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User Innovation and Knowledge Sourcing: The Case of Financial Software

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User innovation and knowledge sourcing: The case of financial software

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ABSTRACT

According to user innovation literature, users can create important innovations and the novel functionalities embedded in those user innovations often become the sources of subsequent innovations by both other users and manufacturers. However, manufacturers are often hesitant in commercializing an innovation created by a single user due to the uncertainty around the market demands. We propose that such hesitancy will decrease when an increasing number of other users source knowledge elements from the focal user innovation and reproduce the novel functionality. Once the focal user innovation is commercialized by manufacturers, other users can purchase the novel functionality from the market rather than reproducing it in house. We propose that users capable of drawing on innovation resources are more likely to maintain in-house reproduction of the focal user innovation than users low on innovation resources. By using the Vector Autoregressive (VAR) model and Impulse Response Function (IRF) analysis method, we analyze knowledge sourcing activities from financial software patents data, and the findings provide empirical supports for our propositions.

1. Introduction

User innovation literature has challenged a taken-for-granted assumption in the traditional management theories that innovations come from manufacturers, not from users (e.g., de Jong & von Hippel, 2009; Franke & Shah, 2003; Lüthje, 2004; Morrison, Roberts, & von Hippel, 2000; von Hippel, 1986; von Hippel, 2005). According to this view, some users can produce important innovations in the technological domains of manufacturers' expertise. Furthermore, user innovations often become the important sources for the subsequent streams of innovations by manufacturers and other users who incorporate the key knowledge elements embedded in the focal user innovations into their own innovations (Franke, von Hippel, & Schreier, 2006; Herstatt & von Hippel, 1992).

This article asks what motivates manufacturers to source knowledge elements embedded in user innovations. Franke et al. (2006) suggest that manufacturers source knowledge elements embedded in user innovations when they find the novel functionalities embedded in those innovations commercially attractive. In turn, according to the lead user theory, commercially attractive innovations are mostly generated by lead users who can predict substantial benefits from innovations and experience the needs for innovations ahead of others (Lilien, Morrison, Searls, Sonnack, & von Hippel, 2002; Schreier & Prügl, 2008; Urban & von Hippel, 1988; von Hippel, 2005). These arguments imply that manufacturers will perceive the innovations generated by lead users as being commercially more attractive, thus sourcing knowledge elements more from the lead user innovations.

Few studies have examined why manufacturers, previously hesitant in becoming the first innovators in response to user needs, source knowledge elements from user innovations later. Evidence from user innovation literature suggests that manufacturers bypass the opportunities for innovation, not because they are unable to innovate or unaware of the opportunities to do so,

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but because they perceive a high level of uncertainty with respect to commercial success (Morrison et al., 2000; von Hippel, 2005: 45–61). However, the uncertainty remains high even when the manufacturers consider becoming the follower-innovators by sourcing knowledge elements from user innovations. The novel functionalities embedded in a user innovation may only satisfy the idiosyncratic needs of the individual user or the single user company that invented the focal innovation. Thus, it is quite uncertain whether the focal user innovation will be indeed demanded by a sufficient number of users such that incorporating it into the products would increase manufacturers' profitability enough to justify the costs and the risks associated with the product development process (Morrison et al., 2000). In this article, we propose that the increasing number of additional user innovations sourcing the knowledge elements from the focal user innovation will reduce such uncertainty around the commercial success perceived by manufacturers.

This article also explores how the degree to which manufacturers source knowledge from a user innovation affects the likelihood of other users sourcing knowledge from the same user innovation. Once manufacturers commercialize the novel functionalities embedded in a focal user innovation, other users in need of the same functionalities have two options: Users can purchase them from the manufacturers or create them in house by sourcing knowledge elements from the focal user innovation. In general, the second option may be costly but offer a higher adaptability with which these users can better customize the focal user innovation in accordance with their own user environments (Oliveira & von Hippel, 2009). We propose that the users more capable of drawing on innovation resources are more likely to continue to reproduce the focal user innovation in house through knowledge sourcing activities even when the associated functionalities are available to purchase in the market.

This article provides empirical analysis on software innovation by financial services firms. An increasing number of firms in the financial services industry employ software technologies developed in house in order to perform tasks such as complex assessments of investment risks as well as prompt executions of customer orders (Frame & White, 2009). In turn, the key knowledge elements embedded in these user innovations are often sourced by software manufacturers and peer user firms in the financial services industry. For instance, a software technology developed by Merrill Lynch & Co to jointly process multiple assets and debts associated with a single customer was incorporated into the software innovations developed by peer users such as Wells Fargo Bank and American Express and into those innovations by software manufacturers such as NCR corporation or CheckFree Corporation. We capture knowledge sourcing activities from citation information contained in the software patent data, and use the Vector Autoregressive (VAR) model and Impulse Response Function (IRF) analysis method to analyze the endogenous nature of knowledge sourcing activities between software manufacturers and financial services companies.

2. Theory and hypotheses

The idea that innovations often originate from users rather than manufacturers is well elaborated in the lead user theory (von Hippel, 1986). Lead users are defined as those who expect great benefit from finding the solutions to improve the product functionalities and experience the needs for the solutions ahead of other users. According to the theory, these lead users are likely to come up with innovations more frequently than non-lead users (Franke & Shah, 2003; Lüthje, 2004; Lüthje, Herstatt, & von Hippel, 2002; Morrison et al., 2000; Urban & von Hippel, 1988) and their solutions are often characterized as having a strong potential to be commercialized in the market (Franke & von Hippel, 2003; Lilien et al., 2002; Urban & von Hippel, 1988).

Empirical studies in user innovation literature provide evidence that manufacturers often source knowledge elements from user innovations in order to develop or modify their commercial products. For instance, Morrison et al. (2000) explored how Australian libraries modified Online Public Access systems (OPACs) in order to adapt the information search systems to their personal needs. In this study, many of the functional improvements made by the libraries were eventually incorporated into the commercial OPACs products developed by software manufacturers. Lüthje (2003) also found that 48% of surgical innovations developed by surgeons for personal use in German university clinics had been or would be introduced as commercial products.

User innovation literature suggests that manufacturers are more likely to source knowledge elements from a user innovation when it is developed by a lead user. Empirical studies suggest that innovations produced by lead users are commercially more attractive than those produced by non-lead users (von Hippel, 2005: 22–31). For instance, Urban and von Hippel (1988) showed that the products incorporating the solutions provided by lead users receive highly positive peer evaluations from many other users, signaling a strong potential of commercialization. Thus, manufacturers whose primary concern is profitability are likely to develop commercial products by sourcing knowledge elements from lead user innovations rather than by sourcing from non-lead users' innovations.

It is doubtful, however, whether the status of users (i.e., lead users vs. non-lead users) is a sufficient indicator of commercial values of user innovations from manufacturers' points of view. Manufacturers are often hesitant to take the initiatives to innovate in response to the newly identified user needs because they cannot find any convincing evidence that the majority of users would experience the same needs (Morrison et al., 2000). This hesitancy remains even when the manufacturers consider commercializing the solutions already developed by users. Unless they rid themselves of the uncertainty associated with the prospective market size, manufacturers will be hesitant to commercialize the solutions developed by a single lead user. Thus, manufacturers are often indifferent to innovations developed by users or are slow, at best, in incorporating user innovations into their products (Shah & Tripsas, 2007).

Manufacturers' hesitancy to commercialize user innovations is augmented by other factors as well. von Hippel (2005: 46–52) discussed three factors as to why users develop their own solutions rather than purchase them from manufacturers. These factors are also likely to have critical implications on manufacturers' decisions to source knowledge elements from user innovations. First, a manufacturer prefers to provide users with a solution that it can develop efficiently based on the resources and capabilities currently available within the firm, while users prefer a solution that works best to solve their problems regardless of what it takes to build the solutions. One implication from this argument is that a manufacturer may often find it difficult to incorporate some of the solutions developed by users into its products unless it considers a costly modification to the current portfolio of firm resources and capabilities.

Second, manufacturers' inclinations to maintain the functional reliability of products at the expense of limitations on the diversity of product functions may inhibit them from sourcing knowledge from user innovations. Users are likely to find more opportunities to experiment with or innovate upon a product when the nature of the product is complex in the sense that there are many subsystems in the product and that these subsystems are highly interdependent in determining the product performance (Franke & Shah, 2003). On the other hand, manufacturers are unlikely to source knowledge elements from user innovation when the product complexity is high. When a product has numerous subsystems that interact with each other, it would be difficult for a manufacturer to anticipate precisely how a new function developed by the third parties will interact with the product subsystems and how the untested solution may affect product reliability and the manufacturer's reputations.

Third, a functional failure in a product due to a user's modification can cost the user a delay in the user's current businesses or problem-solving activities. In this case, the user may resort to the old problem-solving methods while repairing the product or purchase another product from a manufacturer. However, when the functional failure results from a manufacturer's attempt made at product modification, the manufacturer may have to not only pay for the actual costs incurred by users but also face legal charges from a group of users (Barnes & Ulin, 1984). Thus, the potential for legal consequences will magnify the manufacturer's inclination to maintain the product reliability and reduce its incentives to source knowledge elements from user innovations.

Our discussion so far leads to the conclusion that manufacturers are unlikely to source knowledge elements from a user innovation without a strong assurance of commercial success at least (Riggs & von Hippel, 1994). The increasing frequency with which additional users create similar innovations by sourcing knowledge elements from the focal user innovation is likely to reduce manufacturers' hesitancy to employ the same knowledge elements in their products. Baldwin, Hienerth, and von Hippel (2006) suggest the usability of a user innovation among multiple users as a critical determinant of its commercialization. The increasing number of users that source knowledge elements from the focal user innovation will convince the manufacturers of its commercial attractiveness. In addition to signaling commercial values, peer adoptions of the focal user innovation may reduce the manufacturers' concerns on the product reliability. In other words, the peer adoptions provide the manufacturers with an opportunity to observe that the new functionalities embedded in the focal user innovation can be utilized by other users without creating any serious problem to the interdependent product subsystems. The wide application of the focal user innovation to a number of users in different situations gives assurance to the manufacturers that they can incorporate the focal user innovation into their own products without compromising product reliability.

Peer users' knowledge sourcing from a user innovation, as an indicator of commercial value and a tester of functional reliability, should motivate the manufacturers to source knowledge from the same innovation, even at the cost of overcoming the limitation of the manufacturers' current resources and capabilities.

Hypothesis 1. The more frequently users produce innovations by sourcing knowledge elements from a specific user innovation, the more likely manufacturers will source knowledge from that innovation as well.

Once the knowledge elements in a user innovation are sourced by manufacturers who subsequently incorporate them into the commercial products, users have two choices in order to experience the novel functionalities embedded in the user innovation. First, users can source the same knowledge elements and reproduce the focal user innovation in house. Second, they can purchase the commercialized version of the focal user innovation from manufacturers. Oliveira and von Hippel (2009) discussed both positive and negative aspects of the two choices. According to them, the former choice may be costly, but enables users to adapt the focal user innovation to their own special needs, while the latter choice offers lower-cost standardized products at the expense of adaptability (Baldwin et al., 2006; von Hippel & Oliveira, 2010).

Users often develop somewhat different skills or techniques in handling or employing a product to solve their problems (Lüthje et al., 2002; Morrison et al., 2000). From users' perspectives, adapting the novel functionalities embedded in a focal user innovation to their own unique skills will be less cumbersome and time-consuming than adapting their skills to those functionality (von Hippel, 2005: 45–62). For instance, different IT-user firms may have developed different types of IT infrastructure platforms and employed staffs with unique individual skills for IT operations (Nambisan, Agarwal, & Tanniru, 1999). In such cases, introduction of a new software component with a new functionality will be less cumbersome when the software component can be adapted without much disrupting of the user firms' existing IT infrastructures.

While adapting a product to each user's own circumstances may be desirable from the users' perspective, a manufacturer will be hesitant to do so unless it can charge a high premium on each adaptation. Manufacturers are reluctant to adapt the product for each user, because the costs associated with adapting its product to each user's unique skills while maintaining the product reliability will be considerably high (Barnes & Ulin, 1984). In addition, it would be difficult for manufacturers to learn distinctive knowledge and skills employed by users in handling the product since such knowledge and skills are often tacit and sticky to users' sites (Ogawa, 1998; von Hippel, 1985). Thus, if further adaptation of a focal user innovation is critical, users may find it less costly to reproduce the innovation in house by adapting it to their own needs rather than to resort to the manufacturers.

Users may purchase the novel functionalities embedded in a user innovation from manufacturers however, if they are less concerned with adaptation (von Hippel & Oliveira, 2010). Manufacturers can provide standardized products to users with less costs because the variable costs associated with selling an additional product unit are trivial in comparison with the capital costs associated with the initial product development process (Baldwin et al., 2006). For instance, users who want to employ innovative software functions developed by lead users may resort to the market rather than to in-house reproduction, as long as the software functions are easily available in the market and users do not need significant adaptations to the commercialized products.

When a user innovation is commercialized, some users who want to experience the associated functionalities are more likely to maintain in-house reproductions rather than resort to the market. In particular, users capable of drawing on resources for innovation may have established a sophisticated technological in-house expertise or infrastructure (Morrison, Roberts, & Midgley, 2004). If so, the adaptation of the focal user innovation to the established expertise and technological infrastructure becomes an important issue. In addition, based on the resources and expertise available for innovation, they may be able to adapt the focal user innovation to their unique user environments more efficiently than the manufacturers who often find it difficult to obtain sticky information on the unique user environments (Franke et al., 2006; Lüthje, 2004; Ogawa, 1998).

On the other hand, the users unable to easily draw on resources for innovation may find it better to resort to the markets. While adapting the focal user innovation to their own unique situations may be desirable, it should be quite challenging to them due to the associated costs unless they can create cost-effective solutions based on their unique expertise (Lakhani & von Hippel, 2003). Furthermore, users without innovation resources are not likely to be equipped with established technological infrastructure to use in their project, and thus, adaptation may not be as critical an issue to them as it is to the users with more innovation resources. Therefore, these users are more likely to resort to the market in order to experience the new functionalities embedded in the focal user innovation.

In summary, when a user innovation is commercialized, users may obtain the associated novel functionalities from the market instead of reproducing them in house. In particular, users low on innovation resources are more likely to depend on the market, since adapting the user innovation through in-house reproduction is not only costly but also less crucial to them. In terms of knowledge sourcing, when manufacturers innovate by sourcing knowledge elements from a user innovation, users low on resources may find it less critical to commit themselves to innovating activities to source the same knowledge elements. Therefore,

Hypothesis 2. When a user innovation is commercialized by manufacturers, users capable of drawing innovation resources are more likely to maintain knowledge sourcing from the focal user innovation than do users low on innovation resources.

3. Methodology

3.1. Sample

We perform a longitudinal analysis on a monthly basis to examine how knowledge elements embedded in software innovations by financial services firms are sourced by firms in both the software industry and the financial services industry. User innovations actively take place in the area of software developments. A high degree of heterogeneity in user needs for software products often creates situations in which users innovate to tailor software functions to precisely what they want (Franke & von Hippel, 2003). Likewise, many financial services firms often come up with new ideas on software designs that can assist their business activities better and subcontract actual programming to the software manufacturers or, in some cases, carry out software programming in house (Crosman, 2009).

We look into software patents issued for firms in the financial services industry in order to identify user innovations and trace other patents citing these user innovation patents to examine how financial services firms and software manufacturers source knowledge elements from these user innovations. We first identify the financial services firms for which the primary two-digit SIC codes fall between 60 and 64 in Compact Disclosure. Then we look for the software patents issued for these firms on the USPTO website. We use two criteria in order to search for software patents. First, we restrict the focal patent set to those with patent classes 705, 707 and 709 to which patents related to software technologies are most likely to belong (Allison & Tiller, 2003). Second, we single out the patents that include the words such as “software” or “computer program” in patent descriptions (Bessen & Hunt, 2007).

We add two additional remarks on our sample selections. First, our longitudinal analysis on a monthly basis requires a sufficiently long observation period during which the focal user innovation patents will receive citations from other patents. We observe that it took at least two years from the issue date for most software patents to receive the first citation from another patent issued. In order to secure at least a five-year observation period, we only include user innovation patents issued in March 2005 or earlier so that at least five years are guaranteed for each user innovation patent, establishing an observation period between the issue dates and March 2010. We use the patent issue month instead of the application month under the assumption that the key knowledge associated with a patent will be publicly available only after the focal patent is issued. Second, some software programs and associated patents that belong to financial services firms may have actually been developed by software manufacturers under subcontracts. We consider these instances as user innovations as well, since the business methods embedded in the software are developed by the financial services firms.

Based on the procedures explained above, we obtain eighty-two patents as focal user innovations. Among these patents however, four patents received only one citation during the observation periods. In addition, there were nine patents that received citations only from peer financial services firms and one patent that received citations only from software manufacturers. We eliminate these fourteen patents from our analysis since they do not allow us to observe the citation dynamics between financial services firms and software manufacturers. Therefore, the final sample consists of sixty eight patents considered focal user innovations, each of which received citations from both financial services firms and software manufacturers.

We trace patent citations to find out which firms source knowledge elements from the focal patents. Patent citations are frequently employed in research as a way to capture firm's knowledge-sourcing behavior since they show which previous innovations became the foundations for the subsequent innovations (Singh, 2005; Song, Almeida, & Wu, 2003). We obtain the list of ensuing patents that cite the focal user innovation patents and identify whether the firms holding the citing patents belong to the financial services industry or to the software industry. Using the firm names and addresses in the patent assignee information, we find each citing firm's primary businesses from Hoover's Online, Compact Disclosure and firms' Internet homepages. In assigning the industry categories to the firms that hold the citing patents, we closely follow the approaches by Oliveira and von Hippel (2009). In other words, we classify a firm into the software industry if the firm benefits from software sales rather than from utilizing the software to run its own businesses. For instance, we classify Bottomline Technologies, Inc. into the software industry, as it is specialized in providing other firms with software solutions primarily for financial transaction and financial data analysis. On the other hand, the primary business of Bora Payment Systems LLC is to receive and send payments for clients using Internet technology and financial software. Although its core competence lies in information technologies, we classify the firm into the financial services industry as it does not sell the information technologies per se.

3.2. Variables

Testing the two hypotheses in this article requires examination of the endogenous relationship between the frequencies of knowledge sourcing by peer user firms in the financial services industry and those by software manufacturers. We construct a number of variables for each user innovation patent and record monthly values for the variables from the issue month of the focal patent up to March 2010. In order to operationalize the frequencies of knowledge sourcing by software manufacturers, we record the number of citations that the focal patent received from software manufacturers' patents each month. We use the category of private vs. public firms to differentiate peer financial services firms in terms of the capabilities to draw on innovation resources. Thus, the frequencies of knowledge sourcing by peer user firms with strong (weak) capabilities to draw on innovation resources are operationalized as the monthly counts of citations received from public (private) financial services firms. The previous research supports the idea that private firms are less able to collect resources than public firms in general. Contrary to public firms, private firms often find it difficult to signal their values or business prospects (Becchetti & Trovato, 2002; McConnell & Pettit, 1984) and the investors with little information about the firms are unlikely to provide resources for them (Capron & Shen, 2007). We single out the public firms among the knowledge-sourcing financial services firms using Compact Disclosure that contain a complete list of public firms for each year. In addition, we remove self-citations from the citation counts. The financial services firms holding the sixty eight patents that we identify as the key user innovation patents often cite these patents in their subsequent patents. Rather than signaling commercial potentials, these self-citations may indicate that the focal user innovations can serve the user innovators' unique needs only.

We control for extraneous variables that may influence the endogenous relationships between the frequencies of knowledge sourcing activities by software manufacturers and those by peer financial services firms. Lead users are more likely to produce useful innovations according to lead user theory (Lilien et al., 2002; von Hippel, 1986). Thus, the knowledge elements embedded in a user innovation patent are more likely to be sourced by manufacturers or by peer user firms when the user innovator is characterized as a lead user. We control for changes in lead user status over time by the cumulative number of patents issued for the user-innovator firms.

We also control for the total number of citations made by the citing patents. As the citing patents have more citations, the probability that the user innovation patent will be included in the citation list also increases. For each month during which a focal user innovation patent gets cited by n citing patents, we identify the number of citations made by each citing patent and aggregate them over the n citing patents. In doing so, we construct two control variables based on the industry of the firm that produced a citing patent: the total number of citations made by peer financial services firms and the total number of citations made by software manufacturers. We also control for the number of citations received from firms that do not belong to the software or financial services industry. We include this control variable into our statistical model as an endogenous variable, since the number of citations received from these firms may affect and be affected by the number of citations received from software manufacturers or from financial services firms.

3.3. Vector Autoregressive (VAR) model and Impulse Response Function (IRF) analysis

The endogenous relationship between patent citations by software manufacturers and those by peer financial services firms is our central focus in this analysis (see Fig. 1).

Specifically, patent citations by software manufacturers can affect the subsequent frequency of citations by peer financial services firms (carry-over effect). At the same time, patent citations by peer financial services firms can affect the subsequent frequency of citations by software manufacturers (feedback effect). In addition, there may be strong autocorrelations in both variables in the

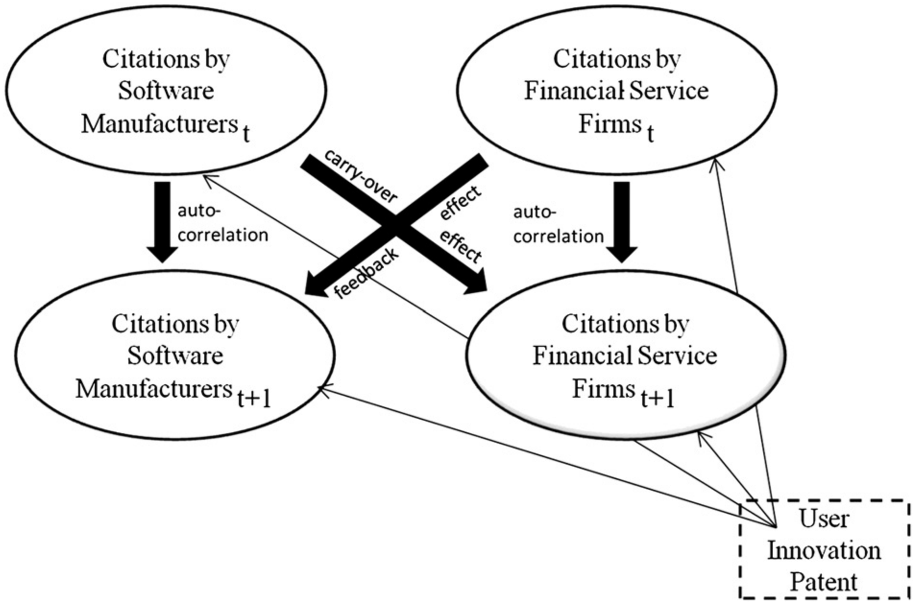

Fig. 1. The endogenous relationship among patent citations.

sense that the previous level of one variable can affect its own subsequent levels. These interdependent, dynamic relationships among the variables may result in "chain reactions" in the system (Dekimpe & Hanssens, 1995), and thus, ignoring such endogeneity among the focal variables may result in biased and inconsistent estimation results (Hayashi, 2000).

To address the endogeneity problem, we apply the Vector Autoregressive (VAR) modeling procedure. The VAR model is an n-equation, n-variable linear system of equations in which each variable is explained by its own lagged values, plus current and past values of the remaining $n-1$ variables. This simple framework provides a systematic way to capture rich dynamics in multiple time series.[3] In particular, we use Impulse Response Function (IRF) analysis within the VAR model, which allows us to fully examine the impact of one endogenous variable on the other endogenous variable in the system (Enders, 2004).

The basic procedure of VAR modeling is as follows. First, we investigate if the two focal endogenous variables, i.e., the number of citations by peer financial services firms and the number of citations by software manufacturers, are stationary or evolving. We also add a control variable, the number of citations by firms in the third industries as well, since we assume its endogeneity with the two focal variables. A priori, these variables are expected to follow I(0) process (i.e., stationary or no unit-root case). If all variables follow I(1) process (i.e., evolving or unit root process), then one should test for the presence of cointegration, which represents a long-term equilibrium among non-stationary variables (Enders, 2004). Depending on the results of unit-root and cointegration tests, VAR models are specified in the levels (no unit roots case), in the differences (unit roots without cointegration case), or in the error-correction format (cointegration case), respectively (Dekimpe & Hanssens, 2004).

We apply the Augmented Dickey–Fuller (ADF) test to see if the variables are stationary (Doldado, Jenkinson, & Sosvilla-Rivero, 1990) and then the KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 2000) for an incremental confirmation. The KPSS test differs from ADF test in that the null hypothesis of KPSS assumes that a series is stationary. We conclude that all variables follow the I(0) process. To determine the appropriate number of lags for each VAR model, we use the Schwarz Bayesian Information Criterion (SBC) and the Akaike Information Criterion (AIC). Once the number of lags is determined, we then estimate the model using the Ordinary Least Squares (OLS) method that provides asymptotically consistent estimates. In addition, OLS is an efficient estimation technique when each equation has identical right-hand-side variables (Enders, 2004).

Accordingly, we set up a stationary model for the focal variables: the number of patent citations by peer financial services firms (CF), the number of citations by software firms (CS) and the number of citations by firms in the third industries (CN).[4] The VAR model in the levels with P lagged periods[5] is constructed as follows:

$$\begin{bmatrix} \mathrm{CF}_t \\ \mathrm{CS}_t \\ \mathrm{CN}_t \end{bmatrix} = \Phi_0 + \sum_{p=1}^{p} \begin{bmatrix} \pi_{11}^p & \pi_{12}^p & \pi_{13}^p \\ \pi_{21}^p & \pi_{22}^p & \pi_{23}^p \\ \pi_{31}^p & \pi_{32}^p & \pi_{33}^p \end{bmatrix} \begin{bmatrix} \mathrm{CF}_{t-p} \\ \mathrm{CS}_{t-p} \\ \mathrm{CN}_{t-p} \end{bmatrix} + \begin{bmatrix} e_{CF} \\ e_{CS} \\ e_{CN} \end{bmatrix}$$

where $[e_{CF}\, e_{CS}\, e_{CN}]^{T} \sim$ white noise$(0, {}_{e})$.

[3] For more detailed discussion on VAR model, refer to Stock and Watson (2001).
[4] VAR model can be augmented using exogenous (control) variables. For ease of exposition, exogenous variables are ignored in the model.
[5] The length of lags, p, can be determined based on Akaike Information Criterion (AIC) or Schwartz' Bayes Information Criterion (SBC) (Enders, 2004).

The coefficient matrices above represent the relationship among the endogenous variables in the system. For instance, the coefficient matrix for the pth lag in this model is interpreted as follows: The three diagonal sub-matrices ($\pi^p_{11}, \pi^p_{22}, \pi^p_{33}$) represent the autocorrelations of citation frequencies within financial services firms, software manufacturers and the firms in the third industries, respectively. The submatrix (π^p_{12}) captures the effects of patent citations by software manufacturers on those by peer financial services firms, while the submatrix (π^p_{21}) represents vice versa.

Based on the estimation results from the equation system above, we perform Impulse Response Function (IRF) analysis, which enables us to trace the impact of a unit shock to any endogenous variable on the other endogenous variable over certain time periods (Enders, 2004). We define one unit shock by one standard deviation of the focal variable and obtain IRFs by computing two forecasts, one based on information set without a shock in the focal variable and another with a shock in the same variable; then the difference between the two forecasts represents the incremental effect of a shock over time (Dekimpe & Hanssens, 1995). We derive IRF estimates for thirty six periods (i.e., thirty six months or three years) using Generalized IRF (GIRF) method. We choose the GIRF method since it is insensitive to the ordering of the variables in the VAR model, contrary to the Choleski Decomposition method. We obtain standard errors by using the Monte Carlo method with one thousand repetitions.

For a pure forecasting purpose, all IRF values should be added together regardless of their significance levels. Econometricians, however, often use "|t-stat| > 1" criterion to identify statistically significant IRF values, and then, they add up only those values to compute the long-run effect size of a focal endogenous variable on the other endogenous variable, considering the multicollinearity problem inherent in VAR specification (e.g., Dekimpe & Hanssens, 1995, 2004; Pesaran, Pierse, & Lee, 1993). We apply a stricter criterion, i.e., |t-stat| > 1.96 for IRF analysis, taking into consideration the possibility of a large sampling error. For each firm, we estimate the VAR model first, and then perform IRF analysis in order to compute the effects among the endogenous variables.[6] Note that the endogenous relationships between the patent citations by software manufacturers and those by financial services firms are the focus of our analysis.

4. Results

Tables 1, 2 and 3 show the descriptive statistics and pairwise correlations among the variables for the three different datasets. Note that the number of user innovation patents employed in each dataset is different from each other. Table 1 shows the descriptive statistics and pairwise correlations based on the dataset that includes all the sixty eight user innovation patents. In Table 1, the number of citations by peer user firms includes the citations from both public and private financial services firms (i.e., total financial services firms). However, there are seven user innovation patents that didn't receive any citation from public financial services firms. Therefore, Table 2 is constructed based on the sixty one user innovation patents and the number of citations by peer users includes the citations by public financial services firms only. Likewise, Table 3 is based on the fifty user innovation patents exclusive of the eighteen user innovation patents that didn't receive any citation from private financial services firms. In addition, Fig. 2 shows the frequencies of citations aggregated over the sample user innovation patents during the observation periods.

Table 4 presents the statistical findings for Hypothesis 1. Our results show that on average, one unit positive shock in the number of patent citations by peer financial services firms increases software manufacturers' citations by 0.6512. This finding confirms our argument in Hypothesis 1 that the more frequently peer users source knowledge elements from a user innovation, the more likely manufacturers will source knowledge from the focal user innovation. In addition, Table 4 shows a strong autocorrelation within the patent citations by software manufacturers (the effect size = 14.0425) and within those by peer financial service firms (the effect size = 12.7862). While not presented in Table 4, the patent citations by user firms outside the financial services industry also had a positive effect on the number of citations by software manufacturers (the effect size = 0.41). The patent citations by software manufacturers have a positive effect on the subsequent citations by peer users that include both private and public financial services firms (the effect size = 0.5319).

As for the control variables, the total number of patents for the user-innovator firm has a positive effect on the patent citations by both peer financial service firms (p-value < 0.001) and software manufacturers (p-value < 0.01). These results are consistent with the expectation that innovation from the user-innovator with higher technological capabilities would receive more attentions from other innovators. In addition, the number of citations included in the citing patents is positively associated with the likelihood that a focal user innovation will be cited. The subsequent analyses for Hypotheses 2 also show similar patterns in terms of effects of control variables.

As mentioned before, Table 4 shows that the patent citations by software manufacturers have a positive effect on the number of citations by peer users when peer users include both public and private financial services firms. However, Tables 5 and 6 show a clear contrast between public and private financial services firms in their citation patterns. We divide the peer financial services firms into two groups, private firms and public firms, and separately analyze the effect of software manufacturers' citations on them in the two tables.

The second row in Table 5 shows how public firms in the financial services industry respond to the citations made by software manufacturers. Similar to the outcome in Table 4, citations by software manufacturers increase the number of citations by public financial services firms. More specifically, one unit positive shock in the number of citations that software manufacturers made on the focal user innovation patents increases the number of citations from public financial services firms by 1.5411. This positive

[6] For more details regarding IRF analysis procedure, see Dekimpe and Hanssens (2004) and Enders (2004).

Table 1
Summary of descriptive statistics and correlations (total financial services firms).

Variable	Mean	Std. dev.	Pair-wise correlations						
			1	2	3	4	5	6	7
1. The number of citations by software manufacturers	0.09	0.35	1						
2. The number of citations by total financial services firms	0.18	0.57	0.08***	1					
3. The total number of patents issued for the user-innovator firm	31.34	46.54	0.04***	−0.02†	1				
4. The total number of citations in the citing patents issued for software manufacturers	7.03	43.22	0.69***	0.14***	−0.00	1			
5. The total number of citations in the citing patents issued for total financial services firms	34.57	193.1	0.03***	0.76***	−0.01	0.09***	1		
6. The number of citations by the third industries	0.12	0.42	0.09***	0.10***	0.04***	0.07***	0.05***	1	
7. The total number of citations in the citing patents issued for the third industries	12.74	105.9	0.07***	0.10***	0.07***	0.05***	0.06***	0.39***	1

Notes:
- The number of user innovation patents employed = 68; total number of observation = 8047).
- † p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

effect on public financial services firms shows a clear contrast with the effect on private financial services firms. Table 6 shows a negative effect of citations by software manufacturers on the number of citations by private financial services firms (the effect size = −0.2877). The contrast between Tables 5 and 6 confirms Hypothesis 2. In other words, when a user innovation is incorporated into commercialized products, user firms low on innovation resources are more likely to reduce knowledge sourcing activities than those better capable of drawing on internal innovation resources.

5. Discussion and conclusion

The current article examines what motivates manufacturers to commercialize user innovations and how peer users react when the focal user innovations are commercialized. We identify user innovations from financial software patents and investigate the endogenous relationship between software manufacturers' knowledge sourcing activities and those of financial services firms. The statistical findings from the VAR analysis show that the frequencies of financial services firms' knowledge sourcing from user innovations are positively related to those of software manufacturers in the subsequent periods (Hypothesis 1) We also find that after the manufacturers commercialize the user innovations, private user firms tend to reduce innovations that source knowledge elements from the user innovations while public user firms maintain innovating activities to source the same knowledge elements. (Hypothesis 2).

Most theories on firm innovation consider manufacturers as the primary origins of innovative ideas that provide novel solutions for buyers. For instance, the knowledge-based view suggests that acquisition of knowledge is crucial for firm performance and survival (Kogut & Zander, 1992; Singh, 2005). However, this view has advanced its theories mostly based on the assumption that the body of valuable knowledge mostly lies with manufactures, not with users. Thus, knowledge diffusions detected by the empirical studies under this view have been implicitly assumed to occur through the network ties devoid of users: interpersonal ties among the manufacturers' employees (e.g., Almeida & Kogut, 1999; Rosenkopf & Tushman, 1998), interorganizational ties such as alliances among the manufacturers with distinct technological capabilities (Rosenkopf & Nerkar, 2001) or within-firm interdivisional ties (e.g., Gupta & Govindarajan, 2000).

Table 2
Summary of descriptive statistics and correlations (public financial services firms).

Variable	Mean	Std. dev.	Pair-wise correlations						
			1	2	3	4	5	6	7
1. The number of citations by software manufacturers	0.08	0.32	1						
2. The number of citations by public financial services firms	0.14	0.49	0.09***	1					
3. The total number of patents issued for the user-innovator firm	29.17	48.72	−0.02†	0.06***	1				
4. The total number of citations in the citing patents issued for software manufacturers	6.63	44.91	0.68***	0.14***	−0.01	1			
5. The total number of citations in the citing patents issued for public financial services firms	32.37	162.6	0.06***	0.81***	0.07***	0.11***	1		
6. The number of citations by the third industries	0.11	0.42	0.10***	0.09***	−0.02†	0.07***	0.07***	1	
7. The total number of citations in the citing patents issued for the third industries	12.62	107.2	0.04***	0.09***	0.05***	0.04***	0.07***	0.39***	1

Notes:
- The number of user innovation patents employed = 61; total number of observation = 7380).
- † p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 3
Summary of descriptive statistics and correlations (private financial services firms).

Variable	Mean	Std. dev.	Pair-wise correlations						
			1	2	3	4	5	6	7
1. The number of citations by software manufacturers	0.1	0.38	1						
2. The number of citations by private financial services firms	0.06	0.30	0.05***	1					
3. The total number of patents issued for the user-innovator firm	20.79	34.91	−0.02	0.03*	1				
4. The total number of citations in the citing patents issued for software manufacturers	9.13	52.76	0.69***	0.05***	0.00	1			
5. The total number of citations in the citing patents issued for private financial services firms	8.72	105.8	0.01	0.55***	0.05***	0.01	1		
6. The number of citations by the third industries	0.14	0.41	0.11***	0.06***	−0.02	0.08***	0	1	
7. The total number of citations in the citing patents issued for the third industries	16.20	121.1	0.04**	0.06***	0.06***	0.05***	0.02	0.47***	1

Notes:
- The number of user innovation patents employed = 50; total number of observation = 6040).
- † p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Based on the user innovation literature, the current study contributed to the knowledge-based view by demonstrating that some users generate innovations from which manufacturers can extend their knowledge sets. In addition, the current study identified a condition under which manufacturers are more likely to source knowledge elements from users. The bounded rationality of software manufacturers (Bogers, Afuah, & Bastian, 2010) makes it difficult for them to detect the commercial values of emerging user innovations, even when they were invented by the leading financial services firms holding many patents in the area of software technologies. The evidence in this study suggests that manufacturers perceive the commercial values of user innovations through peer users' knowledge sourcing behaviors. Manufacturers have not only been aware of knowledge-transfer networks among users but also been active in collecting valuable knowledge from them.

The current study illuminates users' decision making on the two alternatives, reproduce vs. buy, when valuable user innovations are incorporated into commercialized products. A plausible assumption would be that once user innovations are commercialized by manufacturers, the number of users who reproduce the focal user innovations by themselves would decrease, as the manufacturers can do so more efficiently. In line with the assumption, we find that the frequencies with which private financial services firms source knowledge from user innovations decrease once these innovations are incorporated into the manufacturers' innovations. The sample financial software patents identified as user innovations in the current study must have provided valuable tools to the financial services firms, which could be inferred from the amount of citations they received from the patents issued in the subsequent periods. If so, a reasonable explanation for the reduction in knowledge sourcing

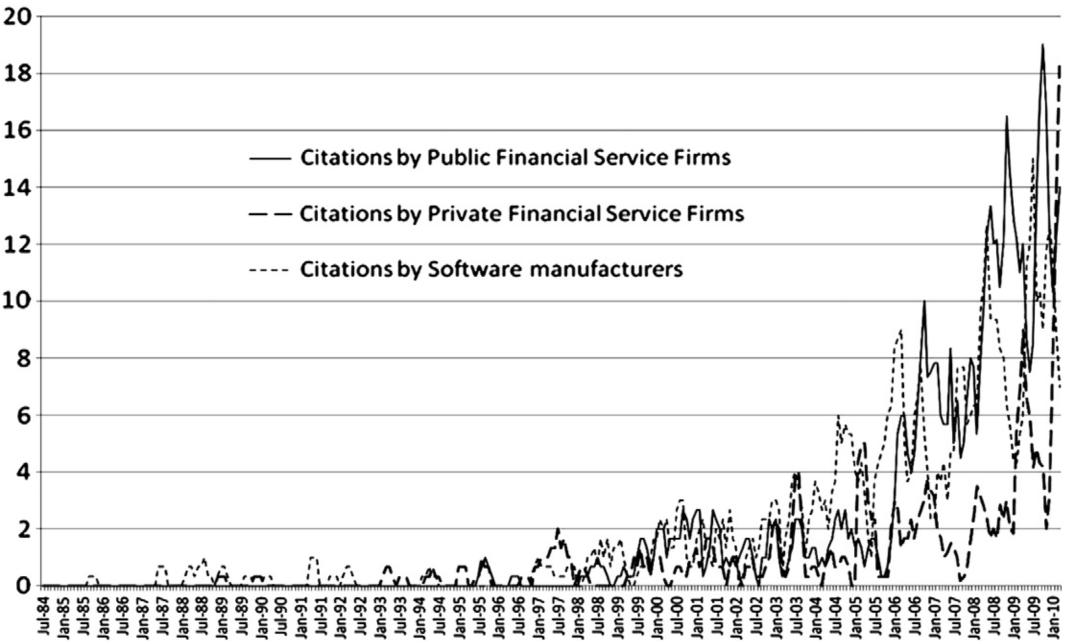

Fig. 2. The frequencies of citations aggregated over 68 user innovation patents during the observation period.

Table 4
The Vector Autoregressive (VAR) modeling and Impulse Response Function (IRF) analysis of patent citations between software manufacturers and peer financial services firms.

	Effects on the patent citations by peer financial services firms	Effects on the patent citations by software manufactures
Endogenous variables[1]		
1. Patent citations by peer financial services firms	12.7862 (autocorrelation)	0.6512 (feedback effect)
2. Patent citations by software manufacturers	0.5319 (carry-over effect)	14.0425 (autocorrelation)
Control variables[2]		
3. The total number of patents issued for the user-innovator firm	0.1099*** (0.0291)	0.0363** (0.0117)
4. The total number of citations in the citing patents issued for software manufacturers	−0.0012 (0.0008)	0.0091*** (0.0007)
5. The total number of citations in the citing patents issued for total financial services firms	0.0014*** (0.0001)	0.0000 (0.0001)
6. The total number of citations in the citing patents issued for the third industries.	0.0001 (0.0001)	0.0000 (0.0001)

1.

a. The significance criterion used for IRF analysis of endogenous variables is $|t| > 1.96$.
b. The number of user innovation patents employed = 68.
c. The total number of observation = 8047.

2.

a. The estimated coefficients and the standard errors of the control variables in this table represent the median t-values from 68 VAR analyses.
b. The numbers in parentheses are standard errors.
c. The degree of freedom for t-distribution in each equation of the VAR analysis is calculated as follows: d.f. = the total number of quarters used in VAR estimation.
 - the number of endogenous variables in each equation × the number of lags.
 - the number of control variables—1.
d. * p-value < 0.05; ** p-value < 0.01; *** p-value < 0.001.

frequencies among the private firms is that these users resort to the software manufacturers instead of reproducing the user innovations in house.

The empirical analysis in the current study revealed, however, that not every user resorts to the manufacturers. The current study provides evidence that public financial services firms reproduce the user innovations even when those innovations are incorporated into the products available in the market. Ongoing reproduction of user innovations by these users indicates that some users have strong technological capabilities to apply in innovating activities. In addition, the finding implies that some users may

Table 5
The Vector Autoregressive (VAR) modeling and Impulse Response Function (IRF) analysis of patent citations between software manufacturers and public financial services firms.

	Effects on the patent citations by public financial services firms	Effects on the patent citations by software manufactures
Endogenous variables[1]		
1. Patent citations by public financial services firms	14.3415 (autocorrelation)	0.9465 (feedback effect)
2. Patent citations by software manufacturers	1.5411 (carry-over effect)	16.7317 (autocorrelation)
Control variables[2]		
3. The total number of patents issued for the user-innovator firm	0.1378*** (0.0312)	0.0317* (0.0154)
4. The total number of citations in the citing patents issued for software manufacturers	−0.0017 (0.0011)	0.0095*** (0.0005)
5. The total number of citations in the citing patents issued for public financial services firms	0.0021*** (0.0006)	0.0000 (0.0001)
6. The total number of citations in the citing patents issued for the third industries.	0.0000 (0.0001)	0.0000 (0.0001)

1.

a. The significance criterion used for IRF analysis of endogenous variables is $|t| > 1.96$.
b. The number of user innovation patents employed = 61.
c. The total number of observation = 7380.

2.

a. The estimated coefficients and the standard errors of the control variables in this table represent the median t-values from 61 VAR analyses.
b. The numbers in parentheses are standard errors.
c. The degree of freedom for t-distribution in each equation of the VAR analysis is calculated as follows: d.f. = the total number of quarters used in VAR estimation.
 - the number of endogenous variables in each equation × the number of lags.
 - the number of control variables—1.
d. * p-value < 0.05; ** p-value < 0.01; *** p-value < 0.001.

Table 6
The Vector Autoregressive (VAR) modeling and Impulse Response Function (IRF) analysis of patent citations between software manufacturers and private financial services firms.

	Effects on the patent citations by private financial services firms	Effects on the patent citations by software manufactures
Endogenous variables[1]		
1. Patent citations by private financial services firms	12.6573 (autocorrelation)	0.2411 (feedback effect)
2. Patent citations by software manufacturers	−0.2877 (carry-over effect)	15.2948 (autocorrelation)
Control variables [2]		
3. The total number of patents issued for the user-innovator firm	0.8965*** (0.0274)	0.0382*** (0.0110)
4. The total number of citations in the citing patents issued for software manufacturers	−0.0002 (0.0003)	0.0093*** (0.0004)
5. The total number of citations in the citing patents issued for private financial services firms	0.0035*** (0.0009)	0.0000 (0.0001)
6. The total number of citations in the citing patents issued for the third industries.	0.0000 (0.0001)	0.0000 (0.0001)

1.

a. The significance criterion used for IRF analysis of endogenous variables is $|t| > 1.96$.

b. The number of user innovation patents employed = 50.

c. The total number of observation = 6040.

2.

a. The estimated coefficients and the standard errors of the control variables in this table represent the median t-values from 50 VAR analyses.

b. The numbers in parentheses are standard errors.

c. The degree of freedom for t-distribution in each equation of the VAR analysis is calculated as follows: d.f. = the total number of quarters used in VAR estimation.
- the number of endogenous variables in each equation × the number of lags.
- the number of control variables—1.

d. * p-value < 0.05; ** p-value < 0.01; *** p-value < 0.001.

be locked into the established ways of problem solving which include tacit knowledge around product usages difficult for them to explain to the manufacturers. In addition, the asset specificity embedded in users' capabilities or resources may increase the uncertainty on “buy” decisions and leaves no better alternatives than to adapt and reproduce user innovations in house. Thus, heterogeneity lies not only in the problems that users desire to solve but also in the tools that users want to utilize in solving the identical problems (von Hippel, 2005). In addition, the current discussion delivers a message to the manufacturers that there are two different markets that prefer different types of products. Some users lacking resources and capabilities to innovate want the end-products that solve their problems without having to apply further modification. Others perceive a higher value in the toolkits or platform products (von Hippel & Katz, 2002) that allow them to develop or modify the end-products.

This study is subject to some limitations. First, patent data we used for this study has an inherent limitation in tracing knowledge flow. While patent data is one of the primary sources that allow us to capture knowledge flow among firms, it limits our attention only to the codified knowledge flows (Rosenkopf & Nerkar, 2001: 303). In addition, some citations are added by patent examiners in USPTO or strategically put in place by firms to avoid litigation (Graham & Mowrey, 2004). We also note that “buy” decisions made by private firms after commercialization of user innovations were inferred from the decreasing frequencies of citations in patent data rather than the direct investigations on firms' purchasing records. Future researchers may consider alternative data collection methods such as survey and focus group interview to gain deeper insights from executives' perspective.

Second, we collected monthly data of financial service-related patents for at least 5 years per patent, resulting in over 6000 observations in total. However, our data size with respect to the number of patents is relatively small (N = 68). This is because we focus on the knowledge flow between financial service industry and software industry. Specifically, due to the “economy of scale” effect, we observe that the financial service industry is dominated by a small number of global players. Accordingly, there are only limited number of lead users who have incentives as well as resources to develop and manage their own patents in financial service industry. Moreover, in order to perform time series analysis such as VAR modeling and IRF analysis, only patents with sufficient time to be cited (i.e., 5 years) were analyzed, which further reduces the number of patents in our dataset. Even though our dataset covers patents filed by major global financial service firms such as Goldman Sachs, Merrill Lynch, Citibank, and Chase Manhattan, we acknowledge that the small number of patents in our dataset can limit the generalizability of our findings.

Third, the conclusion drawn in this study may be limited in its generalization as the direct or indirect involvements by user firms in software innovations may not be observable to the same degree in other settings. While software innovation is a key example in which user involvements are generally high (Franke & von Hippel, 2003), software technologies are becoming one of the key factors that contribute to firms' competitive advantage particularly in the financial services industry (Mearian, 2005; Ritchlin, 2010). Thus, it is not surprising to observe many financial services firms with technological capabilities equivalent to those of software manufacturers (Crosman, 2009; Frame & White, 2009). Thus, investigating individual users or user firms other than the financial services firms may reveal different knowledge sourcing patterns in relation to the software manufacturers. For example, global retailers such as Walmart and Zara spend considerable resources on IT-related investment to improve its distribution channel efficiency, while many B2C firms invest in CRM (Customer Relation Management) system. Investigating knowledge sourcing patterns in such industries would be an interesting topic for future researchers.

Finally, the current research was also silent on the different types of financial services firms. Wide-ranging services in the financial services industry are provided by different types of firms such as banks, savings and loan associations, insurance companies, stock brokerage firms and financial analysts under different federal and state regulations (Gramm & Gray, 1994; White, 1996). For instance, Merrill Lynch developed their Cash Management Account service and its related software technologies as a reaction to the Glass-Steagall Act that prevented securities firms from offering commercial bank services. Such innovations may be applicable to securities firms more than to other types of financial services firms. Likewise, future researchers may want to examine different types of user innovations since they may have different scopes of diffusions according to users' current businesses and legal constraints. In addition, it would be intriguing to study the erosions of boundaries among different types of financial services firms, which may have enabled the particular software technologies to diffuse more quickly than others. We leave these issues to future researchers.

References

Allison, J. R., & Tiller, E. H. (2003). Internet business method patents. In W. M. Cohen, & S. A. Merrill (Eds.), *Patents in the knowledge-based economy* (pp. 259–284). Washington, DC: National Academies Press.

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, *45*(7), 905–917.

Baldwin, C., Hienerth, C., & von Hippel, E. (2006). How user innovations become commercial products: A theoretical investigation and case study. *Research Policy*, *35*, 1291–1313.

Barnes, B., & Ulin, D. (1984). Liability for new products. *AWWA Journal*, 44–47 (February).

Becchetti, L., & Trovato, G. (2002). The determinants of growth for small and medium sized firms: The role of the availability of external finance. *Small Business Economics*, *19*, 291–306.

Bessen, J., & Hunt, R. M. (2007). An empirical look at software patents. *Journal of Economics and Management Strategy*, *16*(1), 157–189.

Bogers, M., Afuah, A., & Bastian, B. (2010). Users as innovators: A review, critique and future research directions. *Journal of Management*, *36*(4), 857–875.

Capron, L., & Shen, J. C. (2007). Acquisitions of private vs. public firms: Private information, target selection and acquirer returns. *Strategic Management Journal*, *28*, 891–911.

Crosman, P. (2009). Goldman Sachs sets gold standard for IT innovation. *Wall Street & Technology*, 27 Oct.

de Jong, J. P. J., & von Hippel, E. (2009). Transfer of user process innovations to process equipment producers: A study of Dutch high-tech firms. *Research Policy*, *38*(7), 1181–1191.

Dekimpe, M. G., & Hanssens, D. M. (1995). The persistence of marketing effects on sales. *Marketing Science*, *14*, 1–21.

Dekimpe, M. G., & Hanssens, D. M. (2004). Persistence modeling for assessing marketing strategy performance. In D. Lehmann, & C. Moorman (Eds.), *Cool tools in marketing strategy research*. : Marketing Science Institute.

Doldado, J., Jenkinson, T., & Sosvilla-Rivero, S. (1990). Cointegration and unit roots. *Journal of Economic Survey*, *4*, 249–273.

Enders, W. (2004). *Applied econometric time series* (2nd ed.). New York: John Wiley & Sons.

Frame, W. S., & White, L. J. (2009). Technological change, financial innovation, and diffusion in banking. *Federal Reserve Bank of Atlanta Working Paper Series 2009–10*.

Franke, N., von Hippel, E., & Schreier, M. (2006). Finding commercially attractive user innovations: A test of leader user theory. *Journal of Product Innovation Management*, *23*, 301–315.

Franke, N., & Shah, S. (2003). How communities support innovative activities: An exploration of assistance and sharing among end-users. *Research Policy*, *32*(1), 157–178.

Franke, N., & von Hippel, E. (2003). Satisfying heterogeneous user needs via innovation toolkits: The case of Apache Security Software. *Research Policy*, *32*(7), 1199–1215.

Graham, S. H., & Mowrey, D. C. (2004). Submarines in software? Continuations in US software patenting in the 1980s and 1990s. *Economics of Innovation & New Technology*, *13*(5), 443–456.

Gramm, W. L., & Gray, G. D. (1994). Scams, scoundrels, and scapegoats: A taxonomy of CEA regulation over derivative instruments. *Journal of Derivatives*, *1*, 6–24.

Gupta, A. K., & Govindarajan, V. (2000). Knowledge flows within multinational corporations. *Strategic Management Journal*, *21*(4), 473–496.

Hayashi, F. (2000). *Econometrics.* Princeton, NJ: Princeton University Press.

Herstatt, C., & von Hippel, E. (1992). From experience: Developing new product concepts via the lead user method. *Journal of Product Innovation Management*, *9*(3), 213–222.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, *3*(3), 383–397.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. C. (2000). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, *54*, 159–178.

Lakhani, K. R., & von Hippel, E. (2003). How open source software works: "Free" user-to-user assistance. *Research Policy*, *32*, 923–943.

Lilien, G. L., Morrison, P. D., Searls, K., Sonnack, M., & von Hippel, E. (2002). Performance assessment of the lead user idea-generation process for new product development. *Management Science*, *48*(8), 1042–1059.

Lüthje, C. (2003). Customers as co-inventors: An empirical analysis of the antecedents of customer-driven innovations in the field of medical equipment. *Proceedings of the 32th EMAC Conference, Glasgow*.

Lüthje, C. (2004). Characteristics of innovating users in a consumer goods field: An empirical study of sport-related product consumers. *Technovation*, *24*(9), 683–695.

Lüthje, C., Herstatt, C., & von Hippel, E. (2002). User-innovators and local information: The case of mountain biking. *Research Policy*, *34*(6), 951–965.

McConnell, J. J., Pettit, R. R., Horvitz, & Pettit (1984). Application of the modern theory of finance to small business firms. *Problems in Financing of Small Business, Vol. 42, Part A*, Greenwich CT: JAI Press.

Mearian, L. (2005). Financial services wary of outsourcing key projects. *Computerworld*, *39*(36), 4–47.

Morrison, P. D., Roberts, J. H., & von Hippel, E. (2000). Determinants of user innovation and innovation sharing in a local market. *Management Science*, *46*(12), 1513–1527.

Morrison, P. D., Roberts, J. H., & Midgley, D. F. (2004). The nature of lead users and measurement of leading edge status. *Research Policy*, *33*, 351–362.

Nambisan, S., Agarwal, R., & Tanniru, M. (1999). Organizational mechanism for enhancing user innovation in information technology. *MIS Quarterly*, *23*(3), 365–395.

Ogawa, S. (1998). Does sticky information affect the locus of innovation? Evidence from the Japanese convenience store industry. *Research Policy*, *26*, 777–790.

Oliveira, P., & von Hippel, E. (2009). Users as service innovators: The case of banking services. *MIT Sloan School Working Paper # 4748-09*.

Pesaran, M. H., Pierse, R. G., & Lee, K. C. (1993). Persistence, cointegration and aggregation: A disaggregated analysis of output fluctuation in the US economy. *Journal of Econometrics*, *56*, 57–58.

Ritchlin, L. (2010). Advisers report benefits from financial planning software. *Journal of Financial Planning*, *23*(12), 10–12.

Riggs, W., & von Hippel, E. (1994). The impact of scientific and commercial values on the sources of scientific instrument innovation. *Research Policy*, *23*, 459–469.

Rosenkopf, L., & Tushman, M. (1998). The coevolution of community networks and technology: Lessons from the flight simulator industry. *Industrial and Corporate Change*, *7*(2), 311–346.

Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: Boundary spanning, exploration, and impact in the optical disc industry. *Strategic Management Journal*, *22*(3), 287–306.

Schreier, M., & Prügl, R. (2008). Extending lead-user theory: Antecedents and consequences of consumers' lead userness. *Journal of Product Innovation Management*, *25*, 331–346.

Shah, S. K., & Tripsas, M. (2007). The accidental entrepreneur: The emergent and collective process of user entrepreneurship. *Strategic Entrepreneurship Journal*, *1*, 123–140.

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, *51*, 756–770.

Song, J. Y., Almeida, P., & Wu, G. (2003). Learning-by-doing: When is mobility more likely to facilitate inter-firm knowledge transfer? *Management Science*, *49*(4), 351–365.

Stock, J., & Watson, M. (2001). Vector autoregressions. *Journal of Economic Perspectives*, *15*(4), 101–116.

Urban, G. L., & von Hippel, E. (1988). Lead user analyses for the development of new industrial products. *Management Science*, *34*(5), 569–582.

von Hippel, E. (1985). In R. D. Buzzell (Ed.), *Learning from lead users in marketing in an electronic age* (pp. 308–317). MA: Harvard Business School Press.

von Hippel, E. (1986). Lead users: A source of novel product concepts. *Management Science*, *32*(7), 791–805.

von Hippel, E. (2005). *Democratizing innovation*. Cambridge, MA: The MIT Press.

von Hippel, E., & Katz, R. (2002). Shifting innovation to users via toolkits. *Management Science*, *48*(7), 821–833.

von Hippel, E., & Oliveira, P. (2010). Users as service innovators: The case of banking services. *MIT Sloan School Working Paper 4748-09*.

White, L. (1996). Technological change, financial innovation, and financial regulation in the U.S.: The challenges for public policy. *Technology and Finance: The Discussion Series of the New York Academy of Sciences, September 30*.