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The effects of exploiting and exploring user knowledge during innovation: evidence from longitudinal analysis

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Abstract

To what extent does the knowledge learnt from various producer-user interactions contribute to producer?s innovation performance? Referring to March (1991), this study categorizes producer?s practices for understanding users into two types - the exploration and exploitation of user knowledge, and then examines their effects respectively. By applying program evaluation methods to longitudinal data from 3150 firms in Denmark, this study finds exploitation and exploration of user knowledge can both enhance producer?s innovation, and exploration of user knowledge has slightly larger effects. In addition, higher returns from innovation investment are found among the firms that integrate more user knowledge into early stage of new product development. Overall, user knowledge exploitation, user knowledge exploration and innovation investment complement each other and contribute to product innovation in a coordinating way.

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ABSTRACT

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Keywords: user knowledge, exploration and exploitation, innovation

1. INTRODUCTION

Prior research on corporate innovation indicates that users are perhaps the most important source of external knowledge for successful innovation (Chatterji & Fabrizio, 2014). However, there is limited empirical study that systematically evaluates to what extent the different practices of learning user knowledge contribute to producer's innovation. The existing related empirical studies mainly focus on evaluating the effects of either a single practice of user integration, such as lead user method, or by treating all the practices of user integration together as one bundle. When business practitioners seek to implement certain practice for tapping into user knowledge, they really need specific guidance as to what its actual effects may be. In particular, comprehensive evaluations are required, so that firms can address whether these methods are effective in general or just exceptions (Greer & Lei, 2012).

Since new methods of tapping user knowledge have been gradually tried out along recent years, it has now become possible to evaluate their effects systematically through longitudinal data. This paper aims to measure to what extent and from which aspect the producer's innovation is affected by integrating the user knowledge (learnt through different practices) into early stage of new product development. Specifically, referring to March (1991), firm's practices of learning user knowledge are first categorized into two groups - the exploitation and exploration of user knowledge, and then the effects of each group are estimated respectively. The data is constructed by linking Statistic Denmark's annual survey on firm's R&D and innovation activities with the registered data of firm basic information. The data of years 2001-2006 is used to generate pre-sample average of innovation outcome and lagged values, while the main regressions are based on 2007-2010 data, which was collected in a more consistent manner. Following Imbens and Wooldridge (2009), the methods designed for program evaluation with panel data, such as treatment effects estimation based on sequential nearest neighborhood matching, are applied to obtain the average causal effects of exploration and exploitation of user knowledge on corporate innovation (see section 3). In addition, following Wooldridge (2010), correlated random effect (CRE) Tobit model is also estimated, and then marginal effects are compared across different subgroups. These methods are quite new in the context for evaluating corporate practices, but their estimators turn out to be quite consistent and robust. The results indicate that both exploration and exploitation of user knowledge have positive impacts on innovation and the effects of exploration are slightly larger. In addition, it finds that the effectiveness of innovation investment is larger among the firms that utilize more user knowledge in early stage of product development. Overall, exploration of user knowledge, exploitation of user knowledge, and innovation investment complement each other and all contribute to product innovation in a coordinate way (see section 4). At the end, there is a brief discussion about the limitation and contribution associated with the measurement of innovation performance used in this study (see section 5).

2. THEORY AND HYPOTHESES

2.1. Previous research on user knowledge and innovation

Interaction with users has been recognized as a crucial to innovation (Foss, Laursen, & Pedersen, 2011; Hippel, 1998). Because innovations are formed mainly from recombination of diverse knowledge (Chatterji & Fabrizio, 2014; Cohen & Levinthal, 1990), producers are able to generate more novel associations and innovative ideas when its knowledge is further diversified by integrating distinct knowledge from users. Another reason is that, when producers understand users' needs better, they will be able to select and prioritizes the innovative ideas that users value most, which in turn translates into higher return of innovation investment. Hence in theory, user knowledge should be able to contribute a great deal to firm's innovation performance.

Having noticed this, firms have increased efforts to learn user knowledge and incorporate it into innovation process, and a series of techniques have been developed

Traditional practices of learning user knowledge usually focus on user's expressed requirements. Examples include using survey to gather users' opinion, or documenting users' feedback through regular contact. These methods are mainly used for exploiting user's real-world experience and identifying current problems of existing products.

The prevalent concern is that these traditional methods may impede or only incrementally improve innovation, because of their narrow focus on current and explicit customer needs (Berghman, Matthyssens, & Vandenbempt, 2006; Pedrosa, 2012). Traditional methods alone are not enough, mainly because user knowledge can also be "tacit" and "sticky". Tacit knowledge is impossible to codify (Collins, 2001), and sticky knowledge is costly to transfer (Von Hippel, 1994). Extracting these kinds of knowledge requires higher degree of user involvement and interaction.

In response, advanced practices have been developed to obtain the tacit and sticky part of user knowledge, which include observation and interview, lead user methods, Toolkit etc. (Leonard & Rayport, 1997; Narver, Slater, & MacLachlan, 2004). For example, producers may use lead user methods to collect information about both users' needs and solutions (Lilien, Morrison, Searls, Sonnack, & von Hippel, 2002). Another example is participatory design (also called design anthropology), in which developers may work and live with the users being studied (Buur & Matthews, 2008; Pals, Steen, Langley, & Kort, 2008). Compared with traditional methods, these advanced methods emphasis future products and potential users, may involve higher risk and reward, and thus are more relevant to radical innovation.

How do these user integration practices actually contribute to corporate innovation outcomes in general? There is no systematic evaluation based on objective longitudinal data from a broad range of industries.

There are some evidences suggesting various positive effects of integrating user knowledge on innovation. For example, collaborating with physicians can enhance innovation of medical device firms (Chatterji & Fabrizio, 2014); relatedly, coordination between marketing/sales and R&D (Ernst, Hoyer, & Rubsaamen, 2010), and customer relationship management (Ernst, Hoyer, & Rübsaamen, 2010) can both affect new product development; in general, opening to external sources can increase innovation performance (Laursen & Salter, 2006).

However, contradicting to the above-mentioned evidences and theories in favor of integrating user knowledge, a few studies indicate that the effects of integrating user knowledge on innovation may not always be positive. Firm's initiatives with users may cause it to miss opportunities for radical innovation, because of a desire to avoid disruption in existing markets (Christensen, 1997). Because users rely on existing products as reference point for expressing preferences, their suggestions may be too conservative (Brockhoff, 2003). Consequently, user's extensive participation can undermine the creativity of in-house innovators; and the process of integrating users may result in "mass mediocrity"(Greer & Lei, 2012). Tzeng (2009) even suggests "firms may be better served by ignoring or not listening to their users".

There are also evidences suggesting that the link between user integration and innovation is indirect or contingent. For example, Foss et al (2011) find the effects of customer integration are completely mediated by organizational practices. Mahr, Lievens and Blazevic (2014) summarizes that the effects of user cocreation is "contingent on the richness and reach of the communication channels enabling cocreation". Fang, Lee, & Yang (2015) suggests that the outcomes of codevelopment are contingent on a firm's position in the value chain and the factors that facilitate effective cooperation.

In sum, unlike earlier theoretical predictions, real-life observations show a rather complicate picture of how user knowledge integration may affect innovation: methods of integration, collaborations with external partners, organizational practices, communication and positions in value chain can all matter. In order to see a general pattern embodied by these observational points, it is necessary to categorize them and analyze the data on a larger scale.

2.2. The exploitation and exploration of user knowledge

Although it is ideal to evaluate each practice of integrating users into innovation separately, it is not feasible due to multi-collinearity and high dimensional problems. In order to balance between the detail of evaluation and the efficiency of estimation, this study first groups the above-mentioned practices into two categories – exploitation and exploration of user knowledge, and then evaluates their effects respectively.

The terms "exploitation" and "exploration" have brought great inspiration to organization research since the publication of March (1991). As he summarized, the essence of exploitation is the refinement and extension of existing competencies, technologies, and paradigms, while the essence of exploration is experimentation with new alternatives (March, 1991). In a systematical review of research on exploitation and exploration, Gupta, Smith, & Shalley (2006) suggests to differentiate these two terms by "focusing on the type or amount of learning rather than on the presence or absence of learning." (2006: 694). Following this interpretation, it should be suitable to apply the terms of exploitation and exploration to the context of learning user knowledge, and distinguish the above-mentioned practices accordingly.

In this study, the exploitation of user knowledge refers to learn from current users through established communication channels. Consistent with the general concept of exploitation, exploitation of user knowledge features with refinement, extension and implementation. Therefore, the traditional marketing methods, which mainly focus on learning from current users about their explicit needs through standardized procedures, belong to this category.

The exploration of user knowledge mainly refers to learn about the potential market through reaching beyond routine communication with current users. Consistent with the general term of exploration, the exploitation of user knowledge features with risk taking, experimentation and flexibility. Therefore, the advanced marketing methods, which are designed for learning tacit knowledge and latent needs from both current and potential users, belong to this category.

Prior discussion indicates that both exploitation and exploration of user knowledge should have direct effects on product innovation, either in a bad or good way - the direction is an empirical matter. To test their effects, the following hypotheses are proposed:

Hypothesis 1: Exploitation of user knowledge directly affects innovation performance.

Hypothesis 2: Exploration of user knowledge directly affects innovation performance.

Because exploration of user knowledge associates with higher risk, a risk-adverse firm may require higher expected returns from exploration to compensate the higher risk than from exploitation. Hence, other things being equal, knowledge learnt in an explorative way should be able to bring higher return. This implies the following hypotheses:

Hypothesis 3: Other things being equal, knowledge learnt in an explorative way should bring higher return to innovation performance.

March (1991) argues that because exploration and exploitation compete for scarce resources, the relation between them can be interpreted as two ends of a continuum. However, Katila and Ahuja (2002) and Gupta et al (2006) suggest these two types of learning process are orthogonal when related resources are not strictly constrained. This makes intuitive sense, because without constraint, the optimal strategy of resource allocation is to continue investing in a certain activity until the return from each type of activity converges, which scenario allows for some degree of independency between exploration and exploitation. In the context of learning knowledge from users, it is very likely that the total resources for explorative and exploitative learning are relatively flexible. This is because learning user knowledge may only take a small fraction of the total resource of the firm, so that the firm can always reallocate more resources to learning from other activities - if the return of learning increases. In sum, as the return from learning user knowledge (through either exploitive or explorative way) increases, the total resources allocated to learning user knowledge can also increase - hence the budget is not strictly constrained. Accordingly, the exploitation and exploration of user knowledge should be orthogonal. Whether there are complementary effects between them depends on the empirical result of the following hypothesis:

Hypothesis 4: Exploitation and exploration of user knowledge complement each other.

Learning from users may also affect innovation indirectly. Because the knowledge learnt from users may affect the allocation of innovation resources (e.g. the knowledge can allow the firm to select and prioritize the new product features that are valued most by users), the effectiveness of innovation investment can differ between the firms with different types of user knowledge, which correspond to different ways of learning. Hence, there is hypothesis 5:

Hypothesis 5: Firms that learn user knowledge in either exploitative or explorative way may experience different returns from innovation investment.

3. EMPIRICAL STATEGY

3.1. Data

The dataset is constructed by merging Statistics Denmark's survey data on firm's R&D and Innovation (FoU) activity with firm's basic information (FIRE) data. FoU survey data is available from 1990s, but only since 2007 have the variables and measurements become highly consistent. It contains information of firm's R&D innovation activities, such as their financial sources, investments, expenditures, number of different related employees, revenue share of new products etc. FIRE data provides basic information of the firm, such as location, industry, total number of employees, asset, etc. Only firms that appear in both datasets are used. Considering the availability and consistency of the variables of interest, this paper mainly uses the data during 2007-2010. Data from 2001-2006 is partially exploited to obtain pre-sample average of outcome variable. Each year's survey between 2007 and 2010 contains around 4000 firms; however, only a proportion of them have innovation activity. Including pre-sample average and lagged values also exclude a large number of observations. For the purpose of this analysis, the sample (so that the population of interest) is further restricted to firms with positive innovation expenditure. Because firm may not participate the survey or have positive innovation expenditures every year, the panel data are unbalanced. In total, the dataset contains observations from 3150 firms.

3.2. Measures

Product Innovation

Following Laursen and Salter (2006), this paper examines corporate innovation level through the share of revenue attributed to new product sales. On one hand, this measure reflects the performance of new products relatives to old ones. Its increase indicates higher return from the new product and continuous improvement of product's market value. On the other hand, this measure reflects corporate product udating level, a higher rate of which indicates a younger product profile. Although it may not be the perfect measure, it does reflect corporate innovation level from an informative angle.

For the convenience of estimation, the original share, y, has been transformed to $y' = \ln(1+y)$, and y' is used in the regressions. Normally y' is approximate to y when y is small. Because $y \le 1$, the difference between y' and y is almost zero.

The exploitation and exploration of user knowledge

The primary independent variables of interest are two binary indicators: each takes up value 1 if the firm integrates the user knowledge learnt in corresponding way into early-stage of new product development (i.e. concept development or innovation implementation) and 0 otherwise.

The binary indicator of user knowledge exploitation takes up value 1 if the firm integrates the knowledge learnt from regular marketing methods, such as contact with users through e.g. daily dialogue and other routines. The binary indicator of user knowledge exploration takes up value 1 if the firm uses the knowledge learnt from at least one of the following advanced methods: observation or interview (e.g., anthropological studies or in-depth interviews), involvement of ordinary users (e.g. prototype tests or internet communities with ongoing feedback in the innovation process), and inclusion of advanced users (e.g. lead user methods).

The key distinction between exploitation and exploration of user knowledge is that, the exploitation of user knowledge attaches more weight on learning from existing users about explicit needs, while the exploration of user knowledge aims to hedge future and implicit needs of both existing and potential users.

Controls

Control variables include the firm's R&D expenditures, innovation expenditures (both in millions of Danish Kroners), the diversity of R&D partners, firm size measured by asset value and the number of employees except for those work on R&D or innovation, salary expenditure, industry and location indicators. When applicable, a one-year lag value of new product's share in total revenue (y') and the average of y' over the pre-sample periods 2001-2006 are also controlled for to capture the unobserved heterogeneity.

3.3. Econometric Methods

The main objective of the econometric analysis is to estimate the effects of incorporating user knowledge in early stage of innovation. The effects of user knowledge from regular customer contact and from advanced marketing methods are distinguished and estimated separately. First, they are estimated as partial effects through correlated random effect (CRE) Tobit model; second, they are estimated as average causal effects following two treatment effect approaches for panel data; third, the possible interactions between these two effects and other interesting factors are examined through comparing marginal effects for different groups of firms.

3.3.1. CRE Tobit Model

Tobit model exploits the fact that there is positive probability of not being able to realize any revenue from new product, even if other determinants of revenue profile are the same. This model may well describe the underlying process in the context of this paper, because the data does show a significant proportion of the firms without any new product revenue. The CRE approach, which dates back to Mundlak (1978), allows correlation between unobserved heterogeneity and explanatory variables. Compared with the traditional random effect (RE) method, CRE requires fewer assumptions and is more general. Following the method that combines Tobit model with CRE device (Wooldridge, 2010), this paper estimates how using user knowledge affects revenue contribution from new products with the model:

$$\boldsymbol{y_{it} = max\big(0,\ \psi + \propto m_{it} + \beta w_{it} + x_{it}\gamma + \delta\bar{m}_i + \rho\bar{w}_i + \bar{x}_i\theta + \lambda\bar{y}_{i,p} + a_i + d_t + u_{it}\big)} \qquad \textbf{(3-1)}$$

Where i is firm indicator and t is year indicator, y_{it} is the share of revenue from new product sales, m_{it} is binary variable indicating whether the firm incorporates user knowledge learnt from regular contact; w_{it} is also a binary variable indicating whether the firm incorporates user knowledge learnt from advanced marketing methods, $\mathbf{x_{it}}$ is a vector of control variables including innovation expenditure, asset, etc.; $\overline{y_{\iota,p}}$ is the pre-sample average of y_i; $\overline{m_\iota}$, $\overline{w_\iota}$, $\boldsymbol{\bar{x}_\iota}$ are the average of m_{it}, w_{it}, $\boldsymbol{x_{it}}$ across years 2008-1010 respectively; a_i is firm specific unobserved heterogeneity; d_t is year dummy variable; $\mathrm{u_{it}}$ is an idiosyncratic error.

Under the assumptions that

$$a_i \big| (\boldsymbol{m_i}, \boldsymbol{w_i}, \boldsymbol{x_i}, \bar{y}_{i,p}, d_t) \sim Normal\ (0, \sigma_a^2)$$

$$\mathrm{u_{it}} \big| (\boldsymbol{m_i}, \boldsymbol{w_i}, \boldsymbol{x_i}, \bar{y}_{i,p}, d_t) \sim Normal\ (0, \sigma_u^2),$$

Model (3-1) can be estimated by joint maximum likelihood estimation.

3.3.2. Treatment Effect Approaches

Incorporating user knowledge into early stage of innovation can also be regarded as a type of treatment and estimated through the treatment effect approach. This approach exploits the binary nature of the treatment variable and is more able to produce the so-called "average causal effects". The validity of treatment effect estimates requires a key assumption - "ignobility of treatment" (also called "unconfoundedness"), which means that the assignment of treatment is independent of potential outcome conditional on covariates. This paper applies two types of treatment effect approach. One exploits the assumption of ignorability conditional on unobserved heterogeneity, and the other exploits the assumption of dynamic ignorability, that is, unconfoundedness conditional on past observables.

Ignorability conditional on unobserved heterogeneity

This assumption means the treatment is independent with potential outcome conditioning on unobserved heterogeneity and a history of covariates. This paper estimates the treatment effects of m and w with the following equation:

$$y_{it} = \alpha + \beta m_{it} + \gamma w_{it} + \boldsymbol{x_{it}\delta} + \lambda m_{it-1} + \mu w_{it-1} + \boldsymbol{x_{it-1}\xi} + \theta d_t + a_i + u_{it} \qquad (3\text{-}2)$$

where $w_{it}, m_{it}, \boldsymbol{x}_{it}, d_t, a_i, u_{it}$ have the same meanings as in (3-1), and $w_{it-1}, m_{it-1}, \boldsymbol{x}_{it-1}$ are the one year lag value of $w_{it}, m_{it}, \boldsymbol{x}_{it}$ respectively. Following Wooldridge (2010), the treatment effects are fixed effect estimators of β and γ in (3-2).

Dynamic Ignorability

Dynamic ignorability assumption requires the treatment is independent with potential outcome given past outcomes and treatments. Under this assumption, sequential matching method (Lechner, 2005) can be applied to obtain treatment effects. The procedure used in this paper is: first estimate the treatment effect in equation (3-3) using nearest neighborhood matching method for each time period, and then use panel bootstrap to obtain overall average treatment effects shown in (3-4).

$$y_{it} = \alpha_t + \sigma_t y_{it-1} + \beta_t m_{it} + \gamma_t w_{it} + \boldsymbol{x_{it}\delta_t} + \lambda_t m_{it-1} + \mu_t w_{it-1} + \boldsymbol{x_{it-1}\xi_t} + a_i + u_{it} \tag{3-3}$$

Where y_{it-1} is one year lagged value of y_{it}, and all the other notations are the same with (3-2).

$$\widehat{\beta, \gamma_{ate}} = T^{-1} \sum_{t=1}^{T} \widehat{\beta, \gamma_{ate,t}} \tag{3-4}$$

Where $\beta, \gamma_{ate,t}$ are nearest neighborhood matching estimators for year t, and $\widehat{\beta_{ate}}$, $\widehat{\gamma_{ate}}$ are the average causal treatment effects.

3.3.3. Heterogeneous Marginal Effects

The marginal effects of CRE Tobit model depend on all covariates. This flexibility allows estimating heterogeneous marginal effects on subgroups with different characteristics. These heterogeneous marginal effects could further reveal the potential interaction among covariates, which could be quite interesting. The later part of this paper also reports marginal effects for different subgroups. These effects are estimated by first obtaining the change in the predicted outcome due to the change in variable of interest for each observation within a certain group, and then averaging the changes across all the observations in the group. Bootstrap methods are applied for the inferences.

4. RESULTS

Table 2 presents fixed effect estimates through treatment effect approach and CRE Tobit estimates. Theoretically, fixed effect estimators are better in terms of consistency, while CRE Tobit estimation is more efficient and able to reveal additional information on the effects of time-invariant characteristics. Comparing the estimates from the two methods, both the magnitude and significance levels of variables of interest are actually highly consistent. On average, incorporating user knowledge learnt through exploration (advanced methods) increases the new product sales among total revenue by approximately 4 percentage point. Both estimates in both models are significant at 5% or even 1% level.

As for control variables, innovation expenditure contributes to revenue share of new product sales significantly. 1% increase in innovation expenditure can increase new product sales by 0.7-0.8 percentage point. Similar pattern is found in diversity of R&D partners: on average, introducing one additional type of R&D partner leads to an increase in the revenue contribution of new product by 2.6 percentage points according to fixed effect estimator and 1.1 percentage point increase according CRE Tobit estimator. Increasing firm size (measured by assets), however, has a lagged negative impact on the revenue contribution from new products.

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INSERT TABLE2 ABOUT HERE

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Table 3 shows estimates from sequential nearest neighborhood matching method. These effects are for the firms who have already integrated user knowledge into innovation development (treatment effect on treated). In addition to average treatment effects across three years, those of each year are also reported. The effects are relatively stable along the years. Compared with fixed effect and CRE Tobit estimates, the estimators of nearest neighborhood matching methods are generally larger. Both effects are almost doubled here: incorporating user knowledge learnt in an explorative way (from advanced marketing methods) leads to approximately 8 percentage point increase in new product revenue contribution, and incorporating user knowledge learnt in an exploitive way (from regular customer contact) increases new product revenue contribution by around 6 percentage point on average.

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INSERT TABLE3 ABOUT HERE

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The results in table 2 and 3 confirms hypotheses 1 and 2 that, both user knowledge exploitation and exploration increase the revenue share contributed by new product sales. Quantifying the effects reveals larger impact of knowledge learnt from user knowledge exploration compared with user knowledge exploitation. Hence hypothesis 3 is supported.

In order to see the potential interaction between the exploration and exploitation of user knowledge and their interactions among other firm characteristics, it is necessary to examine how these marginal effects vary across subgroups, which are presented in Table 4.

From table 4, we can see the decomposition of the overall marginal effects and compare the effects across different subgroups. The average marginal effects are estimated respectively for four types of subgroups: firms that neither exploit nor explore user knowledge, firms that only integrate knowledge learnt in an exploitative way (from regular customer contact), firms that only integrate knowledge learnt in an explorative way (from advanced marketing methods), and firms that only integrate knowledge learnt in both ways. Not surprisingly, the general pattern for almost every significant estimate is that, the effect is larger for firms that use more types of user knowledge. For example, stopping integrating user knowledge learnt through explorative ways leads to a decrease of new product revenue contribution by 5.6 percentage point for firms that have already been incorporating user knowledge from both channels, while beginning to integrating user knowledge learnt through explorative ways only increases new product revenue contribution by 1.8 percentage point for firms that haven't exploited or explored user knowledge before. Similar pattern applies to the effects of incorporating user knowledge from exploitative learning. Hence hypothesis 4 is also supported.

Notably, the return of innovation expenditure also follows this pattern: 1% of increase in innovation expenditure leads 1.1 percentage point increase in new product revenue contribution for firms incorporating both types of user knowledge in early stage of innovation, but only 0.3 percentage point increase in new product revenue contribution for firms using neither type of user knowledge. Hence hypothesis 5 is supported. These observations indicate the potential complementary relationships among the two types of user knowledge, the range of R&D partners, and innovation investment.

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INSERT TABLE4 ABOUT HERE

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5. DISCUSSION AND CONCLUSION

This study provides systematic evidence that both exploitation and exploration of user knowledge contribute to product innovation. Integrating user knowledge into innovation development is able to rejuvenate firm's product profile in general, no matter the knowledge is learnt from leading users, ordinary users, current or potential users. The exploration of user knowledge effect has slightly larger compared with the exploitation of user knowledge. Innovation investment exhibits higher returns among the firms those integrate the user knowledge (learnt from exploration, exploitation or both) into innovation development. Hence, through increasing the effectiveness of innovation investment, the exploitation and exploration of user knowledge also enhance innovation performance indirectly. In addition, the more user knowledge has the firm already integrated into innovation development, the larger are the impacts from the changes in the exploitation and exploration of user knowledge. In sum, user knowledge exploitation, exploration and innovation investment complement each other and contribute to product innovation in a coordinating way.

These findings contribute to the empirical literature that systematically assesses the role of user knowledge in corporate product innovation, which is rather scarce (Chatterji and Fabrizio, 2014). Generally, the findings support the broader notion that firms should be open to diverse external sources during innovation (Laursen & Salter, 2006; Vanhaverbeke, Chesbrough, & West, 2008). Especially, this study closely relates to prior literatures that examine the effects of learning user knowledge either as a whole (e.g. Foss et al, 2011) or through a specific way such as lead user method (e.g. Lilien et al, 2002). In addition, this study zooms into how firms integrate users during product innovation, in which sense it also complements to the literatures that explain why CRM influences new product performance (Ernst et al., 2011) and why sales, marketing and R&D cooperation has a positive effect on new product performance (e.g. Ernst et al., 2010).

Referring to March (1991), this study categorizes the practices of learning from users into two groups: the exploitation and exploration of user's knowledge. This way of classification allows for examining the various practices of learning user knowledge from a comfortable distance, which is neither too near to manage the numerous detailed practices, nor too far to tell the distinct internal patterns. Interestingly, in marketing literature, there is a pair of parallel concepts: responsive and proactive market orientation. They are defined by Narver et al. (2004) with the purpose of extending the measure of market orientation introduced by Narver and Slater (1990) and Kohli and Jaworski (1990). A responsive market orientation addresses producer's attempts of understanding customers' expressed needs, and proactive market orientation addresses producer's attempts of understanding customers' latent needs, which include opportunities for customer value of which the customer is unaware (Narver et al., 2004). Both types of market orientation focus on understanding users; the major difference is that the proactive orientation includes a second round of thinking, i.e. producer's attempts to put itself into its user's shoes and infer user's latent and future needs, which are beyond the reach of responsive market orientation (Blocker, Flint, Myers, & Slater, 2011). The pair concepts of responsive and proactive market orientation and the pair concepts of exploiting and exploring user knowledge can both distinguish producer's efforts of understanding user's current and future needs. However, these two pairs of concepts take different angles to reflect producer-user interaction: while market orientation concepts departure from user's needs, exploration/exploration concepts center at producer's behaviors. Compared with the former pair of concepts, the later pair can be broader, more objective and pining down to actual practices in a more concrete way. For example, while market orientation concepts mainly focus on current and potential needs of existing users, exploitation/exploration concepts also allow some space for an equal emphasize of potential users. This is because the exploitation/exploration angle allows the producer to view existing users from a longer distance (rather than be pushed into current user's shoes), so that producer's view becomes broader enough to reveal alternative opportunities e.g. potential users. In addition, exploitation/exploration concepts are more associated with objective measures of producer's actual behaviors, while market orientation concepts mainly associate with subjective measures of producer's perceptions. Therefore, the findings of this study takes a different angle but still complements with prior market orientation literatures such as Blocker et al. (2011) and Kim, Im and Slater (2013).

The outcome measure of product innovation follows Laursen and Salter (2006), which is revenue share contributed by new product sales. This measure reflects the level of product innovation to some extent; but it actually stands in between the two popular measures for innovation, i.e. the number of patents/innovations (innovation antecedent) and market return (innovation outcome). This niche position allows shedding light on the underlying mechanism of how innovation antecedents are translated into outcomes. In this sense, rather than pointing to any effects on absolute outcomes, a more precise way of interpreting the findings is: integrating user knowledge into product innovation process can rejuvenate product profile. Actually, a youthful product or revenue profile itself is something worthwhile to pursue and monitor, because just as younger organisms have more vitality and stronger momentous to grow, a youthful product profile may imply higher potential and more future revenue. In this sense, it is justified to see the revenue share contributed by new product sales at least as an intermediate goal. Sometimes, this relative measure is sometimes even better than the absolute outcome measures, because the intermediate measure is largely under firm's own control, while the overall outcomes in absolute terms are much noisier. Plus, the innovative activity itself does not necessarily aim to higher profit at the first place. Gaining a younger product revenue profile is good enough: just as exercise neither directly nor purposely makes people richer, but it does slow down the aging process and contribute to well-being in the long run.

Table 2. Impacts of exploration and exploitation of user knowledge on new product revenue contribution: Estimates from fixed effect and CRE Tobit models

Dependent Variable:	***Fixed Effects Model***		***CRE Tobit Model***			
% Revenue from New Products	*Coeff.*	*(S.E.)*	*Coeff.*	*(S.E.)*	*A.M.E.*	*(S.E.)*
User knowledge from:						
exploration (advanced marketing methods)	0.038***	(0.012)	0.096***	(0.027)	0.041***	(0.011)
exploitation (regular customer contact)	0.034***	(0.011)	0.079**	(0.037)	0.031**	(0.013)
exploration (advanced marketing methods)(lag)	-0.015	(0.011)	-0.033	(0.024)	-0.013	(0.009)
exploitation (regular customer contact)(lag)	0.014	(0.011)	0.052	(0.033)	0.021	(0.013)
R&D expenditure (1000.000 DKK)	-9.95E-08	(2.02E-07)	-9.4E-09	(2.60E-07)	-3.910E-09	(1.040E-07)
R&D expenditure (lag) (1000.000 DKK)	3.09E-07*	(1.85E-07)	3.18E-07	(2.99E-07)	1.320E-07	(1.230E-07)
Ln(Innovation expenditure, 1000.000 DKK)	0.008***	(0.002)	0.017***	(0.003)	0.007***	(0.001)
Ln(Innovation expenditure, 1000.000 DKK) (lag)	0.003**	(0.001)	0.005*	(0.003)	0.002	(0.001)
Salary level	-1.23E-07	(1.08E-07)	-2.12E-07	(2.23E-07)	-8.840E-08	(8.730E-08)
Diversity of R&D partners	0.026***	(0.008)	0.027**	(0.012)	0.011**	(0.005)
Ln(number of employees, other type)	0.009	(0.018)	0.039	(0.054)	0.016	(0.023)
Ln(asset, 1000.000 DKK)	-2.81E-04	(1.26E-02)	-0.032	(0.048)	-0.013	(0.020)
Salary level (lag)	2.49E-07***	(8.17E-08)	2.71E-07*	(1.65E-07)	1.130E-07	(7.280E-08)
Diversity of R&D partners (lag)	-0.002	(0.007)	-0.001	(0.010)	-4.780E-04	(4.253E-03)
Ln(number of employees, other type) (lag)	0.003	(0.017)	0.056	(0.053)	0.023	(0.022)
Ln(asset, 1000.000 DKK) (lag)	-0.020**	(0.010)	-0.095**	(0.049)	-0.040**	(0.019)
Pre-sample average of *% revenue from new products: 2001*- 2006	---		0.002***	(4.46E-04)	0.001	(1.907E-04)
Constant	0.170	(0.183)	-0.741	(0.136)		
F Statistic/ Wald chi2	F(18,3149)=9.14					
Log pseudo likelihood	---		-866.8783			
Number of observations	5344		left-censored: 1219; uncensored: 961			
Number of firms	3150		1060			

***: Significant at 1%; **: Significant at 5%; *: Significant at 10%. Panel bootstrap standard errors for CRE model (400 repetitions).

Table 3. Impacts of exploration and exploitation of user knowledge on new product revenue contribution: Treatment effect estimates through dynamic sequential matching based on nearest neighborhood method

Dependent Variable: % Revenue from New Products		*Treatment - using user knowledge learned from:* Exploration (Advanced marketing methods)		Exploitation (Regular customer contact)		*Number of obs*
		Observed Coef.	Bootstrap S.E.	Observed Coef.	Bootstrap S.E.	
	2008	0.0814***	(0.0208)	0.0539*	(0.0319)	1440
ATT in each Year	2009	0.0734***	(0.0189)	0.0508**	(0.0206)	1862
	2010	0.0813***	(0.0156)	0.0780***	(0.0101)	2042
Overall ATT		0.0787		0.0609		

***: Significant at 1%; **: Significant at 5%; *: Significant at 10%.
+: Panel bootstrap standard errors: 400 repetitions, seed 1000.

Table 4. Impacts of exploration and exploitation of user knowledge on new product revenue contribution: CRE Tobit estimates for subsamples

Dependent Variable: % Revenue from New Products	*A.M.E. on E(y*|y>0) For subsamples of firms that incorporate user knowledge learnt from:*							
User knowledge from:	Neither methods		Regular contact		Advanced methods		Both methods	
Explorative methods	0.018***	(0.006)	0.044***	(0.012)	0.031***	(0.008)	0.056***	(0.014)
Exploitive methods	0.015**	(0.007)	0.029**	(0.012)	0.031**	(0.014)	0.047**	(0.019)
Explorative methods (lag)	-0.005	(0.003)	-0.013	(0.009)	-0.012	(0.008)	-0.021	(0.014)
Exploitive methods (lag)	0.009	(0.006)	0.020	(0.013)	0.019	(0.012)	0.032	(0.020)
R&D expenditure (1000.000 DKK)	-1.510E-09	(4.040E-08)	-3.810E-09	(1.020E-07)	-3.370E-09	(9.020E-08)	-5.940E-09	(1.590E-07)
R&D expenditure (lag) (1000.000 DKK)	5.120E-08	(4.850E-08)	1.290E-07	(1.200E-07)	1.140E-07	(1.030E-07)	2.010E-07	(1.870E-07)
Ln(Innovation expenditure, 1000.000 DKK)	0.003***	(0.001)	0.007***	(0.001)	0.006***	(0.001)	0.011***	(0.002)
Ln(Innovation expenditure, 1000.000 DKK) (lag)	0.001	(0.001)	0.002	(0.001)	0.002	(0.001)	0.003	(0.002)
Salary level	-3.420E-08	(3.380E-08)	-8.630E-08	(8.530E-08)	-7.630E-08	(7.690E-08)	-1.340E-07	(1.330E-07)
Diversity of R&D partners	0.004***	(0.002)	0.011***	(0.005)	0.010***	(0.005)	0.017***	(0.008)
Ln(number of employees, other type)	0.006	(0.009)	0.016	(0.022)	0.014	(0.020)	0.024	(0.035)
Ln(asset, 1000.000 DKK)	-0.005	(0.008)	-0.013	(0.020)	-0.012	(0.017)	-0.020	(0.030)
Salary level (lag)	4.360E-08	(2.830E-08)	1.100E-07	(7.100E-08)	9.750E-08	(6.410E-08)	1.710E-07	(1.110E-07)
Diversity of R&D partners (lag)	-1.848E-04	(0.002)	-4.668E-04	(0.004)	-4.129E-04	(0.004)	-0.001	(0.006)
Ln(number of employees, other type) (lag)	0.009	(0.009)	0.023	(0.021)	0.020	(0.019)	0.035	(0.033)
Ln(asset, 1000.000 DKK) (lag)	-0.015	(0.008)	-0.039	(0.019)	-0.034	(0.017)	-0.060	(0.029)
Pre-sample average of *% revenue from new products: 2001*- 2006	2.954E-04	(8.380E-05)	7.462E-04	(1.847E-04)	6.600E-04	(1.780E-04)	1.161E-03	(2.882E-04)

***: Significant at 1%; **: Significant at 5%; *: Significant at 10%. Panel bootstrap standard errors for CRE models (400 repetitions).

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