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Characterizing Award-winning Inventors: The role of Experience Diversity and Recombinant Ability

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Abstract

This paper investigates inventor-level characteristics promoting novel inventive effort. Inspired by the literature on corporate-level technological search, we claim that inventors? experience diversity and recombinant ability play a pivotal role. Experience diversity refers to spread in technological domains an inventor engaged in during its career. Recombinant ability refers to the ability to make more novel or uncommon combinations across different knowledge fields. We test these relationships using a unique data set of 229 inventors that won an R&D100 Award for creating one of the most significant, new inventions of the year. Results show that both experience diversity and recombinant ability are positively related to the probability of being among the award winners. Moreover, the effect of recombinant ability is most outspoken among the inventors with high levels of experience diversity. These findings suggest that novel inventive effort can be the result of leveraging knowledge built up in different technological domains by connecting these domains in an unprecedented manner.

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ABSTRACT

This paper investigates inventor-level characteristics promoting novel inventive effort. Inspired by the literature on corporate-level technological search, we claim that inventors' experience diversity and recombinant ability play a pivotal role. Experience diversity refers to spread in technological domains an inventor engaged in during its career. Recombinant ability refers to the ability to make more novel or uncommon combinations across different knowledge fields. We test these relationships using a unique data set of 229 inventors that won an R&D100 Award for creating one of the most significant, new inventions of the year. Results show that both experience diversity and recombinant ability are positively related to the probability of being among the award winners. Moreover, the effect of recombinant ability is most outspoken among the inventors with high levels of experience diversity. These findings suggest that novel inventive effort can be the result of leveraging knowledge built up in different technological domains by connecting these domains in an unprecedented manner.

Keywords:

Inventor; experience; diversity; invention; novelty

INTRODUCTION

Technological progress is widely accepted to be a key source of free-market economic growth (Schumpeter, 1939; Baumol, 2004). Hence, scholars aim at a better understanding of how technological renewal unfolds. Dosi (1982) describes how technologies evolve along fairly predictable trajectories up until the point a paradigm shift launches a new technological trajectory. At this point, the new approach redefines the course of the trajectory and clears the way for potential leaps in performance. At the heart of such technological discontinuities are inventions that introduce a novel technological approach (Arthur, 2007, 2009). Understanding the mechanisms driving novel inventive effort is therefore crucial to policy makers, as well as managers.

Predominantly, existing research has focused on the origins and effects of this process at the level of the firm (see f.e. Ahuja & Lampert, 2001; Henderson, 1993). However, previous research has not fully disentangled novelty creation at the level of the individual inventor. It focuses on search strategies implemented by the firm and their effect on different dimensions of inventive performance (March, 1991; Ahuja & Lampert, 2001; Rosenkopf & Nerkar, 2001). Yet, the cognitive processes key to generating novelty are taking place at the level of the individual inventor, rather than at the level of an organizational unit. Hence, understanding which features allow inventors to generate different types of inventions, could open up the 'black box' of how potentially radical technological advancement unfolds. In particular, this study deals with the question of finding individual characteristics conducive to creating inventions that introduce a novel technological approach.

Given the relevance of the topic, remarkably few studies have investigated the potential sources of novelty generation at the level of the inventor. Authors linking individual characteristics with innovation outcomes have investigated the role of age, gender and education on inventive performance (Jones 2010; Jung & Ejermo 2013; Gruber et al., 2013). Only few studies have linked innovation outcomes to characteristics reflecting prior knowledge built up through experience of the inventors involved in the process. Conti et al (2013) shows that a larger stock of technological experience has a positive effect on the breakthrough rate of inventors, implying that more established inventors are more productive at generating inventions with high technological impact. Fleming et al. (2007) investigates the effect of collaborative brokerage (having direct ties to collaborators which do not have direct ties to each other) on inventive creativity and finds a positive effect of brokered collaborative structures on the creation of novel connections between technological fields. Moreover, they find a negative effect of brokered collaborative structures on the usage of the new ideas by others.

Present study contributes to the underexplored field of inventor characteristics and their innovative outcomes in three ways. First, we extend existing theory about how inventors' prior experience affects innovative outcomes by looking at the diversity of the accumulated experience and their ability to make unprecedented connections between fields of knowledge. Second, we focus on inventive efforts that introduce a novel approach to a certain problem. As such, we move away from general productivity measures that do not take into account the heterogeneity of research projects and outcomes that are typical for the R&D process (Trajtenberg et al., 1997). Third, to identify these novelty generating inventors, we use an external assessment of field experts provided by the 'R&D100 Awards'. In doing so, we go beyond using patent counts and/or citations to identify remarkable inventive output.

To build our hypotheses we rely on previous research on the evolution of technology. A large stream of literature has established that radical technological novelty arises through the recombination of knowledge from previously unconnected technological domains (e.g.: Hargadon, 1998; Fleming 2001, 2007; Arthur, 2007, 2009; Arts & Veugelers, 2014). Since technological knowledge is accumulated throughout the career of inventors by working with different technologies (Mascitelli, 2000), we expect the sum and nature of the collected knowledge (experience) to have an influence on the potential to create novel inventions. We argue that a diverse experience increases the range of knowledge fields an inventor can draw on and hypothesize that novelty generating inventors have higher levels of experience diversity. Moreover, we claim that an inventor's innate ability to handle the complexity of searching for and rearranging concepts in a novel way is reflected in its prior inventive effort. Hence, we argue that an increased level of recombinant ability in an inventor's prior effort increases the probability to generate novel inventions. Finally, we argue that inventors who leverage their broad experience through connecting previously disconnected technological knowledge, have an advantage in generating technologically novel inventions.

To verify our hypotheses, we collect patent data for a group of inventors who won an R&D100 award for having invented one of the most significant new technologies of the year. We compare the award-winners to a control group of inventors working in the same technological field during the period before the award. Experience diversity is operationalized by an Herfindahl-index of concentration of technological fields the inventor patented in (see Gruber et al., 2013). To proxy recombinant ability, we use the fraction of patents of the inventors in which they recombined technological fields for the first time in history (Fleming et al., 2007; Verhoeven et al., 2014). We estimate binary choice models predicting the probability to be among the award-winners and control for several measures that proxy general ability, working environment, field and timing of experience, as well as mobility and intensity of cooperation to address omitted variable bias.

Results show a positive effect of experience diversity and recombinant ability on the probability to be among the award-winners. Moreover, the relationship between recombinant ability and being among the award-winners seems to be most outspoken among the inventors with the broadest experience. In general, this study suggests that mainly inventors that are able to leverage their broad experience to connect hitherto unconnected fields of knowledge are at an advantage for generating technological novelty.

THEORETICAL BACKGROUND AND HYPOTHESES

Technological Novelty

The main interest of this study is to extend theory about which individual characteristics are conducive to generating technological novelty. To build up theory around this question, one needs a clear conceptualization of what technological novelty implies. Following the work of Arthur (2007, 2009) we define technology as being a means to fulfill some purpose. A technology embodies a principle and consists of components in an architecture that work in relation to each other to exploit the principles of working that meet the purpose at hand. Starting from this definition, one can define a particular technology as novel when it incorporates substantially different components and principles compared to previous technologies with the same purpose. As an example, Arthur describes how the turbojet engine introduced the concept of generating thrust by expelling particles to generate an opposite force to accelerate an airplane. This was a novel technological approach compared to typical propeller engines that generate a drag in order to drive the plane.

It is important to note that technological novelty and subsequent impact are two distinct concepts (Dahlin & Behrens, 2005). Many novel inventions with the potential to have radical impact, may not realize this potential. Moreover, since a truly novel approach or concept often times needs considerable refinements, the invention identified as impactful might not be the one having introduced the novelty, but rather one that builds further on previously introduced novelty. As such, one can distinguish between inventive effort leading to the creation of a truly novel technology, and 'standard engineering' activities where the technology is being refined. Because of this distinction, disentangling novelty from impact (or productivity) is particularly relevant to the identification of inventor characteristics in relation to different types of outcomes (see also Trajtenberg et al., 1997).

Inventive Processes Leading to Technological Novelty

A considerable number of studies have investigated sources of breakthrough creation by firms (e.g. Hargadon, 1998; Ahuja & Lampert, 2001; Rosenkopf & Nerkar, 2001; Fleming, 2001). In general, they investigate technological search strategies that might lead to inventions with high technological impact (as measured by being among the most highly cited patents). Although most of these studies solely focus on impact, the mechanisms underlying their findings, often times include the introduction of considerable novelty. Fleming (2001) shows that experimentation with unfamiliar components leads to lower average technological success, but increases the probability of high impact. Ahuja & Lampert (2001) advise large firms to overcome three 'familiarity traps' in order to be able to generate breakthroughs. Rosenkopf & Nerkar (2001) stress the importance of spanning the boundaries of knowledge in existence of the firm. Hargadon (1998) shows how technological knowledge brokerage can be a source of important inventions.

Findings of firm-level research about breakthrough generation stress the crucial importance of technological search. While searching within the boundaries of what firms know is believed to lead to inventions from an incremental nature, searching outside of what is already known is conducive to more novel inventive effort and breakthrough generation. We rely on these insights to characterize the inventive process leading to novel inventive effort. The work of Arthur (2007,

2009) proves to be a particularly relevant framework in this respect. He characterizes invention as a recursive process which starts with exploiting a new principle of working with regard to a purpose at hand. Reaching proper functionality requires the creation of suitable elements (which are technologies themselves) to exploit the new principle. This might be a lengthy process of solving sub-problems that present themselves along the way.

Using this framework, we assert that inventive activity largely consists of a search process over technological elements and principles of working in existence. Moreover it consists of shaping and reassembling these elements and principles as to serve the purpose at hand. Clearly, the choice of which elements and principles to use in this combinatory process does not consist of randomly matching elements and principles in existence. More plausibly, the inventor is guided by his/her assumptions and beliefs about how reality works. Adhering to this view of the inventive process, it is not hard to argue that the nature of the search process followed is influenced by the inventor's existing technological knowledge, hence the experience built up through prior activities. Moreover, it is not hard to believe that there exist individual differences in terms of the ability to manage the complex process of directing a range of potential concepts, elements and principles towards a goal. We translate these conjectures into expectations about how inventors' experience and recombinant ability play a role in the creation of technological novelty.

Diversity in Experience

We define experience diversity as the variety of technological domains an inventor has built up through accumulated inventive effort. Given a certain magnitude of an inventor's prior work, diversity increases with the number of different fields he contributed to. This view relies on the assumption that there exist boundaries between fields. Indeed, a number of contributions have argued that technological activity clusters around common problems, patterns of social meaning, theories and methods (von Tunzelmann, 1998; Hargadon, 2006; Arthur, 2009). Given this view, we argue that inventors who have built up experience across boundaries of different technological areas have a larger set of components and principles to rely on when facing a technological problem. Consequently, if novelty indeed arises through newly exploiting knowledge and concepts to serve the purpose at hand, we believe having collected knowledge about a larger number of problems, phenomena and theories, increases the probability to come to novel inventive effort.

A second argument in favor of a positive effect of experience diversity on novel inventive outcomes relies on the assumption of path-dependency of technological outcomes (e.g. Dosi, 1997). The main idea behind path-dependency is that a certain technological approach defines well-understood avenues of potential development. As such a technology moves along according to a defined sequence of problems to be solved (Dosi, 1982) within the beliefs and knowledge surrounding the technological approach. Technological novelty typically arises through introducing a new approach to serve the purpose that moves away from the avenues of research proposed by the old approach. In support of this view, Audia & Goncalo (2007) have shown inventors' past success decreases the divergence of the ideas they produce. We argue that inventors who mainly work within few technological areas are ingrained with the assumptions, beliefs, and theories surrounding the typical approaches in these areas. Since novelty generation might require breaking out of such 'common understanding of the world', we expect inventors who concentrated their effort in few areas, are less likely to generate novelty. On the contrary, inventors who have a more diversified experience have been in contact with varying views on how to solve different problems. Hence, they are more likely to challenge the prevailing assumptions and beliefs and generate novel inventions. For these reasons, we expect a positive effect of experience diversity on the probability to generate novel inventions.

Hypothesis 1: The larger the diversity in experience of an inventor, the more likely he/she is to generate technologically novel inventions.

Recombinant Ability

We define recombinant ability as the innate ability to make more novel or uncommon combinations across different knowledge fields. We identify this characteristic in addition to experience diversity to highlight interpersonal differences in the ability to deal with the complexity involved with knowledge recombination. If combining different elements and principles directed towards a goal would be easy, one would just have to collect knowledge in different fields in order to generate novelty (hence, the concept of experience diversity would suffice as an inventor characteristic). However, we believe that knowledge recombination requires tremendous cognitive effort, necessary to deal with the complexity of envisioning multiple solutions to a particular problem. Moreover, different individuals might differ in their cognitive ability to 'think outside of the box' and successfully recombine elements directed towards a solution. In addition, the motivation of individuals to challenge the status quo represented by existing solutions, might vary as well. Hence, we expect inventors who have shown recombinant ability in the past, to be more likely to generate technological novelty.

Hypothesis 2: The larger the recombinant ability of the inventor in the past, the more likely he/she is to generate technologically novel inventions.

Leveraging Diversity through Recombinant Ability

Diversity and recombinant ability are distinct concepts. One can have the ability to recombine different concepts in a novel way while having a focus on a limited number of domains, and the other way around. We argue that building up diverse experience and having recombinant ability reinforce each other. Given recombinant ability, having worked in a wider range of technological domains, increases the number of basic elements and knowledge which are available for recombination. Hence one could see diversity as a necessary condition to successfully express the ability to combine different elements and come to novelty. For this reason, we hypothesize that the effect of recombinant ability is more outspoken for inventors with higher levels of experience diversity.

Hypothesis 3: The effect of recombinant ability of an inventor is more outspoken for inventors with a larger experience diversity.

RESEARCH DESIGN

Data

The R&D100 Awards

To proxy novelty of inventive efforts we make use of a list of inventors that were awarded a prize by R&D Magazine ('R&D100 awards') (other studies using these awards include Carpenter et al., 1981; Scherer, 1989; Block & Keller, 2009 and Fontana et al., 2012). Since 1965 R&D Magazine (formerly known as 'Industrial Research') awards prizes to potentially revolutionary technology products. Some famous winning contributions were the ATM (1973), halogen lamp (1974), fax machine (1975), LCD (1980), anti-smoking patch (1992), Taxol anticancer drug (1993) and HDTV (1998). But also less consumer-oriented products such as next-generation magnetic resonance imaging machines and laser-based metal-forming tools are among the recent winners. Every year the US-based magazine selects about 100 winners out of all applicants.

To apply[1] for an R&D100 award, firms or research institutions have to fill in an application form with detailed information about their invention. Each entry is assessed by the editors of R&D magazine and a jury of experts in the field of the inventions. Assessment is based on technological significance and the ultimate goal of the editors is to 'pick the 100 most technologically significant new products from among the entries'. No monetary prize is awarded, but winning the prize allows firms and research organizations to obtain visibility for their newly invented product. Moreover, the prize presents a signal of quality to potential customers.

The appeal of using award-winning inventors as an identification of inventors that are able to generate novel inventive effort is twofold. First, the awards are a contemporaneous assessment of new technologies with the potential to become a revolutionary breakthrough. The fact that the award is given shortly after the invention, is crucial for this study because we conceptually distinguish between novelty and technological impact. Indeed, commercial success of the invention awarded with the prize is not warranted. Second, R&D magazine uses outside field experts to advise them in their selection which strengthens us to proclaim that the identified

[1] The information reported about the application procedure, R&D magazine and the selection procedure was retrieved from http://www.rdmag.com, accessed on 3/12/2014

inventors effectively introduced a novel approach. This is an advantage compared to the numerous studies using patent citation counts to proxy 'breakthrough characteristics' of innovative outcomes. Although forward patent citation counts have been shown to correlate with commercial value (Harhoff et al., 1999; Hall et al., 2005), it is hard to assess what patent citations mean in terms of the novelty or radicalness characteristics of the underlying inventions. Moreover, this approach minimizes 'common method bias' because information on the dependent variable is drawn from a different source than the information on the independent variables.

To obtain the information on the award-winners, we collected data from the R&D100 awards from 2000 until 2007 from the R&D magazine webpage. We manually extracted the names of the inventors for the prizes where this information is given (about 50 percent of the prizes contain information on the name of one or more inventors). This leaves us with a list of 1388 inventor names that are linked to a prize.

Patent Data

To construct our independent variables, we rely on information contained in patent documents. In a first step we link the inventors that received an R&D award to all their patents. To do so, we use the inventor database as constructed by Li et al. (2014) which contains disambiguated names of all inventors on the population of US patent documents. Such exhaustive disambiguation efforts are, to our knowledge, not available for patent documents from different offices. For this study, this seems not to be a severe problem because R&D magazine is a US based company, so we can assume that a large part of patenting winners, will do so in the US jurisdiction.

To link both data sources, we require an exact match on the full name of the inventors in the list. Since multiple inventors can be linked to one and the same name, we manually select the correct match based on a web search. In case of ambiguity, the inventor is dropped from the sample. After applying this filter, we end up with 614 inventors linked to 376 awards. This approach is likely to underestimate the number of inventors actually occurring on a US patent. However, we do not consider this as a problem since the R&D awards can only give us information on inventors that actually introduced a novel approach and by no account gives an exhaustive picture of the technological advancements in a certain year. Hence, the control group will, in any case, include inventors who made a novel contribution and should be seen as a group of 'average' inventors.

In a second step, we use PATSTAT to retrieve information on the family members of the matched US patents. We use the DOCDB definition of a patent family, which requires a strict form of equivalence between patent documents. Typically, family members contain the equivalents in other patent offices of the patent found in the inventor database. We assume that one patent family represents one invention.

In a third step, we exclude all inventors having less than 5 patent families in the time period between 1980 and the year of the prize. To assign a year of application to each family, we use the application year of the oldest member in the family. We do not use families prior to 1980 because our measure of recombinant ability requires a sufficiently large comparison base of patents making combinations between technological classes (see below). Since our independent variables rely on patent information, we require a sufficiently large (at least 5) set of patented inventions before the prize. This requirement reassures us that inventors identified are sufficiently technologically active to provide us with patent-based measures of experience. Since we perform the same filter for the control group of inventors, this requirement only introduces a conservative bias because we only include ‘productive’ inventors and productivity is expected to correlate with the quality signaled by the awards. Applying this filter leaves us with 285 inventors linked to 213 awards and 4057 patent families containing at least one US application.

We devise a control group of inventors based on a number of conditions. We compare the award-winning inventors with a group of average inventors who were active in the same field as the award-winners around the time they made their award-winning inventions (novel inventive effort). We assume that the award-winning contribution is linked to a patent application during a time period of five years before the prize was awarded and the year of the award. Since our group of award-winners are linked to at least 5 patents, we argue that the assumption of a patent application is reasonable. Moreover, given the fact that the awards are public, one would assume that the patent is applied for before the time of the prize. To identify the field of the inventions, we use the most frequently occurring subclass (4 digit IPC-code[2]) assigned to the inventors’ patents in this time

[2] The International Patent Classification (IPC) was established in 1971 by the Strasbourg Agreement and provides a hierarchical system to classify patents according to the technological areas they belong to. It uses 5 layers of detail to classify a patent documents labeled respectively ‘Section’ (8), Class (±130), ‘Subclass’ (±630), ‘Group’ (±8 000) and ‘Subgroup’ (±70 000). See http://www.wipo.int/classifications/en/ for more information.

period. Then we collect all patent families assigned to this subclass during the time period of five years before the prize until the year of the prize. We select the families with at least one US application and gather inventor information using the inventor table devised by Li et al. (2014). For the identified inventors, we apply the same filters as for the selection of the award-winners. This leaves us with a control group of 193 160 inventors who have at least 5 patent families containing at least 1 US patent during the timeframe 1980 until the year of the prize on which the selection was based (with a total number of patent families of 1 314 196). Our control variables (see below) are chosen to pick up important determinants of the working environment of the inventors driving potential selection into the award-winning group. Yet, we aim to rule out selection effects at the firm level by only using the inventors who shared their last applicant with an award-winning inventor as a control group. In doing so, we introduce a conservative bias if firms focusing on generating novel technologies are more likely to employ individuals with the capacity to generate novelty. Applying this filter strengthens us in believing to have selected those inventors in the sample who could have potentially applied for the award, because the firm was knowledgeable about this prize. With this set-up, we lose 56 inventors in our sample of award winners, and 162 765 inventors in our control sample which leaves us with 229 award-winners and a control group of 31 668 inventors.

To construct our measures of experience diversity and recombinant ability, as well as the control variables, we use information of the retrieved patent families from PATSTAT. We retrieve information on technological classifications, citations received from other patent documents, patent and non-patent references made in the search reports of the focal patents, applicant names and their sector allocation (including companies, not-for-profit organizations, government institutions and hospitals), number of claims, inventors, patent authority and application year. For the construction of the variables of interest we heavily rely on classification information on the patent documents. We use the IPC classification to determine the technological knowledge associated with the invention. Since all families contain a US member, one could use the US Patent Office Classification (USPOC) which is employed by the USPTO to classify patent documents. However, the IPC classifies patents according to the full information present in the application (OECD, 1994), while the USPOC uses only the information in the claims (scope of protection). We follow the line of reasoning in Gruber et al. (2013) which argues in favor of using the IPC when concerned with constructing variables about the recombination of technological knowledge contained in a patent document.

Measures

Experience Diversity

We measure experience diversity relying on the IPC subclasses (this level contains about 630 different classes) assigned to the patents of an inventor. Based on the patent application related to an invention, the examiner assigns one or (often) multiple IPC classes to a patent. The goal of such classification is to provide an instrument of search when determining prior art for all patent applications. Hence, we argue that the different IPC-classes to which a patent is assigned, reflects the knowledge and concepts associated to the inventions. We claim that an inventor working on an invention has built up (part of) the knowledge accumulated in the technological class. When this is true, the IPC-codes assigned to the patents of the inventors, mirror the fields of technological knowledge in which the inventor has gained experience in. As such we use a measure of spread of the technological classes over the patents assigned to an inventor over its career. We use an adapted version of the measure employed in Gruber et al. (2013)[3] since we aim at measuring diversity over an inventors entire patent portfolio, rather than the diversity in the search process of one particular invention. For that reason, we use IPC-codes found on the patent document of an inventor, rather than on the referenced patents in the search report. For an inventor with J patents that are associated with 1, …, K technological classes we can define experience diversity as:

$$D_{JK} = 1 - \sum_{K=1}^{K} \left(\frac{\sum_{j=1}^{J} s_{jk}}{S} \right)^2$$

where s_{jk} is the share of inventor's patent j of technological class K. If an inventor has a patent j, which is associated to class A, B and C, s_{jA} is 1/3. S is the total number of distinct class-patent combinations of the inventor.

[3] We refer to their study for a discussion of various measures of recombinant breadth

Recombinant Ability

To proxy recombinant ability, we use the measure 'New Functionality' as introduced in Verhoeven et al., 2014 (see also Fleming et al., 2007). This measure uses a list of combinations of technological classes (at the group level) related to a patent and consider the patent as incorporating a novel connection between technological fields when a certain combination of technological fields has not occurred before. Hence, it reflects whether a particular invention connects previously unconnected fields of knowledge and, as such, the ability of the inventor to combine knowledge fields for the first time in history. For example, when an inventor has a patent that belongs to classes A, B and C, we list the pairwise combinations made: AB, AC and BC. We then compare these combinations to all combinations previously made by previous patents and check whether the combination has been made before. If the patent contains at least 1 new combination, the patent scores on the indicator.

For the purpose of this study, we adapt the measure to control for ease of making new combinations in a certain technological area and year. This is necessary because we compare an inventor's patents applied for in different years. Since the cumulative number of possible new combinations decreases over time this measure naturally has a downward slope over time. Moreover, if the classification scheme varies in level of detail over fields, a bias might exist when comparing between fields. To address this problem, we correct the measure for the fraction of patents in a field and year that score on the indicator. More specifically, we first fractionally assign patents to their field using its more aggregate subsections (4 digit IPC code). Then we calculate the fractional count of patents that score for each subsection-year combination and divide this number by the total fractional count for the subsection-year combination. For each subsection-year combination we now have the probability (ease) of making new combinations. Next, we assign a value of -1 to non-scoring patents, and a value of 1 to patents making a new combination. In a final step we divide, for each patent, this number by the calculated probabilities (ease) of new combinations weighted over the subsection-year combination the patent is assigned to. To proxy recombinant ability, we use the average score on this measure over the portfolio of patents of the inventors.

Controls

Since our sample does not allow a panel set-up to control for inventor-fixed effects (nor do we use a (quasi-)experiment), the empirical strategy heavily relies on controlling for all factors related to our variables of interest, driving the selection into being an award-winner. We control for several measures that proxy general ability, working environment, field and timing of experience, as well as mobility and intensity of cooperation to address omitted variable bias.

First, general productivity of the inventor might drive selection into the group of award-winners. Moreover, very productive inventors might be asked to cooperate in many projects, and as such they might build up diversity. Therefore we control for the number of inventions made by the inventor by counting the number of patents in an inventor's portfolio. To account for differences in technological areas worked in, we control for the number of patents filed in each of 35 technological areas as defined by Schmoch (2008). Moreover, we control for the extent to which each inventor is specialized in the field based on which he/she was selected by calculating the fraction of its total patents in the field on which the selection was made.

Second, inventors' passed success has been shown to positively affect present inventive rate (Audia and Goncalo, 2007). One could imagine how inventors who have made one or more breakthrough inventions, can build up (diverse) experience by exploiting their success. If, consequently, they are more likely to be involved in another breakthrough (as claimed in Conti et al., 2013) this might also affect the probability of being among the award winners. To address this concern, we control for the number of high-impact inventions they created. We operationalize this concept by calculating the number of highly cited patents they produced. We count the number of families that have cited each patent family of interest. To normalize across technological areas and years, we calculate the average number of citations of patents in each year-subclass combination, as well as the standard deviation. Finally we construct a dummy-variable with a value of one for each patent that is a two standard deviation outlier in its year and field in terms of forward citations.

Third, along the same line of reasoning, inventors with a history of more valuable inventions, might attain more (diverse) experience and be more likely to be among the award winners. Therefore we control for two measures which have been argued to reflect the value of inventions: the number of claims in the patent, and the number of different applications filed to protect an invention. We construct a measure for the average number of claims and average family size (using the DOCDB definition) of each of the inventors.

Fourth, since it is the firm that can be expected to file an application for the award, characteristics at the firm level might influence the probability of being among the award-winners. Moreover, different types of firms might be more/less likely to engage in risky projects and as such hire different types of inventors. To control for this, we take the last applicant of each inventor before the year of the prize (assuming this is the company they worked in at the time the selection effect might occur) and construct two variables on the level of the applicant. First we include a dummy indicating to which sector the firm belonged (we use the sector-allocation as described in Du Plessis at al., 2010). Second we proxy the size of the firm by counting the number of patents in their portfolio. In addition, we include dummy variables indicating the last applicant of the inventor.

Fifth, we want to control for mobility effects. Indeed, mobile inventors have been shown to have higher productivity rates (e.g. Hoisl, 2007) which can affect both our measures of interest, as well as selection into the group of award-winners. To proxy the mobility of the inventors in our sample, we count the number of distinct applicants they have patented with.

Sixth, some inventors might function as a team leader. Team leaders are likely to be on a patent without necessarily having contributed much to the inventive effort leading to the invention. If the same is true for the application for the award, this might bias the coefficients for both experience diversity and recombinant ability. To control for this effect, we count the number of distinct inventors the inventor has patented with over his career.

Seventh, we control for length of the career of the inventors and different intensities of patenting over time. We include dummies for the first and last application year and control for the number of patents filed for in each cohort of 5 years starting from 1980. In addition, we control for the inventor’s career length by calculating the number of years between his/hers first and last patent application before the year of the prize.

Finally, we control for a number of factors that might characterize the search process of the inventor and affect the likelihood of novel inventive effort. For each inventor we calculate the average team size on the patent, the average number of applicants, the number of backward (non-)patent references and the average number of classes assigned to the patent.

Methods

In a first step, we show the distributions of the newly created variables for experience diversity and recombinant ability. We do this to provide an account of how these measures behave when implementing them for a large set of inventors. Second, we show descriptive statistics for both the control group and the group of the award winners and perform independent sample t-tests on the differences in means. As for the multivariate analyses, we estimate 5 probit models predicting the likelihood of being among the award-winners. Model 1 includes the controls only, model 2 includes controls and the experience diversity measure, model 3 includes controls and the recombinant ability measure, model 4 adds both experience diversity and recombinant ability, in model 5 we additionally include the interaction term. We interpret the interaction effect by showing the average estimated probabilities for different values of experience diversity and recombinant ability.

RESULTS

Descriptive Statistics

Insert Figure 1 and Figure 2 about here

Figure 1 and 2 show respectively the distributions of experience diversity and recombinant ability. Experience diversity is clearly skewed to the left, with about 29% of the inventors scoring below the mean of 0.83. Recombinant ability has a strong skew to the right, with about 28% of the inventors having a score below the mean of 0.19. Moreover, for recombinant ability we see a very strong mass on the lowest values. 71 percent of the inventors score between the minimum value of -1.57 and 0, while the remaining 29 percent score between 0 and 51.53 (in the histogram the values above 10 are grouped into the value of 10). Because of the extreme skew in this distribution, one could argue that the information contained by the actual scores above the mean might not be very insightful. For this reason, we recode this variable into a dummy-variable that is 1 if the inventor scores above the mean. The significance levels and signs reported in the multivariate analyses do not change when using the continuous measure instead of the dummy-variable.

Insert Table 1 about here

Table 1 provides descriptive statistics of our key measures for the control group and the group of award-winners. As expected, the award-winners display higher levels of experience diversity and recombinant ability. For experience diversity, the award winners score about 15 percent higher compared to the control group (p-value<0.001). For recombinant ability, award-winning inventors are on average 68 percent more likely to score above the mean. Table 2 provides correlations between our variables of interest and the control variables. The low correlations between the independent variables indicate that collinearity should not be a concern.

Insert Table 2 about here

Multivariate Results

Results of the probit models with robust standard errors predicting the probability of being in the group of award-winners are reported in table 4. The results in column (1) include control variables only. In column (2), (3) and (4) we respectively add our two variables of interest separately and simultaneously. Column (5) adds the interaction term.

Insert Table 3 about here

The results in the first 4 columns of table 3 support our first and second hypothesis. Inventors displaying larger values of experience diversity and recombinant ability have a higher likelihood of being among the award-winners. Note that the coefficients only drop slightly when jointly adding the two variables of interest. Likelihood Ratio tests confirm that adding experience diversity and recombinant ability significantly improves the model fit (p-values<0.01 of chi-squared tests comparing the different models when adding variables).

Model 5 adds the interaction term in order to test our third hypothesis. As can be seen in column (5) of table 3, the interaction term is positive and significant (p-value<0.01). Moreover, an LR-test shows an improved model fit as compared to model 4 (likelihood ratio test: $\chi^2(1)=8.91$, p-value<0.01). The effect of recombinant ability increases with values of experience diversity. For reasons of interpretation of this interaction effect, figure 3 shows the average estimated probabilities over the distribution of experience diversity, broken down by recombinant ability. We see that the effect of recombinant ability is most outspoken among inventors who have higher values of experience diversity. Indeed, for the first three quartiles of diversity, the effect of recombinant ability is negative or insignificant. Only for the fourth quartile the effect is positive and significant. These results provide support for our third hypothesis. The effect of recombinant ability is higher for inventors with a high diversity in experience.

Insert Figure 3 about here

Finally, we draw the attention to some effects of the control variables. The award-winning inventors are more mobile, have a large total number of different co-inventors and are active at the time of winning the prize in firms with a lower number of patents. Moreover, they work on average in a smaller teams and obtain patents with a larger number of claims. Somewhat surprisingly, their inventions are generally patented in a lower number of offices (lower average family size).

DISCUSSION

This study set out to investigate the role of experience diversity and recombinant ability in creating novel inventive effort. A sizeable set of award-winning inventors was selected on the basis of novelty and technological significance has allowed us to empirically verify our hypotheses. The main findings support our hypotheses about the positive effect of experience diversity and recombinant ability on the novelty in inventive outcomes. Moreover we show how inventors who are able to make uncommon connections between knowledge fields by leveraging their diverse experience are most successful in generating novel inventions. Our findings yield a number of implications for innovation researchers and decision makers.

Implications

First, the findings of this study have implications on research about inventors and their innovative output. The studies dealing with the effect of inventor experience on innovative outcomes (e.g. Audia & Goncalo, 2007; Conti et al., 2014) have mainly looked at past productivity (size of experience) and success on present innovative outcomes. Our results add to an understanding of the link between experience and inventive outcomes in two ways. First, we disentangle novelty of inventive outcome from measures of productivity and success. Since novelty is only one of the potential sources of large impact, and since novelty is not a sufficient condition for impact, this give a clearer view on the mechanisms we try to understand. Second, we distinguish between inventors on type of experience built up. Our results help to understand how the nature of prior inventive activity helps to explain the likelihood to produce technological novelty at present. We show the importance of working with many different technologies in in the ability to generate novelty, especially when the inventor has the mental flexibility to connect hitherto unconnected pieces of knowledge.

Second, our findings have implications for research on radical innovation. Many scholars have investigated how firms' technological strategies can explain the likelihood of radical impact (e.g. Ahuja & Lampert, 2001; Rosenkopf & Nerkar, 2001; Fleming, 2001; Arts & Veugelers, 2014), often arguing in favor of how novelty is the ultimate source of impact. We add to their findings by stressing the role of the individual inventor in the process of novelty generation. Since the cognitive effort needed to come to invention is always executed at the level of the inventor, studying inventor-level characteristics provides a more direct assessment of the mechanisms at play. Of course one should not underestimate the role of organizational and strategic factors that play a role. On the contrary, both ways of trying to explain inventive outcomes are likely complementary. Hence, future work could shed light on the extent to which different inventors' outcomes are contingent on the organizational environment they work in.

Third, our study might inform policy makers on devising relevant incentives in order to produce technological novelty. Since focusing on projects aiming at novel technological outcomes might be particularly risky, society might benefit from providing firms and research institutions with sufficient incentives to embark in such risky R&D (Veugelers & Schneider, 2010). Knowledge on the mechanisms that lead to novel inventor effort at individual level, might inspire policy makers to devise more efficient policy instruments to promote this type of innovative outcomes. In particular, this study suggests building up experience in a more diverse range of technologies promotes novelty in future technological outcomes. Consequently, incentivizing individual inventors (for example in research institutions and universities) to work in different parts of the technological landscape, might yield more beneficial outcomes for society. Also, motivating firms to engage in projects that involve cooperation with inventors from different fields might allow inventors to cross knowledge boundaries and make unprecedented connections that lead to novelty.

Fourth, our findings suggest particular hiring strategies for decision makers of firms targeting novel inventive outcomes. Since our findings suggest how particular characteristics in inventors might lead to novel inventive outcomes, firms can target their hiring strategies towards these individuals with a higher likelihood to successfully come up with technological novelty.

Limitations

When interpreting the results of this study, a number of remarks have to be taken into account. First, since we do not have a (quasi-)experimental setting, caution is warranted in interpreting our findings as causal. If we have not been able to control for one or more individual characteristics or characteristics of their environment that are correlated to the variables of interest and drive selection into the group of the award winners, the estimated effects might be unrealistic. Generally, this issue can be remediated by using panel data techniques. However, the dependent variable does not allow a panel set-up. Moreover, when interested in the effect of the accumulated knowledge of an inventor over its career, one can hardly use fixed effects to account for unobserved individual variation. Yet, we proclaim to have accounted for a great deal of the sources for endogeneity by controlling for an extensive number of individual and environment characteristics driving selection into the prize (as evidenced by goodness of fit of our models).

Our independent measures rely on patent information. Hence, known pitfalls of using patent data apply to our study. Not every invention is patented, nor can every patent be seen as a true invention. In addition, our measures heavily rely on classification of patents. Although this classification is given by patent examiners and therefore is unlikely to be biased in favor or against particular types of inventors, we admit they might not give a perfect reflection the technological content of the inventions. Some fields might be described through more IPC-codes than others, hence working in these fields might inflate the diversity measure artificially. This is an issue to the extent our controls for field of activity do not fully account for this effect in the regression models.

CONCLUSION

Inspired by firm-level research on breakthrough innovation, this study has investigated individual characteristics promoting novelty in inventive outcomes. Drawing on a reasonably large set of award-winning inventors, we identified two characteristics promoting novel inventive effort. We have shown that inventors' experience diversity and recombinant ability have a positive impact on the probability to win an award for having invented highly significant and new technologies. Moreover, we have shown how inventors that are able to leverage their experience by the ability to make novel combinations between fields of knowledge are most likely to be among the award winners. Our findings add to the body of research investigating how inventor characteristics relate to their innovative outcomes and have implications for decision makers targeting novelty in their technological outcomes.

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TABLE 1

Descriptive statistics Experience Diversity and Recombinant Ability

	Mean Award-winners (Standard Deviation)	Mean Control Group (Standard Deviation)	Ratio Means	P-value t-test of differences
Experience Diversity	0,91 (0,11)	0,79 (0,25)	1,15	<0,0001
Recombinant Ability (dummy)	0,40 (0,49)	.24 (0,43)	1,68	<0,0001
N	229	31668		

TABLE 2

Correlation matrix of some key variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Award-Winner (dummy)	1														
Experience Diversity	0.0102*	1													
Recombinant Ability (Continuous)	0.0103*	0.2111*	1												
Recombinant Ability (Dummy)	0.0113*	0.2623*	0.7414*	1											
Number of Patent Families	0.0108*	0.0923*	-0.0239*	0.0407*	1										
Share Families Field of Prize	0.0170*	-0.0721*	-0.0179*	-0.0861*	-0.0441*	1									
Nr. of Applicants	0.0204*	0.1581*	0.0269*	0.0736*	0.3756*	0.0033	1								
Nr. of Co-Inventors	0.0038	0.1664*	-0.0019	0.0601*	0.6523*	-0.0075*	0.4252*	1							
Nr. of Families Employer	-0.0122*	-0.0612*	-0.0542*	-0.0827*	0.0503*	0.1021*	-0.1765*	0.1115*	1						
Avg. Number of Forward Citations	0.0203*	0.0402*	0.1115*	0.0829*	-0.0046	0.0277*	0.0740*	0.0497*	-0.0481*	1					
Avg. Family Size	-0.0145*	0.2065*	0.1380*	0.1713*	-0.0075*	0.0295*	0.0697*	0.0824*	-0.1514*	0.1051*	1				
Avg. Nr. of Claims	0.0197*	-0.0146*	0.0664*	0.0228*	-0.0224*	0.0685*	0.0684*	-0.0045	-0.0225*	0.3603*	0.0164*	1			
Nr. Highly Cited Families	0.0214*	0.0984*	0.0945*	0.1261*	0.4495*	-0.0181*	0.2369*	0.2961*	-0.0279*	0.5524*	0.0835*	0.2008*	1		
Avg. Team Size	-0.0082*	0.0686*	0.0385*	0.0192*	0.0093*	0.1078*	0.1048*	0.4405*	0.0754*	0.1534*	0.1543*	0.1189*	0.0656*	1	
Avg. Nr. of Applicants	-0.0070*	0.1536*	0.0724*	0.0801*	-0.0473*	0.0424*	0.1639*	0.1334*	-0.1176*	0.0542*	0.4808*	-0.0033	0.0114*	0.3829*	1

*** $p<0.01$**

TABLE 3

Results Probit regressions

	(1)	(2)	(3)	(4)	(5)
Experience Diversity		0.504***		0.488***	0.474***
		(0.0974)		(0.0967)	(0.0910)
Recombinant Ability (Dummy)			0.220*	0.159°	-0.570*
			(0.0853)	(0.0827)	(0.243)
Experience Diversity x Recombinant Ability					1.459***
					(0.396)
Number of Patent Families	0.163	0.436	0.217	0.455	0.526
	(0.538)	(0.571)	(0.525)	(0.562)	(0.576)
Share Families Field of Prize	0.670***	0.770***	0.674***	0.772***	0.788***
	(0.0850)	(0.0924)	(0.0854)	(0.0924)	(0.0944)
Nr. of Applicants	0.215***	0.218***	0.213***	0.218***	0.219***
	(0.0399)	(0.0411)	(0.0399)	(0.0411)	(0.0420)
Nr. of Co-Inventors	0.0288	0.0240	0.0300	0.0252	0.0209
	(0.0555)	(0.0598)	(0.0564)	(0.0600)	(0.0624)
Log Nr. of Families Employer	0.0301	0.0819	0.00528	0.0624	0.0481
	(0.243)	(0.243)	(0.244)	(0.244)	(0.249)
Length career	0.0232	0.0162	0.0215	0.0150	0.0155
	(0.0194)	(0.0190)	(0.0194)	(0.0190)	(0.0192)
Avg. Number of Forward Citations	0.0427	0.0339	0.0445	0.0362	0.0287
	(0.0394)	(0.0399)	(0.0398)	(0.0400)	(0.0408)
Avg. Family Size	0.0449	0.0362	0.0479	0.0396	0.0417
	(0.0835)	(0.0870)	(0.0845)	(0.0872)	(0.0903)
Avg. Nr. of Claims	0.0812*	0.0872*	0.0861*	0.0906*	0.0922*
	(0.0365)	(0.0396)	(0.0356)	(0.0388)	(0.0382)
Nr. Highly Cited Families	-0.0711	-0.0535	-0.0806	-0.0618	-0.0555
	(0.0485)	(0.0489)	(0.0494)	(0.0496)	(0.0507)
Avg. Team Size	-0.0742	-0.0637	-0.0801	-0.0689	-0.0673
	(0.0576)	(0.0616)	(0.0585)	(0.0622)	(0.0635)
Avg. Nr. of Applicants	-0.277**	-0.301**	-0.278**	-0.301**	-0.304**
	(0.0890)	(0.0923)	(0.0890)	(0.0920)	(0.0925)
Avg. Nr. of Backward Citations	0.0535	0.0711	0.0497	0.0684	0.0630
	(0.0567)	(0.0592)	(0.0573)	(0.0597)	(0.0604)

Avg. Nr. of Non Patent References	-0.0401	-0.0361	-0.0320	-0.0304	-0.0243
	(0.0468)	(0.0472)	(0.0467)	(0.0470)	(0.0476)
Avg. Nr. of IPC codes	-0.0823	-0.274**	-0.138*	-0.315***	-0.422***
	(0.0611)	(0.0855)	(0.0649)	(0.0848)	(0.0885)
Controls Nr of Patents in Technological Areas (fhg35)	Yes	Yes	Yes	Yes	Yes
Controls Nr of Patents in 5 year cohorts starting from 1980	Yes	Yes	Yes	Yes	Yes
First and Last Application Year Dummies	Yes	Yes	Yes	Yes	Yes
Dummies Sector Last Applicant	Yes	Yes	Yes	Yes	Yes
Dummies Last Applicant	Yes	Yes	Yes	Yes	Yes
Constant	-0.212	-0.429	-2.085	-2.421*	-0.625
	(1.191)	(1.183)	(1.167)	(1.164)	(1.197)
Pseudo R-square	0.597	0.609	0.599	0.610	0.615
N	30624	30624	30624	30624	30624

Results from Probit regressions using a restricted sample of inventors having the same last applicant as the award-winners including. Robust standard errors of coefficients in parentheses.

*** p<0.05,**

**** p<0.01,**

*****p<0.001,**

° p<0.1

FIGURE 1

Distribution Experience Diversity

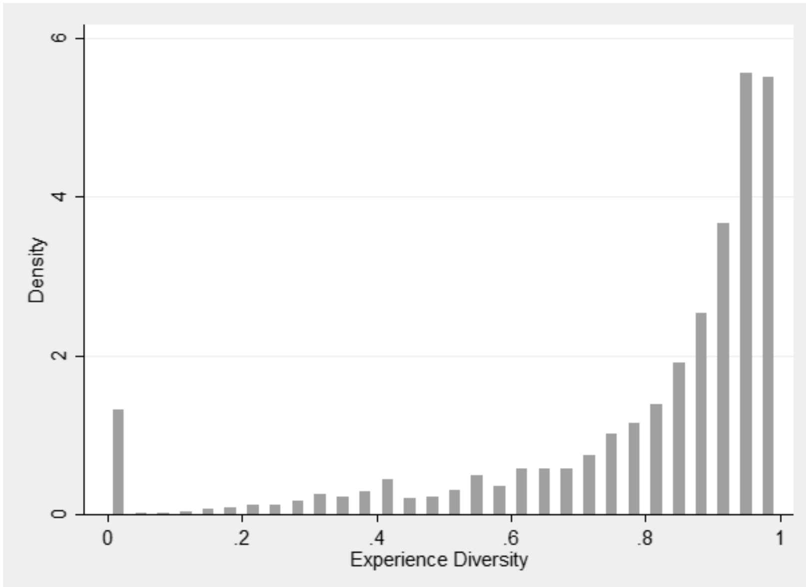


FIGURE 2

Distribution Recombinant Ability

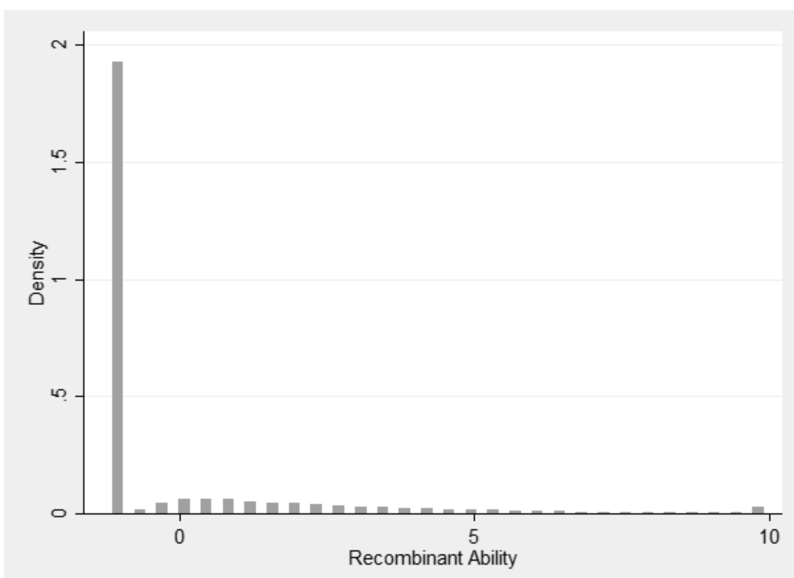
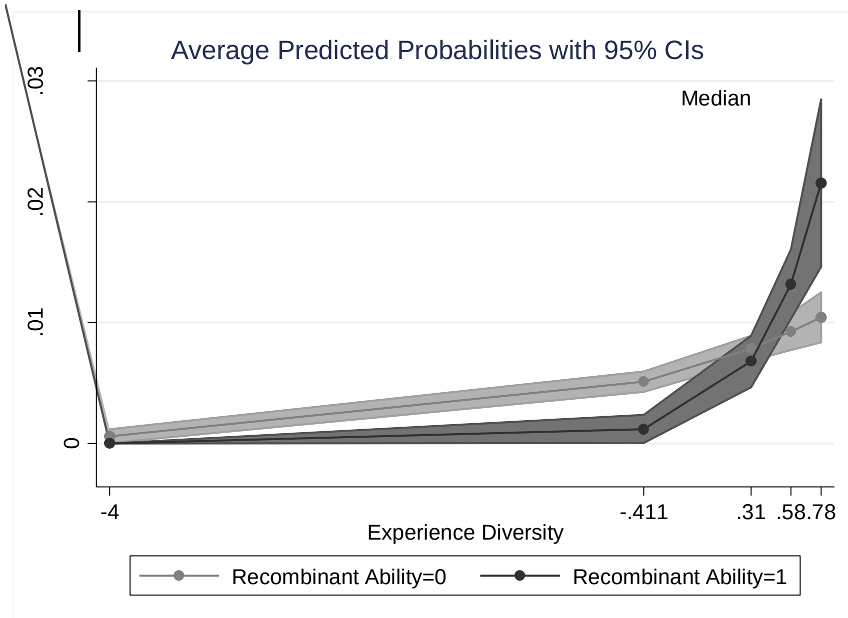
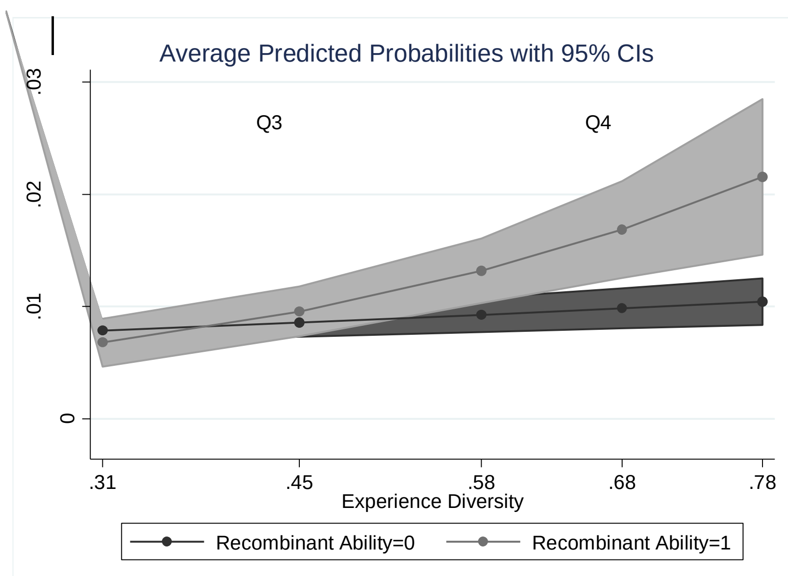


FIGURE 3

Predicted Probabilities





Average predicted probabilities based on model 5 holding other variables at their mean. Shaded areas indicate 95 % confidence intervals obtained using the delta-method[4]. The upper panel shows the estimated probabilities for the entire distribution of Experience Diversity, the lower panel zeroes in on the upper 2 quartiles.

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[4] For more information regarding the delta-method we refer to http://www.indiana.edu/~jslsoc/stata/ci_computations/spost_deltaci.pdf