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The determinants of user innovation in medical imaging devices

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Using a survey specifically designed to collect data on CT scanner users in medical organization, we propose an econometric model investigating different determinants of user innovation. The impact of experience, early adopters, context and slack on both technology and technology-related component user innovation (or technology and complement UI, respectively) is explored. A bivariate probit model shows a positive impact of experience on technology UI (hardware and software) and on complement UI (protocols, materials or services). Early adopters of CT scanners are however not more likely to implement UI. The way machines are used is also important: our results show that R&D activities in CT scanners most probably foster technology UI, providing that these activities are not directed toward academic publications. User context does not influence complement UI. unlike Slack. Scarcity and a high level of slack are dual solutions to achieving UI on CT scanner hardware and software. The two types of UI are interdependent but with different determinants. It thus leads organizations to different trade offs if they want to manage UI

JEL codes: O3 , I1.

Keywords: user innovation, health care industry, CT scanner, slack, scarcity, experience, lead user, user context, technique, technology, complementarity.

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1 Introduction

Innovation is the best way to achieve competitive advantage for companies. Ideas, innovations and their developments are considered in general as being crafted by costly R&D staff in specialized, planned, organized and continuous cognitive activities. Scholars Invested a great deal of time to the study of the determinants of R&D inputs and the management of R&D productivity. However, the literature on user innovation (UI hereafter) underlines that many innovations are not the result of R&D activities. Some are first imagined "on line" and prototyped by intermediate users on machines (Smith, 1776; Rosenberg, 1976; von Hippel 1977, 1988; Lee, 1996), using scientific instruments (von Hippel, 1976), or software programs (Urban and von Hippel, 1988; Franke and von Hippel, 2003). Innovations by users regarding adaptation or improvement of their sports equipment is a good example (Lüthje et al., 2005).

In the two strands of literature on R&D and users, scholars underline that the accumulation of knowledge often occurs informally. Literature on R&D emphasizes the importance of informal, discontinuous, discretionary, decentralized or bootlegged R&D activities (Kleinknecht and Reijnen, 1991; Santarelli and Sterlacchini, 1990; Bönte and Keilbach, 2005; Criscuolo et al., 2012). Several contributions reveal that user innovation happens according to the same organizational traits as for R&D (Rosenberg, 1976; Von Hippel, 1988; Morrison et al., 2000, Lüthje et al., 2005; Gault and Von Hippel, 2009, Schweisfurth and Raasch, 2015). However, few authors (See Morrison et al., 2000; Criscuolo et al. 2012; Schweisfurth and Raasch, 2015) in either strand underline that these informal research activities were possible only because an excess of resources was available, an excess of resource usually named as "resource slack" in the literature (Cyert and March, 1963 Nohria and Gulati, 1996; Greve, 2003). Although many studies have explored the effect of slack on R&D, to our knowledge, no study has yet measured its impact on user innovation.

The literature on R&D also insists that the accumulation of knowledge is based on the accumulation of R&D capabilities, the role of human capital and "star scientists" (See Hall and Rosenberg, 2010 for an overview). The literature fails however to investigate the role of machines and instruments in R&D and the importance researcher expertise with instruments and materials (Stephan, 2012, Chapter 5). On the contrary, user innovation literature insists on the role of field experience accumulated by machine users and the prominent role of some "lead users" (Von Hippel, 2005). Very little empirical evidence is available confirming the impact of experience on UI. Some case studies have found that experience enables users to modify machines and materials (Von Hippel and Tyre, 1995). One econometric study performed by Lüthje et al. (2006) on mountain bikes, confirms the positive impact of users' experience on their ability to innovate.

The present article aims to fill the gaps on slack and on experience in the literature on user innovation. We first draw on the behavioral theory regarding firms, on the literature on slack, and on the recent articles rejuvenating the role of scarcity as a trigger of innovation, to underline that users can rely either on scarcity or on slack to develop their ideas and inventions for the machine they use. This dual mode of research, one based on slack and one based on scarcity, leads us to contend that there is a S-shape curve between the degree of slack and UI. In other words, that the usual inverted U-shape curve (à la Gulati and Nohria, 1996) is a special case, where scarcity based research is limited. We also draw on the literature examining the learning curve and user innovation, in order to identify the different dimensions of users' experience. We propose to clarify the positive role of users' field experience with machines by disentangling the role from two dimensions often cited in the literature which deal with user experience: the positive role of early adoption and the positive role of extreme contexts in which the machines and instruments can be used.

In order to test our predictions on slack and experience, we build a dataset from an original survey combined with administrative data on imaging devices in the medical care industry, a field where physicians, specialists and surgeons, but also patients, have already been identified as important sources for ideas and inventions (Finkelstein et al., 1980; Shaw, 1985; Lüthje, 2003; Lettl et al., 2006; Lettl et al., 2008; Morlacchi and Nelson; 2011; Chatterjee and Fabrizio, 2012; Hinsch et al, 2014; Von Hippel and DeMonaco, 2014). We identify the historical portfolio of each medical organization involved regarding their use of CT scanners and are thus able to measure and characterize different users' experiences as well as the slack time available for CT scanner users. Our econometric results confirm our predictions: machine experience fosters user innovation, either in the modification of technology (hardware or software UI) or the modifications in CT scanner complements (defined as technique, services or intermediate material UI). R&D activities performed with CT scanners are extreme uses driving user innovation in technology. However, early CT scanner adopters are not found to be user innovators. We also show that the relationship between slack and user innovation is positive and linear for user innovation on complements but that there is a S shaped curve for user innovation on technology. The latter result confirms our theoretical hypothesis that scarcity can foster UI and constitute an alternative research mode to resource slack.

The remainder of this paper is organized into five sections. Section two surveys the literature and examines the theoretical arguments as well as the related empirical literature linking experience and slack to user innovation. Section three presents, in turn, our data sources, variables and the econometric method. The fourth section outlines our statistical findings. We draw conclusions in the final section.

2 Literature background and hypotheses

The competence to innovate is considered either accumulated at the organizational level or the individual level. Experience matters both to produce or to absorb new knowledge (Cohen and Levinthal, 1990). Slack is a second moderating factor driving UI which we explore in turn.

2.1 Experience and user innovation

The literature on user innovation first emphasizes that experience with a technology is obtained after a process of "learning by doing", which is something that takes time (von Hippel, 1994; Cattani, 2006). More precisely, the capability to modify and to innovate on machines is, the result of production experience (Rosenberg, 1982; Von Hippel, 1988; Adler and Clark, 1991), which must come from "real life" (Von Hippel, 1988) and "prolonged" experience (Rosenberg, 1982: page 122). The same ideas are also put forward for experience with final goods (Luthje et al., 2006).

The literature underlines the role of time and introduces a distinction between the experience accumulated on a technology before the adoption of a good or a device, and the experience accumulated after their adoption. The post-adoption experience is emphasized, but experience prior to adoption also matters, as it helps users identify and solve problems (Von Hippel and Tyre, 1995). Past-experience involves the experience with or without the same type of machine or good. The preadoption history of machine users is likely to influence the post-adoption behavior of users and their learning path (Jasperson et al., 2005). The literature, ever since Cyert and March (1963), warns that pre-adoption experience can be detrimental to innovation: users will search locally, based on their previous experience, while some radical innovations are more based on explorative research, distant research diverging from previous knowledge (Audia and Goncalo, 2007; Troilo et al, 2014).

Improvements in users' technique are possible without the modification of instruments (Von Hippel, 1988). Recent case studies have underlined that user innovation in different components of a technological system are complementary (Hinsch et al., 2014; Hyysalo, 2009; Hienerth, 2015), suggesting that experience accumulated by users on technique, and material surrounding a technology may also likely to be useful to innovate on technology and vice versa.

Finally, some contributions contend that innovation capabilities improve over time: firms who have already achieved innovation or innovation success are more likely to innovate again or to produce breakthrough innovations (Conti et al., 2013). User innovators are also more likely to innovate when they have already experienced the adaptation of their machine before, in different and changing environments (Von Hippel and Tyre, 1995) and also suggested by Chatterji and Fabrizio (2012) on medical invention.

A problem is that the empirical evidence for the role of experience on user innovation is still scarce. Lüthje et al. (2006) explored a sample of 106 mountain bikers and their likelihood to innovate. The authors measured experience by the different ways each biker spent hs/her time with bicycles. They found that user experience is not relevant when considering the transformation of ideas into prototypes,

but is relevant for the ideation stage. Howver, they also confirmed the positive role of experience on creating prototypes, suggesting that experience matters in the ideation process of users.
Despite the low of number of empirical results, we predict that:

H1: User experience with a machine has a positive impact on UI

A laggard can install several machines at the same time and accumulate rapidly experience. A similar amount of experience accumulated by users can thus cover different timing of adoption and thus UI production. In the literature on UI, the main innovators cited are usually users who experienced the need to innovate earlier (von Hippel 1986) as they were early adopters (Urban and von Hippel, 1988; Franke and Shah, 2003). Furthermore, UI literature also rightly emphasizes that the sooner an innovation is made by users on a machine or complement, the sooner the work load is eased and the derived rent becomes valuable to them. The pace of introduction of new machines or instruments should therefore be rapidly followed by user innovations. Some contributions confirm that the modification of machines is based on post-installation problem-solving activities and on an existing stock of knowledge (Adler and Clark, 1991; Tyre and Orlikowski, 1994; Von Hippel and Tyre, 1995). Considering that these problems can stimulate innovation and exploration, we can expect that user innovation should be triggered right after the installation of new machines.
At the same time, the literature emphasizes that user innovation is based on field experience, as only through lengthy field experience can one acquire the expertise to identify problems and imagine novel uses, functions, other techniques and complements. Therefore, from this point of view, user innovation takes time: the time to observe ideas but also the time to process invention and prototyping based on trial and error (Von Hippel and Tyre, 1995; Desouza et al., 2007). User innovation is thus not likely to occur immediately after the installation of new machines.
The literature usually acknowledges the role of early adoption but does not say much about the final shape of the learning curve. It suggests that organizations benefit from two successive waves of user innovations, the first triggered by post-adoption problems, and the second by post-intensive use expertise. From an empirical point of view, early adopters are in both cases lower on the learning curve than late adopters, even with a similar amount of experience accumulated: they already fixed many different problems. However, similar experience accumulated rapidly using several machines with overlapping problems may not enable an organization to reach the same level of innovation as early adopters.
The literature also emphasizes that early users are probably more likely to invent when a nascent technology is used. Different effects of the adoption during early phases of a technology can be considered here. In line with insights by Von Hippel and Tyre (1995), it is possible that in the early phases of innovation, technical glitches and bugs are more likely to occur and problems to be fixed by users. Second, in early phases, technology usually provides a different and/or a broader scope of opportunities where users are more likely to explore unanticipated uses and therefore more likely to propose subsequent machine and related component modifications. Finally, users may also be more inclined to innovate in new or nascent technologies: they can expect to derive higher gains for their solutions and innovations than for mature technologies (Chatterji and Fabrizio, 2012). Using patent data, Chatterji and Fabrizio (2012) confirmed that patents with a user-inventor cite prior documents that are on average younger than patents without user-inventor, suggesting that UI is more likely to occur during the early stages of the technological cycle because prior art is very recent in this case.
Keeping the last point in mind, we hypothesize that:

H2: Early adoption of instruments has a positive impact on UI

The literature on user innovation shows that learning by users depends on the technology cycle but also on the context of use. Von Hippel and Tyre (1995) underlined that systematic and early problem solving activities occur as soon as a machine is introduced, but are triggered by unanticipated or new contexts. Examples of this were when modifications were made on bikes to be used in mountains – the

beginning of mountain-biking (Luthje et al., 2006), and when kayaks started to be used in tumultuous whitewater (Hienerth, 2004).
The use of CT scanners provides an example of the differences in user contexts since the medical devices are likely to be used in a context that is narrower, more stable and more bounded than sports equipment and materials. CT devices are usually only used for diagnostic and treatment purposes. More extreme uses can however occur in some organizations, which consequently widen the scope of the device' s use and therefore lead to problems and opportunities for solutions for both physicians and technicians. One example of more extreme use occurs in the context of very severe pathologies, especially in teaching hospitals where severe cases are referred to. Another is that CT scanners can also be used for explorative purposes when physicians are involved in R&D tasks for academic purposes, for device suppliers or for pharmaceutical companies. This wider exploitation and exploration of CT scanners is likely to induce some unplanned, unbudgeted and bootlegged user innovations, on the technology side and/or the complement side.
User innovation with CT scanners may not only depend on the kind of extreme tasks being asked of the machine but also on the associated costs of implementing these tasks. Users must cope with a wider range of problems and be able to adapt to this breadth of activities which actively keeping costs low. A larger task range should therefore foster user innovation focusing on increasing integration of modularity of machines, with the aim of lowering the switching costs between tasks.
The role played by the specific user context is not given great consideration in econometric studies on user innovation. Once more, Luthje at al. (2006) were the only one to control for the role of the context in the UI process. The authors measured whether bikes were used in races or in extreme outside conditions and the influences of these two context variables on UI. Once more, they found that user experience in extreme environments significantly increases the probability that users will develop a prototype.
With this in mind, we propose a third hypothesis:

H3: A wider range of machine use is more likely to induce UI

2.2 Slack and user innovation

Slack is often acknowledged as a trigger for innovation (Cyert and March, 1963; Nohria and Gulati, 1996; Ahuja et al., 2008; Laursen, 2012). Resource slack is positively linked to innovation because it introduces decentralization and delegation in organizations: for example, slack resources are used in a decentralized way by employees who can identify opportunity and have the technical knowledge to improve or invent a new process, a product or a service. Furthermore, slack allows explorative research in firms which tend to focus on the exploitation of technologies and practices (Levinthal and March, 1991). Slack allows employees to imagine and develop more radical and uncertain solutions that would not be tolerated by regular budgeting decisions (Bourgeois, 1981; Nohria and Gulati, 1996). In addition, creative people are more likely to innovate freely when they are autonomous (Cyert and March, 1963; Nohria and Gulati, 1996) and do not fear that their tentative investigations will put the team or the firm in danger (See Morrison *et al*., 2000). Finally, slack may alleviate unproductive tensions between units or people competing for the same resources, especially during organizational change (Cyert and March, 1963; Huang and Chen, 2010).
Two main arguments mitigate the enthusiasm for slack (Jensen, 1986). The first is that with risk averse employees, slack can be considered as the opportunity to lower risky activities and thus lower efforts in experimentation inside firms. Slack may thus boost inventive activities but deter radical innovation projects, as on minor technological problems or projects are focused upon. Another problem is that beyond the risk associated with the degree of novelty, employees' self-interests may not be aligned with the firms' strategy. Consequently costly projects unduly adopted and maintained may lead to lower returns.
In the literature, scholars usually conciliate the two sides explaining that slack has an inverted U shape relationship with innovation: the positive effect of slack on firms or on individuals does exist but leads

to decreasing returns and even become negatives at a threshold point (Nohria and Gulati, 1996). On the left side of the curve, the literature agrees on a positive slope: recent developments in incentive design show that firms should tolerate slack and failure in order to promote experiments by employees (See Ederer and Manso, 2013). On the right side of the curve, some consensus also emerges regarding the negative slope: even without opportunism or risk averse behavior some scholars working on problem-based research recognize that individuals tend to be biased toward local solutions when facing a problem and thus may not go beyond incremental solutions based on existing knowledge. Consequently, they do not need a lot of slack (Levinthal and March, 1993; Stuart and Podolny, 1996). Whereas some slack can help for exploration, additional slack may be required but also face sharp decreasing returns and finally hamper the achievement of radical innovation.

Whereas the positive role of slack transformed slack into a Human Resources Management practice in some successful companies (Google, 3M), econometric studies fail to provide clear results on the causality or the inverted U shape of the relationship. Instead, some statistical studies support the idea that slack promotes innovation research (Singh, 1986; Herold et al., 2006; Sidhu et al., 2007; Chen et al., 2012; Li et al., 2013; Troilo et al., 2014). The popular inverted U curve linking innovation value and slack was found by Nohria and Gulati (1996). However, in many other cases, the relationship was not found to be significant (Zajac *et al.,* 1991; Greve, 2003; Salge, 2012; Salge, 2013) or even negative (Voss *et al.,* 2008; Criscuolo *et al.,* 2014). The lack of consensus may be the result of the contradictory effects induced by a mixture of different slacks, and the context in which slack is measured. When disentangled into different types of slacks, evidences is still mixed: Singh (1986), for example, found a positive effect but for absorbed slack only; Voss et al. (2008) found a negative effect, and others found no significant differences between the different slacks (Greve, 2003).

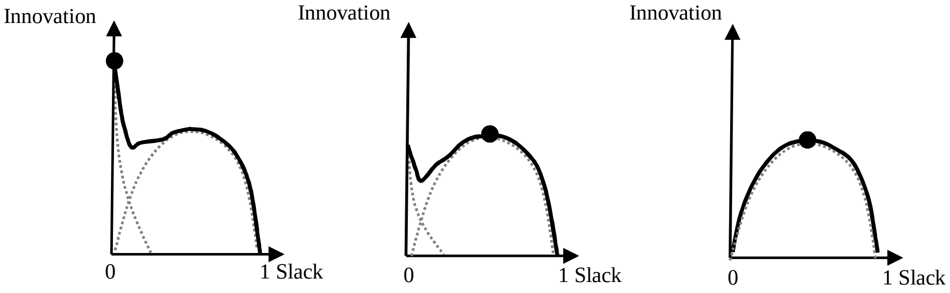
To date, the positive role of resource slack is mentioned only in Morrison et al. (2000) and Schweisfurth and Raasch (2015) who emphasized the role of time slack or leisure, but neither measured or introduced slack as a determinant of user innovation. Resource slack should however be an efficient moderator because users' rewards are mainly non-monetary, are based on the use of their own inventions (von Hippel 1988; Lüthje et al., 2005), and rely on users' own interest at solving and creating things (Lakhani and Wolf, 2005; Franke et al., 2010).

Users with limited and fixed resources are also probably more likely to fail at attaining their aspiration level of performance and are the ones more likely to take risks and implement problem-based research to find solutions and alternatives (à la Cyert and March, 1963). The role of necessity, adversity and resource scarcity as drivers of "bricolage" and invention is detailed in other strands of the literature (see Cyert and March, 1963; Greve, 2003; Baker and Nelson, 2005; Sonenshein, 2014; Weiss et al., 2014; Pina e Cunha et al., 2014) and can also apply to instrument and machine users who are overwhelmed with tasks and search for solutions or alternatives to alleviate their burden, even if they cannot develop them right away.

User research and R&D activities, therefore rely on two antagonistic drivers of technological change: on one left side of the curve we have resource scarcity and perceived instrument problems stimulating users' ideation and development of inventions. On the other side similar cognitive research can be obtained using slack resources (Cyert and March, 1963). Assuming that a similar time horizon for problematic research and slack-based research is perceived by users working with instruments, we contend that the two rationales are not antagonistic and can be integrated, if we suppose that scarcity is simply a lack of slack: the degree of slack induces the traditional U-inverted shape curve for innovation due to the decreasing returns from slack-based research; a null or very small level of slack also encourages users to undertake research with sharp decreasing returns. The influence of slack on user innovation is then the sum of a possible convex left part (scarcity sourcing) and a concave right part (slack sourcing).

In this case, the optimal slack level adopted by firms can be either the absence of slack if scarcity-based research is a dominant strategy (Case (a) in Figure 1), or an intermediate level of slack if slack-based research is dominant (Case (b)). The traditional inverted U shape (case (c)) thus becomes a particular case where scarcity plays no role in cognitive activities. Accordingly, managers can deal with temporary slack (e.g., 3M or Google) and switch between the two modes of search (scarcity and slack) in order to benefit from the two sources of research over time. Even without managerial influence, we believe that users may never stop their research and just adapt it when faced with ephemeral slack.

Figure 1: The role of scarcity research in the shape of the slack curve



(a) High scarcity sourcing (b) High scarcity sourcing (c) No scarcity sourcing

The influence of slack may also affect complementary research activities that are interdependent on user innovation achieved on objects. Case studies on user innovation suggested a positive complementary effect, in the sense that user innovation on one component will foster innovation on other components (Hinsch et al., 2014; Hyysalo, 2009; Hienerth, 2015). Some inquiries were made on the complementarity between technology and related technique or components. The complementarity among outputs is however not incompatible with some arbitrage between user innovation ideas and projects, that can be done by users in front of scarcity or even in front of slack. When a component (e.g. a machine) can be too difficult or too costly to improve, users may choose to focus on its complements (e.g. technique, intermediate goods) that can be improved at lower costs. Innovation on these components can then lead to a certain degree of user innovation on the initial component. Despite some possible substitution between researches or differences in magnitudes, and the lack of information about the relative rate of returns among innovations expected by users, the impact of scarcity and slack on the complement components of a technology may follow the same patterns (depicted in Figure 1) as the influence of scarcity and slack on technology.
We thus propose a final hypothesis:

H4: The relationship between slack and user innovation is a horizontal S shaped curve

3 Data and methods

3.1 Survey data

We explore the determinants of user innovation focusing on Swiss medical organizations using CT scanners. Four different sources of information were used.
Our main source is a self-administered written questionnaire mailed to all Swiss centers equipped with CT scanners, based on the full list of federal licenses granted in Switzerland[1]. The questionnaire was sent in February 2009 by a polling institute on behalf of the EPFL and the University of Lausanne. Centers which did not reply within one month were sent a reminder. Follow-up phone calls attempted to persuade non-respondents to fill in questionnaires. The study ended in mid-May 2009 after a second round of follow-up phone calls had been carried out. The two-page questionnaire was designed by the

[1] As we could not collect information from centers which closed after a CT license had been granted, the current analysis controls for any potential selection bias

authors[2]. It was tested using interviews with radiologists and staff in charge of purchasing imaging equipment in hospitals.

The questionnaire inquired about the historical CT scanner portfolio within health care units, scanner rates of utilization and any R&D activities using CT scanners. The identification of devices encompassed the number of slices in the device, the year of installation, the year of removal and the type of contract (leasing contract or not) with the supplier. The questionnaire also asked whether the CT center had thought of modifying or developing a new CT-related product, technique or related component during the 1998-2007 period. Finally, some focused on impediments faced by those who used CT scanners for research.

As of early 2009, 269 CT devices out of the 343 CT scanners installed since 1983 were in operation throughout Switzerland in a total of 186 health care centers with imaging facilities. Of the 186 facilities contacted and mailed a questionnaire, 126 answered, representing a response rate of 68%. Ten per cent of the centers explicitly refused to fill in the questionnaire while the remaining 22% promised to send the questionnaire back but never did so despite various follow-up phone calls. The total number of active CT devices in 2009 throughout the 126 facilities was 189 (i.e. 70% of total active CT scanners in Switzerland in 2009). These 126 facilities had also dismounted 65 CT scanners over time and so had had experience with a total of 254 CT scanners (74% of total CT scanners installed in Switzerland since 1983). We deleted one respondent from our sample as their CT scanner was entirely used for R&D purposes and was therefore considered an outlier. The final number of health care organizations therefore equaled 125.

We used three additional sources of data. For each center, the experience variable was computed based on the full list of federal licenses granted in Switzerland since the introduction of these technologies. This was provided to the authors by the Federal Office of Public Health. For each device we were able to compute the number of days during which each CT device was actually in operation thanks to the availability of installation and withdrawal dates (for withdrawn devices). The number of employees and medical employees were publicly available from Hospital administrative data for year 2007 and published by the Federal Office of Public Health. Finally, we matched our medical organizations with the publications listed in Scopus in order to identify medical organizations that are involved in academic research.

3.2 Variables

In our questionnaire, using yes/no questions, users' potential ideas and invention achievements were investigated in terms of technologies (e.g. a change in software, hardware), usage patterns (e.g. developing new protocols for device use, introducing new diagnostic tests), complementary goods (e.g. intermediate goods such as radioisotopes), equipment (e.g. robots) and services (e.g. monitoring). In order to reduce categories, we aggregated user innovations in hardware and software into a "technology" category, while innovations in the development of new protocols, and the different intermediate products, instruments and services surrounding the technological device were aggregated into a "complement" category. We thus defined two dichotomous variables equal to the value 1 when the respondent declared some user innovation (ideas or achievement) were introduced over the previous 10 years either in the CT technology (*Technology UI*=1, 0 otherwise) or in the complements to CT scanners (*Complement UI=1*, 0 otherwise).

With respect to the explanatory variable, we first counted the number of full time equivalent years the health care organization had worked with CT scanners. The *Experience* variable was computed for every organization by summing years of every CT device installed in the organization over time. We thus took into account in the Experience computation, the end of life of CTs and not simply le time after the installation of CT scanners.

We also characterized users experience by the timing of the CT scanner adoption. Early users were those who were among the first to adopt a CT scanner or the first to adopt a particular generation of CT scanners. In our data we noted the date of installation of the first CT scanner, as well as the scanners

[2] We gratefully acknowledge Eric Von Hippel and Harold Demonaco for their precious advice on the study questionnaire.

still in use in 2008. We first define early users considering the organizations who were the first to install CT scanners. We set *First_CT* to 1 when an organization adopted its first CT scanner between 1988 and 1997, and 0 when the adoption occurred afterward. A second variable considers the end of the observed period in order to identify organizations who first adopted a CT scanner with 64 slices or more (128 and 256 at the time of the survey) after 2001. An additional dichotomic variable *Early_CT64* is set to 1 when the firm was running a CT scanner with 64 slices or more in 2008. The last adoption variable identifies users who greatly improved their image precision. Indeed, scanners with 64 or more slices provide different opportunities for users which previous increases the number of slices did not. We can then set our dichotomic variable *Early* to 1 when an organization was historically the first to introduce CT scanners in Switzerland and, at the same time, was the first to adopt scanners with at least 64 slices (*Early* = *First_CT* x *Early_CT64)*. In the case of recent large medical imaging devices such as CT scanners, PET scanners and MRI systems we consider that Swiss early adopters implemented the technology shortly after its development, although in fact CT scanner adoption started in Switzerland after their introduction in the USA (See Martin and Mitchell, 1998). Furthermore the evolution of CT scanners was not linear, and the introduction in 2001 of CT scanners with 64 slices can be considered a major improvement compared with previous CT editions. The early adopters of CT scanners with 64 slices are thus expected to be even more prone to innovate than other users. Considering that very few organizations existed in the 1990s, the Early variable thus aims at identifying organizations that have always been early users over time: at the beginning of the 90s but also in the middles of the 00' s. These organizations are presumably the same that were the first to install the intermediate CT vintages (with 4, 16, 32 or 40 slices)[3].

Note that we do not observe users' technical expertise but only their experience with CT scanners despite technical knowledge of users being an important driver of UI (Jeppesen and Lakhani 2010; Franke et al., 2005; Luthje et al., 2006). We believe that the missing explanatory variable is not a major problem here in the context of medical organizations where technical knowledge should be much more similar among physicians than between sport material users on which previous results were based.

After Voss et al. (2008) or Salge (2013), we approximate slack on the operational side with the non-utilization rate of CT scanners declared by respondents. The declared *Slack* variable includes long term resource slack as well as ephemeral slack data? available for CT (Georges, 2005). Our variable thus includes time-related slack due to cancellations, cyclical or seasonal patient examinations, or for reasons of maintenance. We also define the quadratic and cubic variables, respectively $Slack^2$ and $Slack^3$ in order to test the shape the influence of slack on Technology and Complement UI probabilities.

Compared with other instruments or machines, CT scanners are almost exclusively used for applied medical analysis. Still, some differences in the context of use can exist that are likely to influence the way the device is used and improved. CT scanners are likely to be used in extreme cases likely to influence the invention rate of users. We therefore identified organizations investing in R&D. At the CT level, *R&D activity* is the declared percentage of time the installed CT scanners were used for R&D purposes. At the organizational level, we defined a further dichotomic variable *Publication* that was set to 1 when the organization had published at least one academic article over the previous 10 years (From 1998 to 2007) in a journal referenced in Scopus.

As one common strategy adopted by suppliers is to rent CT scanners (leasing contracts) in order to alleviate the financial burden for adopters, to limit the threat of a second-hand market, and to increase the currently low-profit margin generated by the sales of medical imaging devices (Arthur D Little, 2005) especially sales including maintenance contracts. *Leasing* (set to 1 when at least one CT scanner was leased, 0 otherwise) may decrease the incentive for users to innovate as the direct benefit they will derive from their inventions is more likely to vanish when the device is upgraded or replaced. Indeed modification may even be even forbidden in contractual provisions.

We further consider that differences in governance exist depending on whether the organization is "for-profit" or "not-for-profit" in nature. Motives of users and incentives can be different among different types of firms and the motives can influence the propensity to innovate. It may be easier for users to develop ideas in private companies (Bysted & Jespersen, 2014). The way slack is used can be different

[3] The search for all the necessary administrative files is in progress.

in private firms (George, 2005). Furthermore, more sever health cases in Switzerland are likely to be referred to public hospitals, and especially teaching hospitals. In other words, some public hospitals may use CT scanners in more extreme cases than private facilities. *For-Profit* is thus a dichotomic variable set to 1 for private practices and for-profit organizations.
Finally, we control for size, calculating the number of employees working in the organization. In order to avoid collinearity with the *Experience* variable, we define three dummies *Size_1* encompasses firms with fewer than 6 employees. *Size_2* with a number of employees between 5 and 99, and *Size_3* organizations with over 100 employees. The first category is actually the category of imaging private facilities and is used as a reference in our econometric model.

3.3 Econometrics

In order to explain the likelihood of user innovation, we implement a bivariate probit model. As already mentioned, the technology and components are interdependent. To take into account the potential strategic interactions between a user' s decision to innovate in thetechnology or in its complement, we implemented a bivariate probit model where slack and experience influenced the different probability to achieve user innovation. The correlation among residuals controls for complementarity, independence or substitutability among the different types of user innovations by firms (Gourieroux, 2000). The multivariate model is identified using the Geweke-Hajivassiliou-Keane (GHK) simulator to evaluate the integrals in the likelihood function. Partial effects in a bivariate probit model have to be computed considering the expected value of one user innovation given that all other user innovations equal one. For example, the expected value of Technology UI given that all other UI are equal to one is $E_{\text{Technology UI}}$(Technology UI=1 / Complement UI=1). The derivative of the expected value with respect to the explanatory variables ($\delta_{\text{ETechnology}}$ UI / δ x) is computed as the weighted average of the effects calculated in each observation and combined across the multiple imputations. One problem with this is that it is not very interesting to test H4, when computed only at the mean (taking into account the derivative for Slack^2 and Slack^3 at the mean). We thus compute the derivative for Slack for the different values of Slack in order to be able to accurately comment on the shape of the curve. For-profit is correlated with size indicators and induces some collinearity problems. We left both variables in our final model despite the rise of standard errors because they did not change the results on our variables of interest.

4 Results

4.1 Descriptive statistics

In Switzerland, the number of CT scanners increased during the 1990s with a surge at the end. The number then stagnated until the mid-2000s, as shown by Graph 1 (administrative data). At the end of the 1990s, some CT scanners were old and also a new generation of CT scanners with 4 slices was introduced. The next surge came in 2004-2005 with the adoption of the next generation with 16 slices but also with some potential leapfrogging due to the availability of 64-slice CT scanners. Each new generation is thus an improvement on the previous one and is more widely adopted. One original feature is the qualitative improvement coming from the latest generation of CT scanners with 64 slices, as already mentioned. However, scanners from previous generations may persist because they seem perfectly suited to a variety of examinations: as shown in Table 1, approximately 12 CT scanners with a single slice and adopted during the 1990s were still operational in 2008. Several firms still invested in 2 or 4 slice scanners after 2004 when other organizations were already adopting 16 or even 64-slice devices.

INSERT Graph 1 here

INSERT Table 1 here

The table of descriptive statistics (Table 2) reports that 52% of the organizations included in the study declared themselves to be innovative users - where innovation was defined as innovation in technology, in protocols, in the scope of product use, in related goods and services, and in hardware or software. More precisely, the same table highlights that 51% of users had changed protocols or other complements to CT technology over the previous 10 years. Software and hardware innovations both represented together only 26% of cases, suggesting it is harder to modify technology than the CT-related techniques and components. The correlation between user innovation based on technology and user innovation on complements is very high, since almost every user-innovator declaring an innovation on technology is also an innovator on components.

Table 2 reports that user-innovators accumulated full-time equivalent experience with CT scanners of more than 15 years, whereas experience dropped to less than 13 years for non-innovators. A similar dominance was found for Slack: one third of time available where available on CT for users and only 28% for non-innovators. R&D intensity at 2% for innovators was higher than for non-innovators who declared no R&D activity. UI is more likely to occur in for-profit organizations, private facilities or large hospitals rather than medium-sized facilities. However, due to the restricted number of observations, these differences between means are not found significant at 10% using a two tailed t-test. According to Table 2, innovators do not adopt CT scanners earlier than user non-innovators. A significant difference was found regarding publications: 34% of user-innovators had published whereas 42% had not.

INSERT Table 2 here

Table 2 further reports the differences between Technology UI and non-Technology UI (Col. (4) vs col. (5)). Technology UI seems to require more experience, and occurs when more R&D is performed in smaller and for-profit organizations with paid CT scanners. None of the differences between the means are significant however. Organizations involved in technology UI are less involved in academic research than organizations doing only Complement UI. The only significant difference between the two types of IU (Technology and Non-technology) is that slack is smaller for technology UI than for complement UI, suggesting that many organizations invested in scarcity-based research to achieve technology UI whereas Table 2 suggests that the Time slack available for users on CT scanners is determinant to invent new complements.

4.2 Econometric results

We used a bivariate probit model to explain the probability of being a user innovator on technology and on complements. Results are reported in Table 3. In order to explore the shape of the relationship between UI and slack, we first introduce a linear form (Columns 1a and 1b) and a third order term (Col. 2a and 2b). We then propose a final specification (Col.3a and 3b). We do not report the results obtained with the specification with slack squared where neither slack parameter is significant (results available upon request).

The results reported in Table 3 confirm the positive role of device experience on UI for both the technology and complement dimensions. The marginal effect computed for the former shows that at the sample mean, each additional year of experience with a CT scanner increases the probability that users to invent by +0.6%. The marginal effect is low and relatively stable over the range of possible values. This suggests that, starting with 5 years of experience and a probability for users to innovate in technology of 20%, the organization has to accumulate approximately 35 years of equivalent experience on CT scanners to reach a 40% probability that users will innovate. One additional year of experience is more likely to induce Complement UI with a marginal effect of +1.0%. This result therefore supports our first hypothesis (H1). The coefficient for early adopters is negative but not significantly so. This suggests that early adopters are not the only ones doing UI. To some extent, late adopters can thus strike back in UI with an experience acquired rapidly thanks to the simultaneous use of several CT scanners. We thus find little support for H2.

INSERT Table 3 here

As reported in column (1a) and (1b) in Table 3, R&D activities positively impact the probability of Technology UI or Complement UI. In the latter case, the probability rises to 12% in the final specification (Column (3b) in Table 3). In the former, this confirms that inventions on CT technology by users are more the result of extreme or new working contexts. A 1% increase in CT scanner use dedicated to R&D activities increases the probability of technology UI by 1%. R&D activities are costly but constitute a faster means than experience to promote Technology UI in organizations. This conclusion is however counterbalanced by the objectives of R&D. Organizations involved in academic publication activities are less likely to achieve technology UI. A partial effect of -0.40 suggests a decrease of 40% in the probability of Technology UI for a publishing organization. This suggests a possible tradeoff between user innovation and academic research performed by users. Publication activities do not significantly hamper inventions on CT scanner complements. Our results confirm that the context of use of machines (in our case CT scanners) influences the probability of searching for new technological improvements (H3), and the positive role of extreme uses (R&D here). Furthermore, our findings also suggest that resources are limited in this case and that organizations seldom succeed in achieving technology UI and academic output simultaneously.

The relationship between slack and UI is linear when the probability to innovate in technology complements is considered (Col. 3b in Table 3). The marginal effect computed at the mean is 0.56, indicating that an additional slack of 1% leads to an increase in the probability of users innovating complements by +0.6%. The shape of the relationship is however more complex for Technology UI when non-linearities are found. The signs of the coefficient suggest an S curve with negative coefficients for Slack and Slack^3 , whereas a positive coefficient is found for Slack^2. Still, the S curve must be observed between the value 0 and 1 of slack if we are not to reject H4. In order to characterize the shape more precisely, we computed the marginal effects for Slack not at the mean as in Table 3 but for every value between 0 and 1 (with a gap of 10%). Since the probit model is non-linear, we have to manually compute the marginal effect as the combination of the marginal effects of Slack, Slack^2 and Slack^3, computed for the different Slack values. Our results are reported in Table 4 and show that the likelihood that organizations with no slack for their CT scanners will innovate in technology decreases by -8% if they augment slack by 1%. This decrease will continue as long as Slack is lower than 23%. Slack higher than 23% will increase the probability that users will innovate in technology until slack reaches approximately 56%. Beyond this value, additional slack again hampers UI.

INSERT Table 4 here

INSERT Graph 2 here

These results are therefore in line with our theory that user innovation relies on a dual system, either based on resource scarcity or on resource slack (H4). When comparing the impact of slack on both types of UI, it is clear that it is a driver for the Component dimension. Hence, the dual mode of research is a hypothesis that is not confirmed for Complement UI.

Managers should however be careful when they intend to adopt Technology UI because incorporating a slack policy is more complex, and the arbitrage between slack for Technology and slack for Components is not always clear. Our result suggests that the two positive effects on UI co-occur when slack ratio is between 23% and 56%. A more precise look reveals that more slack is more efficient for Technology UI than for Complement UI when slack is between 30% and 40%. An organization with a slack level optimized for Technology UI should thus tolerate a slack up to 56%. However, assuming that returns are similar between Technology UI and Component UI, an organization should tolerate an even higher slack level to the point where the sum of the gain obtained on Complement UI is not canceled by the loss due to excessive slack for Technology UI. Hence, in our opinion, organizations with a Slack research regime should boost slack to 58 or 59%. An alternative is to keep physicians overwhelmed with work in order to foster Technology UI thanks to a scarcity-based search regime.

For-profit organizations are not significantly more prone to UI. Neither is size a relevant driver for UI. When CT scanners are installed with a leasing contract, Technology UI is lower , but not significantly so, when controlling for for-profit organizations and size at the same time. Leasing never influences the probability of UI on complements.

The correlation among residuals is positive and significant, confirming the suggestion that the two types of user innovations are positively interdependent.

Finally, we tested the robustness of our results (available upon request). The lack of results on the *Early variable* was found robust when we used instead First_CT or Early_CT64 variables. We further removed the five teaching hospitals from our sample since these constitute outliers in terms of size and experience with CT scanners. The results did not change except for the *Experience* coefficient which was still positive but no longer significant. We also tested possible cross effects between Early and Experience and then between slack and experience. In both cases, non-significant effects were observed for Technology UI. Furthermore, in both cases, negative and significant parameters were found for Complement UI. These results suggest that laggards do better than other firms with a similar level of experience. They also suggest that experience and slack are substitutes when Complement UI is targeted. Finally, the results did not change when we introduced the different hampering factors we asked about in our questionnaire.

5 Conclusion

Using a survey specifically designed for users of CT scanners and complementary administrative data on medical organizations with CT scanners, we propose an econometric model investigating different determinants of user innovation. The impact of experience, early adopters, context and slack on Technology user innovation, and on related component user innovations is explored. A bivariate probit model shows a positive impact of experience either on technology UI or on complement UI. Early adopters of CT scanners are not more likely to implement UI. The way machines are used also matters: our results show that R&D activities in CT scanners likely foster technology UI, provided that they are not directed toward academic publications. The way the machine is used does not seem however to influence UI on complements. Slack is found to be a driver for complement UI whereas scarcity and a high level of slack are found to be dual solutions to achieving UI on CT scanner hardware and software. Our results are robust even though the sample size limits the precision of our results.

Our article is not without its limitations. First of all, our model is cross-sectional. It thus cannot truly reflect the dynamic of innovative research. Our results suggest that firms can switch from one type of research to another. When large devices are considered, an additional machine can introduce some slack for users and in turn introduce a switch from a scarcity-based research system to a slack-based one. We do not observe this change in research strategy over time. Despite knowing the dates of installation of the different CT scanners, it would be very difficult and costly to measure the innovation outputs derived over time from the two successive research modes and thus to build panel data. Furthermore, we controlled for the complementarity between the different types of user innovation. Panel data would be thus helpful to identify more precisely the causal links between the different types of user innovation: to what extent technology influences technique and vice-versa, and whether there is a coevolution or a cycle between the two types of user innovations.

Another primary limitation is the endogeneity of Slack. We observed the variable on the living set of CT scanners, yet the utilization rate can be modified by user innovation. The introduction of UI can increase the machine slack or improve efficiency such that the utilization rate increases. In a cross-section study, the opportunity to control for such an endogeneity problem is difficult. Another related limitation is that we only controlled for some operational slack with machines, when other types of slack can also interact and influence the ability of organizations to achieve UI. In particular, human capital slack or financial slack can play a role, something that we partly but not completely controlled for with the For-profit, Size and Publication variables. Furthermore, we did not measure the network slack needed by users or their organizations to access external complementary resources and competencies.

A final caveat is the lack of a selection equation. Some bias may arise from the fact that among the 187 medical organizations with CT scanners, user innovators or some types of user innovators were more prone to respond to our questionnaire. Continued collection of information should allow us to add such an equation in a future revision of the work in the present article.

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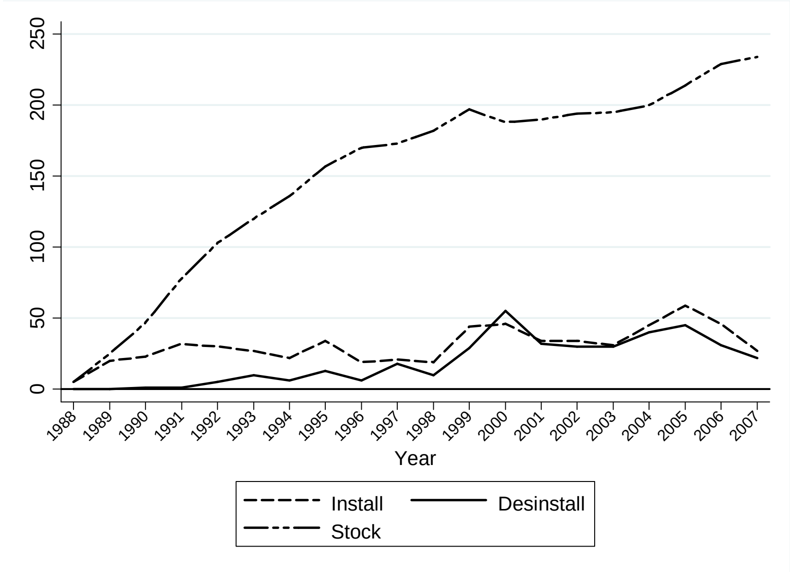
Graph 1: The stock of active CT scanners in Switzerland, since 1988



Data source: OFSP, N= 210 organizations with a CT scanner over time, 186 in 2008

Table 1 : Declared number of CT scanners active in 2008, by year of installation and number of slices

Year Slices	91	92	94	95	96	97	98	99	00	01	02	03	04	05	06	07	08	Total
1	1	1	1	2	2	2	1	1	1									12
2							1			1	2	2			2			8
4				1			1		5	3	3	3		4		2		22
6														2			1	3
12															1			1
16									1		4	4	8	12	4	7	1	41
32											1			1	1	2		5
40														1	1	4	2	8
64										1			2	8	6	4	8	29
128																1	1	2
Total	1	1	1	3	2	2	3	1	7	5	10	9	10	28	15	20	13	131

Data source: authors' survey, N=125, The number of slices is known for 131 out of 189 active CT scanners

Table 2: Descriptive Statistics

	All				UI=0		UI=1					
							All		Techno UI=0		Techno UI=1	
N	125				60		65		32		33	
Col.	(1)=(2)+(3)				(2)		(3)=(4)+(5)		(4)		(5)	
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
UI	0.52	0.50	0	1	-	-	1.00	-	1.00	-	1.00	-
Technology UI	0.26	0.44	0	1	-	-	0.51	0.50	0.00	-	1.00	-
Complement UI	0.51	0.50	0	1	-	-	0.98	0.12	1.00	-	0.97	0.17
Experience	14.03	10.84	0.56	61.74	12.74	8.27	15.22	12.71	13.26	11.65	17.12	13.58
Early	0.26	0.44	0	1	0.25	0.44	0.26	0.44	0.25	0.44	0.27	0.45
Slack	0.31	0.25	0	0.95	0.28	0.21	0.34	0.28	0.41	0.32	0.27**	0.22
Slack^2	0.16	0.21	0	0.90	0.12	0.15	0.19*	0.26	0.27	0.32	0.12**	0.15
Slack^3	0.10	0.19	0	0.86	0.06	0.10	0.13**	0.23	0.20	0.30	0.06**	0.11
R&D	0.01	0.06	0	0.60	0.00	0.01	0.02	0.08	0.01	0.01	0.04	0.11
Publication	0.38	0.49	0	1	0.42	0.50	0.34*	0.48	0.38	0.49	0.30	0.47
Size_1	0.40	0.49	0	1	0.37	0.49	0.43	0.50	0.44	0.50	0.42	0.50
Size_2	0.35	0.48	0	1	0.42	0.50	0.29	0.46	0.25	0.44	0.33	0.48
Size_3	0.25	0.43	0	1	0.22	0.42	0.28	0.45	0.31	0.47	0.24	0.44
For-profit	0.53	0.50	0	1	0.50	0.50	0.55	0.50	0.53	0.51	0.58	0.50
Leasing	0.26	0.44	0	1	0.25	0.44	0.26	0.44	0.31	0.47	0.21	0.42

Note: ** p<0.05, * p<0.1 ; t-test on the different between col. (2) and (3) and between col. (4) and (5) are reported in col. (3) and (5) respectively.

Table 3: Econometric results

	(1a) Techno	(1b) Comp	(2a) Techno	(2b) Comp	(3a) Techno		(3b) Comp	
	coef/(t)	coef/(t)	coef/(t)	coef/(t)	coef/(t)	Partial effects	coef/(t)	Partial effects
Experience	0.026*	0.028*	0.026*	0.028*	0.025*	0.006	0.028*	0.010
	(1.900)	(1.808)	(1.899)	(1.822)	(1.701)		(1.693)	
Early adopt.[d]	-0.419	0.000	-0.403	0.020	-0.323		-0.017	
	(-1.338)	(0.001)	(-1.282)	(0.066)	(-0.963)		(-0.054)	
Slack	-0.713	1.567***	-1.683	0.660	-6.339**	-4.112	1.576***	0.560
	(-1.330)	(3.065)	(-1.126)	(0.451)	(-2.319)		(2.629)	
$Slack^2$			1.169	1.058	21.593**	12.896		
			(0.772)	(0.711)	(2.446)			
$Slack^3$					-18.564**	-11.221		
					(-2.562)			
R&D	10.558**	17.116*	10.332**	17.070*	10.508***	0.958	16.493	
	(2.556)	(1.759)	(2.433)	(1.753)	(2.626)		(1.575)	
Publication[d]	-0.760**	-0.228	-0.805**	-0.267	-0.885***	-0.405	-0.251	
	(-2.409)	(-0.743)	(-2.521)	(-0.859)	(-2.728)		(-0.824)	
Size_2[d]	0.150	-0.038	0.182	-0.008	0.100		-0.067	
	(0.368)	(-0.093)	(0.439)	(-0.021)	(0.236)		(-0.162)	
Size_3[d]	0.330	0.493	0.290	0.458	0.235		0.505	
	(0.614)	(0.930)	(0.529)	(0.852)	(0.364)		(0.884)	
For-profit[d]	0.329	0.336	0.299	0.305	0.356		0.281	
	(0.876)	(0.894)	(0.774)	(0.791)	(0.783)		(0.676)	
Leasing[d]	-0.187	0.108	-0.188	0.113	-0.433		0.121	
	(-0.653)	(0.378)	(-0.641)	(0.387)	(-1.252)		(0.394)	
Log-Likelihood	-118.07		-117.82		-114.03			
H_0: ρ=0 (LR test)	7.16***		24.80***		86.85***			

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ [d] Dichotomic variable

Bivariate probit model. For model (3), he partial effects are $\frac{\partial Prob(Techno\ UI=1|Comp\ UI=1,x)}{\partial Slack}$ and computed only for model (3) computed at the mean for significant coefficient only.

Table 4: Computation of partial effects for the non-linear function of slack

Slack values	$\frac{\partial Prob(Techno\ UI = 1 \mid Comp\ UI = 1, x)}{\partial Slack}$	$\frac{\partial Prob(Techno\ UI = 1 \mid Comp\ UI = 1, x)}{\partial Slack^2}$	$\frac{\partial Prob(Techno\ UI = 1 \mid Comp\ UI = 1, x)}{\partial Slack^3}$	*Partial effects*
0	-8.446	24.258	-21.108	-8.44
0.1	-5.202	15.888	-13.825	-2.44
0.2	-4.048	12.635	-10.994	-0.31
0.3	-3.961	12.450	-10.833	0.58
0.4	-4.168	13.106	-11.404	0.84
0.5	-4.190	13.197	-11.483	0.39
0.6	-3.908	12.459	-10.841	-0.67
0.7	-3.256	10.650	-9.267	-1.97
0.8	-1.797	6.053	-5.267	-2.22
0.9	-0.244	0.842	-0.733	-0.51
1	-0.0008597	0.00299	-0.0026	-0.003

The marginal effect in the last column is computed as the following for the different values of slacks, with all other variables at the mean. The relationship between the columns is:

$$\delta(\text{Slack}) = \frac{\partial Prob(Techno\ UI = 1 \mid Comp\ UI = 1, x)}{\partial Slack} + 2Slack\,\frac{\partial Prob(Techno\ UI = 1 \mid Comp\ UI = 1, x)}{\partial Slack^2} + 3Slack^2\,\frac{\partial Prob(Techno\ UI = 1 \mid Comp\ UI = 1, x)}{\partial Slack^3}$$

Graph 2: Partial effects for Slack, per UI type and at different Slack values