Waseda University Institute of Asia-Pacific Studies
早稲田大学 アジア太平洋研究センター

WIAPS Discussion Paper

Series No. 2020-E-2

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09/2020

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Abstract. The topic on whether team diversity influences innovation outcomes has gained attention in the innovation literature. Our study focuses on national origin, among various team diversity criteria. We use patent data to the Japan Patent Office between 2001 and 2015 to analyze inventors teams. Our analysis reveals that team inventors' diversity measured by national origin positively impacts inventions' quality measures and as national origin diversity increases, its negative effects become dominant, eliciting an inverted-U-shaped effect. The result was consistent though other R&D outcome determinants are controlled for. Our findings provide theoretical and practical implications for innovation policies.

Keywords: Diversity, Inventive activity, National origin, R&D, patent analysis

1. Introduction

Team composition and structure's performance is an important issue in management studies, particularly in the current globalized world. Thus, organizational diversity has attracted much attention not only from scholars but also from society. Although innovation has been recognized as a key source for growth and sustainability only recently, scholars have since studied how workplace diversity contributes to innovation (Shalley & Gilson, 2004; Taylor & Greve, 2006; Hennessey & Amabile, 2010; Singh & Fleming, 2010; Zhou & Hoever, 2014).

Various types of organizational diversity exist and have been studied thus far (Shore et al., 2009; Østergaard et al., 2011), including gender diversity (Hoogendoorn et al., 2013; Xie et al., 2020) and technological diversity (Sampson, 2007; Singh & Fleming, 2010; Huo et al., 2019). Although these diversities have been extensively explored, other dimensions have been examined less, such as national diversity. The reason is because patent databases typically do not contain nationality information.[1]

Thus, this study investigates how national diversity affects team innovation performance. We focus on patent data to the Japan Patent Office (JPO) for our analysis due to the relative ease of national origin identification compared to other patent offices. There are two merits to use the JPO patent data. The first is the availability of three non-Roman characters in patent documents. It helps easily identify inventors' reliable national origins compared with using Roman characters only. The second is unique naming patterns.

Our approach have a number of contributions to the field. First, this study investigates the impact of national diversity on innovation. Few studies found mixed correlations between team national diversity and innovative outcome. Certain studies indicate positive correlations (Franzoni et al., 2014; Gagliardi, 2014; Nathan, 2015; Ferrucci & Lissoni, 2019), whereas others indicate no or negative correlations (Lovelace et al., 2001; Alesina & Ferrara, 2005; van Knippenberg & Schippers, 2007; Shore et al., 2009). We test whether a curvilinear (inverted-U) correlation exist between them. By doing so, we develop further discussion in the field.

Second, this study compares the impact of foreign team members in a focal country with that of any team members residing of the focal country. Foreign team members' contribution to innovative outcomes is generally recognized. However, whether team members in other countries also contribute in a similar way as foreign team members in the same country is unclear.

Third, a deeper micro-level analysis is made. There are a few prior studies focused on Japanese cases to investigate the effects of multi/international research and development (R&D) (Kondo, 1999; Branstetter, 2005; Penner-Hahn & Shaver, 2005). They used firm-level analysis units. Their main measurement was the amount of patents that a firm produced from multi/international R&D. Accordingly, our approach that uses micro-level analyses, such as a team level, and quality measurement of R&D outcomes is a new attempt.

This paper is structured as follows. Section 2 reviews the literature on which the current study is based and sets its hypotheses. Section 3 explains research data. Section 4 presents our data analyses. Section 5 discusses findings and concludes with remarks on policy implications and study limitations.

2. Literature Review and Hypotheses

[1] A database that includes inventors' nationalities has been constructed (Miguélez & Fink, 2013). However, in principle, most countries' patent system requires address and nationality information of applicants, not inventors. Although Miguélez's (2018) database could be a practically proxy method to identify inventor nationalities, it has certain issues (Breschi et al., 2017).

Diversity research has been conducted in two streams (Harrison & Kelin, 2007), namely, task- and non-task-relevant diversities. Task-relevant diversity focuses on knowledge, expertise, and function diversity as determinants of work performance, given cross-domain knowledge utilization is useful to approaching complex problems from various angles and innovative ways (Taylor & Greve, 2006; Singh & Fleming, 2010; Huo et al., 2019; Brixy et al., 2020).

On contrary, non-task-relevant diversity focuses on diversity in ethnic, culture, and gender among others (Shore et al., 2009). The mechanism through which non-task-relevant diversity positively impacts team performance is not as simple as that of task-relevant diversity. Numerous factors of non-task-relevant diversity are investigated to determine the underlying reasons of national origin diversity impacts on innovative outputs.

The first reason is that national origin diversity expands cognitive diversity. Individuals with different national backgrounds provide rich mix of ideas and perspectives (Berliant & Fujita, 2008; Berliant & Fujita, 2009). Rich mix of ideas and perspectives are important factors in knowledge-intensive tasks that require creativeness and innovativeness.

The second reason is minority migrant team members, who face lower opportunity costs of investing in new skills than natives; thus, they are willing to invest in host country-relevant human capital (Duleep et al., 2012). Such efforts positively impact knowledge-intensive works. In addition, migrant workers in high-technology sectors are highly skilled. Furthermore, they try to balance out gains from migration and costs of moving abroad. Accordingly, these workers in a team are a predictor of good performance (Franzoni et al., 2014; Gagliardi, 2014) because they are expected to be better than average workers (selection). They work hard and are more willing to take risks.

The third reason is in a psychological perspective, a team is resistant to group pressure to conformity and transparent and open when the team has minority opinion holders (De Dreu & West, 2001; Park & Deshon, 2010). Minority national origin workers may be a good proxy of minority opinion holders due to different cognitions stemming from different backgrounds. Consequently, decision-making quality, such as novelty and efficiency, improves, as supported by empirical findings. For example, Nathan (2015) used patents and inventors in the United Kingdom and found that team members of minority national origins correlate positively to innovative outcomes.

We also consider geographical proximity in the investing effects of foreign team members on team performance. Certain foreign team members work together in the same location as natives, whereas others work at places other than the host country. In this situation, being in a different place creates innovation performance. Geographical proximity allows frequent formal and informal face-to-face interactions between actors, strengthening other dimensions of proximity (Boschma, 2005). Foreign team members assimilate the host country's locals over time. Accordingly, foreign team members in the host country tend to have less impact on innovation performance than those abroad.

In sum, foreign team members contribute to their team to achieve better, more novel, and cognitively wider outcomes. However, foreign team members in the host country contribute more than those residing abroad. Hence, we hypothesize the following:

H1: Foreign team members in a host country positively impact (technological importance, novelty, and technological scopes) innovation.

H2: Foreign team members residing abroad positively impact (technological importance, novelty, and technological scopes) innovation.

H3: Foreign inventors abroad have larger positive impacts on innovation compared with those in a host country.

Proximity usually has a double-edged effect, the so-called proximity paradox (Boschma &

Frenken, 2010). Proximity may be a crucial driver for agents to connect and share knowledge. However, excessive proximity between them on any dimensions may harm their innovative performance (Broekel & Boschma, 2012). We apply this concept to diversity. National origin diversity tends to have mixed impacts on innovative outcomes. As mentioned, national origin diversity expands cognitive diversity and creates synergies between team members if they engage in good communication and build trust among themselves. Otherwise, national origin diversity worsens team performance (Alesina & Ferrara, 2005). A team with multinational origins is prone to conflicts stemming from different attitudes and values and social ethnic categorization (Lovelace et al., 2001; van Knippenberg & Schippers, 2007). Insufficient communication among team members can easily trigger conflicts, hindering information exchange and integration (van Knippenberg et al., 2004). The team performance creates negative spiral. Hence, we assume that deriving synergies among national origin diversity becomes difficult if such diversity is extremely complicated to manage. As a result, we expect that a diminishing marginal effect will exist after a certain peak, which outweighs the benefit of collaboration. Therefore, we hypothesize the following:
H4: Diversity measure among inventors and its impacts (technological advancement, novelty, and technological scopes) has an inverted-U relationship.

In sum, our framework can be illustrated in a 2 × 2 matrix as shown Table 1. Although we are also interested to learn about team members' contributions dispatched to foreign countries, we have no specific a-priori expectations. Thus, we will not postulate any hypotheses. However, we will add relevant variables into our analytical models.

Table 1. Analytical framework

	Country A inventors	Other-country inventors
Residing in country A		H1
Residing outside country A	H2	

3. Methodology

3.1 Data

We use a Japanese patent database (Goto & Motohashi, 2007)[2] that database contains patent applications filed to the JPO from 1964.

Our dataset is constructed as follows. First, we retrieved all patent applications by applicants whose address is in Japan between 2001 and 2015. Second, we retrieved inventor names of those patent applications. Patent applications with more than one inventor were selected. This procedure drops inventions by a single inventor and keeps inventions by teams. Thus, we obtained sample observations of 7.5 million patent applications.

We identified inventors using the following process. First, we retrieved inventors' address information for all observations to identify inventors residing in or outside of Japan. Second, we distinguished Japanese and non-Japanese inventors based on their name patterns as follows.

[2] The database is called IIP Patent Database. It is a database developed for statistical analysis of patents based on JPO's "standardized data."

First, we identified inventor names that are registered with Chinese characters.[3] This method allowed us to identify North East Asian inventors, i.e. the Chinese, Japanese, Koreans, and Taiwanese. In other words, names registered with non-Chinese characters (including Katakana) are identified as non-North East Asian inventors.

Second, we searched whether each name pattern with Chinese characters, such as Chinese, Korean, and Taiwanese, can be found outside of Japan using the address information. . Finally, the remaining names are identified as Japanese inventors. This method may not be 100% accurate. Nonetheless, the identification result is significantly reliable because of the uniqueness in Japanese name patterns and Chinese, Korean, and Taiwanese names (Kang, 2016).

3.2 Measures and statistical method

3.2.1 Dependent variables

We employ three dependent variables that measure three types of impacts: technological importance, novelty, and technological scopes.

The first dependent variable is a patent's technological importance, which is measured through the normalized number of non-self forward citations. This normalized number is the number of non-self forward citations divided by the average number of forward citations from the same application year and IPC (Jaffe & Trajtenberg, 2002; Nagaoka et al., 2010). A forward citation implies that the more a patent is cited by follow-up patents, the higher is its technological importance. Normalization controls the age effect that older patents tend to have more citations than newer patents. The Tobit model is employed for analysis using the first dependent variable.

The second dependent variable is a patent's radicalness, which is measured using the number of technological fields in which previous patents cited by the given patent are found, though the patent is unclassified (Rosenkopf & Nerkar, 2001; Shane, 2001). Therefore, this patent is not a simple linear progression of past technology but a departure from that trajectory. Various radicalness indicators have been proposed and continuously discussed (Dahlin & Behrens, 2005). We used Rosenkopf and Nerkar's (2001) indicator because it is used by other studies and official documents as an important patent quality measure, for example, Shane (2001) and Squicciarini et al. (2013). The logit model is employed for analysis on second dependent variable.

The third dependent variable is a patent's technological scope. We used the number of claims in a patent as its proxy (Lanjouw & Schankerman, 2004; Novelli, 2015; Marco et al., 2019). Patent claims in a patent document delineate the scope of the conferred or sought protection. Therefore, the more claims, the wider is the scope. A negative binomial model is employed to examine the third dependent variable.

3.2.2 Independent variables

[3] A Japanese translation must be included when filing a patent application to the JPO. Inventor names are recorded with three types of Japanese characters: Chinese characters (Kanji), Hiragana, and Katakana. In modern Japanese writing, Chinese character is used as a standard and Katakana is normally used for loanwords and foreign names. Chinese, Japanese, (most) Korean, and Taiwanese inventors are registered with Chinese characters whereas foreign inventors from non-North East Asian countries are registered with Katakana. A few Japanese names and Korean names, respectively. There are a few exceptions: 1) Hiragana for a few Japanese names, 2) flags for Chinese and Korean names whose Chinese characters are not used in Japan, and 3) Katakana for a few Korean names which are not of Chinese origin. This unique writing system allows us to better identify more reliable inventors' national origins than using Roman characters only.

We employ three independent variables to measure various effects. We investigate (1) if the existence of non-Japanese inventors in Japan and those outside of Japan positively impacts innovative outcomes, (2) if the size of foreign team members positively impacts innovative outcomes, and (3) if their shares positively impact innovative outcomes. As mentioned earlier, excessive diversity could lead to negative (or less positive) impacts. Therefore, we also test for the inverted-U shaped relationship for measurements (2) and (3). We also investigate how these effects differ between non-Japanese inventors in Japan and those outside of Japan. We define the variables below using the information on non-Japanese inventors in Japan and those outside of Japan.

The first independent variables are two dummy variables: whether or not any non-Japanese inventors in Japan exist and whether or not any inventors outside of Japan exist. For each type of inventor, the variable is set to 1 if such an inventor exists. These independent variables are used to test hypotheses 1–3.

The second independent variables are the number of non-Japanese inventors in Japan and those outside of Japan. Their squared terms are added to test whether an inverted-U relationship exists. In sum, four variables are used. These independent variables are used to test hypothesis 4 in addition to hypotheses 1–3.

The third independent variables are the share of non-Japanese inventors over all inventors in a patent and those of outside of Japan. Their squared terms are added to test whether an inverted-U relationship exists. These independent variables are used to test hypothesis 4 in addition to hypotheses 1–3. This variable is added to determine whether the absolute number or share is significant if an inverted-U relationship exists.

We did not postulate any hypotheses on Japanese inventors dispatched to other countries. Thus, we add a relevant variable for comparison.

Table 2 summarizes the application of the analytical framework to our dataset.

Table 2. Analytical framework

	Japanese inventors	Non-Japanese inventors
Residing in Japan	Baseline	Independent variable
Residing outside Japan	Independent variable	Variables for comparison

3.2.3 Control variables

In addition to the independent variables, we added control variables for each observation that may impact the dependent variables. They include team characteristics (team size, invention experience, and repeated members) and patent characteristics (knowledge base and application year).

First, team size is added to control for invention capability and is correlated to innovative outcome quality (Lee et al., 2015). The number of inventors for each patent is used as its team size.

Second, team average experience is added to control for invention capability. We ordered inventions of each inventor in a time series and identified the order of each patent. Then, invention time mean value of all inventors per each patent is calculated. Although we use observations between 2001 and 2015 for regressions, this value is calculated with patent data from the 1970s to 2017. By doing so, we minimize the censored effect.

Third, team repeat experience is added to control for a team's capability of creativity. Repeated collaboration between the same partners sometimes lessens creativity (Skilton & Dooley, 2010). This variable captures the number of years that the same team members worked as a team. Similar to team average experience, this value is calculated with patent data from the 1970s to 2017.

Fourth, patent reference is added to control for an invention's knowledge base volume. The number of backward citations in each patent is used as a proxy. We used patent citations added by patent examiners to minimize inventors' self-citations in inventor citations (Alcácer & Gittelman, 2006).

Fifth, the ICT industry dummy is added. Communications with others are easier in industries where explicit knowledge is dominant than those where tacit knowledge is dominant (Nonaka & Takeuchi, 1995; Haldin-Herrgard, 2000). The ICT industry is a typical industry where knowledge is easy to code and, thus, diffuse well. The dummy is set to 1 if the IPC of the patent is classified into IPCs in the ICT (Inaba & Squicciarini, 2017).

Finally, 14 year dummies (2001–2015) are added to control for year effects (Judge et al., 1988).

4. Findings

Table 3 reports all variables' descriptive statistics and correlations. The independent variables are tested separately because they correlate each other. Regression models (1) and (2) test the impact of technological advancement; regression models (3) and (4) test the impact of novelty; and regression models (5) and (6) test the impact of technological scope.

Table 3. Basic statistics

Table 4. Correlations between variables

The first result tests hypotheses 1–3 with dummy variables and their coefficients and t statistics as shown in Table 5. Independent variables, non-Japanese inventors in Japan and outside of Japan, have positive effects and statistical significance at the 1% level in all regression models. This result implies that team national origin diversity has positive impacts: a diversified team produces technologically advanced and novel outcomes with wide technological scopes, supporting hypotheses 1 and 2.

On the contrary, coefficients of non-Japanese inventors in Japan are not always greater than those of outside of Japan. Coefficients of non-Japanese inventors in Japan are greater than those of outside of Japan when control variables are not added to regression model (1). However, the result is reversed when the control variables are added to regression models (2)–(5). Particularly, coefficients of non-Japanese inventors in Japan are always smaller than those of outside of Japan when control variables are added. Thus, we consider that hypothesis 3 is supported as shown in Table 5.

Coefficients of Japanese inventors outside of Japan show different results for each indicator. They are negative in regression models (1)–(4) and positive in regression models (5)–(6). They contribute to the development of wider technological scopes and decrease the development of technologically important and radical inventions. We will investigate this variable further in the next regression.

Coefficient estimates of control variables are mostly as expected. The estimates for team repeat experiences are significantly negative in all models as expected. These results suggest that inventors working together in the same team for a long period are not conducive to producing innovation. As expected, coefficient estimates for patent references are significantly positive. The coefficient estimates for team size is also within the expectation. For the forward citation and technology scope, team size has positive impacts. On the contrary, team size negatively impacts radical innovation. This result may be due to the case when an organization embarks on a radical innovation with a smaller team. The results for team average invention experience are contrary to our expectations. The estimates are all significantly negative, though the coefficient magnitude is extremely small.

Table 5. Regressions 1: independent variable = dummy of non-Japanese inventors

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Table 6 shows the second result that tests hypotheses 1–4 with count numbers and squared terms and the coefficients and t statistics of each variable. Similar to Table 5, independent variables, non-Japanese inventors in Japan and outside of Japan, have positive effects and statistical significance at the 1% level in all regression models. This result implies that team national origin diversity has positive impacts: it produces technologically advanced and novel outcomes with wide technological scopes, supporting hypotheses 1 and 2.

On the contrary, coefficients of non-Japanese inventors in Japan are not always greater than those of outside of Japan for regression models (1)–(4). However, the coefficients of non-Japanese inventors in Japan are always smaller than those of inventors outside of Japan when control variables are added. For regression models (5)–(6), coefficients of non-Japanese inventors in Japan are smaller than those of outside of Japan. Therefore, hypothesis 3 is supported as shown in Table 6.

In addition, the squared terms of the independent variables have negative coefficients and statistically significant at the 1% level in all regression models. This result implies that non-Japanese inventors in Japan and outside of Japan have an inverted-U correlation to technological advancement, novelty, and technological scopes: inflexion point at 2.5 non-Japanese inventors in Japan and 3.8 non-Japanese inventors outside of Japan, supporting hypothesis 4. The results for coefficient estimates for other variables are similar to those in Table 2.

We investigate further on Japanese inventors' contribution outside of Japan. First, the coefficients of Japanese inventors are inconsistent in regression models (1)–(2). Accordingly, we confirm that Japanese inventors outside of Japan impact the development of technologically important inventions. Second, only the number of Japanese inventors outside of Japan is significantly negative in regression models (3)–(4). In other words, they decrease technological inventions' radicalness. Third, count numbers and their squared terms are positive and negative, respectively, in regression models (5)–(6). In other words, their contributions to the width of technological scopes show an inverted-U correlation.

Table 6. Regression 2: independent variable = counts and squared term of non-Japanese inventors

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Table 7 shows the third result, with the coefficients and t statistics of each variable. The result is consistent with that in Table 6. All independent variables and their squared terms are positive and negative, respectively, with statistical significance at the 1% level. The inflexion point is at 38% and 41% of non-Japanese inventors in Japan and outside of Japan, respectively. Table 7 confirms that hypotheses 1–3 are supported.

Coefficients of Japanese inventors outside of Japan show a similar tendency similar to those in Table 6.

Table 7. Regression 3: independent variable = share of non-Japanese inventors

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5. Discussions and Conclusion

We have investigated the impacts of team national origin diversity on its innovation performance. We used the Japanese patent dataset and found that team national origin diversity positively impacts its innovation performance. However, the positive effect dominates until medium-level dissimilarity beyond the negative effect begins to prevail. Furthermore, we found that foreign inventors abroad have a bigger contribution to the development of innovation outcomes than foreign inventors in the host country.

Our findings provide numerous practical implications. First, our research reconfirms the importance of team national diversity to innovation performance. Team diversity has been considered a determinant of innovation outcomes. Various criteria are required to achieve team diversity. In terms of national origin diversity, team managers should be aware of the importance of national origin diversity within teams while understanding the simultaneous downside of such diversity.

Second, managers must be aware that the national origin diversity has a double-edges effect. Although team national diversity has a positive impact, it also has a downside after a peak. A manager must find proper extent when the best synergy can be achieved. However, indicating the optimum portion of national origin diversity for all is difficult because situations vary between industries, ages, and target markets. Thus, each manager decides the optimum point based on given situations.

Third, foreign team members' location determines an extent of innovative contributions, though a trade-off exists. Our analysis indicated that foreign team members abroad have more innovative contributions than those in the host country. However, recruitment and management of foreign team members abroad require more costs than those in the host country. Therefore, when organizing a team, the trade-off between performance and cost must be considered.

This current study has certain limitations. First, the identification methodology of non-Japanese inventors is insufficient. North East Asian countries are not as multinational as other regions, such as the U.S., Europe, and former Soviet Union countries. Migration between North East Asian countries is extremely limited compared with regions where countries are connected by land. Accordingly, name patterns are significantly different between North East Asian countries. Thus, identifying non-Japanese inventors using their names is reliable. Nonetheless, our identification method cannot determine whether identified Japanese inventors are immigrants or second-generation (or higher) immigrants. However, we believe such cases are rare in the context of North East Asian and negligibly small in our data. A similar problem could occur with the identification methodology of Japanese inventors outside of Japan. Determining whether Japanese inventors found outside of Japan are immigrants or second-generation (or higher) immigrants to the country is difficult.

Acknowledgement

All remaining errors are the authors' own.

Reference

Alcácer, J. & Gittelman, M. (2006) Patent citations as a measure of knowledge flows: The influence of examiner citations, Review of Economics and Statistics 88(4), 774–779.

Alesina, A. & Ferrara, E.L. (2005) Ethnic diversity and economic performance, Journal of Economic Literature 43(3), 762–800.

Berliant, M. & Fujita, M. (2008) Knowledge creation as a square dance on the Hilbert cube, International Economic Review 49(4), 1251–1295.

Berliant, M. & Fujita, M. (2009) Dynamics of knowledge creation and transfer: The two person case, International Journal of Economic Theory 5(2), 155–179.

Boschma, R. (2005) Proximity and innovation: a critical assessment, Regional Studies 39(1), 61–74.

Boschma, R.A. & Frenken, K. (2010) The spatial evolution of innovation networks. A proximity perspective. In R.A. Boschma, and R. Martin (eds), The Handbook of Evolutionary Economic Geography, Edward Elgar, Cheltenham, pp. 120–135.

Branstetter, L.G. (2005) Are knowledge spillovers international or intranational in scope?: Microeconometric evidence from the U.S. and Japan, Journal of International Economics 53(1), 53–79.

Breschi, S., Lissoni, F., & Miguelez, E. (2017) Foreign-origin inventors in the USA: testing for diaspora and brain gain effects, Journal of Economic Geography 17(5), 1009–1038.

Brixy, U., Brunow, S., & D&Ambrosio Anna (2020) The unlikely encounter: Is ethnic diversity in start-ups associated with innovation?, Research Policy 49(4), 103950.

Broekel, T. & Boschma, R. (2012) Knowledge networks in the Dutch aviation industry: the proximity paradox, Journal of Economic Geogrpahy 12(2), 409–433.

Dahlin, K.B. & Behrens, D.M. (2005) When is an invention really radical?: Defining and measuring technological radicalness, Research Policy 34(5), 717–737.

De Dreu, C.K.W. & West, M.A. (2001) Minority dissent and team innovation: the importance of participation in decision making, Journal of Applied Psychology 86 (6), 1191–1201.

Duleep, H.O., Jaeger, D., & Regets, M. (2012) How immigration may affect U.S. native entrepreneurship: Theoretical building blocks and preliminary results. IZA Discussion Paper 6677. Bonn: IZA.

Ferrucci, E. & Lissoni, F. (2019) Foreign inventors in Europe and the United States: Diversity and patent quality, Research Policy 48(9), 103774.

Franzoni, C., Scellato, G., & Stephan, P. (2014) The mover's advantage: The superior performance of migrant scientists, Economics Letters 122(1), 89–93.

Gagliardi, L. (2014) Does skilled migration foster innovative performance? Evidence from British local areas, Papers in Regional Science 94(4), 773–794.

Goto, A. & Motohashi, K. (2007) Construction of a Japanese patent database and a first look at Japanese patenting activities, Research Policy 36(9), 1431–1442.

Haldin-Herrgard, T. (2000) Difficulties in diffusion of tacit knowledge in organizations, Journal of Intellectual Capital 1(4), 357–365.

Harrison, D.A. & Kelin, K.J. (2007) What's the difference? diversity constructs as separation, variety, or disparity in organizations, Academy of Management Review 32(4), 1199–1228.

Hennessey, B.A. & Amabile, T.M., (2010) Creativity, Annuual Review of Psychology 61(1), 569–598.

Hoogendoorn, S., Oosterbeek, H., & van Praag, M. (2013) The impact of gender diversity on the performance of business teams: Evidence from a field experiment, Management Science 59(7), 1514–1528.

Huo, D., Motohashi, K., & Gong, H. (2019) Team diversity as dissimilarity and variety in organizational innovation, Research Policy 48(6), 1564–1572.

Inaba, T. & Squicciarini, M. (2017) ICT: A new taxonomy based on the international patent

classification, OECD Science, Technology and Industry Working Papers, No. 2017/01, OECD Publishing, Paris, https://dx.doi.org/10.1787/ab16c396-en.
Jaffe, A.B. & Trajtenberg, M. (Eds.) (2002) Patents, citations & innovations: A window on the knowledge economy. The MIT Press, Cambridge, MA.
Judge, G.G., Hill, R.C., Griffiths, W.E., Lütkepohl, H., & Lee, T.-C. (1988) Introduction to the Theory and Practice of Econometrics. Wiley, New York, NY.
Kang, B. (2016) What best transfers knowledge? Capital, goods, and labor in East Asia, Economics Letters 139, 69–71.
Kondo, M. (1999) R&D dynamics of creating patents in the Japanese industry, Research Policy 28(6), 587–600.
Lanjouw, J.O. & Schankerman, M. (2004) Patent quality and research productivity: Measuring innovation with multiple indicators, Economic Journal 114(495), 441–465.
Lazzeretti, L. & Capone, F. (2016) How proximity matters in innovation networks dynamics along the cluster evolution. A study of the high technology applied to cultural goods, Journal of Business Research 69(12), 5855–5865.
Lee, Y.N., Walsh, J.P., & Wang, J. (2015) Creativity in scientific teams: unpacking novelty and impact, Research Policy 44(3), 684–697.
Lovelace, K., Shapiro, D.L., & Weingart, L.R. (2001) Maximizing cross-functional new product teams' innovativeness and constraint adherence: A conflict communications perspective, Academy of Management Journal 44(4), 779–793.
Marco, A.C., Sarnoff, J.D., & deGrazia, C.A.W. (2019) Patent claims and patent scope, Research Policy 48(9), 103790.
Miguélez, E., Fink, C. (2013) Measuring the International Mobility of Inventors: A New Database, WIPO Economic Research Working Paper No. 8. Available at: https://www.wipo.int/export/sites/www/econ_stat/en/economics/pdf/wp8.pdf
Miguélez, E. (2018) Inventor diasporas and the internationalization of technology The World Bank Economic Review 32(1), 41–63.
Nagaoka, S., Motohashi, K., & Goto, A. (2010) Patent statistics as an innovation indicator, In: Hall, B.H., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation, vol.2. Academic Press, 1083–1128.
Nathan, M. (2015) Same difference? Minority ethnic inventors, diversity and innovation in the UK, Journal of Economic Geography 15(1), 129–168.
Nonaka, I. & Takeuchi, H. (1995) The knowledge creating company: how Japanese companies create the dynamics of innovation. Oxford University Press, New York, NY.
Novelli, E. (2015) An examination of the antecedents and implications of patent scope, Research Policy 44(2), 493–507.
Østergaard, C.R., Timmermans, B., & Kristinsson, K. (2011). Does a different view create something new? The effect of employee diversity on innovation, Research Policy 40(3), 500–509.
Park, G. & Deshon, R.P. (2010) A multilevel model of minority opinion expression and team decision-making effectiveness, Journal of Applied Psychology 95(5), 824–833.
Penner-Hahn, J., & Shaver, J.M. (2005) Does international research and development increase patent output? An analysis of Japanese pharmaceutical firms, Strategic Management Journal 26(2), 121–140.
Rosenkopf, L. & Nerkar, A. (2001) Beyond local search: Boundary spanning, exploration and impact in the optical disk industry, Strategic Management Journal 22(4), 287–306.
Sampson, R.C. (2007) R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation, Academy of Management Journal 50(2), 364–386.
Shalley, C.E. & Gilson, L.L. (2004) What leaders need to know: a review of social and

contextual factors that can foster or hinder creativity, The Leadership Quarterly 15(1), 33–53.
Shane, S. (2001) Technological opportunities and new firm creation, Management Science 47(2), 205–220.
Singh, J. & Fleming, L. (2010) Lone inventors as sources of breakthroughs: myth or reality?, Management Science 56(1), 41–56.
Shore, L.M., Chung-Herrera, B.G., Dean, M.A., Ehrhart, K.H., Jung, D.I., Randel, A.E., & Singh, G. (2009) Diversity in organizations: Where are we now and where are we going?, Human Resource Management Review 19(2), 117–133.
Skilton, P.F. & Dooley, K.J. (2010) The effects of repeat collaboration on creative abrasion, Academy of Management Review 35(1), 118–134.
Squicciarini, M., Dernis, H., & Criscuolo, C. (2013) Measuring Patent Quality: Indicators of Technological and Economic Value, OECD Science, Technology and Industry Working Papers, No. 2013/03, OECD Publishing, Paris, https://doi.org/10.1787/5k4522wkw1r8-en.
Taylor, A. & Greve, H.R. (2006) Superman or the fantastic four? Knowledge combination and experience in innovative teams, Academy of Management Journal 49(4), 723–740.
van Knippenberg, D., De Dreu, C.K.W., & Homan, A.C. (2004) Work group diversity and group performance: An integrative model and research agenda, Journal of Applied Psychology 89(6), 1008–1022.
van Knippenberg, D. & Schippers, M.C. (2007) Work group diversity, Annual Review of Psychology 58, 515–541.
Xie, L., Zhou, J., Zong, Q., & Lu, Q. (2020) Gender diversity in R&D teams and innovation efficiency: Role of the innovation context, Research Policy 49(1), 103885.
Zhou, J. & Hoever, I.J. (2014) Research on workplace diversity: A review and redirection, Annual Review of Organizational Psychology and Organizational Behavior 1(1), 333–359.

Table 3. Basic statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
1) Dummy: Non-Japanese inventors in Japan	7,456,668	0.2801	0.4491	0	1
2) Dummy: Non-Japanese inventors outside Japan	7,456,668	0.0045	0.0672	0	1
3) Dummy: Japanese inventors outside Japan	7,456,668	0.0025	0.0498	0	1
4) Number: Non-Japanese inventors in Japan	7,456,668	0.3628	0.6883	0	15
5) Squared: Non-Japanese inventors in Japan	7,456,668	0.6053	2.3178	0	225
6) Number: Non-Japanese inventors outside Japan	7,456,668	0.0110	0.2034	0	22
7) Squared: Non-Japanese inventors outside Japan	7,456,668	0.0415	1.5025	0	484
8) Number: Japanese inventors outside Japan	7,456,668	0.0038	0.0927	0	12
9) Squared: Japanese inventors outside Japan	7,456,668	0.0086	0.4219	0	144
10) Share: Non-Japanese inventors in Japan	7,456,668	0.0009	0.0193	0	0.9231
11) Squared share: Non-Japanese inventors in Japan	7,456,668	0.0004	0.0104	0	0.8521
12) Share: Non-Japanese inventors outside Japan	7,456,668	0.0921	0.1761	0	1
13) Squared share: Non-Japanese inventors outside Japan	7,456,668	0.0395	0.1126	0	1
14) Share: Japanese inventors outside Japan	7,456,668	0.0021	0.0333	0	0.9565
15) Squared share: Japanese inventors outside Japan	7,456,668	0.0011	0.0208	0	0.9149
16) Team size	7,456,668	3.9479	2.0755	2	42
17) Team average invention experience	7,328,827	192.254	262.90	1	6128
18) Team repeat experience	7,328,827	1.3418	0.9320	1	36
19) Patent reference	7,456,668	3.1589	3.3304	0	127
20) ICT industry dummy	7,456,668	0.2414	0.4279	0	1

Table 4. Correlations between variables

	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)	12)	13)	14)	15)	16)	17)	18)	19)	20)
1)	1																			
2)	0.007	1																		
3)	-0.0003	0.171	1																	
4)	0.8454	0.0098	0.0002	1																
5)	0.4183	0.0099	0.0005	0.796	1															
6)	0.0059	0.797	0.1274	0.0096	0.0113	1														
7)	0.0012	0.4056	0.0702	0.0035	0.0053	0.8034	1													
8)	-0.0008	0.1304	0.8143	-0.0012	-0.0009	0.0882	0.0435	1												

9)	-0.0011	0.0564	0.4086	-0.0017	-0.0014	0.033	0.0133	0.8217	1											
10)	0.8389	-0.0016	-0.0046	0.8673	0.5693	-0.0046	-0.0048	-0.0059	-0.0046	1										
11)	0.5628	-0.0053	-0.0056	0.7282	0.5968	-0.0071	-0.0053	-0.0065	-0.0046	0.9007	1									
12)	0.0031	0.9181	0.1222	0.004	0.0048	0.8773	0.5186	0.0831	0.0295	-0.0043	-0.0068	1								
13)	0.0005	0.7877	0.0839	0.0001	0.0009	0.8643	0.5733	0.0528	0.0162	-0.0058	-0.0075	0.9619	1							
14)	-0.0041	0.115	0.8926	-0.0047	-0.0033	0.0645	0.0233	0.8938	0.5747	-0.0059	-0.0059	0.0732	0.0444	1						
15)	-0.0054	0.0693	0.7184	-0.0062	-0.0044	0.0325	0.0086	0.8686	0.6699	-0.0063	-0.0056	0.0391	0.0208	0.9452	1					
16)	0.2177	0.0474	0.0231	0.2626	0.2093	0.0763	0.0694	0.029	0.0255	-0.0012	-0.0737	0.0404	0.0361	0.0092	0.0059	1				
17)	0.2132	-0.0254	-0.0117	0.1733	0.0738	-0.0228	-0.0132	-0.0112	-0.0073	0.2144	0.1588	-0.0258	-0.0239	-0.0108	-0.0092	-0.0096	1			
18)	-0.0197	-0.0181	-0.0122	-0.0256	-0.021	-0.0157	-0.0086	-0.011	-0.0062	0.0253	0.043	-0.0166	-0.0144	-0.0105	-0.0085	-0.1593	0.1281	1		
19)	0.028	0.0023	-0.0013	0.027	0.0131	0.0031	0.0017	-0.0006	-0.0001	0.0118	0.0014	0.001	-0.0001	-0.0024	-0.0023	0.0566	0.0099	0.0222	1	
20)	0.0208	0.0167	0.0007	0.0262	0.022	0.0129	0.0043	0.0013	0.0009	0.0233	0.0214	0.0188	0.0186	0.0008	0.0008	0.0076	-0.0043	-0.0061	0.0139	1

Table 5. Regressions 1: independent variable = dummy of non-Japanese inventors

	(1)	(2)	(3)	(4)	(5)	(6)
	DV: Normalized number of forward citations Model: Tobit		DV: Radicalness Model: Logit		DV: Number of claims Model: Negative binomial	
Dummy: Non-Japanese inventors in Japan	0.5144	0.2011	0.0783	0.0466	0.0941	0.0631
	[65.29]***	[24.22]***	[47.53]***	[21.15]***	[176.55]***	[114.63]***
Dummy: Non-Japanese inventors outside Japan	0.4229	0.5146	0.0956	0.0857	0.4467	0.3233
	[7.88]***	[9.17]***	[8.59]***	[5.88]***	[130.41]***	[92.92]***
Dummy: Japanese inventors outside Japan	-0.5603	-0.153	-0.1102	-0.0761	0.1744	0.1344
	[-7.53]***	[-1.99]**	[-7.23]***	[-3.79]***	[36.86]***	[28.36]***
Team size		0.0949		-0.0119		0.0275
		[53.15]***		[-25.16]***		[231.57]***
Team average invention experience		-0.0001		-0.0003		-0.0001
		[-8.32]***		[-78.67]***		[-71.57]***
Team repeat experience		-0.1955		-0.0495		-0.0075
		[-48.58]***		[-47.91]***		[-30.06]***
Patent reference		0.2247		0.5265		0.0213
		[213.74]***		[1279.30]***		[299.54]***
ICT industry dummy		0.8394		0.0331		0.2564
		[102.93]***		[15.09]***		[473.21]***

Year dummies		Included		Included		Included
_cons	-4.645	-2.5876	-0.3357	-1.7619	2.015	1.803
	[-900.94]***	[-176.33]***	[-382.65]***	[-421.25]***	[7054.51]***	[1715.27]***
N	7378024	7253779	7456668	7328827	7455824	7327983
Chi squared	4364.314	800732.7076	2370.5059	3030742.614	53800.5368	445099.9155
df	3	22	3	22	3	22

(* p<0.1, ** p<0.05, *** p<0.01)

Table 6. Regression 2: independent variable = counts and squared term of non-Japanese inventors

	(1)	(2)	(3)	(4)	(5)	(6)
	DV: Normalized number of forward citations Model: Tobit		DV: Radicalness Model: Logit		DV: Number of claims Model: Negative binomial	
Number: Non-Japanese inventors in Japan	0.5675	0.093	0.089	0.042	0.0842	0.0609
	[61.94]***	[10.17]***	[47.62]***	[16.88]***	[145.99]***	[104.03]***
Squared: Non-Japanese inventors in Japan	-0.1135	-0.041	-0.0194	-0.0105	-0.0055	-0.0055
	[-37.78]***	[-14.41]***	[-32.99]***	[-13.45]***	[-31.99]***	[-32.70]***
Number: Non-Japanese inventors outside Japan	0.2385	0.2953	0.0547	0.0523	0.1798	0.1262
	[7.06]***	[8.13]***	[8.11]***	[5.44]***	[108.39]***	[75.13]***
Squared: Non-Japanese inventors outside Japan	-0.0314	-0.0349	-0.0063	-0.0088	-0.0058	-0.0037
	[-5.93]***	[-6.01]***	[-6.19]***	[-5.62]***	[-33.55]***	[-21.38]***
Number: Japanese inventors outside Japan	-0.4452	-0.0962	-0.0866	-0.0608	0.1524	0.1222
	[-6.11]***	[-1.25]	[-6.09]***	[-3.14]***	[34.61]***	[27.67]***
Squared: Japanese inventors outside Japan	0.0057	-0.0189	0.0082	0.0023	-0.0193	-0.018
	[0.33]	[-1.05]	[2.63]***	[0.51]	[-20.52]***	[-19.05]***
Team size		0.0875		-0.0108		0.0262
		[48.30]***		[-22.57]***		[217.59]***
Team average invention experience		-0.0001		-0.0003		-0.0001

		[-8.14]***		[-77.57]***		[-73.03]***
Team repeat experience		-0.1968		-0.0496		-0.0077
		[-48.91]***		[-47.93]***		[-30.85]***
Patent reference		0.2246		0.5265		0.0213
		[213.70]***		[1279.28]***		[299.38]***
ICT industry dummy		0.8356		0.0336		0.256
		[102.46]***		[15.34]***		[472.59]***
Year dummies		Included		Included		Included
_cons	-4.6382	-2.5527	-0.3342	-1.7628	2.0142	1.8084
	[-907.59]***	[-173.55]***	[-386.22]***	[-420.60]***	[7172.48]***	[1717.40]***
N	7378024	7253779	7456668	7328827	7455824	7327983
Chi squared	4556.2291	801579.1677	2534.7232	3030599.976	65095.5549	449065.9945
df	6	25	6	25	6	25

(* p<0.1, ** p<0.05, *** p<0.01)

Table 7. Regression 3: independent variable = share of non-Japanese inventors

	(1)	(2)	(3)	(4)	(5)	(6)
	DV: Normalized number of forward citations Model: Tobit		DV: Radicalness Model: Logit		DV: Number of claims Model: Negative binomial	
Share: Non-Japanese inventors in Japan	3.2693	0.465	0.491	0.2816	0.3203	0.1908
	[69.72]***	[9.56]***	[50.42]***	[22.00]***	[102.68]***	[60.15]***
Squared share: Non-Japanese inventors in Japan	-4.3219	-0.4304	-0.7301	-0.3561	-0.2459	-0.0295
	[-57.66]***	[-5.51]***	[-47.48]***	[-17.64]***	[-51.08]***	[-6.00]***
Share: Non-Japanese inventors outside Japan	2.366	1.7176	0.8204	0.4047	1.1113	0.761
	[5.91]***	[4.12]***	[9.87]***	[3.76]***	[44.16]***	[29.88]***
Squared share: Non-Japanese inventors outside Japan	-2.8786	-1.2985	-1.1599	-0.4645	-0.3192	-0.1558
	[-4.50]***	[-1.94]*	[-8.72]***	[-2.70]***	[-8.06]***	[-3.88]***

Share: Japanese inventors outside Japan	-1.3628	-0.1164	-0.4779	-0.3407	1.1253	0.9286
	[-2.31]**	[-0.19]	[-3.96]***	[-2.15]**	[30.55]***	[25.14]***
Squared share: Japanese inventors outside Japan	-1.0093	-0.6347	0.1862	0.202	-1.4355	-1.2035
	[-0.91]	[-0.56]	[0.83]	[0.69]	[-21.24]***	[-17.74]***
Team size		0.1065		-0.0111		0.0305
		[60.28]***		[-23.62]***		[259.48]***
Team average invention experience		-0.0001		-0.0003		-0.0001
		[-9.90]***		[-78.40]***		[-73.22]***
Team repeat experience		-0.1973		-0.0492		-0.0077
		[-48.99]***		[-47.55]***		[-30.86]***
Patent reference		0.2246		0.5265		0.0213
		[213.72]***		[1279.28]***		[299.69]***
ICT industry dummy		0.8363		0.0334		0.2558
		[102.54]***		[15.24]***		[472.17]***
Year dummies		Included		Included		Included
_cons	-4.6324	-2.6257	-0.33	-1.7652	2.022	1.794
	[-907.38]***	[-178.15]***	[-381.69]***	[-420.53]***	[7170.99]***	[1700.84]***
N	7378024	7253779	7456668	7328827	7455824	7327983
Chi squared	5153.285	801287.2	2767.399	3030805	42819.85	448658.2
df	6	25	6	25	6	25

(* p<0.1, ** p<0.05, *** p<0.01)