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Linkage of Patent and Design Right Data: Analysis of Industrial Design Activities in Companies at the Creator Level[1]

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Abstract

In addition to technological superiority (functional value), attention to design superiority (semantic value) is increasing as a source of competitiveness in product markets. In this research, we have created a linked data set of utility patent and design patent information from the Japan Patent Office to evaluate design patent data as a source of understanding design innovation. First, machine learning was performed on a classification model to disambiguate the same inventor / creator on patent right/design right applications using data from applications from the Japanese Patent Office. By interconnecting the inventor's and creator's identifiers estimated by the learned classification model, we identified design creators who also created the patented invention. Next, an empirical analysis is conducted to characterize the design created by a utility patent inventor. It was found that about half of design patents are found to be created by the same individuals who are involved in the relevant utility patents. However, the division of labor between designers (creators of design patents) and engineers (inventors of utility patents) is advancing, particularly in large firms.

Keywords: Utility Patent, Design Patent, Disambiguation, Design Innovation

JEL classification: O31, O34

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1. Introduction

The design rights is the intellectual property right that protects industrial design. Novelty in a design can only be found in its appearance (design) and shape, and design rights are different to the patent rights that protect industrial technology. In industries where differentiation in design between products is important, such as furniture, food products and home appliances, design rights are important to make product differentiation from competitors (Brown, 2009). Furthermore, design rights have a short approval period compared to patent rights, and filing and maintenance fees are also low, so they have a complementary role to patent rights in protecting product inventions.

As such, design data can provide useful information when analyzing industrial design innovation but, in comparison to patent data, there is little progress in utilizing it as an indicator of technical innovation. One of the reasons behind this is that design patent system is not internationally harmonized such as utility patent for technological inventions. A substantial examination process is required for design patent right in some countries such as Japan and United States, while only formality check is conducted for its registration in other countries/regions such as China and Europe (Yoshioka-Kobayashi, 2018). Therefore, interpretation of design patent information should be made by taking into account the definition of national/regional IP regulation. In addition, the design patent system does not cover all dimensions of design innovation. A recent review paper by Homburg et al. (2015) identifies three aspects of design innovation; aesthetics, functionality and symbolism, and design patents protects mainly functionality of inventions, but no judgements are given for the other two dimensions (Galindo-Rueda and Millot, 2015).

However, design patent data is still a useful tool for systematic understanding of design innovation due to its objectivity and comprehensiveness (Yoshioka-Kobayashi, 2018). In addition, bibliometric information such as right holder, creator, product category and citation data can be used for various empirical analysis, as is the case for the dataset created from utility patent information. This paper is based on the comprehensive database of design patent information registered at JPO (Japan Patent Office), developed by NISTEP (National Institute of Science and Technology Policy) (Motohashi, Ikeuchi, Dang, 2016), with a similar structure of utility patent database such as NBER patent database for USPTO patent (Hall et. al, 2005) and IIP Patent database for JPO patent (Goto and Motohashi, 2017).

This paper provides a first look at systematic understanding of design patent information, by linking with utility patent information, where the data quality and characteristics have been extensively investigates (Nagaoka et. al, 2010). Specifically, connections were made between the NISTEP design database and the IIP Patent Database at individual level (designer creator and patent inventor) to see the relationship between these two patent rights. It is found that about half of all design rights were created by engineers who have also made patented inventions. In other words, in product development, improvement of appearance (design) and development of technology (engineering) are often performed by the same person. However, this trend has been lessening recently and, especially in large companies, so that the division of labor between designers and engineers are progressed over time. It should be noted that the design patent in Japan is registered after its substance examination, its quality of such information is supposed to be better than the same information in other countries where only formality check of design patent application is conducted.

The structure of this paper is as follows. The methodology for linked dataset is described in the next section. First, disambiguation of inventors and creators in the IIP Patent Database and the NISTEP design database are conducted, then two information are merged at inventor/creator level. Then, empirical analysis to characterize design patent database is provided. Finally, the conclusions and managerial implications obtained from this study were detailed.

2. Creating a database of inventors and creators

2-1. Inventor disambiguation in the IIP Patent Database

In order to understand micro nature of design and patent activities, inventor (creator) identification should be made since patent records give only the information of inventor (creator) name and her address. Or, both synonym problem (in which the same person's name appears in several distinct forms due to name changing etc.) and homonym problem (in which many distinct people share the same name) should be treated. In case of Japanese name, which appeared mainly in our database, addressing homonym problem is more important (Ikeuchi et. al, 2017).

The methodology if inventor disambiguation (identification) has been developed extensively. A machine learning becomes a main stream recently, and several studies are conducted for various patent databases (Li et. al, 2014 for USPTO data, Ikeuchi et. al, 2017 for JPO data and Yin et. al, 2019 for China patent data). In this paper, we use the methodology of supervised machine learning, following our previous work on JPO inventor information (Ikeuchi et. al, 2017). Namely, model parameter tuning and model selection (learning) are performed based on training data, and the patterns of the entire dataset are predicted using the best performed model. It is therefore critical that the training data is reliable for the machine learning model to be successfully applied.[1]

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[1] There are three types of methodology in inventor disambiguation, rule based, supervised machine leaning (this study) and unsupervised machine learning. Yin et al. (2019) provides extensive survey on

We use a telephone directory in Japan to create training data. The names of inventors who have only been listed in the telephone directory once or not at all over multiple years are defined as rare names. The training data is constructed in which a group of inventors with the same rare name are defined as the same person. It is natural to assume that the names and characteristics of the inventors are independent of each other and it is thought that this approach is representative of the population as a whole.

Two million pairs of records with the same and different rare names were extracted randomly from the records and a classifier was applied based on a total of 4 million record pairs. As representative classifiers, three types of naive Bayes models (Bernoulli, Gaussian, and Multinomial), two types of discriminant analysis models (linear discriminant and quadratic discriminant analysis), random forest and XGBoost were each applied to the training data. Additionally, the hyper parameters of random forest and XGBoost were determined by the F1 score of the training data using 5-fold cross validation.

The classifier learning is performed on the data formed from the paired records of the patent-inventor units as described above, and the variable used as the predictor is a numerical vector (similarity profile) representing the similarity of each record pair. The vector has the following five elements:

(1) Co-inventors: The number of matching co-inventors (excluding the main person), capped at a maximum of six.

(2) Patent technical classification (primary IPC):
- Match at 4-digit level: 4
- Match at 3-digit level: 3
- Match at 1-digit level: 2
- Missing IPC in any record: 1
- Otherwise: 0

(3) Applicant's name: Number of matching characters (capped at six)

(4) Inventor affiliation:
- If matching: 2
- If the affiliation cannot be determined in either record: 1
- Otherwise: 0

(5) Inventor's address:
- Match at building number level: 5

patent datasets in various countries.

- Match at street name level: 4
- Match at city block level: 3
- Match at municipality level: 2
- Match at prefectural level: 1
- Otherwise: 0

The predicted probability of being the same individual is calculated for each record pair by the learning classifier, but it is necessary to establish a probability threshold at which a pair is determined to be the same person and a set (cluster) needs to be configured with record pairs that refer to the same individuals. With this in mind, clustering is performed using a learning classifier. If the name is different then there is a high probability that the records refer to different individuals, so the data is divided into groups with the same name using the same methodology as Ikeuchi et al. (2017), and all records within each name group are given a prediction probability that is calculated from the learning classifiers, and a prediction probability matrix is constructed. Clustering is then performed based on this matrix. It is necessary to select a clustering method and adjust the parameters at this time, and teaching data is required for this purpose.

As the clustering is performed within groups of people who have the same name, it is necessary to prepare training data that includes two individuals with the same name. However, it is challenging to construct training data that relates to patent inventors and includes individuals who possess the same given name and family name. Accordingly, this study uses rare names and the distribution information of the appearance frequency of the full name in telephone directory listings to virtually construct the training data for clustering that includes individuals with the same name, and to select clustering methods and parameters.

The construction method of the training data for the clustering process is as follows. Firstly, the appearance frequency of each name that is listed in the telephone directory is calculated in order to obtain the distribution of the appearance frequency for each name. Next, names are extracted at random from the list of patent inventors with unique names and an experience distribution of the appearance frequency of each patent inventor's name is constructed. After this, names are randomly extracted from the list of rare names, and groups are randomly formed according to the experience distribution of the appearance frequency of each patent inventor’s name. This means that there is a group composed of a single rare name and a group composed of many rare names, and this rare name information can be used as training data for clustering. In this study, 20,000 groups are extracted and used as teaching data.

The candidate clustering methods are hierarchical clustering, DBSCAN, and graph partitioning. The parameters of each method were adjusted via grid search using the teaching data created above, and a model was selected. The F1 score is used as a criterion for parameter and model selection, in the same way as is the case with classifier learning.

The patent-inventor data to be analyzed consists of 23,299,337 records, which include 1,675,133 unique names. The classifier that is ultimately selected on the basis of the F1 score is "Random Forest" (the F1 score is 96.3%), while the clustering method is the “graph partition method” and verification is performed using random extracts of the teaching data used for clustering. The accuracy rate of the data is 98%, the recall rate is 96.3% and the F1 score is 97.1%. After applying the learning classifier and clustering methodology to all the available data, 2,577,432 unique inventors were identified out of 10,695,520 patents (the average number of patents per inventor is 9.04).

2-2. Creator identification in the NISTEP design database

Identifying individual design creators was performed in the same manner as described above for patent inventors. However, co-creators were used instead of co-inventors and design product classifications were used instead of technical classifications as attributes for the learning of the classifier. Additionally, the empirical distribution of the frequency of name appearance that was used to construct teacher data for clustering was estimated separately for the names of design creators, as the number of unique names differed greatly between patent inventors and design creators.

The analysis included 672,815 design creators, of which 110,270 were unique names. The classifier that was selected based on the F1 score criteria was "random forest" (the F1 score is 98%) and the clustering method is "graph partitioning." The precision of the verification data is 99.9%, the recall is 99.4% and the F1 score is 99.7%, which indicates a very high degree of accuracy. After applying the trained classifier and clustering method to all data, 118,027 unique creators were identified, which means that the average number of creative designs per creator is about 5.7.

2-3. Linkage between inventors and creators

The process of identifying the same person from the inventors in the IIP Patent Database and the creators in the NISTEP database is described below. This was mainly done using first and last name information and information about organizational affiliation (i.e. affiliation with companies that hold design rights and patents). Here it should be noted that there are cases where individuals with the same family and given names are affiliated with the same organization. There are 2,769,242 different first and last name + affiliated institution pairs. Of these, 2,685,389 cases were identified as unique individuals as a result of the identification work. In other words, the identification process revealed about 80,000 cases where individuals with the same name were affiliated with the same organization (such as companies like Panasonic with large numbers of inventors). Furthermore, this means that a match between the name and institutional affiliation records between databases is not necessarily enough to say that the records refer to the same person, as there may be more than one engineer or designer with the same name.

Accordingly, we decided to connect the two by referring to corresponding contents of the patents and designs, in addition to the name and institution. Specifically, the following rules are adopted:

- Pairs in which the patent and design application timings are different refer to different individuals.

- Cases with high relevance between the patent application and the design application refer to the same individual.

The former policy suggests that the pairs in two dataset correspond to different people if there is a gap between the time of the patent application and the time of the design application (in other words, if the year of the last patent application is not the same as the year of the first design application or vice versa). After analyzing the different pairs using the first rule, then we look at the contents of patents and design for the pair.

In order to implement the second rule, a concordance table for IPC classification of patent and product category classification of design, by using patent and design pairs by same name and affiliated organization. This concordance table is used to convert the patent application vector (the number of applications per IPC class) into a design classification vector (the number of applications for each major category of Japanese Design Classification). Then, the cosign similarity between this vector and the design classification vector of comparing creator is calculated.

We need to determine the threshold point of this cosign similarity. If the threshold value is set too low, the probability of false positives (matching different people into the same one) increases, while the probability of false negatives (not matching the same person into one) increases, if the value is too high. We use the value of cosign similarity for rare name people to set the appropriate threshold value.

From the distribution of these cosign similarities, True Positives (TP: the ratio of correctly identified pairs) and True Negatives (TN: the ratio of correctly identified pairs) for each threshold value is shown in Figure 1. For example, if the threshold for cosign similarity is set to 0.1, the ratio of TP is 80% (conversely, the False Negative rate is 100-80: 20%), the TN ratio is 50% (False Positives are 100-50: 50%). When the threshold is raised, the TP decreases (because the probability of being falsely judged to be the same individual increases) and the TN increases (because the probability of different people being correctly determined as such increases). As can be seen in Figure 1, the accuracy rate (taken as an average of TP and TN) was determined to be a maximum of the value of 0.2 for cosign similarity, where the ratio of TP to TN is almost balanced.

(Figure 1)

Furthermore, although the telephone directory data is used to indicate rare name data in this model, there is a possibility that there are inaccuracies in the correct answer data as there are a considerable number of people who are not listed in the telephone directory.[2] Accordingly, a robustness check is performed by breaking down the rare names in the telephone directory into family and given names to see the rarity of both types of names. Then, the relative rarity of full names in rare name database is determined. Specifically, rare names are filtered in two stages of the top 5% and top 25% by rarity (filtering of names that have an even higher possibility of being rare) and are compared with the results for the aforementioned Same Person (True Positive). Figure 2 shows there has been almost no change in the relationship between Cosign similarity and TP.

(Figure 2)

The threshold value for the cosign similarity (0.2) looks quite low. But, it is not caused by a problem with the rare name information but rather that the concordance table between patent technology classification and design product classification does not give accurate information. It should be noted that that there are a considerable number of errors (both FP and FN) in the results of this work.

3. Empirical Analysis

In this section, empirical analysis to characterize NISTEP design database (roughly 380,000 designs that were filed between 1998 and 2013) is provided. Table 1 shows the ratio of design patent with any of creator who is also an inventor of utility patents. It can be seen that, of about 380,000 designs, around 220,000 (roughly 60%) feature the patent inventor as the designer. L group (civil engineering and construction supplies) has a rate of 72.4% and H group (electrical, electronic and communication equipment) has a rate of 69.0%. In groups such as group A

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[2] Listing telephone number to the directory is based on voluntary disclosure of the owner of the telephone number.

(manufactured foodstuffs and luxury grocery items) and group B (clothing and personal belongings), the ratio of with-inventor designs is low.

(Table 1)

Figure 3 shows the time trend of design applications, both with- and without-inventor. The number of design applications has been declining since the early 2000s, but the decrease mainly comes from the falling number of with-inventor designs. In other words, it can be seen that the ratio of with-inventor designs is trending downwards. It should be all design rights applications that are filed are subject to examination, and only registered designs appear as public record. On the other hand, all utility patent application information is disclosed after 18 month of application date. Here, all patent application information up to September 2015 is included, sot that this downward trend is not caused by truncation bias of patent statistics.

(Figure 3)

Figure 4 shows the with-inventor ratio by applicant. Here, in addition to looking at those classified as belonging to companies with more than 1,000 patent applications (relatively large firms) and those with 1,000 or less patent applications (smaller firms). The number of with-inventor designs is higher for large patent applicants but the decreasing trend is also more pronounced in these cases. Since around 2007, the overall trend has been almost the same for companies with more than 1,000 applications and those with 10,000 or more applications, in that the ratio of with-inventor patented designs has been decreasing. This shows that the division of labor between engineers (inventors) and designers (creators) in new product development process is progressed mainly in large firms.

(Figure 4)

Figure 5 shows the characteristics of with-inventor design rights. Here we can see the share of "partial design", "related design" and "design with forward citation". In all cases, the number of with-inventor designs exceeds the number of without-inventor designs. "Partial design" is the right granted to a part of product design. The right holder can protect its design for a particular part of the product, which is likely to increase the functional utility of the product, in addition to a design of a whole product. "Related design" refers to the rights protection for multiple variations based on a single design concept as having the same value. In both cases, the overall costs such as application fees are increased due to multiple filings so that such design (of product features and series) has a greater economic value than regular design rights.

The citation information in NISTEP design patent database is created by an examiner as a reference of existing design rights similar to the examining design application. Therefore, the design right cited by other designs (forward citation) is also more valuable one. One difference from utility patent system is that the examination of design rights only looks at the novelty of a design's appearance and shape, and does not represent a basis for technical progress. That said, designs with a high number of citations are likely to be pioneers in new styles (Chan et al, 2018). When interpreted in conjunction with the partial and related design results, it is likely that design rights involving a patent applicant will have superior functionality in addition to aesthetic advantages (as a result of good design), when compared to a design right where this is not the case.

(Figure 5)

Finally, in order to comprehensively examine the characteristics of design rights based whether they are with- or without-inventor designs, a descriptive regression analysis was performed using the presence or absence of an inventor as the dependent variable. The explanatory variables are as follows:

- Log (Number of citations +1)
- Log (Number of related designs +1)
- With related design dummy
- Partial design dummy
- Log (number of patents filed by the design applicant +1) : pcount
- Log (number of design applications filed by the design applicant +1) : dcount
- Post-2006 dummy: after
- Interaction terms of "pcount" and "dcount" with "after"

In addition, design product category dummies and application year dummies are included in some modes (not using "after" ones), and a logistic model is used to estimate the probability of design with patent inventors. The results are presented in Table 2.

(Table 2)

The results of this analysis confirm that firstly, the relationship between partial design, related design and cited design seen in Figure 4 are statistically significant, even after controlling for application year and design product category. Furthermore, the related design dummy (whether or not a related design is related to the original design) is also positive and statistically significant, which confirms that the proportion of with-inventor design rights is high across the entire design family, including the related designs (the original design and related designs are likely to have the same creator, so in a sense, perhaps this result is obvious).

With regards to time trends, "*after*" being negative and statistically significant is a result of the overall division of labor between the designer and the inventor. Furthermore, an intersection between pcount and "*after*" being negative and statistically significant (model 4), supports the view that the division of labor between the creator and inventor is more likely to be found in large patent applicant organizations.

4. Conclusion

In this study, creator/inventor disambiguation works are conducted for both NISTEP design patent data and IIP patent database, and linked each other at individual creator and inventor level, to evaluate the characteristics of design patent information. First, it is found that more than half of the design rights creators were also patent inventors. Second, the ratio of design rights with inventor decreases over time, which suggests that the division of innovative labor between invention and design activities is progressed. Furthermore, such trend is more likely to be found in large firms. Third, the design patents with patent inventor are more valuable as is suggested by higher propensity to having partial and related design rights and forward citations.

Design activities have been shown to be an important factor in corporate competitiveness in many empirical studies (D'lippolito, 2014). As developing countries increasingly catch up technologically, non-technological features become more and more important for a firm in developed countries including Japan in global competitive market. A product design, stressing new "meaning" of product or customer value proposition, is one of promising factors to pursue such avenue (Verganti, 2009). In this environment, expectations for design rights data as a means of analyzing design innovation and strategy are increasing.

However, a care must be taken when using design rights as a proxy variable for innovation in design. Firstly, it should be recognized that more than half of current design rights were created by the patent inventor and that they include the technical characteristics of products to a great extent. Design rights are intellectual property rights that only protect industrial designs, and do not focus on design characteristics such as external aesthetics. A design right requires newness in outer shape, which does not always lead to "better" design. Therefore, it is risky to evaluate design capability and performance by only looking at design rights.

With such reservation, design patent information is still a useful tool to analyze a general trend of product development organization. For example, it is found that movement towards splitting the roles of designers and engineers, particularly in large companies. In product development, this seems to reflect a move away from engineering-type industrial design, in which engineers at a company also create designs, to a system of independent designers who focus not only on function but also the design itself (semantic value). In this regard, it is important to conduct a more detailed analysis that focuses on the characteristics of each applicant (company). For example, multiple studies deal with design award information to take into account overall value of design innovation aspects (In terms of aesthetics, it is effective to use objective indicators for design such as the Good Design Award (Gemser and Wijnberg, 2002; Hertenstein et al., 2005).

Furthermore, this study focused on design results involving inventors but conversely, it should be possible to analyze patented inventions that involve the design creator. Designers are renowned for playing an important role in breakthroughs in technological innovation (Yoshioka-Kobayashi, 2018). Clarifying the characteristics of design creators in detail enables the quantitative analysis of a patent for an invention of superior product design that involves a creator. Analysis using design rights data has not made progress in Europe and the United States, and it is expected that world-leading research results could be derived from the data that is available in Japan.

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Table 1: Presence or absence of inventor by individual design classification group

	Without in	With inver	With ratio
A Group (Food products)	436	105	19.4%
B Group (Clothes)	15,000	6,313	29.6%
C Group (Home commodities)	21,045	16,912	44.6%
D Group (House appliance)	14,433	31,032	68.3%
E Group (Sports gppds, amusement)	8,488	6,784	44.4%
F Group (Office suppy)	22,206	21,258	48.9%
G Group (Transportation equipement)	11,569	10,565	47.7%
H Group (Electronics and comm equipment)	24,031	53,483	69.0%
J Group (General machinery)	10,574	16,831	61.4%
K Group (Industrial machinery)	12,763	16,288	56.1%
L Group (Construction machinery)	11,955	31,385	72.4%
M Group (Other manufacturing products)	9,443	11,376	54.6%
Total	161943	222332	57.9%

Table 2: Descriptive regression analysis results

	(1)	(2)	(3)	(4)
Log(forward citation+1)	0.193 [0.010]**	0.144 [0.010]**	0.025 [0.003]**	0.149 [0.010]**
Log(# of related designs+1)	0.23 [0.014]**	0.181 [0.014]**	0.18 [0.004]**	0.182 [0.014]**
Dummy with related designs	0.264 [0.010]**	0.208 [0.011]**		0.205 [0.011]**
Partial design dummy	0.213 [0.009]**	0.162 [0.010]**		0.161 [0.009]**
Log(# of patents by applicant+1) :pcount		0.014 [0.002]**		0.024 [0.003]**
Log(# of designs by applicant+1) :dcount		0.189 [0.003]**		0.173 [0.004]**
Dummy after 2006 : after			−0.146 [0.024]**	−0.165 [0.024]**
pcount*after			−0.021 [0.004]**	−0.023 [0.004]**
dcount*after			0.036 [0.006]**	0.041 [0.006]**
Constant	−1.866 [0.433]**	−3.316 [0.434]**	−2.814 [0.433]**	−2.95 [0.433]**
Design class dummy	Yes	Yes	Yes	Yes
Application year dymmy	Yes	Yes	No	No
# of samples	345,822	345,822	345,826	345,826

* p<0.05; ** p<0.01

Figure 1: Cosign similarity threshold tuning using rare names

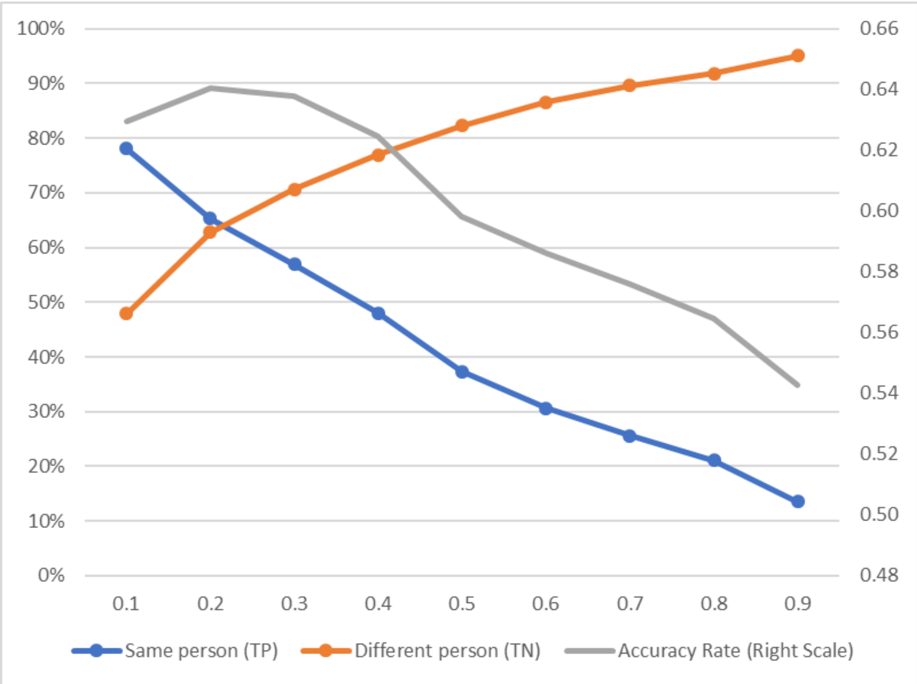

Figure 2: Robustness check results for rare names in the telephone directory

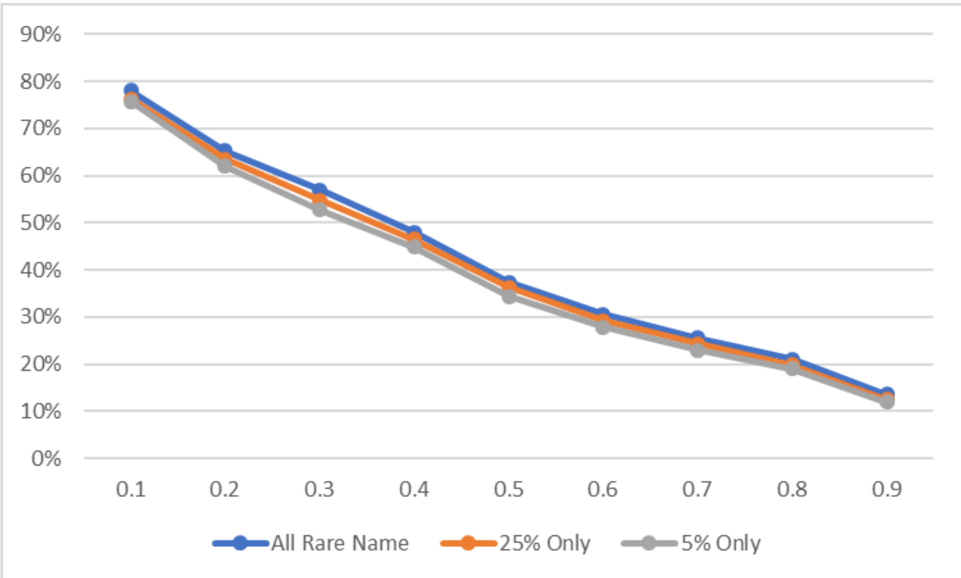

Figure 3: Trends in the number of design right applications by inventor status

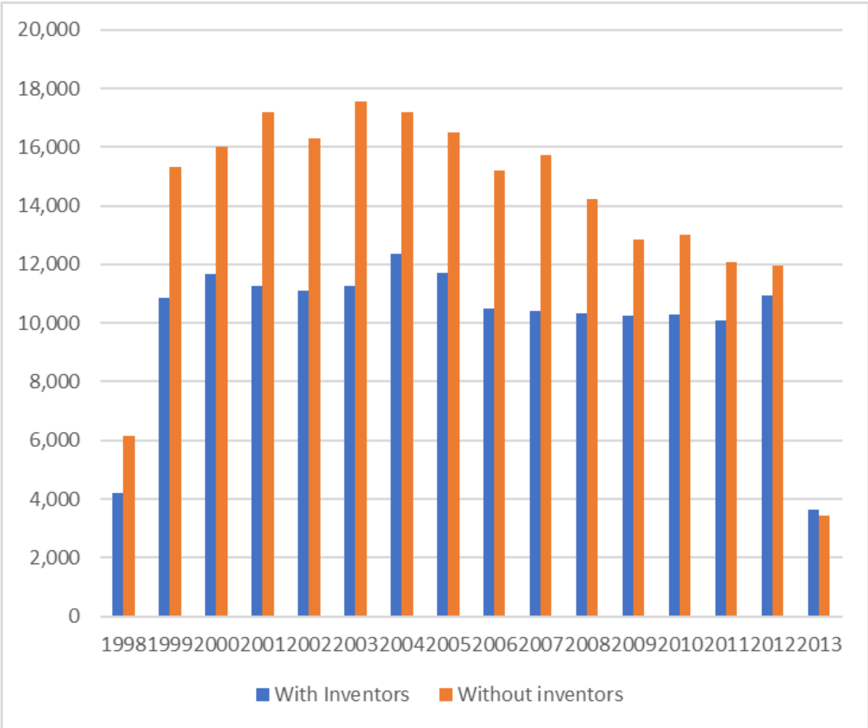

Figure 4: With-inventor patent ratio (by applicant with # of patents)

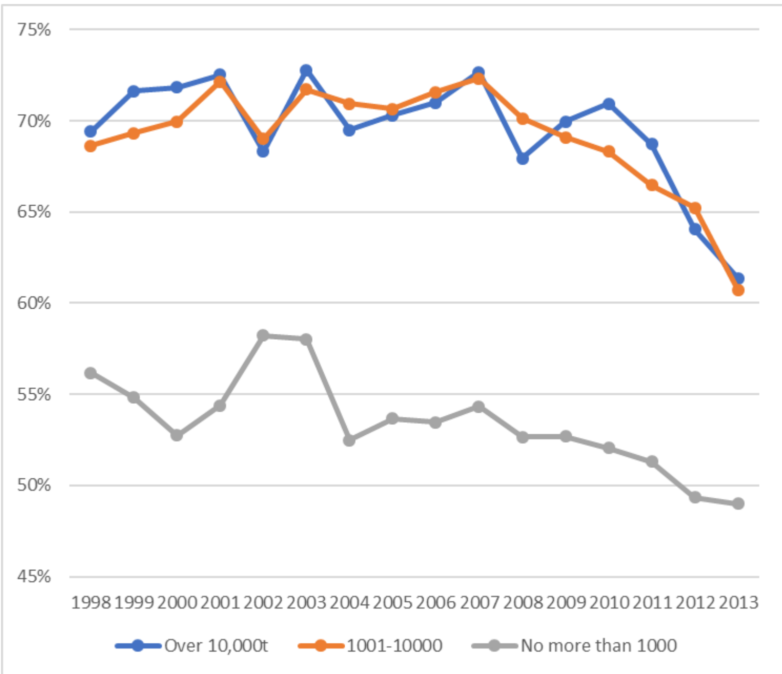

Figure 5: Differences in with- and without-inventor design rights