47.8	23	10.3	100.0
Office Supplies	6	3.8	75.0	2	3.1	25.0	8	3.6	100.0
Specialty	11	7.0	64.7	6	9.2	35.3	17	7.6	100.0
Sporting Goods	11	7.0	73.3	4	6.2	26.7	15	6.7	100.0
Toys/Hobbies	2	1.3	40.0	3	4.6	60.0	5	2.2	100.0
Total	158	100.0	70.9	65	100.0	29.1	223	100.0	100.0

Table 3.8. Strategy change events during 2012 by merchandise category in the sample.

Merchandise Category	Total Make/Buy Ratio Change (binary)								
	No Change			Change			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	40	25.8	67.8	19	25.7	32.2	59	25.8	100.0
Automotive Parts/Accessories	3	1.9	100.0	0	0.0	0.0	3	1.3	100.0
Books/Music/Video	9	5.8	81.8	2	2.7	18.2	11	4.8	100.0
Computers/Electronics	14	9.0	63.6	8	10.8	36.4	22	9.6	100.0
Flowers/Gifts	3	1.9	75.0	1	1.4	25.0	4	1.7	100.0
Food/Drug	8	5.2	80.0	2	2.7	20.0	10	4.4	100.0
Hardware/Home Improvement	4	2.6	66.7	2	2.7	33.3	6	2.6	100.0
Health/Beauty	10	6.5	71.4	4	5.4	28.6	14	6.1	100.0
Housewares/Home Furnishings	18	11.6	81.8	4	5.4	18.2	22	9.6	100.0
Jewelry	4	2.6	66.7	2	2.7	33.3	6	2.6	100.0
Mass Merchant	12	7.7	50.0	12	16.2	50.0	24	10.5	100.0
Office Supplies	4	2.6	50.0	4	5.4	50.0	8	3.5	100.0
Specialty	13	8.4	65.0	7	9.5	35.0	20	8.7	100.0
Sporting Goods	10	6.5	66.7	5	6.8	33.3	15	6.6	100.0
Toys/Hobbies	3	1.9	60.0	2	2.7	40.0	5	2.2	100.0
Total	155	100.0	67.7	74	100.0	32.3	229	100.0	100.0

Table 3.9. Strategy change events during 2013 by merchandise category in the sample.

Merchandise Category	Total Make/Buy Ratio Change (binary)								
	No Change			Change			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	26	33.8	43.3	34	23.0	56.7	60	26.7	100.0
Automotive Parts/Accessories	1	1.3	33.3	2	1.4	66.7	3	1.3	100.0
Books/Music/Video	2	2.6	16.7	10	6.8	83.3	12	5.3	100.0
Computers/Electronics	8	10.4	38.1	13	8.8	61.9	21	9.3	100.0
Flowers/Gifts	2	2.6	50.0	2	1.4	50.0	4	1.8	100.0
Food/Drug	1	1.3	12.5	7	4.7	87.5	8	3.6	100.0
Hardware/Home Improvement	1	1.3	14.3	6	4.1	85.7	7	3.1	100.0
Health/Beauty	7	9.1	53.8	6	4.1	46.2	13	5.8	100.0
Housewares/Home Furnishings	7	9.1	31.8	15	10.1	68.2	22	9.8	100.0
Jewelry	1	1.3	20.0	4	2.7	80.0	5	2.2	100.0
Mass Merchant	6	7.8	25.0	18	12.2	75.0	24	10.7	100.0
Office Supplies	2	2.6	28.6	5	3.4	71.4	7	3.1	100.0
Specialty	7	9.1	35.0	13	8.8	65.0	20	8.9	100.0
Sporting Goods	4	5.2	30.8	9	6.1	69.2	13	5.8	100.0
Toys/Hobbies	2	2.6	33.3	4	2.7	66.7	6	2.7	100.0
Total	77	100.0	34.2	148	100.0	65.8	225	100.0	100.0

The summary statistics and table of correlations of the variables in the dataset are presented in Table 3.11 and Table 3.12. Looking at the initial statistics about the variables used, there was some disparity of size within our sample when looking to web sales. The initial dataset includes some observations that were identified as outliers and whose specificities may pose some risks to the present analysis. Even though the dataset is composed of the largest e-retailers in the US, some of those firms have now a size that is very different from their peers. This is the case of Amazon, the largest one, that has now evolved to a marketplace providing the intermediation of third-party vendors (Bensinger, 2016). For the purpose of this study, Amazon is clearly an outlier when compared with the rest of the sample and was excluded from this study. Similarly, to account for other outliers, it was calculated the z-score of the variables accounting for the performance changes, and some observations were excluded using this metric (included only values greater than -4 and less than 4).

Table 3.10. Strategy change events during 2014 by merchandise category in the sample.

Merchandise Category	Total Make/Buy Ratio Change (binary)								
	No Change			Change			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	39	25.5	63.9	22	28.6	36.1	61	26.5	100.0
Automotive Parts/Accessories	1	0.7	50.0	1	1.3	50.0	2	0.9	100.0
Books/Music/Video	7	4.6	58.3	5	6.5	41.7	12	5.2	100.0
Computers/Electronics	12	7.8	54.5	10	13.0	45.5	22	9.6	100.0
Flowers/Gifts	3	2.0	60.0	2	2.6	40.0	5	2.2	100.0
Food/Drug	9	5.9	90.0	1	1.3	10.0	10	4.3	100.0
Hardware/Home Improvement	3	2.0	42.9	4	5.2	57.1	7	3.0	100.0
Health/Beauty	9	5.9	75.0	3	3.9	25.0	12	5.2	100.0
Housewares/Home Furnishings	15	9.8	65.2	8	10.4	34.8	23	10.0	100.0
Jewelry	3	2.0	50.0	3	3.9	50.0	6	2.6	100.0
Mass Merchant	15	9.8	65.2	8	10.4	34.8	23	10.0	100.0
Office Supplies	5	3.3	62.5	3	3.9	37.5	8	3.5	100.0
Specialty	15	9.8	83.3	3	3.9	16.7	18	7.8	100.0
Sporting Goods	12	7.8	80.0	3	3.9	20.0	15	6.5	100.0
Toys/Hobbies	5	3.3	83.3	1	1.3	16.7	6	2.6	100.0
Total	153	100.0	66.5	77	100.0	33.5	230	100.0	100.0

Table 3.11. Summary statistics.

		Mean	St. Dev.	Min.	Max.
Logistics & Operations Make/Buy Ratio Change	(1)	−0.01	0.07	−0.75	0.63
Marketing Make/Buy Ratio Change	(2)	−0.02	0.10	−0.67	0.50
Sales Make/Buy Ratio Change	(3)	−0.01	0.08	−0.75	0.70
Web Sales (USD 10^6) Change	(4)	0.12	0.17	−0.55	1.08
Web Sales (USD 10^6) Level	(5)	0.03	0.09	0.00	1.00
Conversion Rate Change	(6)	−0.01	0.14	−0.65	0.84
Conversion Rate Level	(7)	0.14	0.12	0.00	1.00
Average Ticket (USD) Change	(8)	0.01	0.07	−0.40	0.40
Average Ticket (USD) Level	(9)	0.11	0.13	0.00	1.00
Monthly Unique Visitors Change	(10)	0.14	0.70	−0.93	5.54
Monthly Unique Visitors Level	(11)	0.03	0.05	0.00	1.00
Monthly Visits Change	(12)	0.09	0.34	−0.90	1.77
Monthly Visits Level	(13)	0.04	0.09	0.00	1.00

Table 3.12. Correlation matrix. Correlation table built handling missing values by pairwise deletion.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Logistics & Operations Make/Buy Ratio Change	(1)	1.00												
Marketing Make/Buy Ratio Change	(2)	0.16	1.00											
Sales Make/Buy Ratio Change	(3)	0.26	0.08	1.00										
Web Sales (USD 10^6) Change	(4)	0.01	0.00	−0.03	1.00									
Web Sales (USD 10^6) Level	(5)	0.02	0.04	0.03	−0.04	1.00								
Conversion Rate Change	(6)	0.01	0.03	0.01	0.18	0.00	1.00							
Conversion Rate Level	(7)	0.01	0.02	0.04	−0.03	0.16	−0.15	1.00						
Average Ticket (USD) Change	(8)	−0.03	−0.01	0.01	0.19	0.03	0.01	0.01	1.00					
Average Ticket (USD) Level	(9)	0.03	−0.01	0.01	−0.13	0.17	0.03	−0.21	−0.02	1.00				
Monthly Unique Visitors Change	(10)	−0.09	−0.02	−0.05	0.11	−0.01	−0.15	−0.00	−0.04	−0.03	1.00			
Monthly Unique Visitors Level	(11)	0.04	0.05	0.03	0.09	0.56	0.05	−0.07	0.04	−0.06	−0.08	1.00		
Monthly Visits Change	(12)	−0.03	−0.06	−0.07	0.23	−0.06	−0.35	0.03	−0.11	−0.04	0.40	−0.06	1.00	
Monthly Visits Level	(13)	0.03	0.05	0.02	0.06	0.66	0.05	−0.07	0.05	−0.02	−0.02	0.91	−0.09	1.00

Table 3.13 presents the results of the estimation of several models whose details are provided in Appendix B - Tables B.1, B.2, and B.3. The estimation of the model provides evidence of the importance of the effect of a change in performance as an antecedent of a change in strategy. It is clear that the impact of past performance as an antecedent of changes in performance is observed but it is not similar across all groups of technologies. The technologies included in the logistics and operations are changed in response to changes in the monthly unique visitors, while the ones related to marketing are changed as a response to changes in the conversion rate. This result was obtained by controlling for the performance level as well as for temporal differences during the observed period through the inclusion of "Year" dummies. These results provide support for the impact of changes in performance as antecedents of changes in strategy in the observed sample.

Table 3.13. Model estimation. Fixed effects regression models with cluster-robust standard errors.

	M3.1 Logistics & Operations Make/Buy Ratio Change	M3.2 Marketing Make/Buy Ratio Change	M3.3 Sales Make/Buy Ratio Change
Web Sales (USD 10^6) Change	−0.002	0.012	−0.009
Web Sales (USD 10^6) Level	0.178	0.238	0.149
Conversion Rate Change	0.004	0.049*	−0.018
Conversion Rate Level	0.029	0.130	−0.142
Average Ticket (USD) Change	−0.032	−0.007	−0.022
Average Ticket (USD) Level	0.159	0.076	−0.078
Monthly Visits Change	0.007	−0.005	−0.009
Monthly Visits Level	0.054	0.079	−0.028
Monthly Unique Visitors Change	−0.009**	0.004	−0.004
Monthly Unique Visitors Level	−0.072	0.050	0.042
Year (ref. '2009')			
2010	−0.008	−0.013	0.002
2011	−0.009	−0.015*	0.011*
2012	−0.001	−0.006	0.015*
2013	−0.032****	−0.034****	−0.009
2014	−0.006	−0.007	−0.006
Constant	−0.026	−0.044	0.016
Number of observations	1363	1363	1363
Number of clusters	239	239	239
R-squared for within model	0.043	0.019	0.019
R-squared for overall model	0.010	0.005	0.002
R-squared for between model	0.003	0.005	0.006
corr(μ_i ,Xb)	−0.631	−0.569	−0.453
F statistic	3.276	1.887	1.759
Numerator degrees of freedom for F statistic	15	15	15
Degrees of freedom for absorbed effect	238	238	238
ρ	0.234	0.184	0.178
Panel-level standard deviation	0.038	0.050	0.039
Standard deviation of ϵ_{it}	0.069	0.106	0.085

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

3.5. Discussion

3.5.1. Theoretical Implications

It was proposed to study the make/buy sourcing decision based on the impact of performance feedback as an antecedent of changes in strategy. The existing studies about technology sourcing lack the dynamic perspective that was proposed by Lages *et al.* (2013) based on the work of Cyert and March (1963). The dynamic nature of environments challenges managers ability to acquire and process information. The filters that are used by managers to select the information considered as relevant are not taken into consideration in existing studies about make/buy strategies. Indeed, performance feedback is widely employed in organizations through the use of instruments as balanced scorecards and is an important source of information about the results of past strategic choices. However, it is often forgotten in research about technology sourcing. Investors and stakeholders closely monitor the results of firms and derive the performance of its past decisions by using well-established metrics. Managers are also assessed by external stakeholders using these metrics that provide a quick test whenever more detailed information is not available. This study accounts for the behavioral response to performance feedback in the case of make versus buy strategy.

In the sample used in this study, it was found that changes in performance are one of the antecedents of changes in make/buy strategy by e-retailers. This result was obtained controlling for some of the most important metrics used by e-retailers. Web sales variable is naturally a measure of the size of the e-retailer. While some of the types of products account for very different total web sales with similar net profits, it is an important and highly visible measure of performance. One of the reasons for the lack of response to changes in web sales may indeed be the fact that an increase in web sales may not translate into higher net profits.

Conversion rate is an important measure for e-retailers because online shoppers do not incur in the time and transportation costs observed by offline consumers, so they often delay the purchase and return later to buy (Moe and Fader, 2004). Indeed, it is a good proxy for the ability to transform visitors into buyers (McDowell, Wilson and Kile, 2016). Not surprisingly, the functions associated with marketing respond to changes in conversion rate favoring an increase in in-house development as the conversion rate increases.

While the number of monthly visits was not found to affect changes in the in-house/outsourcing mix, the number of unique visitors was found to play a role in decisions about technologies related to logistics and operations. Here, an increase in the number of unique visitors results in an increase in the outsourcing. The investment that would be needed to accommodate such a change may explain

this reaction. It was also interesting to find that, within the sample, the firms were not responding to performance to engage in changes in the technologies related to sales.

The present study makes several contributions to the literature. First, it incorporates performance feedback in the study of make/buy sourcing strategies. Feedback from performance is well established in firms through the use of reporting tools but this trigger is usually absent from the academic discussion about make/buy sourcing strategies. By considering that managers may not be able to fully rationalize the decisions about technology adoption and are dependent on clues from performance feedback, this study incorporates the high complexity involved in these decisions. Second, this study brings the dynamic nature of environments in the study of technology adoption and it looks at changes in performance rather than at performance level only. Third, it accounts for differences in the decisions associated with three groups of technologies: logistics and operations, marketing, and sales. Fourth, the use of a large panel with eight years of information provides a rich empirical setting to test the proposed claim.

3.5.2. Directions for Future Research

One interesting development based on the current study is the test of these propositions in a dataset with more than one country. It would be relevant to consider different countries from Europe and test if there is a difference between the language, English or other, affects the choice of make/buy strategy. While the fragmentation of this market into a smaller number of e-retailers with a larger focus on their domestic market may provide some empirical challenges, the insights may be very relevant.

3.5.3. Managerial Implications

This study contributes to give awareness to the role of motivations in the decisions about technology adoption and specifically the impact of negative past performance in the increase of the probability of a change in strategy. This is an important aspect for several types of stakeholders as make/buy strategies are in the public domain. Even in the case these decisions are not disclosed by the firms, the use of some of the technologies is, by their nature, public and easily monitored by their peers (e.g., “Payment systems”). Managers that want to avoid a “performance trap” and do not anticipate the need for a change as long as the results are positive but not as good as they could be will benefit to account for the present approach. Investors and other outside stakeholders that aim to understand the reasons behind the changes, or their absence, should also take these results into consideration. Regarding competition, managers can use the findings to better understand the actions of their peers.

3.6. Conclusion

The understanding about make/buy technology sourcing is an important strategic decision whose analysis usually focuses on the performance of each one of the alternatives rather than the reasons behind the acknowledgement of the need for a change. The study of make/buy degree of sourcing by e-retailers proposed by Tsai *et al.* (2013) looked at the problem with a static perspective. Using the organizational learning perspective can provide valuable insights to the discussion. Without this dynamic perspective, researchers are not taking into consideration that there is knowledge that is created by past experiences. This experiential learning combined with the complexity of the environments can lead to decisions that do not always follow a purely rational approach. By considering that changes in performance trigger the mechanism of evaluation and search for better alternative choices in the technology mix used by the firms, this study contributes with a dynamic approach based on the organizational learning theory. Accounting for the behavioral response to performance feedback in the case of *make* versus *buy* strategy, it is possible to better understand the phenomenon and understand some of the motivations behind it.

To pursue this research path, the current study collected information regarding the adoption of 14 different technologies by a large sample of firms using eight years of data. Using a fixed effects model, it was possible to identify the metrics that provide insights about the need for a strategic change regarding the mix of in-house and outsourced technologies. By dividing the technologies into three groups according to the specifics of the business model where they operate, it was possible to identify different metrics that are expected to be more informative of the effectiveness of the installed technologies. It was found that changes in performance play a role in the decisions about strategy and that managers attend to the different metrics depending on the type of technology.

4. Assessing Institutional Pressures from Post-Adoption Behaviors

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> "We then posit that different forms of fit and misfit will trigger different patterns of practice adaptation and that this understanding will allow us to predict both the timing (i.e., early versus late) and the form of practice adaptation by an organization." (Ansari, Fiss and Zajac, 2010: 68)

4.1. Introduction

Adopting a new technology or procedure is not just a one-moment decision. Ansari *et al.* (2010) aggregate two theoretical streams about innovation adoption into rational accounts, based on rational actor model, and social accounts, based on response to social pressures. It is important to highlight that the use of the term "rational" for one of the streams of literature does not imply that that social arguments are "irrational" or resulting from a mere ritualistic phenomenon (Lieberman and Asaba, 2006). One of the most important challenges with the adoption of innovations has to do with their implementation (Kennedy and Fiss, 2009). In contrast to the classic diffusion model, that argues in favor of invariant practices and decisions based on rational assumptions, researchers have found that companies change and adapt procedures after the initial decision of adoption (Ansari *et al.*, 2010; Kennedy and Fiss, 2009). According to Ansari *et al.* (2010), who focus on what happens after the adoption, practices "evolve" during their implementation. They argue that a fit/misfit between the organization and the technology will lead to different patterns of adoption and of practice adaptation in the implementation phase. These changes in post-adoption behavior may result from pre-adoption motivations (Kennedy and Fiss, 2009; Nikolaeva, 2014). Thus, the underlying motivation for adoption would be conditioning the post-adoption implementation efforts. Kennedy and Fiss (2009) find evidence that organizations that perceive economic or social gain before adoption tend to implement practices more thoroughly and extensively. On the other hand, perceived economic or social losses as drivers of adoption result in lower levels of implementation. This research suggests that misfits may simply result from the wrong imitative pressures, not surprisingly leading to low efforts during the implementation phase.

The current study claims that the prevalence of the rational or social argument will result in different efforts to implementation and patterns of utilization, noticeable at the industry level. According to the rational argument, later adopters possess the information from prior adopters' experiences they need to decide about the adoption of innovation. If there is no fit between the innovation and the strategy of the firm, it is not rational to engage in its implementation. The social argument follows the neo-institutional perspective and sees imitation in adoption as a result of conformity and legitimacy pressures. In this case, adopters may just perform a symbolic adoption, without the full knowledge about the real value of the innovation for their operations. As those pressures mount, later adopters will adopt even if they do not need the technology resulting in misfit and lower utilization (Terlaak and Gong, 2008; Ansari *et al.*, 2010).

It is proposed to assess the reasons for different post-adoption behaviors looking to the Twitter usage by a dataset composed by the largest e-retailers in the United States and Europe accord-

ing to the web sales in recent years. By focusing on the largest e-retailers, it is possible to rule out alternative explanations about the slowness of adoption and implementation due to lack of resources. Social media changed the way companies communicate with customers and is, nowadays, an important source of information about the vendor and their products (Michaelidou *et al.*, 2011). Simultaneously, social networks provide an important link to the community of shoppers (Karimov and Brengman, 2011) and allow firms to interact and learn with their clients.

A social media presence does not end with the adoption of a platform (e.g., Facebook, Twitter). Indeed, being active and engaging the audience is a requirement for a successful presence in this new media (Kaplan and Haenlein, 2010). The real-time updates of micro-blogging platforms like Twitter are a powerful tool accessible to even the smallest companies (Kietzmann, Hermkens, McCarthy and Silvestre, 2011). However, actively managing the online presence may expose companies to unforeseen social media blunders. There are numerous examples of this type of mistakes resulting in negative viral publicity (Samson, 2015) with high costs regarding reputation. One of them was portrayed by Coca-Cola about the borders of Russia and Ukraine (Makortoff, 2016), and constitutes a clear example of what can go wrong when managing a social network presence.

This study makes several contributions to the existing literature. First, it brings together the study of social networks adoption and implementation, the ultimate competitive ground for e-retail companies, in the context of neo-institutional theory. Social media is increasing its importance among other marketing tools in consumer markets, but it is in an “embryonic stage” in terms of research (Michaelidou *et al.*, 2011). Second, it studies the phenomenon within a context of zero adoption costs. While there have been other studies of practice implementation, the adoption and implementation of a technology or practice have always had to deal with the cost component. Some organizations might be late adopters or non-adopters due to resource constraints. By setting the study in a context of zero adoption costs, the focus is centered around implementation stage and how its strategic consideration can affect the results of the adoption decision. Third, the present study does not rely on self-reported measures that could bias the results. Objective data avoid managerial biases in survey responses. Finally, this study includes firms from the US and Europe (EU), taking into consideration the differences between the two groups.

4.2. Theoretical Background

Sometimes innovations fail not because of anything related to adoption but because of problems during the phase of implementation, a lapse of time where firms have to commit to its use (Klein and

Knight, 2005). Implementation is a key phase in innovation adoption and the investment that firms do can help reveal the intentions of firms regarding the new technology or process. According to March (2006: 205), "environments are often complicated, endogenous, subjective and contested. Some of the complications stem from properties of human actors." These authors argue that limitations in "cognitive, attention and memory capabilities" (March, 2006: 205) make it difficult to decision makers to overcome these complications.

Kennedy and Fiss (2009) argued that the motivations for adoption should be noticed after the adoption period, namely that framing the adoption as an opportunity to follow or a threat to avoid will influence its implementation. They found that an economic and social gain is associated with a large extension of practice implementation and that an economic and social loss motivation is associated with less effort through implementation. Size also affects the implementation with larger organizations showing less extensive implementation. Their research was based on self-reported measures collected through a survey conducted in 1993 to a large dataset of hospital leaders. Ansari *et al.* (2010) focused on the change of practices during the diffusion process rather than seeing them as "off-the-shelf" solutions, and that the fit with the organization will condition adoption, namely the timing and the adaptation dimensions.

There are several dichotomies about the motivations leading to adoption but a common characteristic is the opposition of a more rational perspective against a more sociological transmission one (Tolbert and Zucker, 1983; Sturdy, 2004; Kennedy and Fiss, 2009; Ansari *et al.*, 2010; Nikolaeva, 2014). This dichotomy will be followed by this study.

Ordanini *et al.* (2008) suggested that the theoretical development of the study of imitative behaviors could be achieved through the test of the causal explanations proposed by different streams of literature about the subject.

According to the social accounts perspective, companies respond to pressure to conform to prevailing norms. Social accounts explanations follow the neo-institutional perspective and see imitation as a result of conformity and legitimacy pressures. By mimicking the behavior of technically-driven decisions "organizations avoid social censure, minimize demands for external accountability, improve their chances of securing necessary resources and raise their probability of survival" (Greenwood *et al.*, 2008: 4). This view of the diffusion process disagrees with the "efficient choice" view that innovations are always beneficial to firms (Abrahamson, 1991). If later adopters look for legitimacy and social benefits, as proposed by DiMaggio and Powell (1983) and Tolbert and Zucker (1983), they will adopt but they are not expected to put the same efforts in the implementation phase as the companies with a value creation perspective about this specific innovation. With the pressure for adoption increasing, companies will adopt to be legitimate among their peers but without a real

belief in the benefits resulting from the innovation. As those pressures mount, later adopters will adopt even if they do not need the technology resulting in misfit and lower utilization, a pressure that has not influenced early adopters (Ansari *et al.*, 2010). As Terlaak and Gong (2008: 854) stated, "research suggests that symbolic adoption due to institutional pressures occurs most frequently during later stages of a diffusion process" so the difference in implementation efforts between early and later adopters should increase. This hypothesis is consistent with information cascades and the existence of bandwagons. If ambiguity prevails in later stages of the adoption curve, the social considerations inferred from the bandwagon effect will replace the economic rationals to sustain the decision process (Abrahamson and Rosenkopf, 1993).

The decoupling mechanism proposed by Meyer and Rowan (1977) explains the phenomenon behind this behavior: "decoupling enables organizations to seek the legitimacy that adaptation to rationalized myths provides while they engage in technical 'business as usual"' (Boxenbaum and Jonsson, 2008: 79), by staying in a "loosely coupled state".

The rational perspective is well illustrated by the process of recognizing a problem, engaging in the search for a solution through evaluation of alternatives and finally a decision about adoption (Rogers, 2003; Sturdy, 2004). As it was proposed by Ordanini *et al.* (2008), using the term "rational" does not imply that the alternative hypothesis is "sub-optimal". Indeed, Haunschild and Miner (1997) suggest a multitude of mixed responses between two poles including the diffusion of innovation of Rogers (2003) and the inter-organizational learning of Levinthal and March (1981). Rogers (2003) views innovation adoption as a continuum rather than existing large discontinuities, like Moore (1999), and describes some characteristics of the five classes of adopters based on "ideal types" and defined according to the moment of adoption. These classes are defined according to behaviors based on rational arguments.

The rational perspective argues that agents assess the technology and decide based on "efficient choices" and later adopters have more information to avoid innovations that are not delivering the expected results across the industry or are not suited for their firms (Ansari *et al.*, 2010). According to these authors, early adopters may face misfit and adapt their practices while later adopters, based on the observation of others, may avoid practices with a low fit for their needs. In this case, we expect that later adopters know more about the technology and are better informed before they adopt. As the ones that adopt should have more information to decide, the rate of misfits should be lower among later adopters. Hence, if rational perspective explanation is prevalent, *the level of implementation of an innovation increases with adoption timing, i.e. later adopters are more likely to demonstrate more extensive implementation*.

4.3. Data and Methodology

4.3.1. Data Collection

To be able to explore the hypothesis of adopting a technology without ever using it, we will focus on a type of adoption that is free. One of the issues when studying imitative behaviors in new industries results from the difficulty of observing the behavior of competitors (Ansari *et al.*, 2010; Terlaak and Gong, 2008). To account for these issues, the focus will be on the adoption of a social media platform, Twitter, by e-retailers using a dataset composed of the largest e-retailers in the US and EU based on the yearly data collected from IR Top 500 Guide (top500guide.com). This dataset was already used in several research settings and was considered a reliable source of data (e.g., Chuang *et al.*, 2014; Tsai *et al.*, 2013; Griffis *et al.*, 2012; Karimov and Brengman, 2011). Besides being free and publicly visible to the competitors, Twitter is a web technology that should be easy to adopt by companies managing an online store because they are used to web communication and to the management of Internet platforms. Most of these firms are used to manage an Internet presence and to develop content to publish online, as developing banners to advertise or hosting and running an online forum.

The preparation of the dataset begun with 1,427 companies that have been part of the yearly top e-retailers in US during the last eigth years or in EU during the last four years. The first step was to compile a list of e-retailers present in any of the IR cross-sections. Then it was collected information regarding the presence of the firm in the social network by directly visiting their websites and looking for a link for Twitter or by using a search engine. For the firms with more than one account, it was selected the first to be registered on the website. In the beginning of October/2015 it was collected information regarding the use of Twitter, namely the time of adoption and the number of tweets already published. Each one of the Twitter accounts were visited again at the beginning of December/2015 to collect the number of tweets published until that date. The final dataset used for estimation (after excluding outliers) contains 1,310 firms with a Twitter account.

As dependent variable this study will use the number of tweets posted during the observation period [see Table 4.1]. As independent variable this study will use the time of adoption, expressed in the number of months and considering decimals, accounting for the positioning of each firm in a timeline that starts from the official date of foundation of Twitter, March 21, 2006.

Berthon, Pitt, Plangger and Shapiro (2012) proposed that social media strategies depend on a country's technology, culture, and government. One way of introducing a generic control for some of these dimensions within the sample is to group the merchants in two geographically distinct zones,

Table 4.1. Variable definitions.

Variables	Description
Dependent Variable	Number of tweets (including retweets) issued between the two data collections.
Time of Adoption	Time of adoption of Twitter (expressed in months) since the official foundation date of the firm (March 21, 2006).
Merchandise Category	Product category of the retailer.
US dataset	Dummy variable: 1 if it is from US dataset, 0 if from EU dataset.
Merchant Type	Type of merchant (web only, catalog/call center, consumer brand manufacturer or retail chain).
Average of New Tweets in Merchandise Cat.	Average of new tweets among firms from the same Merchandise Category as the e-retailer.
Capability index	Index based on the rarity of the features implemented [scaled] (Tsai *et al.*, 2013).
Sourcing propensity	Average degree of internal sourcing (Tsai *et al.*, 2013).
Foundation of service index	Foundational service functions index [scaled] (Chuang *et al.*, 2014; Tsai *et al.*, 2013; Chou, 2013).
Value-added index	Value-added service functions index [scaled] (Chuang *et al.*, 2014; Tsai *et al.*, 2013; Chou, 2013).
Customer-centered index	Customer-centered service functions index [scaled] (Chuang *et al.*, 2014; Tsai *et al.*, 2013; Chou, 2013).

US and EU. The dummy variable “US dataset” accounts for the differences between those two groups. Namely, if the corporate culture is more innovative or more closed will affect the propensity to use and explore those new tools (Ansari *et al.*, 2010). Another motive for some differences is the fact that the Twitter is a public US company, which has received a big coverage from media because of its initial public offer in November/2013 (following the one from Facebook). A set of dummy variables accounts for the merchant type (web only, catalog/call center, consumer brand manufacturer, or retail chain). One of these dummies, ‘Web Only’, is used to assess differences in the usage of the technology if the merchant is a pure online retailer or is one of the other three types of merchant. The inclusion of a set of dummies controlling for the merchandise category of the e-retailers accounts for differences in the importance of the usage of the technology for their relationship with their customers and other stakeholders.

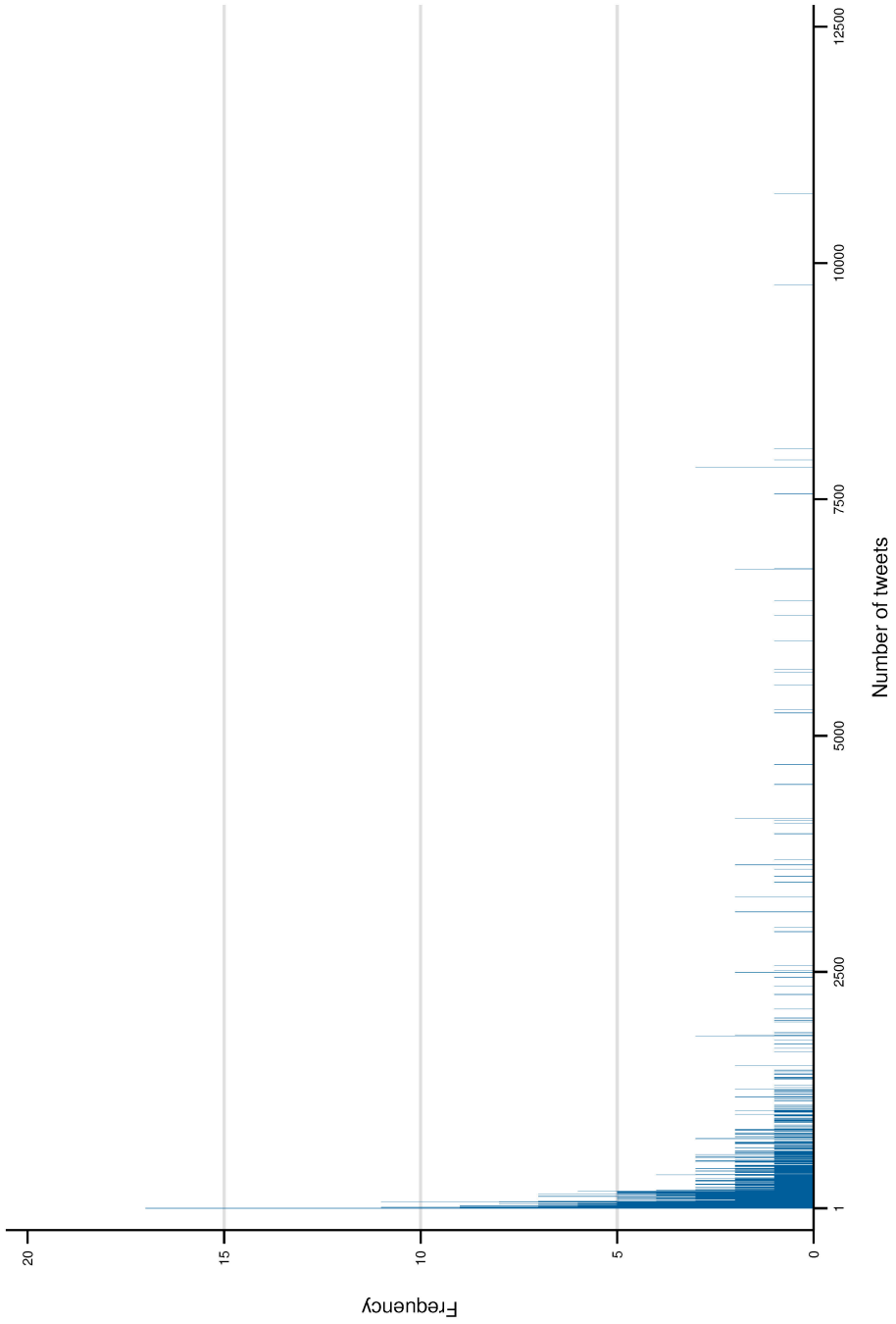


Figure 4.1. Histogram by number of tweets (including retweets) issued between the two data collections. Considering only firms with one or more tweets.

Some other variables were included to control for other factors that may influence the way managers perceive and use social networks. While it is expected and reasonable that motivations drive the success in implementing, not all firms have the same ability to adopt new technologies. Indeed, an important factor is the ability to successfully implement the strategic decision of technology adoption. The ability to effectively use the technology may explain why some firms are capable of implementing it and others are not. Tsai *et al.* (2013) studied technology sourcing strategies and uses two variables that allow differentiating the firms in the sample: capability index and sourcing propensity. Capability index "reflects the intensity of the capabilities of the firm relative to other firms" (Tsai *et al.*, 2013: 352) and is calculated by taking the ratio of one over the number of firms that have that feature and summing the results for the following list: "Affiliate Program", "Auction", "Catalog Quick Order", "Coupons/Rebates", "Customer Reviews", "Daily/Seasonal Specials", "E-Mail a Friend", "Enlarged Product View", "Frequent Buyer Program", "Mapping", "Mobile Commerce Platform", "Online Circular", "Online Gift Certificates", "Outlet Center", "Pre-Orders", "Product Comparisons", "Product Customization", "Registry", "Site Personalization", "Social Networking", "Store Locator", "Syndicated Content", "Top Sellers", "Videocasts", "Wish List", "What's New". The final value is scaled to an interval between zero and one. Sourcing propensity measures the average degree of internal sourcing among the merchandise category of the firm. It considers the sourcing strategy followed in choosing the vendors of 14 technologies of logistics & operations ("Content Deliver", "Content Management", "Site Design", "Web Analytics", "Web Hosting", "Web Performance Monitoring"), marketing ("Affiliate Marketing", "e-Mail Marketing", "Search Engine Marketing"), sales ("e-Commerce Platform", "Fulfillment", "Order Management", "Rich Media", "Site Search"). The degree of internal sourcing is calculated for each one of the firms and the sourcing propensity is the average among firms in the same merchandise category.

Chuang *et al.* (2014) proposed a "sand cone" model of e-service based on the previous work by Voss (2003). They divided the service functions into foundational ("What is expected"), customer-centered ("What differentiates") and value-added ("What excites?") Chuang *et al.* (2014: 1163). Following the specifications defined by (Chuang *et al.*, 2014; Tsai *et al.*, 2013; Chou, 2013), an index is calculated for each one of the three types of service functions. These variables account for the type of investment in service functions done by the retailer.

4.3.2. Model Specification

The benefits from participating are not equal for all e-retailers and sometimes they have to first register with the social network and just then they are able to see if it matches with the intended

audience (Internet Retailer, 2010). Indeed, there are numerous stories of success and fit between the way the social network is used and the response from their online community (Zaroban, 2013). As the adoption is free, there are no barriers to trying the social network to assess if it is beneficial for the firm. This typically results in initial adoptions of the technology that are not maintained and updated. If someone looks to the typical timeline of the users that are not updating their Twitter page, there will be no new posts for a long time. As the dataset comprises information from two points in time, it captures the effective use of the platform between the two dates. So, firms that do not actively use Twitter will have no new information posted during the observation period between the two dates of data collection. To test the hypothesis, the estimation will be based on a hurdle model that considers that zeros and positive values of the dependent variable do not come from the same process (Cameron and Trivedi, 2009: 569). In fact, it considers that it is a combination of a binary model generating the zeros and a Poisson or negative binomial model generating the positive outcomes (Mullahy, 1986; Cameron and Trivedi, 2013; Long and Freese, 2014). This methodology assumes that there are two separate decisions: a first one about posting a tweet and a second one about the actual level of participation (i.e. number of tweets posted during the period). Those two decisions are independent so the first part uses the full sample and the second part uses only the observations with a positive value of the dependent variable (Cameron and Trivedi, 2009: 570). According to the model, if a firm does not post a tweet during the period, it will only be considered in the logit estimation.

One of the popular choices for the hurdle model is to use a logit to estimate the "zero-versus-positive" part, and a Poisson or a truncated negative binomial to estimate the second stage of the model (Cameron and Trivedi, 2009: 571). To account for inconsistent estimation resulting from overdispersion in the truncated Poisson model, the zero-truncated negative binomial regression model (ZTNB) will be used. A problem with fitting the model with a two-step procedure is that the standard errors are incorrect, so they have been corrected using Stata's '`suest`' command (Long and Freese, 2014: 528). This command takes into account the fact that the models are "dependent on one another" and provides the correct standard errors (Long and Freese, 2014).

Following Long and Freese (2014), the first part of the estimation will use a logit model to estimate the probability of obtaining: $y = 0$ or $y > 0$:

$$\Pr(y_i = 0 \mid x_i) = \frac{\exp(x_i\gamma)}{1 + \exp(x_i\gamma)} = \pi_i \tag{4.1}$$

In this stage, the first model that will be estimated is:

$$\begin{aligned}\ln\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_1 &+ \beta_2 \text{ Time Since Adoption }_i \\ &+ \beta_3 \text{ US dataset }_i \\ &+ \beta_4 \text{ Merchant Type (Catalog/Call Center) }_i \\ &+ \beta_5 \text{ Merchant Type (Consumer Brand Manufacturer) }_i \\ &+ \beta_6 \text{ Merchant Type (Retail Chain) }_i \\ &+ \epsilon_i,\ i = 1, ..., n \end{aligned} \tag{4.2}$$

The probability of obtaining a positive outcome is $1 - \pi_i$. Considering that the mean rate of the positive counts is

$$\mathrm{E}(y_i \mid x_i) = (1 - \pi_i)\,\mathrm{E}(y_i \mid y_i > 0, x_i) \tag{4.3}$$

the zero-truncated model will estimate the unconditional probability

$$\Pr(y_i \mid x_i) = (1 - \pi_i)\Pr(y_i \mid y_i > 0, x_i) \text{ for } y \succ 0 \tag{4.4}$$

and the base model that will be estimated is

$$\begin{aligned}\mathrm{Y}_i = \beta_1 &+ \beta_2 \text{ Time Since Adoption }_i \\ &+ \beta_3 \text{ US dataset }_i \\ &+ \beta_4 \text{ Merchant Type (Catalog/Call Center) }_i \\ &+ \beta_5 \text{ Merchant Type (Consumer Brand Manufacturer) }_i \\ &+ \beta_6 \text{ Merchant Type (Retail Chain) }_i \\ &+ \epsilon_i,\ i = 1, ..., n \end{aligned} \tag{4.5}$$

The estimation was conducted using Stata 14.2 software (StataCorp, 2015b) and the commands '`logit`', '`tnbreg`' and '`suest`'.

4.4. Results

The sample is composed of 1,310 companies that have a Twitter presence. Among the firms that have a presence in this social network, there were some of them that presented an unusually high number of tweets. Namely, there were five outliers, observations that have a z-score for the number of new tweets higher than four. These firms were not used in the estimation as they probably are using a different method for uploading content to the social network. Table 4.2 and Table 4.3 present the result of the summary statistics for the samples used in each stage of the estimation.

Table 4.2. Summary statistics and correlation matrix for the full sample. Correlation table built handling missing values by pairwise deletion.

		Mean	St. Dev.	Min.	Max.	(1)	(2)	(3)	(4)
Number of New Tweets	(1)	405.18	996.39	0.00	10736.00	1.00			
Time of Adoption	(2)	42.32	15.34	8.43	113.47	−0.06	1.00		
US dataset	(3)	0.57	0.50	0.00	1.00	−0.07	−0.27	1.00	
Average of New Tweets in Merchandise Cat.	(4)	405.18	159.91	143.48	983.14	0.16	0.01	−0.10	1.00

Table 4.3. Summary statistics and correlation matrix for the sample used in the truncated negative binomial regression. Correlation table built handling missing values by pairwise deletion.

		Mean	St. Dev.	Min.	Max.	(1)	(2)	(3)	(4)
Number of New Tweets	(1)	462.36	1051.93	1.00	10736.00	1.00			
Time of Adoption	(2)	41.63	14.82	8.43	113.47	−0.05	1.00		
US dataset	(3)	0.56	0.50	0.00	1.00	−0.07	−0.27	1.00	
Average of New Tweets in Merchandise Cat.	(4)	411.54	160.54	143.48	983.14	0.16	0.03	−0.08	1.00

The dataset contains two characteristics that are very relevant when choosing the estimation model: “excess zeros” and overdispersion. The “excess zeros” problem is easily seen when looking to the frequencies of the dependent variable where the number of firms that did not publish (or re-publish) any tweet represents 12.4% of the total or 162 firms [see Table 4.4].

Table 4.4. Twitter adoption by retail categories in the sample.

Merchandise Category	Published 1 or more tweets								
	No			Yes			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Computers/Electronics	35	21.6	19.4	145	12.6	80.6	180	13.7	100.0
Apparel/Accessories	21	13.0	6.1	322	28.0	93.9	343	26.2	100.0
Automotive Parts/Accessories	7	4.3	24.1	22	1.9	75.9	29	2.2	100.0
Books/Music/Video	13	8.0	14.6	76	6.6	85.4	89	6.8	100.0
Flowers/Gifts	4	2.5	12.5	28	2.4	87.5	32	2.4	100.0
Food/Drug	4	2.5	6.9	54	4.7	93.1	58	4.4	100.0
Hardware/Home Improvement	15	9.3	26.8	41	3.6	73.2	56	4.3	100.0
Health/Beauty	7	4.3	11.1	56	4.9	88.9	63	4.8	100.0
Housewares/Home Furnishings	19	11.7	17.0	93	8.1	83.0	112	8.5	100.0
Jewelry	5	3.1	15.6	27	2.4	84.4	32	2.4	100.0
Mass Merchant	11	6.8	9.4	106	9.2	90.6	117	8.9	100.0
Office Supplies	6	3.7	20.0	24	2.1	80.0	30	2.3	100.0
Specialty	7	4.3	8.9	72	6.3	91.1	79	6.0	100.0
Sporting Goods	7	4.3	11.7	53	4.6	88.3	60	4.6	100.0
Toys/Hobbies	1	0.6	3.3	29	2.5	96.7	30	2.3	100.0
Total	162	100.0	12.4	1148	100.0	87.6	1310	100.0	100.0

To assess overdispersion and analyze the adequacy of the selected estimation model, this study will look at the summary statistics and correlation tables of the two samples for each part of the model: the one used in the logit regression and the one used in the truncated negative binomial part of the estimation. The dependent variable has a variance that is much larger than the mean [see Table 4.2], a sign of overdispersion and confirmation that the use of a Poisson would be inappropriate. The same can be inferred from looking at the sample used in the truncated negative binomial [see Table 4.3]. This can also be observed in Figure 4.1.

To test the relevance of some of the controls that were proposed, some of the variables will be submitted to a two-sample *t* test. This test provides an assessment of the relevance of the variable in discriminating two groups regarding their Twitter activity. According to the results of Table 4.5, the differences between US and EU firms are statistically significant for most characteristics at the commonly used levels and this variable will be included in the estimation. The differences between types of merchants are significant, namely between the pure internet players and the remaining. The variable “Web Only” allows to differentiate this group of firms. By looking at Table 4.6, it is

noticeable the difference among pure online retailers and those combining a web presence with other offline channels. Even though the difference between “Web Only” e-retailers (e.g., firms similar to Amazon.com‘s e-retailing unit) and the other ones, we will introduce dummies for each one of these groups. This allows to account for differences between the remaining groups.

Table 4.5. Two-sample *t* test of mean differences using groups. The groups were defined using the dummy variable 'US Dataset' considering that 'Diff. = mean(0) - mean(1)', where mean(1) is the mean of the group with a 'true' value in the variable and mean(0) is the corresponding statistic for the group with a 'false'. The null hypothesis for the P-value statistics is 'H_0 : diff $=$ 0'.

	Group 1 (0) mean	Group 2 (1) mean	Diff.	P-value (Lower Side) H_A: diff < 0	P-value (2 Sided) H_A: diff $\neq$ 0	P-value (Upper Side) H_A: diff > 0
Monthly Average Number of Tweets	141.74	123.67	18.07	0.92	0.15	0.08
Monthly Average Number of New Tweets	252.07	176.34	75.73	0.99	0.01	0.01
Monthly Average Number of Photos and Videos	14.69	11.36	3.33	1.00	0.00	0.00
Monthly Average Number of New Photos and Videos	48.19	41.46	6.73	0.94	0.12	0.06
Followers / Months	1156.26	1884.14	-727.88	0.04	0.07	0.96
Monthly Average Number of New Followers	1616.91	2481.42	-864.51	0.12	0.25	0.88
Following Accounts / Months	21.87	60.55	-38.69	0.00	0.00	1.00
Number of New Accounts Following	21.89	46.51	-24.62	0.11	0.22	0.89

Table 4.6. Two-sample *t* test of mean differences using groups. The groups were defined using the dummy variable 'Web Only' considering that 'Diff. = mean(0) - mean(1)', where mean(1) is the mean of the group with a 'true' value in the variable and mean(0) is the corresponding statistic for the group with a 'false'. The null hypothesis for the P-value statistics is 'H_0 : diff $=$ 0'.

	Group 1 (0) mean	Group 2 (1) mean	Diff.	P-value (Lower Side) H_A: diff < 0	P-value (2 Sided) H_A: diff $\neq$ 0	P-value (Upper Side) H_A: diff > 0
Monthly Average Number of Tweets	149.79	109.41	40.37	1.00	0.00	0.00
Monthly Average Number of New Tweets	256.51	151.79	104.72	1.00	0.00	0.00
Monthly Average Number of Photos and Videos	14.54	10.74	3.81	1.00	0.00	0.00
Monthly Average Number of New Photos and Videos	50.77	36.75	14.02	1.00	0.00	0.00
Followers / Months	2144.96	880.77	1264.18	1.00	0.00	0.00
Monthly Average Number of New Followers	3284.94	696.38	2588.56	1.00	0.00	0.00
Following Accounts / Months	39.31	49.41	-10.11	0.24	0.47	0.76
Number of New Accounts Following	31.09	41.70	-10.60	0.32	0.65	0.68

Table 4.7 summarizes the results of the estimation of the hurdle model using the time of adoption as the dependent variable. As time passes, firms that adopt later have a lower probability of

publishing, at least, one tweet. Among the observed firms, the utilization of Twitter decreases for those adopting later.

Table 4.7. Hurdle model (M4.1). Simultaneous estimation of the number of tweets published using a logit and a truncated negative binomial regression. Using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Logit Regression						
Time of Adoption	0.976****	0.005	−5.122	0.000	0.967	0.985
US dataset	0.659**	0.122	−2.250	0.024	0.458	0.948
Merchant Type (ref. Web Only)						
Catalog/Call Center	2.300***	0.725	2.643	0.008	1.240	4.265
Consumer Brand Manufacturer	3.515***	1.358	3.254	0.001	1.648	7.494
Retail Chain	2.917****	0.618	5.053	0.000	1.926	4.417
Truncated Negative Binomial Regression						
Time of Adoption	0.986**	0.005	−2.567	0.010	0.976	0.997
US dataset	0.646***	0.087	−3.243	0.001	0.496	0.841
Merchant Type (ref. Web Only)						
Catalog/Call Center	0.683**	0.120	−2.172	0.030	0.484	0.963
Consumer Brand Manufacturer	1.882***	0.400	2.978	0.003	1.241	2.853
Retail Chain	1.775****	0.269	3.783	0.000	1.318	2.389
N (Logit)	1310					
N (TNB)	1148					
TNB chibar2(01) p-value [LR test of $\alpha = 0$]	0.0000					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
Exponentiated coefficients

To test the robustness of these results, Table 4.8 presents the results of the model with the inclusion of more controls. More details of these estimations are provided in Table 4.7 as well as in Appendix C - Tables C.1 and C.2. US firms have a lower probability of using Twitter, and the ones that use it use it less than their EU competitors. The same remark can be made to web only companies when compared with the ones that have a physical store. These results provide evidence that companies that adopt later are following a social accounts logic. These results are not compatible with the prevalence of rational accounts explanation.

Table 4.8. Hurdle model. Simultaneous estimation of the number of tweets published using a logit and a truncated negative binomial regression. Using Huber/White/sandwich estimator of the variance-covariance matrix.

	M4.1	M4.2	M4.3
Logit Regression			
Time of Adoption	0.976****	0.975****	0.976****
US dataset	0.659**	0.721*	0.665**
Average of New Tweets in Merchandise Cat.		1.002***	
Merchant Type (ref. Web Only)			
Catalog/Call Center	2.300***	2.271***	2.150**
Consumer Brand Manufacturer	3.515***	3.307***	3.007***
Retail Chain	2.917****	2.824****	2.762****
Merchandise Category (ref. Computers/Electronics)			
Apparel/Accessories			3.544****
Automotive Parts/Accessories			0.879
Books/Music/Video			1.720
Flowers/Gifts			2.006
Food/Drug			3.459**
Hardware/Home Improvement			0.913
Health/Beauty			2.086
Housewares/Home Furnishings			1.250
Jewelry			1.488
Mass Merchant			2.537**
Office Supplies			1.239
Specialty			3.113**
Sporting Goods			1.664
Toys/Hobbies			7.152*
Truncated Negative Binomial Regression (TNB)			
Time of Adoption	0.986**	0.988**	0.987***
US dataset	0.646***	0.708***	0.689***
Average of New Tweets in Merchandise Cat.		1.002****	
Merchant Type (ref. Web Only)			
Catalog/Call Center	0.683**	0.637***	0.657***
Consumer Brand Manufacturer	1.882***	1.996***	2.215****
Retail Chain	1.775****	1.730****	1.797****
Merchandise Category (ref. Computers/Electronics)			
Apparel/Accessories			1.121
Automotive Parts/Accessories			0.615
Books/Music/Video			1.610
Flowers/Gifts			0.826
Food/Drug			2.697***
Hardware/Home Improvement			0.668
Health/Beauty			1.017
Housewares/Home Furnishings			0.715
Jewelry			0.895
Mass Merchant			1.614*
Office Supplies			0.829
Specialty			1.310
Sporting Goods			1.154
Toys/Hobbies			1.057
N (Logit)	1310	1310	1310
N (TNB)	1148	1148	1148
TNB chibar2(01) p-value [LR test of $\alpha = 0$]	0.0000	0.0000	0.0000

Exponentiated coefficients
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

To test the relevance of other features in the studied behavior regarding social networks among firms of the same merchandise category, a new model was estimated. Some of the control variables are not available to EU firms so the estimation is only considering US e-retailers. The summary statistics, including the correlation matrix, for these models are presented in Table 4.9 and Table 4.10. Table 4.11 presents the results from the estimation using this dataset with additional variables. The detailed results tables are provided in Appendix C - Tables C.3, C.4, and C.5. The introduction of new controls does not change the results that were previously reported. There is not a statistically significant relationship between the capabilities and the use of Twitter. The ability to implement functionalities on the website that are unusual does not provide any insights about the use of the social network. An increase in the sourcing propensity, i.e. of the mean among peers of the degree of internal sourcing of technologies over the total of internal and externally sourced, has a reduction in the odds of posting the first tweet during the period. The impact of adoption of specific service functions is not relevant in the first publication but having a higher focus on customer-centered functions will increase the probability of a lower participation. These results may point to the use of Twitter as a replacement for some of the social features of their websites rather than an addition to what they already have. Firms that have more ability to develop new features and functions inside their websites seem to rely less on social networks managed by external organizations, like Twitter. Taking into consideration the coefficients of “Merchant Type” dummies, a retail chain has a considerably higher base odds that a web only firm of twitting for the first time. Retail chains and consumer brand manufacturers have a considerably higher base rate of publication of tweets conditional on having at least one tweet published.

Table 4.9. Summary statistics and correlation matrix for the full sample. Correlation table built handling missing values by pairwise deletion.

		Mean	St. Dev.	Min.	Max.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of New Tweets	(1)	421.19	953.45	0.00	10736.00	1.00							
Time of Adoption	(2)	37.49	13.66	8.43	113.47	−0.09	1.00						
Web Only	(3)	0.40	0.49	0.00	1.00	−0.14	−0.02	1.00					
Capability Index	(4)	0.46	0.21	0.00	1.00	0.01	−0.13	−0.30	1.00				
Sourcing Propensity	(5)	0.33	0.07	0.25	0.45	−0.04	−0.03	0.16	0.05	1.00			
Value-added index	(6)	0.44	0.29	0.00	1.00	0.00	−0.16	−0.09	0.73	0.11	1.00		
Customer-centered index	(7)	0.52	0.24	0.00	1.00	−0.03	−0.12	−0.14	0.85	0.07	0.49	1.00	
Foundation of service index	(8)	0.27	0.22	0.00	1.00	0.06	−0.07	−0.38	0.67	−0.00	0.34	0.40	1.00

Table 4.10. Summary statistics and correlation matrix for the sample used in the truncated negative binomial regression. Correlation table built handling missing values by pairwise deletion.

		Mean	St. Dev.	Min.	Max.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of New Tweets	(1)	461.03	988.35	1.00	10736.00	1.00							
Time of Adoption	(2)	36.77	12.99	8.43	113.47	−0.07	1.00						
Web Only	(3)	0.37	0.48	0.00	1.00	−0.13	−0.06	1.00					
Capability Index	(4)	0.47	0.21	0.00	1.00	0.00	−0.10	−0.29	1.00				
Sourcing Propensity	(5)	0.32	0.07	0.25	0.45	−0.03	−0.04	0.15	0.06	1.00			
Value-added index	(6)	0.44	0.29	0.00	1.00	−0.01	−0.13	−0.06	0.73	0.12	1.00		
Customer-centered index	(7)	0.52	0.24	0.00	1.00	−0.05	−0.10	−0.13	0.85	0.08	0.49	1.00	
Foundation of service index	(8)	0.27	0.22	0.00	1.00	0.05	−0.05	−0.38	0.67	−0.00	0.35	0.40	1.00

Table 4.11. Hurdle model (extended). Simultaneous estimation of the number of tweets published using a logit and a truncated negative binomial regression using variables that are only available for US firms. Using Huber/White/sandwich estimator of the variance-covariance matrix.

	M4.4	M4.5	M4.6
Logit Regression			
Time of Adoption	0.965****	0.967****	0.966****
Capability Index	1.380		
Sourcing Propensity	0.009*		0.008*
Foundation of service index		0.607	0.550
Customer-centered index		1.129	1.206
Value-added index		1.637	1.727
Merchant Type (ref. Web Only)			
Catalog/Call Center	1.858	2.034	1.993
Consumer Brand Manufacturer	2.295	2.779*	2.432
Retail Chain	4.508***	5.578***	5.145***
Truncated Negative Binomial Regression (TNB)			
Time of Adoption	0.986*	0.984**	0.984**
Capability Index	0.788		
Sourcing Propensity	0.900		0.927
Foundation of service index		1.384	1.383
Customer-centered index		0.449**	0.450**
Value-added index		1.292	1.296
Merchant Type (ref. Web Only)			
Catalog/Call Center	0.925	0.941	0.940
Consumer Brand Manufacturer	2.390***	2.372***	2.372***
Retail Chain	2.214****	2.070***	2.064****
N (Logit)	486	486	486
N (TNB)	444	444	444
TNB chibar2(01) p-value [LR test of $\alpha = 0$]	0.0000	0.0000	0.0000

Exponentiated coefficients
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

4.5. Discussion

This study began by proposing that the motivations for the adoption of a new social network would be evident on the use in the post-adoption period, allowing to infer the prevalent reasoning among a population composed of e-retailers.

4.5.1. Theoretical Implications

The high visibility of the selected technology offers an interesting research ground to discuss the alternatives of a rational or a social perspective on technology adoption. Despite the long tradition

of research on adoption, social network platforms offer new research opportunities. Not only social networks allow a closer monitoring of competitors but is also a free technology that does not imply a costly initial investment.

The results point toward an increase in the utilization of the technology consistent with firms following a social accounts perspective. Even though rational accounts explanation is not ruled out for all firms, as it may apply in some of the individual cases, the estimation provided support for the adoption of Twitter as based on social accounts. As social arguments were prevailing among adopters, we observed that later adopters used a logic of "follow the crowd" and adopted regardless of the adequacy of the technology to their business model. If rational accounts were the main reasons for adoption, it would be expected that later adopter would have more information available and would not engage in the active use of the technology if they were not sure of its usefulness. However, the data that was collected offers evidence against this view. What was found may result from e-retailers seeking to adopt without being sure about the adequacy for their own strategy, resulting in a decrease of the utilization among later adopters.

Even in the case that there is a rational perspective among the initial adopters according to information cascades, agents may start disregarding their own private information. This would result in herding behavior with firms following a defensive strategy, even though with lower returns, and adopting without exploring the benefits of the technology (Lieberman and Asaba, 2006). The increasing number of misfits may result from the bandwagon pressure mounting with time, as firms expect to mitigate uncertainty. Focusing on ambiguity, it is possible to find additional clues to analyze the results. The adoption of social networks in 2006 can be considered one of those situations when there are few insights about the future of social networking for businesses. According to Abrahamson and Rosenkopf (1993), a higher ambiguity will result in a larger portion of the firms following social rather than economic reasonings. In fact and as observed, later adopters face a reduction in ambiguity so that there should be a lower number of misfits. These misfits are consistent with the adoption because of social accounts.

According to the organizational learning lenses, organizations may wait to have more evidence before they adopt (Levinthal and March, 1993; Ordanini *et al.*, 2008). Firms observe the results of their peers before they adopt and choose the technologies that are believed to be beneficial, even though after the uncertainty is resolved it seems that it was an irrational move (Kraatz, 1998; Ordanini *et al.*, 2008). By waiting to have more information, firms do not blindly adopt but wait to be able to reduce the uncertainty. In fact, there are reports about the positive impact of the adoption of some social networks. Adobe Systems Inc. reported a metric about the revenue of its clients generated from shoppers that entered the store from social networks and found that, in the third quarter of 2013,

each shopper coming from Facebook had generated an average of 93 cents per visit (Stambor, 2013). The differences between Facebook and Twitter may explain the difference in the results.

It is interesting to notice that "Consumer Brand Manufacturers" and "Retail Chains" have higher base odds of having a more tweets posted than "Web Only" firms and that "Catalog/Call Center" has a lower value for the same control. It is possible that "Consumer Brand Manufacturers" and "Retail Chains" acknowledge that social networks have a larger incremental value for them while other firms see it as inducing their customers to leave the website. Firms that do not have physical stores see their e-commerce website differently than those that rely more heavily on it.

The first contribution is the use of neo-institutional theory to study the adoption and use of a social network looking to the motivations behind the adoption. Namely, it looks for patterns that result from the prevalence of social or rational arguments and to the expected usage patterns at the industry level. The second contribution is the focus on social networks, a technology highly dependent on the implementation but with a zero adoption cost. The success of the adoption of social media is highly dependent on post adoption behavior and the effort during its implementation. After the development of social networks like Facebook and Twitter, there are numerous platforms aiming to aggregate smaller specialized communities. This phenomenon is expanding and changing continuously posing new challenges to marketing departments focusing on consumer markets that have more platforms to choose from and to manage. Even though the use of these tools have a large impact with a low (or zero) adoption cost, the cost of implementation can be high and the research about it is in an early stage of development (Michaelidou *et al.*, 2011). Also, there is a tendency to focus on technological innovations rather than on administrative ones (Damanpour, 1987; Westphal, Gulati and Shortell, 1997). The third contribution is the use and collection of data that does not rely on self-reported assessments. Unlike Kennedy and Fiss (2009), who rely on qualitative measures supplied by the top management and by each department, this study focus on objective data collected by independent third-party organizations. Moving away from questionnaires directly applied to the firms, it was possible to collect information that was not filtered by the current views of the management team. Furthermore, this study accounts for international differences by including US and EU firms.

4.5.2. Directions for Future Research

One of the directions for future research will be the collection of panel data, allowing more controls while estimating the models. By collecting regularly data about each of the firms, it will be possible to overcome some of the econometric challenges and analyze a broader spectrum of effects.

Another avenue can be the use of samples from other geographies, like Asia or South America, as well as other business sectors. With the number of firms that engage in the use of social networks increasing exponentially, future studies could explore a more geographically diverse dataset.

4.5.3. Managerial Implications

This research contributes to the understanding of the phenomenon of implementation of new technologies after the initial adoption decision. Imitation may generate dysfunctional behavior like speculative bubbles (Lieberman and Asaba, 2006) so it is of the utmost importance to understand the dynamic of technology adoption. While many new technologies are free, their implementation requires investment in terms of money and time as well as a commitment to its successful management. E-commerce managers are frequently exposed to a multitude of technologies to choose from. As an example, the area of Big Data is expanding at a very fast pace with multiple technologies and vendors offering different solutions for each task.

The present research addresses an issue that it is central to two different groups. E-retailers, as well as other industries, have now the ability to choose from several competing vendors but are challenged to identify what are the trends and distinguishing the technologies that are becoming widespread within the industry from those that are just “fads and fashion”. Software developers and cloud computing service providers need to understand the reasons underlying the choices of their customers to address their expectations. An example is the need for a closer support service to ensure that implementation is not preventing customers from getting the expected results.

4.6. Conclusion

Implementation plays a major role in technology adoption. Besides the initial decision, there is a considerable investment in the post-adoption phase. Social media platforms, like Twitter, are a major opportunity for firms to stay in contact with a large audience in a rich dialog. The attention that the media and the public has placed on this new platforms transforms this decision on a large statement about the firm and its managers. Contrasting the rational arguments of the classic adoption model with the neo-institutional perspective and imitative behavior, we proposed to investigate the predominant perspective among a population composed of e-retailers, in US and EU. Using a hurdle model with a logit and a truncated negative binomial, it was found evidence of the prevalence of the social arguments over the rational perspective. The firms in our sample behave consistently with a socially driven adoption of Twitter.

5. Conclusion

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> “But businesses that understand how imitation works can at least try to gird themselves against its worst effects - by accounting for it in their forecasts and risk-management plans, by becoming more sensitive to unexpectedly changing circumstances, and by avoiding mindless imitation of other companies’ moves.” (Bonabeau, 2004: 46)

The present thesis is the result of several years of work. Along the way, some of the results were presented at conferences and published as proceedings (Nikolaeva and Azambuja, 2015b,a). Other parts of the current research were already submitted to presentation at conferences.

5.1. Topic and Research Objectives

Although diffusion of innovation is being researched for decades, it is a topic that remains interesting and important. New products launched by companies or new business models tested by entrepreneurs continue to challenge managers to decide under uncertainty. The technical rationality of decisions has long been challenged by theories like neo-institutionalism or the organizational learning theory. While it is very difficult to collect a large sample of reliable information on the adoption of certain innovations, social networks offer new opportunities regarding the research of these subjects because it is recent and highly visible.

Social networks, and media coverage in general, pose new challenges to managers deciding about technology adoption. They have to balance the present and future results while fulfilling the expectations of shareholders and stakeholders about what constitutes a good strategy. There are two important drivers that condition their choices. The first one is the expectations of the industry and the strategies of their competitors. The institutional perspective supply an explanation based on the mimetic forces. The second one is based on past performance as an important antecedent on the decisions. Experiencing results below what was expected triggers the need for action and change.

Starting by defining the research problem as *What are the roles of imitation and past performance in technology adoption?*, this thesis studied the motivations behind technology adoption. The first study investigated if it is possible to infer the predominant reasons behind the adoption of a new technology as it is expected that firms present different responses to the same institutional pressures (Kennedy and Fiss, 2009; Nikolaeva, 2014). Young (2009) provided a grouping of the diffusion models into three classes, contagion, social influence, and social learning. Discarding contagion, this study tested the main reasons behind adoption using the social learning and the social influence diffusion models claiming that the predominant perception about the technology will result in different shapes of the effect of prior adopters on the probability of subsequent adoption. Following the study of Lages *et al.* (2013) , the second study focused on the effect of past performance feedback on changes in technology sourcing mix. Indeed, the results provided by Tsai *et al.* (2013), that studied if e-retailer develop some of their tools in-house or through outsourcing, do not account for changes of performance as an antecedent of changes in strategy. The third study focused on the impact of

motivations for adoption in the post-adoption period, following a long list of calls (Kennedy and Fiss, 2009; Nikolaeva, 2014). Ansari *et al.* (2010) aggregate two theoretical streams about innovation adoption into rational accounts and social accounts. The reasons for adoption will lead to different efforts to implement it. Implementation is a key phase in innovation adoption and the investment that firms do can help reveal their intentions regarding the new technology or process. Perceiving the opportunity for gains was expected to result in a larger effort to implement while following the crowd and adopting as a response to social pressures was expected to result in a lower use of the technologies.

New data and new technological platforms provided rich new data and the opportunity to revisit several theoretical streams and test new hypotheses that were, otherwise, very difficult to empirically validate. In the last five years there was a considerable expansion of the information that is collected and is available for firms to explore. The emergence of new technologies to assess big data and implement machine learning techniques allow managers to address questions that before were not possible to estimate. This trend, that is expected to accelerate in the coming years, should be built based on existing knowledge and not on the vacuum. It is important that these forward looking techniques of prediction are based on solid reasonings and theoretical foundations allowing the development of stronger predictive models. This thesis contributes for a richer discussion about technology adoption.

5.2. Data

E-retailers are highly exposed to this issue and offer a very promising research ground. It is an industry that is characterized by the fast pace of technological innovations, challenging the ability to derive a fully rational decision. Within a competitive industry where the physical distance to customers is mitigated by the use of Internet, having a social network presence and an effective service strategy can have a major contribution to their success. Social media adoption can result in an excellent opportunity to get closer to stakeholders, but the risks associated with the management of an on-line community can be high. It is an important strategic decision with a strong link to performance: changes in strategy result in a performance output, and this feedback will influence the strategic response.

This research was based on the selection of a sample of e-commerce retailers from the IR Top 500 Guide (top500guide.com), both in the US and EU. The data included in this publication is commonly used in the research of e-retailing because it is considered a reliable source of information

(e.g., Chuang *et al.*, 2014; Griffis *et al.*, 2012; Tsai *et al.*, 2013; Karimov and Brengman, 2011). The US dataset was available from 2008 till 2015, consisting of information regarding the years from 2006 till 2014, and the one of EU was available from 2011 until 2015, regarding information from 2010 to 2014. Some of the firms appear just once while others were present in this list every year. This can be the result of several reasons. First, the variations of web sales from one year to the next may lead to a new inclusion, if the firm was not present, or the exclusion of the list. Second, mergers and splits also contribute to changes in the list of firms. The selected sample includes the most relevant players in the industry, with a minimum size (measured in terms of sales volume) that assures the need for an organizational structure and professional management.

There was an extensive work combining the records of each year so that they grouped into a panel. Merging the yearly information regarding the e-retailers from the annual datasets resulted in 1,430 retailers, 799 in the United States sample and 631 in the European sample (see Table 5.1). Our sample includes firms from 15 merchandise categories (see Table 5.2) and four merchant types (see Table 5.3). The most important part of the data used for studying the adoption and utilization of each social network (Facebook and Twitter) was manually collected for each firm. This includes the collection of information about multiple social network pages for some of the firms (e.g., some of their brands have a dedicated Facebook/Twitter presence).

Table 5.1. Number of firms included in each year list.

	Year								
Dataset	2007	2008	2009	2010	2011	2012	2013	2014	Total
EU	0	0	0	300	400	500	500	500	2200
US	500	500	500	500	500	500	500	500	4000
Total	500	500	500	800	900	1000	1000	1000	6200

5.3. Methodology

The first study used a discrete time survival model based on a logit estimation. The two views, more based on social learning or more based on social influence, will result in different effects of the density of prior adopters in the probability of subsequent adoption and it is possible to test it at the

Table 5.2. Merchandise type distribution by dataset.

Merchandise Category	Dataset								
	EU			US			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Apparel/Accessories	176	27.9	47.7	193	24.2	52.3	369	25.8	100.0
Automotive Parts/Accessories	12	1.9	38.7	19	2.4	61.3	31	2.2	100.0
Books/Music/Video	49	7.8	50.0	49	6.1	50.0	98	6.9	100.0
Computers/Electronics	113	17.9	57.7	83	10.4	42.3	196	13.7	100.0
Flowers/Gifts	12	1.9	35.3	22	2.8	64.7	34	2.4	100.0
Food/Drug	27	4.3	42.2	37	4.6	57.8	64	4.5	100.0
Hardware/Home Improvement	14	2.2	22.6	48	6.0	77.4	62	4.3	100.0
Health/Beauty	21	3.3	32.8	43	5.4	67.2	64	4.5	100.0
Housewares/Home Furnishings	46	7.3	38.3	74	9.3	61.7	120	8.4	100.0
Jewelry	12	1.9	33.3	24	3.0	66.7	36	2.5	100.0
Mass Merchant	90	14.3	66.7	45	5.6	33.3	135	9.4	100.0
Office Supplies	8	1.3	23.5	26	3.3	76.5	34	2.4	100.0
Specialty	20	3.2	22.7	68	8.5	77.3	88	6.2	100.0
Sporting Goods	21	3.3	33.9	41	5.1	66.1	62	4.3	100.0
Toys/Hobbies	10	1.6	27.0	27	3.4	73.0	37	2.6	100.0
Total	631	100.0	44.1	799	100.0	55.9	1430	100.0	100.0

Table 5.3. Merchant type distribution by dataset.

Merchant Type	Dataset								
	EU			US			Total		
	No.	Col %	Row %	No.	Col %	Row %	No.	Col %	Row %
Catalog/Call Center	42	6.7	26.6	116	14.5	73.4	158	11.0	100.0
Consumer Brand Manufacturer	40	6.3	29.0	98	12.3	71.0	138	9.7	100.0
Retail Chain	261	41.4	54.6	217	27.2	45.4	478	33.4	100.0
Web Only	288	45.6	43.9	368	46.1	56.1	656	45.9	100.0
Total	631	100.0	44.1	799	100.0	55.9	1430	100.0	100.0

aggregate level. It is also important to consider non-linear types of relationships (Pierce and Aguinis, 2013) among the variables, offering a better understanding of the phenomenon.

The second study looked at the impact of changes in performance to changes in strategy about technology sourcing (*make* versus *buy*) in e-retail through the use of a logit model and panel data. The estimation used data collected from 14 technologies from a large dataset of firms followed for eight years resulting in a final panel with six years (two years of lags).

The third study looked into the post adoption period to determine if it is possible to distinguish between a social accounts dynamic from a rational accounts one in Twitter adoption. A two stage hurdle model was used, considering that there is a first decision about the participation (the first tweet) and a second one about the level of participation (the number of tweets) The first stage estimation was conducted using a logit model. The second stage used a ZTNB model.

The estimation was conducted using Stata 14.2. However, several tools were developed to prepare the dataset for estimation using Microsoft SQL Server 2014. The database front-end was created using Microsoft Visual Basic.NET and Microsoft Access 2016. Several Stata user-written commands were used to perform specific intermediate task in the estimation or to produce the tables and graphs included in the final document that was prepared using LaTeX, XeLaTeX and BibTeX (Jann, 2005, 2007; Newson, 2001; Watson, 2004; Cox and Longton, 2008; Ender, 2010; Wada, 2010; Kessler, 2012).

5.4. Theoretical and Managerial Implications

The present research intended to contribute to the understanding of innovation dynamics focusing on technology adoption motivations at the industry level. This was accomplished by studying a group of firms composed by the largest e-retailers in the US and EU. The major contributions were:

- The study of social networks was underdeveloped at the industry level with most of the studies focusing on smaller groups with a more qualitative approach. Ordanini *et al.* (2008) asked for more empirical research aimed at testing alternative imitation theories, and the current datasets provided an excellent testing ground. The use of survival models is also an approach that has been suggested as further contributing to the area of imitation (Lieberman and Asaba, 2006). The use of a large panel answers several calls among scholars. Kennedy and Fiss (2009) suggested the study of adoption using more longitudinal models.
- Advanced with the analysis of technology sourcing through the study of the effects of the past performance in decisions about strategy. Reverting the analysis of performance in the study of

technology sourcing contributes to the discussion of how do managers deal with performance feedback.

- Researching the impact over the post-adoption period of the motives behind the adoption of social networks. As a relatively new media, there were very few empirical studies about social networks, compared to the impact and changes they introduced. Only now we are starting to have large datasets that can be adequately explored by more powerful quantitative methods. This study aims to contribute to the emerging literature on the impact of corporate social media adoption.

Moreover, the present thesis aims to help managers in the assessment of the motivations of their decisions and the analysis of expected value creation of their investments when assessing technology adoption. The emergence of new technologies, namely those associated with social networks, challenges firm's ability to decide, adopt and implement. Managers are frequently challenged by the emergence of new technologies. Innovations in social media profoundly change the way they interact and communicate with their customers.

There are several avenues for future contributions that were not explored in this thesis due the natural limits of the scope and time constrains. New technologies and methodologies continue to challenge managers to decide under uncertainty and new research opportunities subsist. As the datasets that are available are expanding in number and extension, it is expected that the studies that were limited to one or two geographies will soon be possible to extend to Europe or Asia. New research opportunities are expected to appear as more data is being generated by these technologies and becoming available for firms to explore.

5.5. Final Remarks

The technological development that firms now face increase the challenges they face when innovating. The entrepreneurial culture that is widely accepted within new ventures and large corporations creates a rapid flow of new ideas and solutions. Due to the cost of learning and experimenting, managers have to decide under limited information. By observing the actions of their peers and the performance resulting from their own decisions, they react and define strategies. These deviations from the rational behavior are usually absent from the study of decisions about technology adoption. Through the three studies that were developed, this thesis aims to provide a different perspective about these problems and contribute to the discussion. While these assessments are not easy to

derive, nowadays researchers have information that enables them to look differently at these decisions. Indeed, not only big data and data science are technologies that can be studied using the same approach, but they also provide data to explore many different decision processes.

Table 5.4. Summary of the results from the research.

	Study 1 (Chapter 2)	Study 2 (Chapter 3)	Study 3 (Chapter 4)
Research Question	Is it possible to empirically distinguish predominant imitation motives within an industry?	To what extent changes in performance influence changes in strategy?	Is there empirical evidence, at the aggregate level, about the rational or social perspectives of innovation adoptions?
Data	US panel of e-retailers from 2007 to 2014	US panel of e-retailers from 2007 to 2014	US and EU e-retailers
Methodology	Discrete-time survival model (logit)	Fixed effects model	Hurdle model (logit and ZTNB)
Results	Rejected adoption as a response to social pressure (support for H2.1b)	Consistent with response to performance feedback	Consistent with social arguments
Contribution	1. Found evidence that framing can be empirically inferred from the adoption curve; 2. Accounted for non-linearities in the adoption curve; 3. Empirically tested the adoption of social media.	1. Incorporated performance feedback in the study of make/buy technology decisions 2. Accounted for dynamic nature of environments; 3. Segregated decisions for different processes as they may respond to different metrics; 4. Used of large panel with eight years of information.	1. Studied of social networking using large dataset at industry level in the context of neo-institutional theory; 2. Focused on implementation of a technology with a large administrative component; 3. Used diverse dataset without relying on self reported measures.

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Appendix A. Additional Reports on Chapter 2

Table A.1. Restricted model estimation (M2.1). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	3.690****	0.890	4.145	0.000	1.945	5.434
Proportion of Adopters sq.	−2.766***	0.928	−2.982	0.003	−4.584	−0.948
Year (ref. 2007)						
2008	0.989****	0.180	5.488	0.000	0.636	1.342
2009	1.408****	0.269	5.229	0.000	0.880	1.935
2010	1.013***	0.316	3.209	0.001	0.394	1.631
2011	0.670*	0.358	1.869	0.062	−0.033	1.372
2012	0.172	0.399	0.431	0.667	−0.611	0.955
2013	−0.377	0.504	−0.748	0.454	−1.366	0.611
2014	−0.658	0.518	−1.271	0.204	−1.672	0.357
Constant	−3.956****	0.127	−31.248	0.000	−4.205	−3.708
Number of obs.	9427					
Number of clusters	799					
Log pseudolikelihood	−2374.918					
Chi-squared	390.709					
Model deg. freedom	9					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.093					
AIC	4769.836					
BIC	4841.349					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.2. Restricted model estimation (M2.2). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	3.604****	0.898	4.014	0.000	1.844	5.364
Proportion of Adopters sq.	−2.728***	0.934	−2.919	0.004	−4.559	−0.896
Year (ref. 2007)						
2008	1.002****	0.181	5.521	0.000	0.646	1.357
2009	1.459****	0.272	5.373	0.000	0.927	1.991
2010	1.102****	0.319	3.455	0.001	0.477	1.727
2011	0.762**	0.363	2.102	0.036	0.051	1.473
2012	0.260	0.403	0.644	0.520	−0.530	1.050
2013	−0.297	0.506	−0.587	0.557	−1.289	0.694
2014	−0.584	0.524	−1.116	0.265	−1.611	0.442
Web Only	−0.293****	0.081	−3.601	0.000	−0.452	−0.134
Constant	−3.832****	0.128	−29.990	0.000	−4.082	−3.581
Number of obs.	9427					
Number of clusters	799					
Log pseudolikelihood	−2368.041					
Chi-squared	394.814					
Model deg. freedom	10					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.095					
AIC	4758.081					
BIC	4836.746					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.3. Restricted model estimation (M2.3). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	3.537****	0.901	3.926	0.000	1.771	5.303
Proportion of Adopters sq.	−2.812***	0.937	−3.001	0.003	−4.649	−0.976
Year (ref. 2007)						
2008	1.017****	0.180	5.659	0.000	0.665	1.370
2009	1.429****	0.275	5.195	0.000	0.890	1.968
2010	1.014***	0.327	3.101	0.002	0.373	1.654
2011	0.701*	0.368	1.906	0.057	−0.020	1.422
2012	0.286	0.403	0.709	0.478	−0.504	1.076
2013	−0.063	0.517	−0.122	0.903	−1.076	0.950
2014	−0.448	0.522	−0.858	0.391	−1.471	0.575
Web Only	−0.297****	0.082	−3.639	0.000	−0.457	−0.137
Quarterly Perc. Growth of Media Mentions	0.000*	0.000	1.789	0.074	−0.000	0.000
Constant	−3.855****	0.127	−30.405	0.000	−4.103	−3.606
Number of obs.	9427					
Number of clusters	799					
Log pseudolikelihood	−2366.417					
Chi-squared	406.629					
Model deg. freedom	11					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.096					
AIC	4756.834					
BIC	4842.650					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.4. Full model estimation (M2.4). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	3.909***	1.216	3.214	0.001	1.525	6.293
Proportion of Adopters sq.	−3.532***	1.348	−2.621	0.009	−6.173	−0.890
Year (ref. 2008)						
2009	0.718****	0.209	3.440	0.001	0.309	1.127
2010	0.544*	0.328	1.659	0.097	−0.099	1.188
2011	0.233	0.468	0.499	0.618	−0.683	1.150
2012	−0.789	0.663	−1.191	0.234	−2.089	0.510
2013	−0.767	0.721	−1.063	0.288	−2.181	0.647
2014	−0.197	0.657	−0.300	0.764	−1.484	1.091
Web Only	−0.343***	0.118	−2.908	0.004	−0.574	−0.112
Quarterly Perc. Growth of Media Mentions	−0.000	0.000	−1.128	0.259	−0.000	0.000
Share of Web Sales in Merchandise Category	−0.251	0.874	−0.287	0.774	−1.964	1.463
Constant	−2.653****	0.178	−14.945	0.000	−3.001	−2.305
Number of obs.	2840					
Number of clusters	456					
Log pseudolikelihood	−1069.159					
Chi-squared	109.828					
Model deg. freedom	11					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.051					
AIC	2162.318					
BIC	2233.737					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.5. Full model estimation (M2.5). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	3.864***	1.209	3.196	0.001	1.494	6.234
Proportion of Adopters sq.	−3.491***	1.337	−2.611	0.009	−6.112	−0.871
Year (ref. 2008)						
2009	0.724****	0.208	3.487	0.000	0.317	1.131
2010	0.570*	0.329	1.735	0.083	−0.074	1.214
2011	0.247	0.473	0.522	0.601	−0.680	1.173
2012	−0.770	0.664	−1.159	0.246	−2.071	0.531
2013	−0.738	0.724	−1.020	0.308	−2.156	0.680
2014	−0.105	0.660	−0.159	0.874	−1.399	1.190
Web Only	−0.327***	0.119	−2.748	0.006	−0.560	−0.094
Quarterly Perc. Growth of Media Mentions	−0.000	0.000	−1.118	0.264	−0.000	0.000
Product Recommendations	0.255**	0.124	2.067	0.039	0.013	0.498
Share of Web Sales in Merchandise Category	−0.281	0.903	−0.312	0.755	−2.051	1.488
Constant	−2.835****	0.203	−13.986	0.000	−3.232	−2.438
Number of obs.	2840					
Number of clusters	456					
Log pseudolikelihood	−1067.006					
Chi-squared	112.386					
Model deg. freedom	12					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.053					
AIC	2160.011					
BIC	2237.381					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.6. Full model estimation (M2.6). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	3.943***	1.216	3.243	0.001	1.560	6.326
Proportion of Adopters sq.	−3.569***	1.348	−2.647	0.008	−6.211	−0.927
Year (ref. 2008)						
2009	0.706****	0.208	3.391	0.001	0.298	1.114
2010	0.533	0.329	1.617	0.106	−0.113	1.178
2011	0.201	0.472	0.425	0.671	−0.725	1.127
2012	−0.832	0.667	−1.248	0.212	−2.139	0.475
2013	−0.759	0.724	−1.047	0.295	−2.179	0.661
2014	−0.177	0.665	−0.266	0.790	−1.480	1.126
Web Only	−0.386***	0.126	−3.070	0.002	−0.633	−0.140
Quarterly Perc. Growth of Media Mentions	−0.000	0.000	−1.100	0.272	−0.000	0.000
Share of Web Sales in Merchandise Category	−0.316	0.906	−0.349	0.727	−2.092	1.460
Product Recommendations	0.225*	0.124	1.815	0.070	−0.018	0.468
Blog	0.234*	0.136	1.720	0.085	−0.033	0.501
Constant	−2.861****	0.204	−14.043	0.000	−3.260	−2.462
Number of obs.	2840					
Number of clusters	456					
Log pseudolikelihood	−1065.321					
Chi-squared	114.677					
Model deg. freedom	13					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.055					
AIC	2158.641					
BIC	2241.963					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.7. Model estimation controlling for performance (M2.7). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	4.048****	1.135	3.565	0.000	1.822	6.273
Proportion of Adopters sq.	−3.929***	1.245	−3.155	0.002	−6.369	−1.488
Year (ref. 2007)						
2008	0.970****	0.214	4.535	0.000	0.551	1.390
2009	1.601****	0.324	4.939	0.000	0.966	2.237
2010	1.463****	0.385	3.800	0.000	0.708	2.217
2011	1.281***	0.477	2.688	0.007	0.347	2.216
2012	0.696	0.564	1.235	0.217	−0.409	1.801
2013	0.772	0.641	1.204	0.228	−0.485	2.029
2014	0.587	0.725	0.810	0.418	−0.835	2.009
Conversion Rate	0.378	1.596	0.237	0.813	−2.751	3.506
Constant	−3.758****	0.154	−24.472	0.000	−4.059	−3.457
Number of obs.	5012					
Number of clusters	595					
Log pseudolikelihood	−1400.191					
Chi-squared	269.683					
Model deg. freedom	10					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.107					
AIC	2822.382					
BIC	2894.097					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.8. Model estimation controlling for performance (M2.8). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	3.832****	1.128	3.396	0.001	1.620	6.043
Proportion of Adopters sq.	−3.609***	1.237	−2.917	0.004	−6.034	−1.184
Year (ref. 2007)						
2008	1.004****	0.212	4.731	0.000	0.588	1.420
2009	1.619****	0.322	5.033	0.000	0.989	2.250
2010	1.402****	0.382	3.669	0.000	0.653	2.151
2011	1.140**	0.473	2.408	0.016	0.212	2.068
2012	0.521	0.564	0.924	0.356	−0.584	1.626
2013	0.569	0.648	0.879	0.380	−0.700	1.839
2014	1.111*	0.590	1.884	0.060	−0.045	2.267
Monthly Visits	−0.000	0.000	−1.215	0.224	−0.000	0.000
Constant	−3.739****	0.144	−25.997	0.000	−4.020	−3.457
Number of obs.	5185					
Number of clusters	610					
Log pseudolikelihood	−1441.493					
Chi-squared	268.814					
Model deg. freedom	10					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.105					
AIC	2904.985					
BIC	2977.074					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table A.9. Model estimation controlling for performance (M2.9). Logit model using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Facebook Adpt.						
Proportion of Adopters	4.105****	1.134	3.619	0.000	1.882	6.328
Proportion of Adopters sq.	−3.988***	1.246	−3.202	0.001	−6.430	−1.547
Year (ref. 2007)						
2008	0.962****	0.214	4.497	0.000	0.543	1.382
2009	1.590****	0.324	4.907	0.000	0.955	2.225
2010	1.461****	0.385	3.790	0.000	0.705	2.216
2011	1.300***	0.479	2.716	0.007	0.362	2.239
2012	0.725	0.569	1.274	0.203	−0.390	1.840
2013	0.769	0.641	1.201	0.230	−0.487	2.025
2014	0.597	0.730	0.817	0.414	−0.835	2.029
Conversion Rate	0.243	1.606	0.151	0.880	−2.905	3.390
Monthly Visits	−0.000	0.000	−0.807	0.419	−0.000	0.000
Constant	−3.746****	0.153	−24.413	0.000	−4.047	−3.445
Number of obs.	5012					
Number of clusters	595					
Log pseudolikelihood	−1399.479					
Chi-squared	270.750					
Model deg. freedom	11					
Prob. > Chi-squared	0.000					
Pseudo R-squared	0.108					
AIC	2822.958					
BIC	2901.194					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Appendix B. Additional Reports on Chapter 3

Table B.1. Model estimation (M3.1). Fixed effects regression models with cluster-robust standard errors(dependent variable: Logistics & Operations Make/Buy Ratio Change).

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Web Sales (USD 10^6) Change	−0.002	0.015	−0.127	0.899	−0.031	0.027
Web Sales (USD 10^6) Level	0.178	0.195	0.913	0.362	−0.206	0.563
Conversion Rate Change	0.004	0.012	0.360	0.719	−0.020	0.029
Conversion Rate Level	0.029	0.056	0.523	0.602	−0.082	0.140
Average Ticket (USD) Change	−0.032	0.031	−1.019	0.309	−0.094	0.030
Average Ticket (USD) Level	0.159	0.249	0.640	0.523	−0.331	0.650
Monthly Visits Change	0.007	0.009	0.793	0.428	−0.011	0.025
Monthly Visits Level	0.054	0.127	0.426	0.671	−0.196	0.303
Monthly Unique Visitors Change	−0.009**	0.004	−2.428	0.016	−0.016	−0.002
Monthly Unique Visitors Level	−0.072	0.081	−0.893	0.373	−0.232	0.087
Year (ref. '2009')						
2010	−0.008	0.006	−1.373	0.171	−0.020	0.004
2011	−0.009	0.007	−1.352	0.178	−0.022	0.004
2012	−0.001	0.006	−0.155	0.877	−0.013	0.011
2013	−0.032****	0.007	−4.836	0.000	−0.045	−0.019
2014	−0.006	0.008	−0.780	0.436	−0.022	0.010
Constant	−0.026	0.029	−0.899	0.370	−0.084	0.031
Number of observations	1363					
Number of clusters	239					
R-squared for within model	0.043					
R-squared for overall model	0.010					
R-squared for between model	0.003					
corr(μ_i ,Xb)	−0.631					
F statistic	3.276					
Numerator degrees of freedom for F statistic	15					
Degrees of freedom for absorbed effect	238					
ρ	0.234					
Panel-level standard deviation	0.038					
Standard deviation of ϵ_{it}	0.069					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B.2. Model estimation (M3.2). Fixed effects regression models with cluster-robust standard errors(dependent variable: Marketing Make/Buy Ratio Change).

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Web Sales (USD 10^6) Change	0.012	0.025	0.475	0.635	−0.037	0.060
Web Sales (USD 10^6) Level	0.238	0.245	0.973	0.331	−0.244	0.720
Conversion Rate Change	0.049*	0.028	1.753	0.081	−0.006	0.104
Conversion Rate Level	0.130	0.117	1.110	0.268	−0.101	0.361
Average Ticket (USD) Change	−0.007	0.042	−0.177	0.860	−0.090	0.076
Average Ticket (USD) Level	0.076	0.286	0.265	0.791	−0.488	0.640
Monthly Visits Change	−0.005	0.015	−0.298	0.766	−0.035	0.025
Monthly Visits Level	0.079	0.168	0.470	0.639	−0.252	0.410
Monthly Unique Visitors Change	0.004	0.004	0.991	0.322	−0.004	0.011
Monthly Unique Visitors Level	0.050	0.105	0.478	0.633	−0.156	0.257
Year (ref. '2009')						
2010	−0.013	0.012	−1.136	0.257	−0.037	0.010
2011	−0.015*	0.009	−1.711	0.088	−0.032	0.002
2012	−0.006	0.011	−0.608	0.544	−0.027	0.014
2013	−0.034****	0.010	−3.452	0.001	−0.053	−0.015
2014	−0.007	0.010	−0.736	0.462	−0.027	0.012
Constant	−0.044	0.035	−1.279	0.202	−0.112	0.024
Number of observations	1363					
Number of clusters	239					
R-squared for within model	0.019					
R-squared for overall model	0.005					
R-squared for between model	0.005					
corr(μ_i ,Xb)	−0.569					
F statistic	1.887					
Numerator degrees of freedom for F statistic	15					
Degrees of freedom for absorbed effect	238					
ρ	0.184					
Panel-level standard deviation	0.050					
Standard deviation of ϵ_{it}	0.106					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B.3. Model estimation (M3.3). Fixed effects regression models with cluster-robust standard errors(dependent variable: Sales Make/Buy Ratio Change).

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Web Sales (USD 10^6) Change	−0.009	0.016	−0.569	0.570	−0.040	0.022
Web Sales (USD 10^6) Level	0.149^{+}	0.094	1.593	0.113	−0.035	0.334
Conversion Rate Change	−0.018	0.021	−0.820	0.413	−0.060	0.025
Conversion Rate Level	−0.142	0.121	−1.181	0.239	−0.380	0.095
Average Ticket (USD) Change	−0.022	0.042	−0.534	0.594	−0.105	0.060
Average Ticket (USD) Level	−0.078	0.175	−0.446	0.656	−0.423	0.267
Monthly Visits Change	−0.009	0.010	−0.963	0.337	−0.028	0.010
Monthly Visits Level	−0.028	0.088	−0.323	0.747	−0.202	0.145
Monthly Unique Visitors Change	−0.004	0.004	−0.859	0.391	−0.012	0.005
Monthly Unique Visitors Level	0.042	0.100	0.417	0.677	−0.155	0.238
Year (ref. '2009')						
2010	0.002	0.009	0.288	0.774	−0.014	0.019
2011	0.011*	0.007	1.685	0.093	−0.002	0.024
2012	0.015*	0.008	1.908	0.058	−0.000	0.030
2013	−0.009	0.008	−1.132	0.259	−0.024	0.007
2014	−0.006	0.008	−0.678	0.498	−0.022	0.011
Constant	0.016	0.026	0.632	0.528	−0.034	0.067
Number of observations	1363					
Number of clusters	239					
R-squared for within model	0.019					
R-squared for overall model	0.002					
R-squared for between model	0.006					
corr(μ_i ,Xb)	−0.453					
F statistic	1.759					
Numerator degrees of freedom for F statistic	15					
Degrees of freedom for absorbed effect	238					
ρ	0.178					
Panel-level standard deviation	0.039					
Standard deviation of ϵ_{it}	0.085					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Appendix C. Additional Reports on Chapter 4

Table C.1. Hurdle model (M4.2). Simultaneous estimation of the number of tweets published using a logit and a truncated negative binomial regression. Using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Logit Regression						
Time of Adoption	0.975****	0.005	−5.169	0.000	0.966	0.985
US dataset	0.721*	0.134	−1.755	0.079	0.501	1.039
Average of New Tweets in Merchandise Cat.	1.002***	0.001	2.941	0.003	1.001	1.004
Merchant Type (ref. Web Only)						
Catalog/Call Center	2.271***	0.712	2.616	0.009	1.228	4.200
Consumer Brand Manufacturer	3.307***	1.285	3.079	0.002	1.545	7.081
Retail Chain	2.824****	0.600	4.888	0.000	1.863	4.283
Truncated Negative Binomial Regression						
Time of Adoption	0.988**	0.006	−2.192	0.028	0.977	0.999
US dataset	0.708***	0.089	−2.751	0.006	0.554	0.905
Average of New Tweets in Merchandise Cat.	1.002****	0.000	5.493	0.000	1.001	1.002
Merchant Type (ref. Web Only)						
Catalog/Call Center	0.637***	0.097	−2.951	0.003	0.472	0.860
Consumer Brand Manufacturer	1.996***	0.441	3.128	0.002	1.294	3.077
Retail Chain	1.730****	0.251	3.774	0.000	1.301	2.300
N (Logit)	1310					
N (TNB)	1148					
TNB chibar2(01) p-value [LR test of $\alpha = 0$]	0.0000					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
Exponentiated coefficients

Table C.2. Hurdle model (M4.3). Simultaneous estimation of the number of tweets published using a logit and a truncated negative binomial regression. Using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Logit Regression						
Time of Adoption	0.976****	0.005	−4.919	0.000	0.966	0.985
US dataset	0.665**	0.130	−2.090	0.037	0.454	0.975
Merchant Type (ref. Web Only)						
Catalog/Call Center	2.150**	0.672	2.446	0.014	1.164	3.969
Consumer Brand Manufacturer	3.007***	1.207	2.743	0.006	1.369	6.604
Retail Chain	2.762****	0.619	4.528	0.000	1.779	4.286
Merchandise Category (ref. Computers/Electronics)						
Apparel/Accessories	3.544****	1.079	4.155	0.000	1.951	6.438
Automotive Parts/Accessories	0.879	0.426	−0.267	0.790	0.340	2.273
Books/Music/Video	1.720	0.643	1.451	0.147	0.827	3.578
Flowers/Gifts	2.006	1.089	1.282	0.200	0.692	5.811
Food/Drug	3.459**	1.973	2.176	0.030	1.131	10.580
Hardware/Home Improvement	0.913	0.339	−0.245	0.807	0.442	1.889
Health/Beauty	2.086	0.947	1.619	0.105	0.856	5.079
Housewares/Home Furnishings	1.250	0.415	0.671	0.502	0.652	2.397
Jewelry	1.488	0.758	0.780	0.436	0.548	4.039
Mass Merchant	2.537**	0.992	2.380	0.017	1.179	5.461
Office Supplies	1.239	0.654	0.406	0.685	0.440	3.488
Specialty	3.113**	1.412	2.503	0.012	1.279	7.572
Sporting Goods	1.664	0.759	1.116	0.264	0.681	4.066
Toys/Hobbies	7.152*	7.352	1.914	0.056	0.954	53.631
Truncated Negative Binomial Regression						
Time of Adoption	0.987***	0.005	−2.682	0.007	0.978	0.997
US dataset	0.689***	0.082	−3.137	0.002	0.546	0.869
Merchant Type (ref. Web Only)						
Catalog/Call Center	0.657***	0.098	−2.803	0.005	0.490	0.881
Consumer Brand Manufacturer	2.215****	0.469	3.757	0.000	1.463	3.354
Retail Chain	1.797****	0.248	4.241	0.000	1.371	2.357
Merchandise Category (ref. Computers/Electronics)						
Apparel/Accessories	1.121	0.252	0.508	0.611	0.722	1.742
Automotive Parts/Accessories	0.615	0.221	−1.353	0.176	0.304	1.244
Books/Music/Video	1.610	0.525	1.463	0.144	0.850	3.049
Flowers/Gifts	0.826	0.229	−0.690	0.490	0.479	1.422
Food/Drug	2.697***	0.847	3.162	0.002	1.458	4.990
Hardware/Home Improvement	0.668	0.189	−1.425	0.154	0.383	1.164
Health/Beauty	1.017	0.289	0.058	0.954	0.583	1.774
Housewares/Home Furnishings	0.715	0.195	−1.229	0.219	0.419	1.221
Jewelry	0.895	0.554	−0.179	0.858	0.266	3.013
Mass Merchant	1.614*	0.440	1.753	0.080	0.945	2.755
Office Supplies	0.829	0.352	−0.441	0.659	0.361	1.906
Specialty	1.310	0.366	0.968	0.333	0.758	2.265
Sporting Goods	1.154	0.462	0.359	0.720	0.527	2.527
Toys/Hobbies	1.057	0.408	0.144	0.886	0.496	2.254
N (Logit)	1310					
N (TNB)	1148					
TNB chibar2(01) p-value [LR test of $\alpha = 0$]	0.0000					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
Exponentiated coefficients

Table C.3. Hurdle model (M4.4). Simultaneous estimation of the number of tweets published using a logit and a truncated negative binomial regression. Using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Logit Regression						
Time of Adoption	0.965****	0.009	−3.983	0.000	0.948	0.982
Capability Index	1.380	1.185	0.375	0.708	0.257	7.423
Sourcing Propensity	0.009*	0.024	−1.824	0.068	0.000	1.416
Merchant Type (ref. Web Only)						
Catalog/Call Center	1.858	0.948	1.214	0.225	0.683	5.052
Consumer Brand Manufacturer	2.295	1.335	1.429	0.153	0.734	7.175
Retail Chain	4.508***	2.443	2.779	0.005	1.558	13.042
Truncated Negative Binomial Regression						
Time of Adoption	0.986*	0.008	−1.837	0.066	0.971	1.001
Capability Index	0.788	0.349	−0.540	0.590	0.331	1.875
Sourcing Propensity	0.900	1.220	−0.078	0.938	0.063	12.845
Merchant Type (ref. Web Only)						
Catalog/Call Center	0.925	0.234	−0.308	0.758	0.564	1.518
Consumer Brand Manufacturer	2.390***	0.695	2.998	0.003	1.352	4.225
Retail Chain	2.214****	0.496	3.550	0.000	1.428	3.434
N (Logit)	486					
N (TNB)	444					
TNB chibar2(01) p-value [LR test of $\alpha = 0$]	0.0000					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
Exponentiated coefficients

Table C.4. Hurdle model (M4.5). Simultaneous estimation of the number of tweets published using a logit and a truncated negative binomial regression. Using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Logit Regression						
Time of Adoption	0.967****	0.009	−3.780	0.000	0.950	0.984
Foundation of service index	0.607	0.704	−0.430	0.667	0.063	5.885
Customer-centered index	1.129	0.992	0.138	0.890	0.202	6.314
Value-added index	1.637	1.147	0.704	0.482	0.415	6.461
Merchant Type (ref. Web Only)						
Catalog/Call Center	2.034	1.093	1.321	0.186	0.709	5.830
Consumer Brand Manufacturer	2.779*	1.633	1.739	0.082	0.878	8.794
Retail Chain	5.578***	3.178	3.017	0.003	1.826	17.040
Truncated Negative Binomial Regression						
Time of Adoption	0.984**	0.007	−2.158	0.031	0.970	0.999
Foundation of service index	1.384	0.566	0.795	0.427	0.621	3.084
Customer-centered index	0.449**	0.171	−2.098	0.036	0.212	0.949
Value-added index	1.292	0.402	0.825	0.409	0.703	2.377
Merchant Type (ref. Web Only)						
Catalog/Call Center	0.941	0.244	−0.234	0.815	0.567	1.564
Consumer Brand Manufacturer	2.372***	0.672	3.049	0.002	1.361	4.132
Retail Chain	2.070***	0.474	3.175	0.001	1.321	3.243
N (Logit)	486					
N (TNB)	444					
TNB chibar2(01) p-value [LR test of $\alpha = 0$]	0.0000					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
Exponentiated coefficients

Table C.5. Hurdle model (M4.6). Simultaneous estimation of the number of tweets published using a logit and a truncated negative binomial regression. Using Huber/White/sandwich estimator of the variance-covariance matrix.

	Coef.	Rob. S.E.	z	P > z	95% Conf. Int. Lo. Bound	95% Conf. Int. Up. Bound
Logit Regression						
Time of Adoption	0.966****	0.009	−3.896	0.000	0.949	0.983
Sourcing Propensity	0.008*	0.020	−1.886	0.059	0.000	1.211
Foundation of service index	0.550	0.626	−0.525	0.599	0.059	5.130
Customer-centered index	1.206	1.036	0.218	0.827	0.224	6.496
Value-added index	1.727	1.208	0.781	0.435	0.439	6.801
Merchant Type (ref. Web Only)						
Catalog/Call Center	1.993	1.068	1.287	0.198	0.697	5.698
Consumer Brand Manufacturer	2.432	1.452	1.489	0.137	0.755	7.838
Retail Chain	5.145***	3.000	2.810	0.005	1.641	16.132
Truncated Negative Binomial Regression						
Time of Adoption	0.984**	0.007	−2.146	0.032	0.970	0.999
Sourcing Propensity	0.927	1.218	−0.057	0.954	0.071	12.172
Foundation of service index	1.383	0.564	0.795	0.427	0.622	3.076
Customer-centered index	0.450**	0.172	−2.084	0.037	0.212	0.954
Value-added index	1.296	0.388	0.865	0.387	0.720	2.332
Merchant Type (ref. Web Only)						
Catalog/Call Center	0.940	0.237	−0.246	0.806	0.573	1.541
Consumer Brand Manufacturer	2.372***	0.674	3.041	0.002	1.359	4.138
Retail Chain	2.064****	0.441	3.391	0.001	1.358	3.137
N (Logit)	486					
N (TNB)	444					
TNB chibar2(01) p-value [LR test of $\alpha = 0$]	0.0000					

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
Exponentiated coefficients