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Business value of social media technologies: Evidence from online user innovation communities

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ABSTRACT

Social media technologies allow user-generated content and provide new opportunities and challenges for firms to transform their business. In particular, more and more firms have started strategically using the online user innovation communities (OUICs) for open innovation initiatives. The extent to which firms are able to derive business value from OUICs, however, has not been systematically examined. Drawing on a multi-theoretical foundation from the framework of dynamic capabilities and the view of innovation value chain, we conceptualize two OUIC-enabled capabilities, which are, ideation capability related to collecting user-generated ideas about potential innovation from OUIC, and implementation capability related to selecting user-generated ideas for innovation development and introducing developed innovation via OUIC. Using a large-scale panel data set consisting of 1676 firm-day observations from Dell and Starbucks, we examine the impacts of OUIC-enabled capabilities on firm value. We find robust evidence that OUIC-enabled ideation capability actually does not influence firm value, whereas OUIC-enabled implementation capability increases firm value. Novel theoretical and managerial implications are discussed.

"Generating lots of good ideas is one thing; how you handle (mishandle) them once you have them is another matter entirely."
[Hansen and Birkinshaw, 2007, p. 123]

Introduction

With the advances in information technology (IT), social media technologies support a large volume of user-generated content that provides opportunities and challenges for business transformation (Jarvenpaa and Tuunainen, 2013; Kane and Fichman, 2009; Majchrzak, 2009). As firms increasingly leverage IT in various innovation activities (Dong, 2010; Dong and Yang, 2015; Joshi et al., 2010; Kleis et al., 2012; Pavlou and El Sawy, 2010; Tambe et al., 2012; Xue et al., 2012), they can use a particular social media technology—online user innovation communities (OUICs)—for open innovation by crowdsourcing the ideas about new products, services and processes (Di Gangi and Wasko, 2009; Di Gangi et al., 2010).

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In OUICs, users can post, comment on, and vote for new ideas about innovation. Firms select the pertinent ideas from OUICs for their innovation development to improve their products, services, and processes. OUICs can also help firms to diffuse developed innovation by posting the announcements on innovation launch in the marketplace. For example, a user "jervis961" posted his idea in Dell's OUIC—IdeaStorm—entitled "Improve the look of Inspiron laptops by removing some of the rubber nubs from the screen". Other users then left comments to extend this idea. Dell selected this idea and improved its design of Inspiron laptop by removing the ugly rubber nubs. After launching the improved Inspiron laptop to the marketplace, Dell made an announcement in IdeaStorm to let its users know this innovation.

This social media technology—OUICs—supports firms to strategically use IT for innovation.[1] Although firms' use of OUICs is popular in practices with the assumption that it can create business value, the extent to which OUICs actually contribute business value to firms remains largely unclear. In particular, how firms can derive business value from their strategic use of OUICs has not been fully understood. Common belief often suggests that OUICs are valuable for crowdsourcing by enabling firms to collect large amount of user-generated ideas (Bayus, 2013; Huang et al., 2014). Less focus is put on the following stages of innovation development and diffusion. A better understanding of the ways in which firms increase their business value through the strategic use of OUICs has important implications on the business value of social media technologies, as recent studies on the business value of IT have switched the focus to the IT enablement of innovation (e.g., Aral and Weill, 2007; Bardhan et al., 2013; Tambe et al., 2012; Xue et al., 2012).

To fill the aforementioned gaps in the IS literature, we theorize two specific IT capabilities in the OUIC context and empirically examine their effects on firm value. Drawing on the framework of dynamic capabilities (Teece, 2007; Teece et al., 1997) and the view of innovation value chain (Hansen and Birkinshaw, 2007), OUIC-enabled ideation capability and OUIC-enabled implementation capability are conceptualized to characterize firms' strategic use of OUICs. We define *OUIC-enabled ideation capability* as a firm's ability to collect user-generated ideas such as posts and comments about potential innovation from its OUIC. Furthermore, we define *OUIC-enabled implementation capability* as a firm's ability to select user-generated ideas from its OUIC for innovation development and then introduce the developed innovation to the desired users via its OUIC. In this study, we propose that collecting ideas and dealing with ideas by using OUICs reflects different capabilities, and the latter has long been ignored but is critical for creating business value. Although OUIC-enabled ideation capability supports a firm to collect a large number of user-generated ideas, it does not directly influence firm value; only a good idea converted to and introduced as an innovation by OUIC-enabled implementation capability can increase firm value. OUIC-enabled implementation capability allows a firm to select the pertinent ideas as the inputs to its innovation development in the organization and communicate with the desired customers about innovation launches in the marketplace. By using a large-scale, firm-day panel data set from Dell and Starbucks over a four-year period, we find robust empirical evidence that corroborates our theory.

Our study has three major contributions to the IS literature. *First*, we contribute to the IT capabilities literature by theorizing two innovation capabilities based on firms' strategic use of social media technologies. Specifically, we conceptualize OUIC-enabled ideation capability and OUIC-enabled implementation capability by a multi-theoretical lens consisting of dynamic capabilities and the innovation value chain. OUIC-enabled ideation capability is useful for idea generation, whereas OUIC-enabled implementation capability is functional for idea conversion and diffusion. *Second*, we contribute to the literature on the business value of IT by explaining and testing distinct effects of OUIC-enabled ideation capability and OUIC-enabled implementation capability on firm value. To the best of our knowledge, this study is among the first attempts to examine the business value of firms' strategic use of social media technologies in crowdsourcing. Our findings suggest that a firm's OUIC-enabled ideation capability to collect ideas merely provides the potential of business value; a firm's OUIC-enabled implementation capability to select and implement ideas can actually realize the business value. *Finally*, our study contributes to the emerging literature on IT and innovation. It broadens this research by exploring new insights on how firms could build digitally enabled dynamic capabilities through strategically using social media technologies. We find that firms' use of OUICs enables idea generation, conversion and diffusion, which can generate new products, services, and processes.

The rest of the paper proceeds as follows. In the next section, we present our theoretical framework and hypotheses. We then report the methodology and empirical results. Finally, we conclude by discussing the theoretical and managerial implications of this study, as well as the limitations and directions for future research.

Theory and hypotheses

Dynamic capabilities and the innovation value chain

Dynamic capabilities are a solid theoretical framework that explains firms' capabilities to innovate constantly in a fast-changing market environment to sustain competitive advantage (Eisenhardt and Martin, 2000; Teece, 2007; Teece et al., 1997; Winter, 2003). Therefore, it is particularly suitable as the theoretical foundation for innovation research. Dynamic capabilities refer to the organizational routines that change existing routines through innovation (Winter, 2003). Dynamic

[1] Aral and Weill (2007) defined four types of IT use: infrastructural, transactional, informational, and strategic. According to their definition, the strategic use of IT refers to IT use for innovation purposes by developing new products, services, or business models. Because OUICs are increasingly used by firms to develop new products, services and processes (Chesbrough, 2003; Nambisan, 2002, 2013), we focus on this technology to investigate firms' strategic use of social media.

capabilities can be harnessed by firms to create, deploy, and protect innovation that supports superior performance (Teece et al., 1997). Such routines include organizational activities to sense opportunities, to seize opportunities, and to maintain competitiveness through the reconfiguration (Teece, 2007).

To explain the value-creating mechanisms in firm innovation activities, Hansen and Birkinshaw (2007) recommended viewing innovation as a value chain comprised of three phases—idea generation, the conversion of ideas, and the diffusion of developed concepts. They suggested that firm innovation activities can be viewed as a process of transforming ideas into commercial outputs, which is rather like Porter's (1985) value chain for transforming raw materials into finished goods. Economic value is created in the innovation outcomes resulted from the completion of this value chain. The view of innovation value chain is essentially complementary to the dynamic capabilities framework. Idea generation is the sensing of opportunities, and idea conversion and diffusion are ways of seizing opportunities. However, the view of innovation value chain provides additional insights on the condition under which value can be created in an innovation process.

Drawing on the complementary perspectives from dynamic capabilities and the innovation value chain, we identify two categories of innovation activities that composite a firm's innovation capabilities: sensing/idea generation, and seizing/idea conversion and diffusion. Sensing describes scanning, creating, learning, and interpretive activities (Teece, 2007). To identify market opportunities, firms need to search for new ideas. Similarly, the key task of idea generation is collecting new ideas on potential innovation. Firms need to source new ideas not only from in-house personnel but also from suppliers, customers, and, in particular, end users outside the company (Hansen and Birkinshaw, 2007).

Seizing is addressing the sensed new opportunities through investing in, developing and introducing new products, services, and processes (Teece, 2007). To seize a market opportunity, firms need to select product architectures, investing in research and development, and then introduce the innovation to marketplace. Similarly, idea conversion activities start with selecting good ideas, followed by developing innovation based on selected ideas, and idea diffusion activities are introducing developed innovation. Idea selection mechanisms are necessary for efficient idea conversion, and idea diffusion needs to be carried out in effective information channels to desired customers (Hansen and Birkinshaw, 2007).

OUIC-enabled ideation and implementation capabilities

Individual customers or end users have been recognized as an important source of innovation (Nambisan, 2002). Teece (2007) suggested that customers are sometimes amongst the first to perceive the potential for new invention. Similarly, Jespersen (2010) regarded the involvement of users in new product development as a key dimension of open innovation. OUICs provide a social media platform for user-generated ideas on innovation (Di Gangi and Wasko, 2009; Di Gangi et al., 2010; Nambisan, 2013). This technology allows users to post, comment on, and vote for new ideas on new products, services, and processes. In OUICs, firms also assign some internal employees as the idea partners to evaluate and select the ideas posts, comments and votes by users. They support managerial decision making for innovation and release information about innovation launch in the marketplace via OUICs.

Based on the two categories of innovation activities identified from the framework of dynamic capabilities and the view of innovation value chain, we theorize two different capabilities based on firms' use of OUICs: OUIC-enabled ideation capability and OUIC-enabled implementation capability. OUICs can be used to collect external idea posts and comments from users. Therefore, we define OUIC-enabled ideation capability as a firm's ability to collect user-generated ideas such as posts and comments about potential innovation from its OUIC. For example, Starbucks collected an idea from a user "evanschwa" entitled "Alternatives to dairy and soy" in its OUIC—MyStarbucksIdea, as well as 90 following comments made by other users to enrich this idea. They suggested that soy is highly allergenic and unhealthy in large quantities, and many people also cannot tolerate cow's milk. They asked for rice, almond, or coconut milk as the alternatives of cow's milk.

On the other hand, OUICs can support idea selection based on users' votes and idea partners' evaluation, which are the inputs to managerial decisions for developing what innovation in the firm. When a selected idea has been developed into an innovation and launched to marketplace, idea partners can make an announcement about the innovation launch via OUICs to introduce the innovation to desired users in OUICs. Accordingly, we define OUIC-enabled implementation capability as a firm's ability to select user-generated ideas from its OUIC for innovation development and then introduce the developed innovation to the desired users via its OUIC. Related to above example, hundreds of users voted for the idea posted by "evanschwa" and Starbucks selected this idea and developed new coffee products with coconut milk. Finally, Starbucks' idea partner—Christine Barone—released the announcement "Coconut Milk Is Here!" to let desired customers know that Starbucks begun to offer customized coffee with coconut milk.

OUIC-enabled ideation capability and firm value

In today's market environment, where customer needs are rapidly changing, emerging market opportunities are hard to discern; new information on customer needs is thereby important for sensing opportunities (Teece et al., 1997). To identify new opportunities, firms must constantly scan, search and gather new information from market environment. In this process, overcoming a narrow search horizon contributes to a broad menu of opportunities (Teece, 2007). If a firm is unable to gain access to enough new ideas, it results in missed opportunities (Hansen and Birkinshaw, 2007). Sourcing external ideas from customers is a solution to extend the scope of search because customers are often able to anticipate the shift of demand (Nambisan, 2002).

OUIC-enabled ideation capability refers to a firm's ability to collect user-generated ideas such as posts and comments about potential innovation from its OUIC. By using OUIC for idea generation, a firm is able to search beyond the local spectrum and across organizational boundaries. OUIC-enabled ideation capability can therefore collect ideas from outside the company by tapping into the opinions of end users (Nambisan, 2013). For example, Dell has gathered more than 22,000 posts and 100,000 comments on new ideas from its OUIC—IdeaStorm, which are related to its desktops and laptops, mobile devices, servers and storage, software, printers and ink, accessories, broadband and mobility, advertising and marketing, retail, service and support.

However, a sensed market opportunity must be addressed through screening, development and commercialization to create economic value. Regardless of how good an idea is, it must be turned into a revenue-generating product, service or process to gain returns in the marketplace (Hansen and Birkinshaw, 2007). Idea generation only provides the potential of innovation and requires conversion and diffusion to realize the value. It is likely that a firm senses an opportunity but fails to seize it (Teece, 2007). Idea posts and comments resulted from a firm's OUIC-enabled ideation capability therefore provide the potential of value creation, but business value must be created in the implementation of good ideas. Although OUIC-enabled ideation capability helps collect posts and comments about potential innovation from users, it cannot increase firm value before the ideas have been selected and introduced to the marketplace. Thus, we have the following hypothesis.

H1. Idea posts and comments collected in a firm's OUIC that result from OUIC-enabled ideation capability are not associated with firm value.

OUIC-enabled implementation capability and firm value

Ideas will not prosper without strong filtering mechanisms. For instance, in 1999, the U.K. media company Emap aggressively invested in whatever business ideas were put forward, but most of businesses shut their doors as a result (Hansen and Birkinshaw, 2007). Managerial attention is a scarce resource (March and Simon, 1958); management needs to carefully allocate attention in search and discovery of innovation (Helfat and Peteraf, in press). Gathered ideas must be selected so that attention is not diverted to every opportunity that the search reveals. Only when a firm is able to efficiently select ideas based on appropriate disciplines and convert the good ideas to viable products, services and processes can the firm generate valuable innovation outcomes (Nohria and Gulati, 1996). To realize economic value, a firm must eventually introduce the innovation developed from a good idea to the desired customers via effective information channels (Hansen and Birkinshaw, 2007).

OUIC-enabled implementation capability refers to a firm's ability to select user-generated ideas from its OUIC for innovation development and then introduce the developed innovation to the desired users via its OUIC. With this capability, a firm can use OUIC to filter ideas and introduce innovation. In OUICs, users can vote for new ideas posted by others. Idea partners will evaluate the ideas based on users' votes and their expertise and then present the good ideas to managers (Jespersen, 2010). The ideas that receive management support will be developed into new products, services, or processes, and finally will be launched to marketplace. OUICs are also an effective information channel to let desired users know the innovation launch in the marketplace. For example, Starbucks has announced more than 260 innovation launches in the marketplace via its OUIC—MyStarbucksIdea, including new coffee drinks, other beverages, food, atmosphere and shop locations, merchandise, music, membership cards, new technology, ordering, payment and pick-up, social responsibility, and international business. All of these innovations were developed by Starbucks based on pertinent user-generated ideas. Since OUIC-enabled implementation capability leads to innovations that have been developed and launched to the marketplace, we expect that the innovation launches announced in the OUIC indicating positive innovation outcomes can increase firm value. Thus, we have the following hypothesis.

H2. Innovation launches announced in a firm's OUIC that result from OUIC-enabled implementation capability are positively associated with firm value.

Methodology

Research sites

We select two firms that are prominent in using OUICs—Dell and Starbucks—as our research sites because of the following reasons. First, sampling both Dell and Starbucks can increase the generalizability of our findings. There are a number of differences in these two firms. Dell is an IT company, whereas Starbucks is a coffee company. Dell is a high-technology company, and its product innovation is complex, whereas Starbucks is a low-technology firm, and its innovation seems relatively simpler. Dell's products are durable goods, whereas Starbucks' products are consumable goods. Second, their OUICs—IdeaStorm (ideastorm.com) and MyStarbucksIdea (mystarbucksidea.com)—have similar features, making the data collected from these two OUICs comparable. Finally, Dell and Starbucks have used OUICs for a few years, which allow us to collect longitudinal data. Fig. 1 shows the screenshots of IdeaStorm and MyStarbucksIdea.

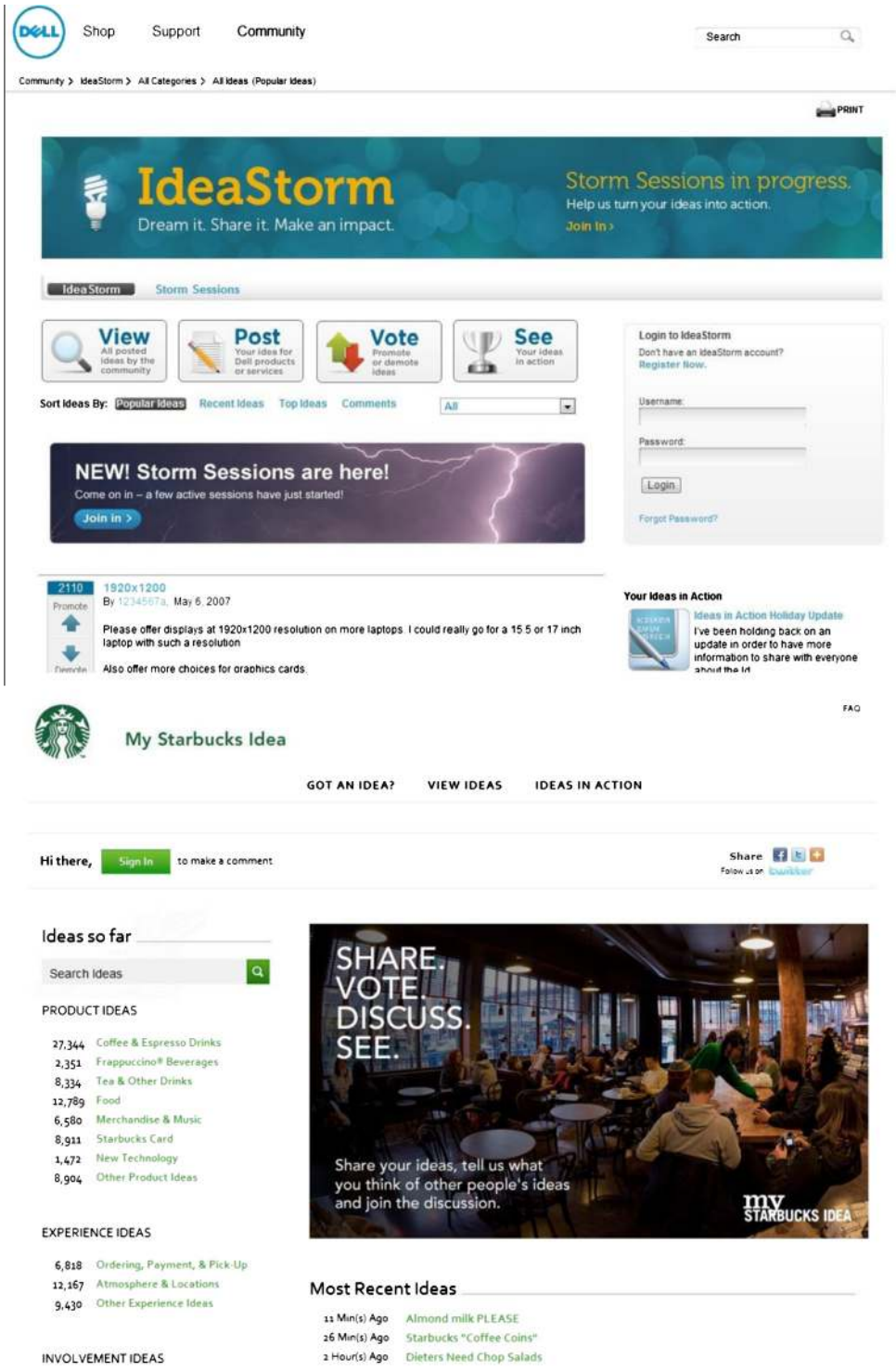

Fig. 1. Screenshots of Dell IdeaStorm and MyStarbucksIdea.

IdeaStorm: On 16 February 200, Dell created IdeaStorm website to gauge the ideas from consumers. Till 2 September 2011, the date of our data collection, IdeaStorm has collected 13,472 posts about potential innovation from users. After registration, users can post new ideas about the company, products, services, and processes. Users can also comment on others' posts and promote or demote them by voting. As ideas are promoted, their votes increase; while the votes are

decreased as they are demoted. This voting system allows Dell to rank which suggestions and requests are considered as the most important by customers.

Dell assigned a group of employees—the idea partners—handling the ideas in IdeaStorm. Idea partners maintain a page to demonstrate how Dell is acting upon the ideas; the page changes when the status of a new idea changes to "Implemented". Idea partners also make announcement on the innovation that is developed and launched to the marketplace by Dell based on the implemented idea. With IdeaStorm, Dell responds quickly to users' suggestions and has made various improvements and changes in its products, services, and processes. For example, the most popular suggestions in early days concerned the inclusion of free software and operating systems in Dell computers. Dell quickly knew that customers preferred Linux distributions, and started selling three computer systems with Ubuntu 7.04 preinstalled on 24 May 2007.

MyStarbucksIdea: Following Dell, on 28 March 2008, Starbucks opened MyStarbucksIdea to collect suggestions and feedback from customers. On 2 September 2011, our data collection date, MyStarbucksIdea has collected 117,153 posts about innovation from consumers. The design of MyStarbucksIdea is quite similar to that of IdeaStorm. Registered users can make suggestions in a wide range of categories that cover the products, experience and services, and social involvement of the company. Users can also comment on and vote for others' posts.

More than 40 idea partners, who are Starbucks employees and experts in respective fields, take responsibilities to select ideas and introduce innovation. Similar to IdeaStorm, a voting system is used to help idea partners select ideas that are the most welcomed by users. Idea partners present selected, pertinent ideas to the key decision makers of the company, and also maintain a page called "Ideas in Action" to inform the users about the implementation process. When an innovation is developed by Starbucks based on selected idea and is finally launched to the marketplace, idea partner makes an announcement on the innovation launch in MyStarbucksIdea. With MyStarbucksIdea, Starbucks has introduced hundreds of new products, services, and social activities. For example, the popular ideas include "the availability of Wi-Fi in Starbucks stores" and "convenient power connections for laptops". Starbucks also used MyStarbucksIdea to introduce the new flavors of the coffee, the change to the membership policy, and the cup art contest to the users.

In this study, we collected data from four primary sources: (1) IdeaStorm website, (2) MyStarbucksIdea website, (3) stock return data from the Center for Research in Security Prices (CRSP) database, and (4) newspaper information from the LexisNexis database. After merging the data from these multiple sources, we constructed a panel data set with a total of 1676 firm-day observations. Specifically, we have 975 daily observations from Dell and 703 daily observations from Starbucks.

Research design

We adopt an event study methodology to test our hypotheses. Under the efficient market hypothesis (Fama, 1970; Jensen, 1978), the effect of an event on firm value will be reflected immediately in the stock price. In accounting and finance research, event study has been applied to a variety of firm-specific and economy-wide events. Examples include the effects of mergers and acquisitions (e.g., Andrade et al., 2001) and earnings announcements (e.g., Brown and Warner, 1985) on firm value. In the field of law and economics, event study has been used to examine the effect of a change in the regulatory environment (e.g., Schwert, 1981). In IS literature, event study has been applied to investigate the value of the CIO position (Chatterjee et al., 2001), IT investment (Dehning et al., 2003), ERP investment (Ranganathan and Brown, 2006), e-commerce initiatives (Dewan and Ren, 2007), open innovation alliances (Han et al., 2012), and Wikipedia company profiles (Xu and Zhang, 2013). Thus, event study is deemed suitable for our purpose of testing the business value of OUICs.

Beginning with Fama et al. (1969) in the late 1960s, event study has been widely used to examine the value of new information. Using stock return data, an event study measures the effect of a specific event on the value of a firm in the financial market. Mackinlay (1997) reviewed related studies and described a general guideline for event study. The initial task is to define the event of interest and identify the event window. Event window is often expanded to multiple days, including the day of the announcement and the days before and after the announcement because some investors might know about the event slightly earlier or later.

The appraisal of an event's effect on firm value requires a measure of the abnormal return. The abnormal return is the actual *ex post* return of the stock minus the normal return of the stock over the event window. The normal return is defined as the expected return without conditioning on the event that takes place. Given the selection of a normal stock return model, the period of return estimation needs to be defined. The most common choice, when feasible, is to use the period prior to the event window for the return estimation. With the parameter estimates for the normal stock return model, the abnormal return can be calculated. Next is the design of the testing for the abnormal return. Important considerations are defining the null hypothesis and determining the techniques for aggregating the individual firm's abnormal returns in event windows.

Generally speaking, the efficient market hypothesis suggests that stock prices in the financial market can "fully reflect" all available information in a timely manner (Fama, 1970). There are three major versions of the hypothesis: the weak form, the semi-strong form, and the strong form. We adopt the semi-strong form, which represents the widely accepted paradigm in prior literature (Jensen, 1978). In the semi-strong form, the information set includes all publicly available information at time t, and stock prices instantly change to reflect new information. Under a semi-strong form of efficient market hypothesis, investors in the financial market will react timely to any good or bad public information about the firms through buying and selling the stocks of the firms to protect their wealth in an averagely efficient way. As long as any public information appears

on social media or traditional media, investors will adjust their purchasing and selling behavior of the stocks leading to the change of firm value in the financial market that we can observe.

Dependent variable

The information on social media has started to play an important role in the financial market. For example, Chen et al. (2012) demonstrated that the views expressed in the peer advice articles in Seeking Alpha are associated with stock returns. Bollen et al. (2011) revealed that collective mood states derived from large-scale Twitter feeds are correlated with the value of the Dow Jones Industrial Average. Similarly, Xu and Zhang (2013) used Wikipedia as a case to show that the advent of social media has improved the contemporary information environment for investors in the financial market. In summary, the information about firms' actions on social media is public and has an impact on firm value in the financial market.

Therefore, the business value of OUICs could be evaluated by the abnormal returns over a relatively short time period around firms' actions in OUICs. Compared to accounting-based measures, our measure of firm value is more appropriate to capture the intangible and long-term value of IT (Bardhan et al., 2013; Bharadwaj et al., 1999; Dehning et al., 2003; Ranganathan and Brown, 2006). Because the magnitude of abnormal returns indicates the collective beliefs of investors about a specific event, we could examine the business value of OUIC-enabled ideation capability and OUIC-enabled implementation capability by testing the effects of idea posts and comments collected and innovation launches announced in IdeaStorm and MyStarbucksIdea on the abnormal returns of Dell's and Starbucks' stocks in event windows.

Thus, we capture the change of firm value by the Cumulative Abnormal Returns (CARs) in a short event window, which is calculated by the market model[2] based on a linear relationship between the returns on stock and the returns on the market over the period of return estimation (Brown and Warner, 1985). Following prior literature, we first estimate an OLS model, as Eq. (1) shows (MacKinlay, 1997):

$$R_t^{FIRM} = \beta_0 + \beta_1 R_t^{MKT} + \varepsilon_t \tag{1}$$

R_t^{FIRM} denotes the actual return of a firm's stock on day t, and R_t^{MKT} is the return of the market on day t as proxied by the equally weighted CRSP index. The residuals of above OLS model ε_t were the daily abnormal return of the stock on day t. We use a 5-day window[3] (e.g., Chatterjee et al., 2002; Xu and Zhang, 2013) to calculate CARs from 2 days before the event day to 2 days after the event day, as Eq. (2) shows.

$$CAR_t^{FIRM} = \sum_{t-2}^{t+2} \varepsilon_t \tag{2}$$

We collected daily stock return data for Dell and Starbucks from the CRSP database (NASDAQ ticker: DELL, SUBX). When we accessed the CRSP database in September 2011, the stock return data were available until 31 December 2010.

Independent variables

We use the events resulted from OUIC-enabled ideation capability and OUIC-enabled implementation capability as the independent variables. By definition, OUIC-enabled ideation capability results in idea posts and comments collected in a firm's OUIC, which can be measured by the daily numbers of collected posts and comments. OUIC-enabled implementation capability results in innovation launches announced in a firm's OUIC, which can be measured by the daily number of announced launches.[4] If OUIC-enabled ideation capability can increase firm value, we should observe greater CARs when there is a larger number of posts and comments collected in a firm's OUIC. If OUIC-enabled implementation capability can increase firm value, we should observe greater CARs when there is a larger number of launches announced in a firm's OUIC.

Because 31 December 2010 is the end of our stock return data, we pruned our data in specific time periods. For Dell, we used the daily numbers of posts, comments and launches from 16 February 2007 (the beginning of IdeaStorm) to 31 December 2010 (the end of stock return data). For Starbucks, we similarly use the daily numbers of posts, comments and launches from 18 March 2008 (the beginning of MyStarbucksIdea) to 31 December 2010 (the end of stock return data). Furthermore, because stock return data are not available for weekends and public holidays, we excluded the observations in non-trading days,[5] which resulted in a total number of 8730 posts, 55,030 comments, and 591 launches in 977 days in IdeaStorm and 52,966 posts, 97,948 comments, and 79 launches in 705 days in MyStarbucksIdea. We present the distribution of our sampled ideas and all ideas across different categories in Tables 1 and 2. As observed, our idea sample has a similar distribution to the distribution of idea population.

[2] Since another way of calculating abnormal returns by mean-adjusted model does not account for market trend, it is common to use the market model to calculate abnormal returns (Mitra and Singhal, 2008).

[3] We also tried a 3-day window in a robustness check, which generated consistent results (see Table 6).

[4] One may worry that innovation launches that result from OUIC-enabled implementation capability are also the outcomes of idea posts and comments that result from OUIC-enabled ideation capability. To address this concern, we created another ratio measure in a robustness check as the percentage of innovation launches over idea posts, which generated consistent results (see Table 6).

[5] A robustness check by counting the ideas, comments and launches announced in non-trading days to the observations in the first following trading days generated consistent results (see Table 6).

Table 1
Distribution of ideas in IdeaStorm.

	All ideas (2007/02/16–2011/09/02)		Sampled ideas (2007/02/16–2010/12/31)	
	n	%	*n*	%
Product ideas				
Accessories (keyboards, etc.)	2487	18.46	1630	18.67
Alienware	0	0.00	0	0.00
Broadband and mobility	326	2.42	215	2.46
Desktops and laptops	1682	12.49	900	10.31
Mobile devices	125	0.93	24	0.27
New product ideas	736	5.46	426	4.88
Operating systems	992	7.36	747	8.56
Printers and ink	133	0.99	90	1.03
Servers and storage	401	2.98	299	3.42
Software	902	6.70	624	7.15
Total	7784	57.78	4955	56.76
Dell ideas				
Advertising and marketing	639	4.74	409	4.68
Dell community	229	1.70	139	1.59
Dell web site	988	7.33	679	7.78
IdeaStorm	896	6.65	658	7.54
Retail	148	1.10	55	0.63
Service and support	1580	11.73	1084	12.42
Total	4480	33.25	3024	34.64
Topic ideas				
Building community	0	0.00	0	0.00
Education	190	1.41	114	1.31
Enterprise	76	0.56	48	0.55
Environment	332	2.46	241	2.76
Gaming	381	2.83	222	2.54
Healthcare and life sciences	42	0.31	15	0.17
Small business	163	1.21	105	1.20
Storm session topics	6	0.04	0	0.00
Women's interest	18	0.13	6	0.07
Total	1208	8.97	751	8.60
Overall	13,472	100	8730	100

Table 2
Distribution of ideas in MyStarbucksIdea.

	All ideas (2008/03/18–2011/09/02)		Sampled ideas (2008/03/18–2010/12/31)	
	n	%	*n*	%
Product ideas				
Coffee & espresso drinks	26,177	22.34	6134	11.58
Frappuccino® beverages	2135	1.82	538	1.02
Tea & other drinks	8069	6.89	4067	7.68
Food	12,268	10.47	5937	11.21
Merchandise & music	6188	5.28	3397	6.41
Starbucks card	8402	7.17	3799	7.17
New technology	1152	0.98	203	0.38
Other product ideas	8490	7.25	4419	8.34
Total	72,881	62.21	28,494	53.80
Experience ideas				
Ordering, payment, & pick-up	6575	5.61	3451	6.52
Atmosphere & locations	11,606	9.91	6306	11.91
Other experience ideas	9112	7.78	5458	10.30
Total	27,293	23.3	15,215	28.73
Involvement ideas				
Building community	3771	3.22	2230	4.21
Social responsibility	7451	6.36	3806	7.19
Other involvement ideas	4844	4.13	2893	5.46
Outside USA	913	0.78	328	0.62
Total	16,979	14.49	9257	17.48
Overall	117,153	100	52,966	100

Table 3
Description of variables.

Variable	Description	Source
Number of posts	The daily number count of ideas posted in IdeaStorm/MyStarbucksIdea	IdeaStorm, MyStarbucksIdea
Number of comments	The daily number count of comments posted in IdeaStorm/MyStarbucksIdea	IdeaStorm, MyStarbucksIdea
Number of launches	The daily number count of innovation launches announced in IdeaStorm/MyStarbucksIdea	IdeaStorm, MyStarbucksIdea
News dummy	One indicates that major U.S. newspapers released innovation launch news for Dell/Starbucks in a specific day; zero otherwise	LexisNexis database
Cumulative Abnormal Returns (CARs)	The sum of abnormal returns over an event window, where abnormal return is calculated by the residuals derived from regressing daily actual return on daily return on the market as proxied by equally weighted CRSP index	CRSP database

Table 4
Descriptive statistics and correlations.

	Obs.	Mean	SD	Min	Max	(1)	(2)	(3)
Dell								
(1) Number of posts	977	7.202	13.940	0	236			
(2) Number of comments	977	47.421	110.729	0	1222	0.635		
(3) Number of launches	977	0.590	0.770	0	4	−0.046	−0.041	
(4) CARs	975	−0.005	0.048	−0.223	0.255	0.036	0.065	0.017
Starbucks								
(1) Number of posts	705	75.129	132.510	0	2333			
(2) Number of comments	705	138.933	256.510	0	5931	0.621		
(3) Number of launches	705	0.112	0.316	0	1	0.081	0.023	
(4) CARs	703	−0.002	0.011	−0.055	0.042	0.042	−0.022	0.115

Controlling for traditional media

Event study methodology is essentially a quasi-experiment research design with an assumption that the repeated effect over a long period is not likely to be random or induced by omitted variables (Mackinlay, 1997; Binder, 1998). Thus, this methodology does not require a thorough set of controls. However, it is important to figure out whether the business value comes from social media channels or traditional media channels. While Dell and Starbucks do not periodically make announcements about innovation launches on traditional media, we use news coverage related to Dell's and Starbucks' innovations in all major U.S. newspapers to control the impact of information on traditional media (Xu and Zhang, 2013).

We searched Lexis-Nexis database for all articles published in major U.S. newspapers about Dell's and Starbucks' innovations and collected the publication date and the content of the news. It resulted in 225 pieces of news about Dell from 16 February 2007 to 31 December 2010 and 847 pieces of news about Starbucks from 18 March 2008 to 31 December 2010. We then used six keywords to identify the news about innovation. In prior research with news coding for innovation, Joshi et al. (2010) used three terms: "introduce", "unveil", and "launch". In addition to these terms, we also included "innovation", "innovative" and "innovate" to better identify innovation-related news. If at least one key word appears in the news content, we counted it as a piece of innovation-related news. Otherwise, we considered the news as irrelevant to innovation.

This procedure generated 92 pieces of news about Dell's innovations and 217 pieces of innovation-related news about Starbucks' innovations. To avoid repeating information in the news from traditional media, we used a dummy variable to capture the fixed effects of innovation-related news on traditional media, where 1 indicates that there was information about innovation on traditional media in a specific day and 0 otherwise.[6] Finally, we found 80 trading days for Dell with news about innovation on traditional media and 160 trading days for Starbucks with news about innovation on traditional media. Table 3 summarizes all variables used in this study and indicates their data sources. Descriptive statistics and correlations are presented in Table 4.

Results

Hypotheses testing

In our analysis, we control the effect of innovation-related news on traditional media (Xu and Zhang, 2013). We also dynamically control the lagged dependent variable to capture the effects of omitted variables that influence CARs and to

[6] We also measured the number of and analyzed the content of innovation-related news on traditional media by conducting several robustness checks, which generated consistent results (see Table 7).

Table 5
Hypotheses testing.

		Control model	Partial model	Partial model	Full model	Fixed effects model	Random effects model
Number of posts	H1: n.s.		0.000		0.000	0.000	0.000
			(0.000)		(0.000)	(0.000)	(0.000)
Number of comments	H1: n.s.		−0.000		−0.000	−0.000	−0.000
			(0.000)		(0.000)	(0.000)	(0.000)
Number of launches	H2: +			0.002*	0.002*	0.003**	0.002*
				(0.001)	(0.001)	(0.001)	(0.001)
News dummy		0.001	0.001	0.001	0.001	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lagged CAR		0.776***	0.776***	0.778***	0.778***	0.777***	0.778***
		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Intercept		−0.001	−0.001	−0.002*	−0.002*	−0.002*	−0.002*
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2		0.602	0.602	0.604	0.603	0.604	0.604
F/Wald Chi-sq.		1269.58***	634.09***	850.68***	509.94***	508.96***	2549.71***

Note: $n = 1676$. Dependent variable is CARs. Unstandardized coefficients are reported. Standard errors are in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

avoid auto-regressive issues (Achen, 2001; Hou and Moskowitz, 2005; Keele and Kelly, 2004). Eq. (3) shows our empirical model, where i indicates firm and t indicates day. Ordinary least squares (OLS) regression is used to estimate the model.

$$CAR_{it} = \alpha_0 + \alpha_1 POST\#_{it} + \alpha_2 COMMENT\#_{it} + \alpha_3 LAUNCH\#_{it} + \alpha_4 NEWS_{it} + \alpha_5 CAR_{it-1} + \varepsilon_{it} \quad (3)$$

To address potential endogeneity issues, we further use a fixed effects model shown in Eq. (4) to control for time-invariant, unobservable firm characteristics, indicated by u_i (e.g., Wang et al., in press). In the fixed effects model, the observed quantities in terms of explanatory variables are treated as if the quantities are non-random. We also estimate a random effects model using generalized least squares (GLS) regression to relax this assumption and examine our model specification.

$$CAR_{it} = \beta_0 + \beta_1 POST\#_{it} + \beta_2 COMMENT\#_{it} + \beta_3 LAUNCH\#_{it} + \beta_4 NEWS_{it} + \beta_5 CAR_{it-1} + u_i + \varepsilon_{it} \quad (4)$$

Table 5 reports our results for hypotheses testing. To test our hypotheses, our aim is to examine whether the regression coefficients are statistically significant (Aiken and West, 1991; Greene, 2003). We estimate the control model, partial model, and full model, respectively. In a partial model for testing H1, neither the number of posts nor the number of comments had a statistically significant effect on CARs. Thus, H1 was supported. In another partial model for testing H2, the number of launches had a statistically significant and positive effect on CARs ($p < 0.05$). Thus, H2 was supported. We found that the news control was non-significant, suggesting that the information on traditional media did not influence CARs in event windows. OLS results for the full model revealed similar results. The results of the fixed effects model and random effects model also confirmed our findings.

We plot the CARs for Dell and Starbucks, respectively, in Fig. 2. The solid line represents the CARs in the days with launches announced in OUICs, whereas the dashed line represents the CARs in the days without launches announced in OUICs. The figure shows that for both Dell and Starbucks, the CARs in launched days are above the CARs in non-launched days, which is consistent with our regression results. Next, we report several robustness tests.

Robustness checks

We conducted nine robustness checks. Table 6 reports some results for examining the sensitivity of our results. First, we used a split sample approach and re-estimated our model with the data from Dell and Starbucks, respectively. For both Dell and Starbucks samples, neither the number of posts nor the number of comments was significant. Again, the number of launches was positively related to CARs. Second, we estimated our model with data by excluding the daily observations with innovation-related news on traditional media, as an alternative way to rule out the confounding effect. We found that our results did not change materially.

Several alternative measures for our independent and dependent variables were also considered. In the third robustness check, we used cumulative numbers of posts and comments instead of daily numbers of posts and comments to capture the ideas collected by a firm from its OUIC.[7] Consistent results were observed. Fourth, instead of using the number of launches, we created a ratio measure as the number of launches divided by the cumulative number of posts. This ratio measure still had a positive effect on CARs. Fifth, we considered the ideas and launches in non-trading days and counted them into the observations in the first following trading days. Again, we found the results were consistent with our main results. Sixth, we took a more

[7] We thank one anonymous reviewer who suggested this alternative measure to us.

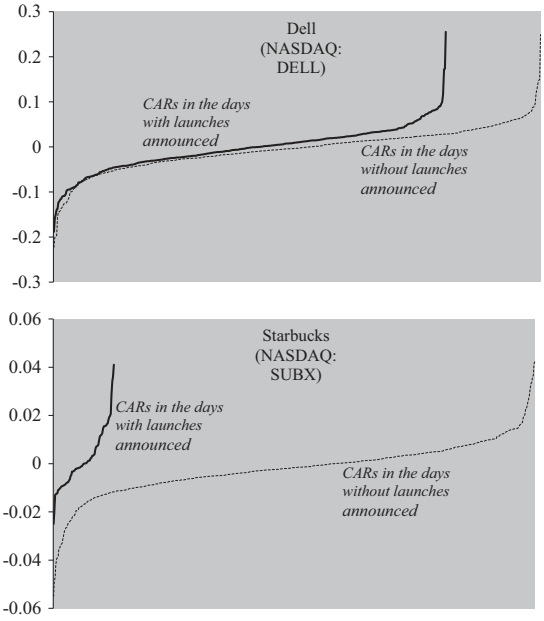

Fig. 2. Comparison of Cumulative Abnormal Returns (CARs).

Table 6
Split samples and alternative measures.

	Split samples			Alternative measures			
	Dell	Starbucks	No news days	Cumulative numbers	Ratio measure	Non-trading days	Shorter window
Number of posts	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of comments	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of launches	0.003*	0.002*	0.002*	0.003**	9.650*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(4.442)	(0.001)	(0.001)
News dummy	0.002	−0.000		0.001	0.001	0.001	0.001
	(0.004)	(0.001)		(0.002)	(0.002)	(0.002)	(0.002)
Lagged CAR	0.776***	0.790***	0.774***	0.776***	0.778***	0.778***	0.778***
	(0.020)	(0.023)	(0.017)	(0.015)	(0.015)	(0.015)	(0.015)
Intercept	−0.003*	−0.000	−0.002*	−0.000	−0.002*	−0.002*	−0.002*
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.601	0.633	0.597	0.604	0.603	0.603	0.603
F	293.88***	243.03***	532.08***	511.72***	509.35***	510.07***	509.93***
n	974	702	1438	1676	1676	1676	1676

Note: Dependent variable is CARs. Unstandardized coefficients are reported. Standard errors are in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

conservative approach in the event study and shortened the event window from a 5-day period to a 3-day period (e.g., Chatterjee et al., 2001; Dehning et al., 2003), which generated similar results.

Our news dummy control was non-significant in the main results, stimulating us to explore alternative ways of controlling the information on traditional media and examine whether it can lead to market reaction.[8] Table 7 reports the results with alternative news controls. In the seventh robustness check, we controlled the number of news instead of news dummy in the analysis. The results were consistent with our main results and revealed that the number of news was non-significant. Eighth, we constructed two news measures based on the content of the news, which potentially reflect the public mood toward innovation. Specifically, we took a machine learning approach and conducted sentiment analysis to identify the proportion of positive and negative words used in the news. After controlling for the content of the news, we still found similar results

[8] We thank the anonymous reviewers who provided us the comments on these alternative news controls.

Table 7
Alternative controls for traditional media.

	News without lag			News with lag		
	News number	News content	Full model	News number	News content	Full model
Number of posts	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of comments	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of launches	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of news	−0.000		−0.002	0.001		0.001
	(0.001)		(0.001)	(0.001)		(0.001)
Positive news ratio		0.070	0.132		0.024	−0.008
		(0.093)	(0.103)		(0.093)	(0.103)
Negative news ratio		0.019	0.124		0.005	−0.049
		(0.193)	(0.208)		(0.193)	(0.208)
Lagged CAR	0.778***	0.778***	0.776***	0.778***	0.777***	0.778***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Intercept	−0.002*	−0.002*	−0.002*	−0.002*	−0.002*	−0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.603	0.603	0.603	0.603	0.603	0.603
F	509.75***	424.98***	364.75	510.00***	424.56***	363.88***

Note: $n = 1676$. Dependent variable is CARs. Unstandardized coefficients are reported. Standard errors are in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

showing that these news measures are not significant. Finally, we took into account the lagged effect of news on traditional media, which might not be as timely as the information on social media. We replaced the news controls by one-day lagged values and found consistent results again. While the valuable information on social media is associated with significant abnormal returns, the information on traditional media is not likely to be a confounding factor associated with market reaction. Therefore, we conclude that our results are robust across different model specifications, subsamples, measures and controls.

Discussion and conclusion

Main findings and contributions

Open innovation is growing rapidly as the emergence of social media technologies. With the increasing popularity of crowdsourcing based on the strategic use of social media technologies (e.g., OUICs), the nature of firms' innovation capabilities is evolving. Online interactions between firms and their customers are more frequent. OUICs allow firms to develop dynamic capabilities and constantly innovate with customers, in order to adapt to the fast-changing market environment. In this study, we draw on the framework of dynamic capabilities and the view of innovation value chain to characterize firms' strategic use of OUICs and examine its business value. To the best of our knowledge, this study is among the first attempts to systematically theorize and empirically test the effects of strategic use of OUICs on firm value. *Overall, our findings challenge the common belief that OUICs are valuable by enabling firms to collect large amount of user-generated ideas. We found that simply collecting ideas from OUICs is not valuable whereas another often overlooked aspect related to how firms deal with the ideas from OUICs matters for value creation.* With these nuanced findings, our study provides three contributions to the IS literature.

First, this study contributes to IT capabilities literature (e.g., Aral and Weill, 2007; Bharadwaj, 2000; Chae et al., 2014; Mithas et al., 2011; Rai et al., 2012) by theorizing digitally enabled innovation capabilities based on firms' strategic use of social media technologies. Specifically, we conceptualize OUIC-enabled ideation capability and OUIC-enabled implementation capability by a multi-theoretical lens. OUIC-enabled ideation capability refers to a firm's ability to collect user-generated ideas such as posts and comments about potential innovation from its OUIC, and OUIC-enabled implementation capability refers to another firm's ability to select user-generated ideas from its OUIC for innovation development and then introduce the developed innovation to the desired users via its OUIC. These IT capabilities constructs are specific to firms' strategic use of social media technologies and enrich our understanding of IT capabilities in the open innovation context.

Second, we contribute to the literature on the business value of IT (e.g., Aral and Weill, 2007; Bardhan et al., 2013; Hitt and Brynjolfsson, 1996; Hitt et al., 2002; Mithas et al., 2012) by theorizing and testing the distinct effects of OUIC-enabled ideation capability and OUIC-enabled implementation capability on firm value. We shift the focus from aggregate IT investment to a specific social media technology (i.e., OUICs) and examine the value of IT not in terms of "how much" firms invest in IT but regarding "how" firms actually use specific technology for innovation tasks. This angle helps address the "missing link" of actual use in the value creation of IT (Devaraj and Kohli, 2003). To the best of our knowledge, this study is among the first attempts to examine the business value of social media technologies for crowdsourcing with large-scale, longitudinal

data from multiple firms. We found that OUIC-enabled ideation capability just provides the potential of business value, whereas OUIC-enabled implementation capability is critical for realizing the business value.

Finally, this study contributes a new understanding of strategic use of OUICs to IT and innovation literature (e.g., Dong, 2010; Dong and Yang, 2015; Joshi et al., 2010; Kleis et al., 2012; Pavlou and El Sawy, 2010; Tambe et al., 2012; Xue et al., 2012). We broaden this emerging research by understanding how firms could develop digitally enabled dynamic capabilities through strategically using social media technologies (e.g., OUICs). We propose that OUIC-enabled ideation capability is useful for idea generation and OUIC-enabled implementation capability is functional for idea conversion and diffusion. These constructs explain how firms use OUICs to support open innovation initiatives. Furthermore, our findings highlight the key role of OUIC-enabled implementation capability in the value creation in open innovation initiatives.

Managerial implications

This study allows for important managerial implications with respect to the business value of OUICs. For managers who aim to increase firm value via crowdsourcing, it is important to carefully design the procedures of implementing ideas via OUICs. Unlike common belief, in crowdsourcing, merely gathering ideas on new products, services and processes from OUICs is not sufficient to generate business value. Collection of a large number of user-generated ideas can only provide the potential of value creation. A mechanism to effectively select and implement collected ideas is the key of realizing the potential value. Thus, firms need to select and convert good ideas from OUICs into innovations and introduce developed innovations to desired users via OUICs to generate the business value.

For example, Dell and Starbucks not only are able to gather a large amount of idea posts and comments about innovation from users but are more importantly good at selecting the pertinent ideas and transforming them into new products, services and processes. A large number of users participate in voting, thereby providing an initial screening for idea partners. There are more than 10 idea partners in IdeaStorm, who are experts in specific fields from product development to pricing and sales. MyStarbucksIdea has more than 40 idea partners who are experts in the fields spanning from coffee to entertainment and community programs. Idea partners are capable in selecting good ideas and then presenting them to the managers of the company. By doing so, they provide an efficient filtering mechanism that facilitates managers to allocate their scarce attention to the ideas with high potential. Idea partners also present developed innovation to desired users by making announcements on innovation launches in the marketplace. The innovations developed and introduced in this process are valuable and rewarded by investors in the financial market. Therefore, firms that are willing to innovate via crowdsourcing can adopt similar design in their use of OUICs to support value creation.

Limitations and future research

Our study has some limitations. First, we adopted event study methodology and measured the observable events that resulted from OUIC-enabled ideation capability and OUIC-enabled implementation capability in the empirical test. Although these measures are objective and detailed, they may not fully capture all aspects of OUIC-enabled capabilities. Future research can complement our study by adopting survey methods and developing more fine-grained measures. Second, our longitudinal data are limited to two firms. This is because firms' use of OUICs is an emerging phenomenon, and the data are still accumulating as more firms start to use OUICs. While Dell and Starbucks are two representative early adopters of OUICs, future studies may be able to collect data from other firms to test our theory.

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