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Numerical labor flexibility and innovation outcomes of start-up firms: A panel data analysis

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Abstract: Using a panel data set based on repeated questionnaire surveys in Japan, this study examines the effects of numerical labor flexibility on innovation outcomes of start-up firms, a topic that has not been well examined in the literature. Using a random-effects probit model, the estimation results indicate that the use of temporary employees significantly increases the probability of product innovation. In addition, numerical flexibility, measured as external labor turnover of regular employees, initially increases and then decreases the probability of patent application. The implications of our findings are discussed.

Keywords: start-up firm; numerical flexibility; regular employee flexibility; nonregular employee flexibility; innovation outcome; panel data

JEL Classifications: M13; M50; J63; O32.

1. Introduction

Scholars and policy makers have generally considered the emergence of start-up firms important for economic development because of their role in spurring innovation, creating new industries, and contributing to job creation and wealth generation (e.g., Acs and Audretsch, 1987; Audretsch, 1995; Birch, 1987; Folster, 2000; Reynolds, 1997; Rickne and Jacobsson, 1999). Although a number of studies have examined various determinants of innovation, such as the personal characteristics of entrepreneurs (e.g., Baron and Tang, 2011; Marcati et al., 2008), organizational characteristics (e.g. Damanpour, 1991; Okamuro, 2007), and environmental characteristics (e.g., Edwards et al., 2005; Romijn and Albaladejo, 2002), there still exist knowledge gaps concerning the factors that promote innovation in firms during the start-up period.

To the best of the authors' knowledge, labor flexibility has rarely been considered as a factor in the innovation of start-up firms. However, numerical flexibility may be an important means by which start-up firms can innovate. Numerical flexibility reflects the ability of firms to make use of the external labor market through easy hiring and firing of regular employees, or to make use of temporary employees on fixed-term and part-time contracts or dispatched employees from temporary employment agencies. Numerical flexibility may be an effective strategy, allowing the firm to respond quickly to changes in the environment, including labor demand (e.g., Beatson, 1995; Michie and Sheehan, 2003; Zhou et al., 2010). Start-up firms can complement limited resources by utilizing numerical flexibility without incurring a large financial burden (e.g., Cardon, 2003). In practice, as some scholars have argued, flexibility may be critical for firms during the start-up period (e.g., Autio, 2005; Baughn and Neupert, 2003; Baughn et al., 2008).

This study explores the role of numerical labor flexibility in the innovation outcomes of firms during the start-up period. Using a panel data set based on original questionnaire surveys conducted annually in Japan during the period 2008 to 2011, we examine the effects of numerical flexibility (measured as external labor turnover of regular employees and the proportion of nonregular employees) on product innovation and patent application.[1] By estimating a random-effects probit model, we show that the relationship depends both on the dimensions of numerical flexibility and on the types of innovation outcomes. While external labor turnover of regular employees shows an inverted U-shaped relationship with patent applications, the proportion of nonregular employees demonstrates a positive relationship with product innovation.

The remainder of the study is organized as follows: Section 2 reviews the background to this study. Section 3 presents our hypotheses. Section 4 explains the data and model used in the analysis. Section 5 shows the estimation results, and Section 6 discusses the results and their implications.

2. Background

Over the past two decades, the question of whether to make the labor market flexible has been a topic of political debate in most developed countries. Since the publication of a study by the Organization for Economic Cooperation and Development (OECD) (1994), a rich stream of literature in favor of flexible labor markets has emerged. Flexibility not only contributes to employment but also allows for economic and productivity growth (e.g., Nicoletti and Scarpetta, 2003). Recent firm-level analyses of data from established firms in European

[1] We use the terms 'regular employee' and 'nonregular employee,' since the distinction between regular and nonregular employees is common in Japanese context. In practice, it is used in the Labor Force Survey by the Ministry of Internal Affairs and Communications in Japan. See, for example, Kuroda and Yamamoto (2011) and Japan Institute for Labor Policy and Training (2016).

countries have suggested that flexible labor contracts have a significant impact on innovation through their influence on knowledge processes (e.g., Amabile et al., 1996; Guest, 1997; Trott, 1998). While functional flexibility achieved through reallocating regular employees in a firm's internal labor market is generally considered good for innovation (e.g., Arvanitis, 2005; Chadwick and Cappelli, 2002; Kleinknecht et al., 2006; Michie and Sheehan, 1999, 2001; Zhou et al., 2011), the effects of numerical flexibility are rather mixed. The inconsistent results are explained by two dominant theoretical views.

On the one hand, mainstream economists tend to be in favor of the 'Anglo-Saxon' labor market model, which allows easy hiring and firing of regular employees (e.g., Kleinknecht et al., 2014; Zhou et al., 2011). A number of arguments have been developed in favor of more numerical flexibility. First, easier firing enhances the inflow of 'fresh blood' with novel ideas and networks. Ichniowsk and Shaw (1995) show that long-tenured employees are more conservative and reluctant to adopt significant changes or to implement novel innovation. This reluctance might be attributable to the 'lock-in' effect caused by past investment in education. Second, redundant employees can be easily replaced, and this may encourage labor-saving process innovations (e.g., Bassanini and Ernst, 2002; Nickell and Layard, 1999; Scarpetta and Tressel, 2004). Third, easy firing allows firms to replace poor and underperforming employees with better and more productive staff. The (latent) threat of firing can also prevent shirking by employees (e.g., Zhou et al., 2011). Fourth, easy hiring and firing could help keep wages low, and this in turn reduces fixed labor costs (e.g., Storey et al., 2002; Zhou et al., 2011). Fifth, without strong protection against dismissal, employees may become less powerful in negotiating high wages to be paid from the profits from innovation. This may stimulate investment in innovation activities.

On the other hand, Schumpeterian economists, emphasizing firms' stability, continuity of learning, and firm-specific knowledge generation, argue against high levels of numerical flexibility (e.g., Zhou et al., 2011). They argue that high external labor turnover can diminish the trust, loyalty, and commitment of employees to their firms (e.g., Naastepad and Storm, 2006). Easy hiring and firing leads to shorter job duration. Employees expecting a short stay in the firm will be demotivated to acquire firm-specific knowledge and to share information about knowledge related to their work. There is thus less likelihood of there being continuity of organizational learning in the firm (e.g., Belot et al., 2007; Chadwick and Cappelli, 2002; Michie and Sheehan, 1999, 2001). Under a flexible hiring and firing regime, it is difficult for firms to store firm-specific historical memory and innovative knowledge, and to implement innovations in the labor-saving process efficiently. This is because 'tacit' knowledge, which is poorly documented and idiosyncratic, is embedded in individuals' memories (e.g., Lorenz, 1999; Malerba and Orsenigo, 1995; Polanyi, 1966). Less loyal and less committed employees can easily leak knowledge to competitors, which discourages investment in knowledge creation and innovation. Short-term employees may shirk their responsibilities, as they expect their contracts to be ended (e.g., Bentolila and Dolado, 1994). Furthermore, employers are less likely to invest in firm-sponsored training owing to high external labor turnover (e.g., Coutrot, 2003; Ichniowski and Shaw, 1995).

Table 1 provides a summary of previous studies on the relationship between numerical flexibility and innovation activities, on which four important observations may be made. First, recent empirical studies indicate that modes of numerical flexibility and the novelty of innovation matter in explaining the relationship. For instance, Arvanitis (2005), using Swiss firm-level data, shows that hiring specialists on a temporary basis has a positive impact on the R&D process, while the use of part-time employees is negatively correlated with innovation.

Based on Dutch firm-level data, Zhou et al. (2011) find that while using employees on temporary contracts has a positive effect on new product sales, this effect is mainly captured by products with less novelty, namely 'imitative products.' They examined temporary employees with truly 'innovative' innovation separately from other employees, observing a significantly negative coefficient.[2] The second observation relates to the samples used in the existing literature. Previous studies, except for that of Voudouris et al. (2015), have focused on established firms, whereas evidence concerning start-up firms has been quite limited. There may be large differences in resources and employment practices between the established firms and start-up firms. Third, while most previous studies used data from European countries, no study has been made in Japan.[3] There may be some differences between countries in terms of employment practices, including protection legislation. Fourth, most previous studies utilized cross-sectional data from certain points in time, whereas a panel data analysis allows us to control for unobservable heterogeneity.

Taking into account the limitations presented in previous studies, this study differentiates between regular employee flexibility and nonregular employee flexibility as measures of numerical flexibility. Regular employee flexibility refers to external labor turnover, that is, the ratio of regular employees who join or leave the firm within a year. Nonregular employee flexibility refers to the proportion of nonregular employees, including temporary employees, fixed-term/part-time employees hired directly by employers, and dispatched employees from agencies. In addition, we adopt two innovation measures—product innovation and patent application—which differ in terms of the novelty of the

[2] The most recent paper by Wachsen and Blind (2016), using linked employer–employee microdata from the Netherlands also supports the view that the relationship between flexibility and innovation depends heavily on the type of innovation. Martínez-Sánchez et al. (2011), using a sample of Spanish first-tier suppliers of automotive systems/components, show that reliance on temporary/fixed-term employees is negatively associated with innovativeness, whereas the use of employees from consulting/contracting firms has a positive association.
[3] Few studies have investigated the innovation activities of firms in Japan during the start-up period, with the exceptions of Lynskey (2004), Honjo et al. (2014), and Kato et al. (2015), perhaps because data are unavailable.

innovation. Furthermore, our study uses panel data on start-up firms in Japan. Empirical evidence derived from start-up firms as well as Japan would also be interesting.

3. Hypothesis development

3.1. Regular employee flexibility and innovation

While the impact of numerical flexibility is mixed in large established firms, it is not necessarily evident in the context of start-up firms. Numerical flexibility may favor innovation in start-up firms. The resource-based view of the firm suggests that start-up firms generally face resource constraints and high risks because of the liabilities of newness and size (e.g., Autio, 2005; Baughn and Neupert, 2003). Numerical flexibility achieved through easy hiring and firing of regular employees allows start-up firms to utilize labor forces according to their capital interests. They can adjust easily whenever unexpected changes in labor demand occur. Reduced bargaining power for labor allows start-up firms to set lower wages, which reduces fixed labor costs. Thereby, they can allocate more capital to innovation. In addition to financial capital constraints, start-up firms have limited human capital; therefore, efficiently utilizing their personnel is the key to success (Baughn et al., 2008). The innovation performance of start-up firms is more vulnerable to an individual employee's performance. Therefore, such firms are less tolerant of underperformers and there is no room for redundancy. Easy hiring and firing allows start-up firms to replace unqualified employees and to bring in highly skilled personnel, who infuse the firm with new ideas and connect it to networks that may foster innovation (e.g., Malcomson, 1997; Matusik and Hill, 1998).

Based on these considerations, we argue that given their financial conditions, start-up firms need flexibility in hiring and firing regular employees to find the right personnel and to adjust to labor demand. However, regular employees are also crucial for innovation activities for firm-specific knowledge generation and accumulation processes, as Schumpeterian economists indicate. Therefore, excess external labor turnover may be harmful, and a certain level of stability for regular employees is required to promote innovation activities in start-up firms. Taking into account both views, we propose the following hypothesis.

> **Hypothesis 1a**: While external labor turnover of regular employees increases the probability of innovation outcomes for start-up firms, this probability decreases if the level of external labor turnover exceeds its inflection point.

Furthermore, as discussed above, the role of regular employee flexibility is particularly important for the processes of firm-specific knowledge generation and path-dependent knowledge accumulation. Therefore, we suspect that the hypothesized inverted U-shaped relationship between external labor turnover and innovation outcome is more significant when there is a strong need for novel firm-specific knowledge, as exists for patent applications. For R&D-oriented start-up firms, patents are important intellectual property assets that create a unique competitive advantage for the firm. Patents represent new and technically feasible devices, and prevent firm-specific knowledge from imitation for a set period, so that start-up firms can enjoy the benefits of their investment in R&D. Investment in firm-specific knowledge and the continuity of such knowledge are crucial for this type of innovation process. Therefore, we postulate the following hypothesis.

> **Hypothesis 1b**: The inverted U-shaped relationship between external labor turnover of regular employees and the probability of innovation outcomes is more significant when the novelty of innovation is high.

3.2. *Nonregular employee flexibility and innovation*

The term ‘nonregular employees’ refers to temporary employees hired directly by employers on fixed-term or part-time contracts and to dispatched employees hired from indirectly through temporary employment agencies (e.g., Beatson, 1995; Michie and Sheehan, 2003; Zhou et al., 2010). In Japan, temporary employees are all nonregular employees, although nonregular employees are not necessarily temporary, as open-ended, part-time contracts are possible (e.g., Aoyagi and Ganelli, 2013). As Storey et al. (2002) argue, temporary employees are normally employed to cope with fluctuations in production, to reduce fixed labor costs, or to perform certain tasks at a particular time when regular employees are not available. Firms rarely consider temporary employees to be a magical source of innovation.

The negative association between the use of temporary employees and innovation is consistent with the Schumpeterian view. Temporary employees usually have shorter-term contracts, so those hired directly by employers may feel less commitment than regular employees (Michie and Sheehan, 2003, 2005; Posthuma et al., 2005). Temporary agency employees have an even weaker sense of association with the company (De Ruyter et al., 2008), and are considered outsiders (Mitlacher, 2008). Thus, they are likely to have poorer relationships with regular employees and less organizational commitment, and to be involuntarily left out of innovation teams (Martínez-Sánchez et al., 2011; Mitlacher, 2008). Ng and Feldman (2008) indicate that organizational commitment is the factor that ties individual and organization together, which is important for innovation at the firm level. Committed employees are more likely to devote extra time and effort to innovation, while less committed employees are reluctant to acquire firm-specific knowledge and tend to bind their tacit knowledge to a specific innovation project (Belot et al., 2007; Chadwick and Cappelli, 2002; Michie and Sheehan, 1999, 2001). Acharya et al. (2013) indicate that security and stability provided by employers are necessary conditions to incentivize employees to engage in risky innovation projects.

The majority of previous empirical studies support the negative association between the use of temporary employees and innovation (Beugelsdijk, 2008; Broschak and Davis-Blake, 2006; Byoung-Hoon and Frenkel, 2004). However, this relationship is not necessarily negative in the context of start-up firms. Because of resource constraints and high internal costs, temporary employees can be a good alternative for start-up firms to complement their limited human capital in innovation activities, particularly those who do not require firm-specific knowledge but are necessary for improving the efficiency of the innovation process. For instance, temporary employees can perform non-core activities, such as administrative jobs, to make operations more efficient. Especially for start-up firms located in an institutional environment with strict employment protection regulations, such as Japan, the use of temporary employees avoids the severe restrictions on terminations of regular labor contracts, and gives firms greater freedom and flexibility to search for the right personnel before concluding a regular contract. Based on these considerations, we propose the following hypothesis.

Hypothesis 2a: The use of nonregular employees increases the probability of innovation outcomes for start-up firms.

As mentioned above, security and stability are necessary conditions to incentivize employees engaging in firm-specific knowledge processes. Firms that make use of temporary employees for their innovation activities do so for different reasons, such as to acquire workers with similar knowledge but at lower cost, or in the expectation of acquiring skilled temporary employees who bring new ideas and networks to create and implement new knowledge (Kalleberg and Mardsen, 2005; Malcomson, 1997; Matusik and Hill, 1998;

Martínez-Sánchez et al., 2011). For these purposes, there is no incentive for firms to invest in firm-specific knowledge for temporary employees. Therefore, we suspect that the positive relationship between the use of temporary employees and innovation outcomes entailing a high degree of novelty in firm-specific knowledge will be less obvious. Based on these considerations, the following hypothesis is posited.

> **Hypothesis 2b**: The positive relationship between the use of nonregular employees and the probability of innovation outcomes is less significant when the novelty of innovation is high.

4. Data and model

4.1. Data

This study is based on original questionnaire surveys conducted in Japan. To the best of the authors' knowledge, there exists no publicly available data source on innovation activities by start-up firms in Japan. To construct a panel data set of start-up firms, we conducted postal questionnaire surveys annually from 2008 to 2011 (four surveys in total). In the first survey, we sent questionnaires to 13,582 firms in the Japanese manufacturing and software industries that were incorporated between January 2007 and August 2008. Target firms were selected based on information obtained from Tokyo Shoko Research (TSR), a major Japanese credit reporting company. In the questionnaire surveys, we asked founders about firm-specific characteristics, including R&D activities.

In the first survey, the number of effective responses was 1,514 (for a response rate of approximately 11%). In the second and third surveys, the questionnaires were sent to the respondents of the first survey, that is, 1,514 firms. The numbers of effective responses in the second and third surveys were 899 and 727, respectively. Questionnaires were then sent to those firms that had participated in the third survey, and effective responses were obtained from 508 firms. Thus, one-third of respondents to the first survey answered all survey rounds until 2011.

From among the responses, 1,060 start-up firms that had been established in 2007 or 2008 were identified by excluding those founded before 2007 and incorporated later. Meanwhile, because this study focuses on start-up firms that undertake R&D, these were identified based on whether the founders had conducted R&D or whether the firm had employed R&D personnel at the time of start-up or afterward. In the first survey, 672 such firms were identified. Dropping firms with missing values left an unbalanced panel of 469 R&D-oriented start-up firms (916 observations) for the period from 2008 to 2011.

4.2. Model

In this study, we estimate the effects of numerical labor flexibility on innovation outcomes for firms during the start-up period. Our *dependent variable* is the probability of innovation outcomes. Two types of innovation outcomes are considered: product innovation and patent application (*INN* and *PAT*). Both variables are measured as dummy variables. Product innovation takes a value of 1 if the firm achieves product innovation between periods t and t+1, and a value of 0 otherwise. Patent application takes a value of 1 if the firm applies for a patent between periods t and t+1, and 0 otherwise. While patents represent the development of a new and technically feasible device, which indicates the quality of a firm's technological innovation (Ayerbe et al., 2014; Chang, 2012; Hsu and Ziedonis, 2008), product innovations are new or significantly improved products (goods or services). These two innovation measures not only capture the intermediate and final outputs of the innovation process, but also allow us to compare levels of the novel firm-specific knowledge required in the innovation process.[4]

Our key *independent variable* is numerical flexibility. We use two indicators: 1) external labor turnover of regular employees (*R_FLEX*), measured by the gross change in regular labor inflow and outflow between periods t and t+1 as the proportion of the total number of employees in period t, and 2) the proportion of nonregular employees (*NR_FLEX*), measured by the number of nonregular employees including part-time and fixed-term employees as well as employees dispatched from agencies divided by the total number of employees in period t. A set of control variables, such as firm age, firm size, R&D intensity, sector dummies, and year dummies, is included in the empirical model. The definitions of variables are shown in Table 2.

Our empirical model for factors affecting *INN* and *PAT* is as follows:

$$\text{Prob}\ (INN \text{ or } PAT = 1) = f\ (Flexibility, Firm, Sector, Year) \qquad (1),$$

where *INN* and *PAT* are the probabilities of product innovation and patent applications, respectively, while *Flexibility*, *Firm*, *Sector*, and *Year* stand for the variables representing numerical flexibility measures, and firm-, sector-, and year-specific characteristics.

Empirical studies on start-up firms tend to employ cross-sectional data across firms (Arvanitis, 2005; Beugelsdijk, 2008; Kleinknecht et al., 2014; Martinez-Sanchez et al., 2011; Michie and Sheehan, 1998, 2003; Voudouris et al., 2015). Therefore, to overcome heterogeneity caused by unobservable firm-specific characteristics, we employ a panel data structure for this study. Because our dependent variables are binary, we apply a random-

[4] For example, Amara et al. (2008) examine the determinants of novelty of innovation as well as the probability of innovation in small and medium-sized enterprises and found that their results differed between the innovation measures, suggesting the importance of distinguishing between innovation types.

effects probit model to test our proposed hypotheses. To examine the effects of numerical flexibility on the innovation outcomes of start-up firms, we use a one-year lag for independent variables, except for the variable of external labor turnover. This approach to a certain extent reduces potential endogeneity problems (Wooldridge, 2010).

5. Results

5.1. Estimation results

Before considering the estimation results for the effects of numerical flexibility on innovation outcomes, we briefly discuss the descriptive statistics shown in Table 3. Regarding dependent variables, Table 3 indicates that on average 38% of the observations achieved at least one product innovations (*INN*) and 14% of them filed at least one patent application (*PAT*). With respect to key independent variables, the mean value of external labor turnover of regular workers (*R_FLEX*) is 0.248, indicating that an average of 25% of employees in the sample firms are hired or leave every year. The mean value of the proportion of nonregular employees (*NR_FLEX*) is 0.139, indicating that about 14% of employees in the sample firms are nonregular.[5]

Table 4 shows the estimation results of a random-effects probit model that distinguishes between product innovations (*INN*) and patent applications (*PAT*), which are the dependent variables. Columns (i) and (ii) show the effects of external labor turnover of regular employees (*R_FLEX*) with and without its squared term (R_FLEX^2) on product innovations (*INN*), respectively. The coefficients of these variables are insignificant. Columns (iii) and (iv) show the effects of *R_FLEX* with and without its squared term (R_FLEX^2) on patent applications (*PAT*), respectively. The coefficient of *R_FLEX* is negative but insignificant in

[5] The correlation matrix of variables is shown in Appendix Table A. None of the correlations between our independent variables exceeds 0.5; therefore, multicollinearity is not a serious concern.

the model without *R_FLEX*^{2} in column (iii). In contrast, in column (iv), the coefficient of *R_FLEX* is positive and significant after including the squared term in the model, while *R_FLEX*^{2} indicates a negative and significant coefficient. It means that the probability of patent applications increases with external labor turnover by regular employees and then declines after exceeding an inflection point. This finding suggests that while firms with more flexibility are more likely, to a certain extent, to file patent applications, excess flexibility is likely to be harmful for start-up firms to achieve innovation outcomes based on novel firm-specific knowledge, such as patents.

Turning to nonregular employee flexibility (*NR_FLEX*), columns (v)–(viii) of Table 4 show its effects on product innovations (*INN*) and patent applications (*PAT*). The results with and without *NR_FLEX*^{2} indicate that the proportion of nonregular employees (*NR_FLEX*) has a positive and significant effect on product innovations (*INN*) in columns (v) and (vi). Furthermore, the squared term (*NR_FLEX*^{2}) is not significant in column (vi). It suggests that firms with more flexibility by making use of nonregular employees are more likely to achieve product innovation. In contrast, as shown in columns (vii) and (viii), we do not obtain any significant results regarding the effects of nonregular employee flexibility on patent applications (*PAT*).

Regarding control variables, Table 4 shows that the effects of firm age (*AGE*) are positive and significant for product innovations (*INN*), but not significant for patent applications (*PAT*). This indicates that the probability of product innovation tends to increase with firm age. The variable for R&D intensity (*RDINT*) is positive and significant in all models shown in Table 4, indicating that firms investing more in R&D are more likely to achieve innovation outcomes, regardless of whether product innovations (*INN*) or patent applications (*PAT*) is used as a dependent variable. The variable for the intensity of competition perceived by firms (*COMP*) is positive and significant in columns (iii)–(viii), indicating that less competition favors innovation, in particular in terms of patent application.

So far, we have examined the effects of numerical labor flexibility on innovation outcomes, using panel data from original questionnaire surveys in Japan. Our findings indicate the following. 1) Regular employee flexibility has an inverted U-shaped relationship with the probability of patent applications—used to represent novelty in innovation—but not with the probability of product innovations that do not necessarily entail novelty. Hypotheses 1a and 1b are thus supported. 2) Nonregular employee flexibility has a positive relationship with the probability of product innovation. However, there is no significant relationship between the use of nonregular employees and patent application. These results support Hypotheses 2a and 2b. In summary, we observe a general consistency between our empirical results and the proposed hypotheses in Section 2.2.

5.2. Robustness checks

To ensure the reliability of the findings in this study, we conduct some robustness checks to estimate alternative empirical models. First, we estimate a random-effects tobit model, because factors affecting the probability that firms can achieve innovations may be different from those affecting the actual number of innovations that firms can achieve. The dependent variables are the numbers of product innovations (*N_INN*) and patent applications (*N_PAT*) achieved in each year during the period of 2008–2011.[6] The descriptive statistics for these variables are shown in Table 3.

[6] In the third questionnaire survey, we asked the founders of firms that responded to the second survey about the numbers of product innovations and patent applications achieved between the surveys. When firms had not responded to the second survey, we asked about the numbers of product innovations and patent applications between the first and third surveys. Therefore, we divided these numbers (over two years) by two to obtain mean values per year. Therefore, a tobit model is more appropriate than a negative binomial model, because it takes no integral numbers into account.

Table 5 reports the estimation results from a random-effects tobit model. Column (iv) indicates that the coefficients of external labor turnover of regular employees (*R_FLEX)* and its squared term (R_FLEX^2) have significantly positive and negative signs, respectively, suggesting an inverted U-shaped relationship with the number of patent applications (*N_PAT*). These results are consistent with those reported in Table 4, from a random-effects probit model. Regarding nonregular employee flexibility, the coefficient of *NR_FLEX* is positive and significant in the model without the squared term in column (v), whereas it is not significant in the model that includes the squared term (NR_FLEX^2) in column (vi). These findings are also consistent with those reported in Table 4.

Second, considering the possibility of the error terms being correlated between the two models using product innovation and patent applications as dependent variables, respectively, we re-estimate Equation (1), presented in Section 4.2, using a bivariate probit model as a robustness check. Again we find similar results.[7]

In summary, we conclude that our results shown in Table 4 concerning the relationship between numerical flexibility and innovation outcomes are robust and support our proposed hypotheses.

6. Discussion and conclusions

Based on random-effects probit regression, we have investigated the relationship between numerical flexibility and innovation outcomes in the context of start-up firms. Unlike existing studies in the literature, the majority of which indicate a negative association, we find that numerical flexibility achieved by using the external labor market of regular employees; or the use of nonregular employees, in general favors the innovation outcomes of start-up firms.

[7] The results of the bivariate probit model are available from the authors upon request.

First, concerning regular employee flexibility, we observe an inverted U-shaped relationship between external labor turnover and patent applications, while no effects are found between external labor turnover and product innovation. This finding supports our theoretical arguments based on the resource-based view and that of Schumpeterian economists.

On the one hand, because of resource constraints and high risk (Autio, 2005; Baughn and Neupert, 2003), efficient use and management of regular personnel is key to the success of start-up firms (Baughn et al., 2008). Therefore, start-up firms may be less tolerant of underperforming people. There is no room for redundancy. External labor turnover of regular employees allows start-up firms to replace unqualified and conservative employees at low cost and bring in highly skilled workers (who meet their real needs) to infuse the firm with new ideas and link it to networks that may foster innovation (Ichniowsk and Shaw, 1995; Malcomson, 1997; Matusik and Hill, 1998). Furthermore, the need for growth also triggers high external labor turnover in start-up firms. They need to develop effective human resources to survive and implement efficient growth strategies.

On the other hand, the performance of start-up firms is dependent on the individual performance of regular employees. Therefore, incentivizing regular employees to invest in firm-specific knowledge generation and accumulation is important for the innovation output of firms. By providing security and stability, start-up firms can motivate their regular employees to commit to the firm and to become more willing to invest in firm-specific knowledge (Acharya et al., 2010). Thus, allowing some flexibility for start-up firms to lower transaction costs in finding the right personnel, who bring new ideas and networks, is beneficial for innovation. At the same time, retaining the right personnel in the firm is also important for long-term innovation performance, particularly for innovation, which requires high levels of accumulated novel, firm-specific knowledge, such as patents. From our sample, we find that when the turnover ratio of regular employees is less than 1.4, it is beneficial for the probability of patent applications by start-up firms. However, when the turnover ratio exceeds 1.4, excess flexibility reduces the probability of patent applications.

Second, we find that nonregular employees, both part time and fixed term, have a positive impact on product innovations but no effect on patent applications by start-up firms. This finding is consistent with those of Zhou et al. (2011), who used Dutch firm-level data. Again, because of limited human resources and available capital, start-up firms cannot do everything in house. Nonregular employees can be used to perform routinized tasks during the innovation process and to reduce the cost of innovation, where the requirement for firm-specific knowledge is trivial. However, this is not the case for writing patent applications, where novel knowledge and the development of firm-specific knowledge is crucial. Given the short incumbency of nonregular employees, they are less likely to be motivated to acquire firm-specific knowledge. On the other hand, there is no incentive for the firm to invest in imparting firm-specific knowledge to nonregular employees. Firms that make use of nonregular employees for their innovation activities do so for different reasons, such as to gain inputs of similar knowledge but with lower labor costs or because they expect to employ skilled temporary employees who can bring new ideas and links to networks, and thus create and use new knowledge (Kalleberg and Mardsen, 2005; Malcomson, 1997; Martínez-Sánchez et al., 2011; Matusik and Hill, 1998).

To conclude, while the existing literature argues that numerical flexibility in general does not favor innovation in relatively large and old European establishments, this paper shows that numerical flexibility may be a tremendous source of innovation for start-up firms. Numerical flexibility provides an alternative means for start-up firms to seek the right personnel with relatively low transaction costs. From a macroeconomic perspective, promoting the emergence of start-up firms and stimulating innovation through increasing labor mobility are both on the political agenda in Japan, which has faced low start-up rates and stagnant economic growth for a long time (e.g., Honjo, 2015). In fact, the government has promoted labor flexibility through the deregulation of employment protection legislation. However, little is known about the effects of promoting labor flexibility. To provide some clues for policy makers, we used an original panel data set of Japanese start-ups to shed light on the effects of labor flexibility on innovation at the firm level. We provide empirical evidence on the effect of numerical flexibility on innovation outcomes.

As one of the few exploratory studies focusing on the relationship between numerical labor flexibility and innovation in the context of start-up firms, this study contributes new and fresh empirical evidence to the literature, the majority of which focuses on larger and older firms in Europe. Our findings suggest that firm characteristics provide a better explanation of the relationships between numerical flexibility and innovation in start-up firms than in larger established firms. Numerical flexibility may not only reduce fixed labor costs, but may also help start-up firms optimize their resources for firm-specific knowledge generation. However, for innovations with a high degree of novelty, such as patent applications, start-up firms should be aware of the importance of retaining their regular employees. Excessive external turnover of regular employees may harm the novel innovation of the firm. Among nonregular employees, temporary employees play a significant role in the innovation process of start-up firms.

A few limitations should be pointed out. We propose several directions for future research on the relationships examined in this paper. First, for better policy implications, it may be interesting to investigate what kinds of employment systems promote innovation by firms. For instance, an optimal value can be calculated based on the division between regular and nonregular employees in start-up firms. Second, additional detailed information on employees may provide more insights, given that types of employees may differ between industries. Finally, although we claim that the characteristics of firms may explain the relationships between numerical flexibility and innovation more accurately for start-ups than for established companies, data limitations prevent us comparing them empirically. Future research could consider using a data set that includes both types in samples for comparative studies.

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Table 1. Review of the literature on the relationship between numerical flexibility and innovation activities.

Author	Flexibility measure	Innovation measure	Effects of flexibility	Sample	Estimation method
Altuzarra and Serrano (2010)	Rate of fixed-term contracts	Product innovation, process innovation, R&D activity	Inverted U-shape (insignificant)	Panel data: 4,886 Spanish firms (large firms, age not considered)	Random-effects logit model
Arvantis (2005)	Relevance of part-time work, importance of temporary work, use of flexible working time	Labor productivity, product innovation, process innovation	Positive effects on product and process innovation	Cross-sectional data: 1,382 Swiss firms (SMEs and large firms, age not considered)	OLS and probit model
Beugelsdijk (2008)	Flexible working hours, standby contracts	Proportion of new products in total sales (incremental and radical innovations)	Negative effects	Cross-sectional data: 988 Dutch firms (23 years old, size not considered)	Tobit and Heckman models
Kleinknecht et al. (2014)	Proportion of temporary workers	R&D investment, occasional R&D, and permanent R&D	Negative effects on R&D investment and permanent R&D	Cross-sectional data: 1,216 Dutch firms (at least five employees, age not considered)	Logit model
Martinez-Sanchez et al. (2011)	Proportion of fixed-term contracts	Newness of product and process innovations	Positive effects	Cross-sectional data: 123 Spanish automotive firms (26 years old, size not considered)	OLS
Michie and Sheehan (1998)	Proportion of part-time and temporary contracts	R&D investment and the introduction of advanced technical change	Negative effects	Cross-sectional data: 480 UK firms (at least 25 employees, age not considered)	IV probit model
Michie and Sheehan (2003)	Proportion of part-time and temporary contracts	Probability of innovation	Negative effects	Cross-sectional data: 240 UK firms (at least 50 employees, age not considered)	Probit model
Voudouris et al. (2015)	Proportion of flexible staff	Product innovation (incremental and radical innovations)	Positive effects on radical innovation	Cross-sectional data: 143 Greek firms (less than eight years old, size not considered).	OLS and 2SLS
Wachsen and Blind (2016)	Proportion of employees who left, proportion of temporary workers	Product innovation, process innovation	Negative effects	Panel data: 16,453 Dutch firms (small and large firms, age not considered)	Random-effects probit model
Zhou et al. (2011)	Proportion of fixed-term contracts	Sales of imitative and innovative new products	Positive effects on imitative new products, negative effects on innovation new products	Panel data: 1,032 Dutch firms. Full sample (27 years old, at least five employees); SME sample (26 years old, at least five employees)	OLS, tobit, Heckman and tobit–Heckman models

Table 2. Definition of variables

Variable	Definition
(Dependent variable)	
INN	Dummy variable: 1 if the firm achieves a product innovation between periods *t* and *t*+1, 0 otherwise.
PAT	Dummy variable: 1 if the firm applies a patent between periods *t* and *t*+1, 0 otherwise.
N_INN	Number of product innovations the firm achieves between periods t and t+1.
N_PAT	Number of patent applications by the firm between periods t and t+1.
(Independent variable)	
R_FLEX	Number of hired employees plus the number of retired employees between periods *t* and *t*+1, divided by the number of employees in period *t*.
R_FLEX^2	$TURN \times TURN$
NR_FLEX	Number of part-time and fixed-term employees (including ones hired from agency) divided by the number of workers in period *t*.
NR_FLEX^2	$FLEX \times FLEX$
AGE	Number of months since foundation.
SIZE	Number of workers in period *t*.
RDINT	Research and development (R&D) expenditures divided by the number of employees in period *t*.
COF	Dummy variable: 1 if the firm was established by multiple founders, 0 otherwise.
IND	Dummy variable: 1 if the firm is an independent start-up, 0 if a subsidiary or affiliated firm.
COMP	Five-point Likert scale on the intensity of competition perceived by the firms in period t, ranging from 1 (competition is strong) to 5 (competition is weak).

Table 3. Descriptive statistics of variables

Variable	*N*	Mean	Std.Dev.	Min.	Max.
(Dependent variable)					
INN	916	0.383	0.486	0	1
PAT	892	0.139	0.346	0	1
N_INN	892	1.496	7.386	0	100
N_PAT	888	0.381	2.632	0	67.5
(Independent variable)					
R_FLEX	889	0.248	0.743	0	12
R_FLEX^2	889	0.613	5.635	0	144
NR_FLEX	916	0.139	0.231	0	0.946
NR_FLEX^2	916	0.073	0.156	0	0.895
AGE	916	22.985	13.786	4	58
SIZE	916	6.620	24.620	1	401
RDINT	916	102.987	252.050	0	2500
COF	916	0.472	0.499	0	1
IND	916	0.870	0.336	0	1
COMP	916	2.786	1.374	1	5

Table 4. Estimation results from a random-effects probit model

Variable	Regular employee flexibility				Nonregular employee flexibility			
	(i) *INN*	(ii) *INN*	(iii) *PAT*	(iv) *PAT*	(v) *INN*	(vi) *INN*	(vii) *PAT*	(viii) *PAT*
R_FLEX	–0.131	–0.016	0.025	1.012**				
	(0.092)	(0.212)	(0.132)	(0.473)				
R_FLEX^2		–0.032		–0.354**				
		(0.043)		(0.140)				
NR_FLEX					0.463*	1.617**	–0.232	0.945
					(0.253)	(0.769)	(0.405)	(1.165)
NR_FLEX^2						–1.801		-1.927
						(1.168)		(1.668)
AGE	0.024*	0.024*	0.014	0.017	0.027**	0.027**	0.011	0.011
	(0.013)	(0.013)	(0.024)	(0.024)	(0.012)	(0.013)	(0.018)	(0.018)
SIZE	0.002	0.002	–0.002	–0.001	–0.001	–0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
RDINT	0.001***	0.001***	0.001**	0.001**	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COF	0.088	0.084	0.174	0.141	0.123	0.104	0.127	0.123
	(0.139)	(0.139)	(0.257)	(0.257)	(0.135)	(0.135)	(0.194)	(0.194)
IND	0.094	0.099	0.024	0.053	0.156	0.149	0.282	0.281
	(0.195)	(0.194)	(0.333)	(0.335)	(0.193)	(0.192)	(0.283)	(0.281)
COMP	0.067	0.069	0.316***	0.333***	0.0816*	0.0820*	0.285***	0.283***
	(0.045)	(0.045)	(0.080)	(0.081)	(0.045)	(0.045)	(0.068)	(0.068)
Constant term	–1.229***	–1.242***	–3.433***	–3.594***	–1.449***	–1.461***	–3.120***	-3.123***
	(0.306)	(0.307)	(0.640)	(0.663)	(0.298)	(0.297)	(0.508)	(0.508)
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	889	889	861	861	916	916	892	892
Number of firms	469	469	460	460	495	495	493	493
Log pseudolikelihood	–525.614	–525.434	–278.114	–275.279	–534.930	–533.640	–291.895	-291.291

Note: Robust standard errors are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

Table 5. Estimation results from a random-effects tobit model

	Regular employee flexibility				Nonregular employee flexibility			
Variable	(i) *N_INN*	(ii) *N_INN*	(iii) *N_PAT*	(iv) *N_PAT*	(v) *N_INN*	(vi) *N_INN*	(vii) *N_PAT*	(viii) *N_PAT*
R_FLEX	–0.332	0.395	0.428	2.843**				
	(0.478)	(1.087)	(0.403)	(1.353)				
R_FLEX^2		–0.180		–0.834*				
		(0.262)		(0.501)				
NR_FLEX					8.136***	9.548	–3.267	2.757
					(2.595)	(7.190)	(2.537)	(7.242)
NR_FLEX^2						–2.184		–10.050
						(10.370)		(11.500)
AGE	0.191	0.191	–0.085	–0.079	0.234*	0.235*	–0.040	–0.041
	(0.118)	(0.118)	(0.096)	(0.097)	(0.133)	(0.133)	(0.117)	(0.117)
SIZE	0.029	0.030	0.012	0.013	0.009	0.009	0.025	0.026
	(0.018)	(0.018)	(0.015)	(0.015)	(0.031)	(0.031)	(0.025)	(0.025)
RDINT	0.001	0.001	0.003***	0.003***	0.008***	0.008***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
COF	–0.064	–0.098	1.091	1.051	0.621	0.599	1.060	1.059
	(1.235)	(1.236)	(0.998)	(1.015)	(1.383)	(1.387)	(1.197)	(1.193)
IND	–0.180	–0.129	0.517	0.628	0.807	0.801	1.361	1.382
	(1.743)	(1.743)	(1.439)	(1.457)	(2.024)	(2.024)	(1.876)	(1.876)
COMP	–0.138	–0.124	0.678**	0.775**	0.297	0.297	1.686***	1.682***
	(0.253)	(0.254)	(0.294)	(0.308)	(0.430)	(0.430)	(0.413)	(0.412)
Constant term	–6.375***	–6.500***	–13.880***	–14.380***	–13.270***	–13.290***	–18.290***	–18.310***
	(2.426)	(2.432)	(2.125)	(2.204)	(2.975)	(2.977)	(3.038)	(3.033)
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	868	868	859	859	892	892	888	888
Number of firms	463	463	459	459	487	487	491	491
Log pseudolikelihood	–1419.051	–1418.755	–544.204	–542.167	–1535.166	–1535.144	–586.529	–586.132

Note: Robust standard errors are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

Table A. Correlation matrix of variables (N = 762)

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	*INN*	1													
(2)	*PAT*	0.358	1												
(3)	*N_INN*	0.296	0.111	1											
(4)	*N_PAT*	0.068	0.359	0.060	1										
(5)	*R_FLEX*	–0.065	–0.020	–0.029	–0.004	1									
(6)	R_FLEX^2	–0.051	–0.026	–0.017	–0.010	0.849	1								
(7)	*NR_FLEX*	0.052	–0.063	0.141	–0.032	–0.083	–0.055	1							
(8)	NR_FLEX^2	0.029	–0.077	0.157	–0.036	–0.074	–0.044	0.946	1						
(9)	*AGE*	0.182	0.096	–0.002	–0.006	–0.072	–0.050	0.101	0.065	1					
(10)	*SIZE*	–0.017	–0.001	0.015	0.045	–0.026	–0.020	0.196	0.172	0.139	1				
(11)	*RDINT*	0.182	0.246	0.083	0.072	0.053	–0.001	–0.070	–0.059	–0.055	0.022	1			
(12)	*COF*	0.048	0.050	–0.042	0.051	–0.037	–0.048	0.045	0.011	0.051	0.104	0.050	1		
(13)	*IND*	0.029	0.012	–0.029	–0.009	–0.001	0.022	–0.134	–0.131	0.070	–0.245	–0.058	–0.095	1	
(14)	*COMP*	0.094	0.183	–0.049	0.084	–0.076	–0.057	–0.086	–0.073	–0.020	–0.037	0.054	–0.060	0.039	1