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Does R&D investment drive employment growth? Empirical evidence at industry level from Japan

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Abstract

Strong demographic headwinds have motivated Japan to strengthen its economy by fostering innovation. This paper draws on a panel of business enterprises operating in 33 industries in Japan to examine how research and development (R&D) activities affect employment. Our findings suggest that employment gains are associated with innovation, both at the aggregate level and within groups of major industries. The positive impact of technological advancement is more pronounced in the manufacturing sector. The results reveal heterogeneous patterns of the key determinants of employment growth based on the level of industries' routine intensity, but they accord well with the compensation theory concerning the connection between innovation and job creation. These results will be of interest for policymakers to design targeted economic strategies by supporting technological development in Japan and could also serve as a compass for other countries with similar workforce structures and macroeconomic characteristics.

KEYWORDS

employment, industry-level analysis, innovation, manufacturing, R&D expenditure, routine intensity

1 | INTRODUCTION

Japan is experiencing substantial demographic changes. With meagre fertility rates and a growing average lifetime duration, the country has the world's most rapidly ageing population (Colacelli & Corugedo, 2018). Given the challenges arising from a shrinking population and an ageing workforce, the development of technological capital is emerging as the best solution to improving Japanese economic growth, which can compensate for the decrease in the number of employed persons while maintaining the level of production (David, 2017). This move is supported by a significant body of policy and scholarly literature, which considers innovation as a central component of economic growth. This is also echoed by the positive employment prospects through specific compensation mechanisms (Vivarelli, 2014). On the contrary, there are concerns that the so-called 'Fourth Industrial Revolution' (that is, the era of digitalisation and 'intelligent automation') will negatively affect employment, particularly the routine occupations (Schwab, 2017). The introduction and expansion of computerisation and new technologies (e.g., AI, digitalisation, smart machines) may adversely influence the demand for particular skills/

occupations, resulting in a decline in overall employment.

Several empirical studies to date have explored the impact of technological innovation on economic growth in the US and Europe (Autor et al., 2003; Autor & Dorn, 2013; Bogliacino et al., 2012; Cirillo, 2017) and conflicting conclusions are drawn. For instance, Mtar and Belazreg (2021) found that innovation is positively correlated with economic growth in some European countries (Italy, Norway, Sweden) but has an adverse effect in others (e.g., Spain), suggesting that country-specific characteristics play a role in determining the relationship between these two variables. Within this first strand of literature, there is little research on the direct effect of technological innovation on economic growth in Japan, especially in terms of employment opportunities (David, 2017; Fukao et al., 2017). This takes us to the second strand of the research, which explores how technological development affects employment structure (or technological unemployment).

In this context, the voluminous literature assesses the evidence on whether employment becomes vulnerable to the influence of technology advancement and innovation (e.g., Brouwer et al., 1993; Dachs et al., 2017; Goos & Manning, 2007; Harrison et al., 2014; Lachenmaier & Rottmann, 2011; Van Reenen, 1997). The sign and magnitude of the impact of innovation on labour demand is not clearly identified in the literature, because of different compensation mechanisms. There is a distinction between innovations related to new product development and those associated with process improvements (such as the enhancement in the production process). Most of these studies, such as Vivarelli and Pianta (2000), Bogliacino et al. (2012), Vivarelli (2014) amongst others, suggest that product-related investments in R&D typically have a positive impact on employment. Conversely, there are more divergent results for process-oriented expenditures on R&D. However, the empirical research addressing the contribution of R&D on job creation across occupations and sectors in Japan is very limited, particularly when employees' characteristics are taken into account.

To overcome this limitation and gap in the existing literature, we examine the effect of innovation on employment in Japan for the years 2002–2017 and identify opportunities and risks associated with technological advancement. We measure the effect of innovation using R&D expenditure, because these terms are closely related to each other, as argued by Fukao et al. (2017) and Parisi et al. (2006).[1] For this reason, we assess product innovation using R&D expenditure and apply the terms ‘innovation’ and ‘R&D expenditure’ interchangeably throughout the paper. Secondly, we investigate the heterogeneous patterns of innovation on employment across industries (manufacturing and non-manufacturing) and occupation profiles (medium and high routine-intensity industries). Thirdly, we assess the effect of innovation using three measures of R&D expenditure (total intramural R&D spending, self-financed R&D expenditure, external R&D funds received) to elicit the diverse impact of technological innovation on employment and evaluate the robustness of our results.

This study advances the extant literature in two ways. First, we explicitly present the effect of technological advancement on employment in business enterprises undertaking R&D activities in Japan. This allows estimating the extent to which the level of labour demand changes in the presence of technology innovation. Second, unlike the previous studies on the Japanese labour market (Fukao et al., 2017; Ikenaga, 2009; Ikenaga & Kambayashi, 2016), we employ capital variables extracted from the Survey of R&D, rather than the standard ‘Career Matrix’ database from the ‘Japan Institute for Labour Policy & Training’. The nature of our data provides significant advantages in regard to the coverage and the high representativeness of the population, and hence provides greater statistical power.

In contrast to the US-based study by Autor et al. (2003), we find that technological innovation has a positive influence on employment across all industries in Japan. The estimated impact of innovation on employment is consistent with the compensation theory prediction, which reports that a 10% average increase in intramural R&D expenditure raises employment by 3.4%, when all other factors remain constant. In addition, innovation has a more pronounced impact on job creation in the manufacturing sector compared to other sectors, including the services and agricultural sectors. Therefore, it is suggested that policymakers should boost employment in Japan by supporting innovative companies, especially those in the manufacturing and high routine-intensity sectors.

By delving deeper into the results by looking at industries with a different level of routine intensity, we show that this positive relationship remains across both high and medium levels of routine intensity. Our study also finds an inverse correlation between inflation and job creation (especially in the non-manufacturing sectors and medium routine-intensity industries), while real GDP growth contributes very little to employment gains. We attribute this picture to specific structural issues faced by the Japanese economy, which are reflected in the slow GDP growth and inflation rates.

This study proceeds as follows: Section 2 outlines the main literature relevant to this field across different periods and countries and describes the underlying theoretical framework. This is followed by descriptive evidence and a discussion of the methodology employed in this research (Section 3). Section 4 presents the results underpinned by a theoretical explanation, and Section 5 concludes and offers some policy suggestions.

2 | LITERATURE AND ECONOMETRIC FRAMEWORK

2.1 | Previous literature

Since the 'First Industrial Revolution' (18th century), European countries have experienced many different kinds of technology shocks, which have led to substantial changes in their employment structure (Crafts, 1989). Technology innovation has been at the centre of discussions in much of the research pertaining to economic growth. The broader concern of the literature has been to mainly examine the connection between technological innovation and economic growth, as this is a concern of great relevance to government policy. If technology does drive economic growth, then the question is whether employment is susceptible to the influence of technology advancement. In general, we classify the literature into two strands. While the first strand relates to the direct impact of technological innovation on economic growth, the second strand of the literature concentrates on the microeconomic consequences innovation may have on employment.

In the absence of R&D data, most of the early studies (Machlup, 1962; Porat, 1978) do not explore the impact of innovative technologies on levels of employment. Their focus is on changes in the demand for employment over differing industries and they explain this phenomenon from the perspective of technological forces. Martin (1998) has analysed the changes to employment levels in the information sector across the US between 1970 and 1995 through examining jobs that require routine as well as non-routine information management. She finds the number of workers in the information sector was expanding at decreasing rates during the period, due to the decline in routine information work caused by technological advances. The share of routine information work in total information employment lost ground to the occupations handling information in a non-routine manner.

The literature also extends the scope of the research to include the extent to which innovation directly alters labour demand. This has been mostly addressed by assessing the specific undertakings within the occupations. Autor et al. (2003) present a statistical analysis on the impact of computer technology on job task content, and hence the demand for labour capital in the U.S. labour market from 1960 to 1998. Their study suggests routine jobs could be superseded by robots or computers. However, the computer capital should be regarded as complementary to non-routine tasks. Roughly the same results are obtained by Goos and Manning (2007) based on the U.K. labour market from 1975 to 1999. Also, Acemoglu and Autor (2011) found a significant fall in employment in routine jobs across the United States, regardless of whether their jobs are factory or office based. This could offer an explanation for the divisions within the U.S. job market, with the decline of middle-skilled employment and the rapid growth in both high- and low-skilled employment.

Job polarization can also be seen along the lines of globalization, as 'routine' activities are more exposed to relocation (offshoring) than 'non-routine' occupations. In this context, Reijnders and de Vries (2018) introduce a 'model of production in global value chains' (GVCs). This model allows a joint analysis of labour market development to explain the growth in the demand for 'non-routine' workers in 37 developed and emerging countries during 1999–2007. Their findings suggest that the routine jobs relocation has augmented the demand for non-routine occupations in developed economies. In contrast, it has reduced the demand in the offshoring economies, such as Poland and China, although technological improvement has played the same role in all countries.

Using World Bank data for the years 1998–2015, Yildirim et al. (2022) clustered 12 European countries into two groups according to their innovation levels. By adopting panel threshold regressions, they find that innovation (measured by patent applications) increases unemployment across both groups of countries, although the negative impact is more pronounced in countries with low-innovation regimes. However, their study does not explore whether there are disproportionate effects across industries.

We contribute to the literature by accounting for sectoral differences. It is, therefore, useful to look at the degree to which innovation influences employment, which is subject to sectoral variations and which previous studies have ruled out. A handful of micro-econometric studies have found important discrepancies in the effect of innovation on job creation across industries. For example, Buerger et al. (2012) demonstrated that patent growth has a positive and statistically significant impact on employment in two industries (i.e., 'medical and optical equipment' & 'electrics and electronics'). Nonetheless, this relationship does not hold in the more traditional industries (i.e., 'chemicals' and 'transport equipment'). More recently, Van Roy et al. (2018) reported a positive association between innovation and employment in high-technology industries, as the employment level increases by 5% if a company doubles its patents. However, this relationship does not hold for the low-tech and services industries. They also found heterogeneous effects of innovation according to the differences in industry characteristics.

Other studies utilize data relating to specific occupations to explore the effect of technological development on the nature of the labour market and group jobs depending on the technical requirements and sector. Cirillo (2017) studied the European labour market for 2000–2014 and showed that innovation benefits managers, whereas it negatively affects clerks, craft, and manual workers. In addition, Dachs et al. (2017) built on the approach of Harrison et al. (2014) to estimate the marginal effects of technological innovation on employment across various stages of the business cycle.

However, there has been little research conducted in the context of Japan. The existing studies ignore the specific features of Japan's employment structure. Ikenaga and Kambayashi (2016) studied the Japanese labour market for the period 1960 to 2005, using a dataset supplied by the 'Japanese Institute for Labour Policy and Training' that categorizes jobs into five forms of intensity depending on the level of routine involved. Using the approach of Autor et al. (2003) alongside that of Goos and Manning (2007), they concluded that non-routine tasks complement innovation, whereas technological advancement substitutes for routine tasks. Ikenaga (2009) found that this trend has been observed since the 1980s and attributed it to the IT capital. In contrast, Ikenaga and Kambayashi (2016) indicated that this pattern has its roots in the 1960s, well before the adoption of computer technology. This second result suggests there were other variables affecting this phenomenon prior to the 1980s. These results are comparable to the situation in the United States described by Autor et al. (2003), with the difference that Japan has experienced a similar trend only since the 1990s. The main reason for these different empirical findings is that the two nations have differences across the organizations in the employment market, including differences in the types of jobs, the value of techniques and proportion of task inputs. Section 4.3 provides a comparison of these findings based on data from specific industries.

A study by David (2017) explored the possibilities of the loss of employment due to the Japanese technological advances. He discovered that roughly 55% of employment (8 percentage points higher than in the United States) can be automated and could soon be handled and replaced by computer capital. Fukao et al. (2017) analysed the influence of technological advances on the jobs market from 1991 to 2010 utilizing micro data from the 'Basic Survey of Japanese Business Structure and Activities'. Their results suggest companies carrying out R&D have a greater chance of boosting employment and this finding is supported by the compensation mechanisms in VivareIli (2013). Fukao et al. (2017) investigated the same relationship by using industrial-level data, utilizing R&D expenditure and capital investment as a proxy for innovation. They found that employment and technological advances are positively related in both the productive and non-productive manufacturing sectors. In this study, we follow their approach and approximate innovation using three different technological measures.

This paper offers an empirical contribution to the literature in the Japanese context by extending the work of Autor et al. (2003) as well as that of Goos and Manning (2007) to measure the impact of innovation on job creation across major industries in Japan. In line with their approach, we also include supply-side characteristics, such as gender and age as control variables in our model.

2.2 | Analytical and econometric framework

In theory, technological advances and the jobs market are related in two differing ways from both a classical and more recent economic perspective. The two approaches are unemployment due to technological change and a compensation-based approach (VivareIli, 2013). Unemployment arising from advances in technology represents the immediate effects of innovation whereas the theory of compensation is a more indirect effect.

There are two schools of thought concerning the role of innovation on employment. The first view, which is adopted by the works of Zimmermann (1991) and Feldmann (2013) claims that labour-saving innovations generate unemployment due to technological progress (known as 'technological unemployment'). The second school of thought follows the arguments of Marx (1867), Coad and Rao (2011), VivareIli (2013); Vivarelli (2014) and Calvino and Virgillito (2018), which posit that the combination of product innovations and indirect effects of income and prices could offset the direct effect of job losses caused by innovation processes encompassed in new equipment and machinery (compensation theory). The compensation theory highlights indirect effects (through income and price), which, combined with product innovation, compensate for job destruction caused by technological advancement. Specifically, the compensation theory, which was introduced by Marx (1867), suggests that innovation can increase the efficiency of production, and therefore, increase demand and employment in competitive markets. The theory also indicates a labour-friendly nature of innovation, suggesting that product innovation and other indirect effects can boost employment and counterbalance job losses incurred from the introduction of new technologies. Many researchers support the argument that technology innovation can positively impact employment (Evangelista & Savona, 2003; Greenan & Guellec, 2000; Lachenmaier & Rottmann, 2011; Van Roy et al., 2018).

A way in which the process of compensation can be expressed is with regard to the introduction of more advanced production machinery. Say (1964 [1803]) mentioned that, although new machines lower the labour input required to produce the same quantity of output, it still benefits the buyers (this includes jobs affected by technological advances) in two ways. First, the construction of machinery employed to aid production is a time-consuming process, while these machines are usually brought into use slowly. This provides adequate time for public administration to support workers who are at risk of becoming unemployed. Second, manufacturing the machinery needs a substantial amount of manpower. As a result, new jobs are created in areas which are more capital intensive, providing new forms of employment for those who lose out due to the rise in AI and robots.

Given the above discussion, we use the static approach to the demand for labour from the neoclassical perspective to capture immediate impacts arising from technological innovation. This approach holds despite assuming that both output markets and the employment market are competitive. Consider a perfectly competitive firm maximizing its profit according to its constant elasticity of substitution (CES) production function:

$$Y = A\left[(\alpha L)^{\lambda} + (\beta K)^{\lambda}\right]^{\frac{1}{\lambda}} \tag{1}$$

where Y represents output, L is labour, K is the existing capital stock, and A is the potential technological progress. The coefficients α and β measure the return of labour and capital to a technology change, respectively, and $0 < \lambda < 1$. A movement in A measures labour augmenting technological progress, while a shock in A is nearly costless when it requires no important use of factor inputs. A rise in A is labour augmenting when it works in the direction of increasing the labour input (leaving capital unchanged). Let W be the cost of labour and P be price of output. Solving the profit maximization problem results in the below labour demand function[2]:

$$l = y - \delta w + (1-\delta)\, ln(\alpha), \tag{2}$$

where $w = ln(W/P)$ represents the real wages and $1/(1-\lambda)$ is the elasticity of substitution between capital and labour. All lower-case letters (l, y, w) of Equation (2) are expressed in their logarithm form.

Following Piva and Vivarelli (2018), Equation (2) can be expressed in a stochastic form and augmented to include the main treatment variable, innovation, and the set of control variables as follows:

$$l_{it} = \gamma + \beta_y y_{it} + \beta_w w_{it} + \beta_{inn} inn_{it} + X'_{it}\beta + u_{it} \tag{3}$$

where $i = 1, \ldots, N$ denotes industries and $t = 1, \ldots, T$ denotes time. γ refers to the overall intercept, and slopes β_y, β_w and β_{inn} are coefficients representing the population marginal effects of real income (y), real wages (w) and innovation (inn) on employment (l), respectively. The vector β is a $K \times 1$ column vector and X_{it} is a $K \times T$ matrix of control variables. The model in (3) is a one-way error component model where the error term, u_{it}, is defined as:

$$u_{it} = \mu_i + v_{it} \tag{4}$$

where μ_i captures the unobservable individual characteristics that are constant over time and v_{it} is the remainder of the error term. Under the assumption of homogeneity, all the industries are pooled into one data set, and the i subscript should be dropped from the model. The model is therefore treated as a standard multiple linear regression model and can be estimated using a Pooled OLS (POLS). This is, however, a very restrictive assumption and needs to be tested by allowing heterogeneity across cross-sections. In this context, we allow for two types of effects: fixed effects (FE) and random effects (RE). FE model treats the unobserved individual characteristics, μ_i, as fixed parameters and assumes that the remainder error term v_{it} is independent of the set of explanatory and control variables across industries and over time (i.e., $v_{it} \sim IID(0, \sigma_v^2)$). The FE model, however, may not validly represent the data if the firms in our data are randomly drawn from the population. Thus, the validity of the FE needs to be tested against an alternative of the RE model, which allows for the firms to be a random draw of the population. Furthermore, the estimation of the FE imposes a mean deviation-based transformation, which forces all the time-invariant effects and variables to be dropped off the model (thus, losing very important information that explains the variations in the outcome variable). Hence, against these drawbacks, the RE model may be used as a better alternative to explain the interaction between the set of explanatory variables and employment.

In this paper, we proceed as follows. We first perform a 'poolability' test, which tests the null hypothesis of joint insignificance of all individual effects (i.e., $H_0: \mu_i = 0$ for $i = 1, \ldots, N-1$) against the alternative of the overall significance of all individual effects using an *F* test. Under the null hypothesis, the appropriate model should be a POLS model where all firms are treated as homogenous. The rejection of the null hypothesis implies that the FE model validly represents the data. If the null hypothesis is rejected, we apply the Hausman test to examine whether the RE model is valid against the alternative of FE model. In other words, we estimate three models including POLS, FE and RE models. We also account for the cross-sectional dependencies within the data. For this purpose, we use a battery of tests – CD (Breusch & Pagan, 1980), LM and scaled LM and CD (Pesaran, 2004) – to examine whether there is cross-sectional dependence between the industries. These tests are implemented to obtain more accurate test statistics when comparing a random-effects model with a pooled model.

3 | DATA AND METHODOLOGY

3.1 | Background and sample overview

The data used in this study is obtained from the 'Japanese Survey of Research and Development' (Statistics Bureau of Japan, Ministry of Internal Affairs and Communications), which covers enterprises from 33 medium-level industries over the period 2002–2017. These 33 industries are classified into three sectors: agriculture, manufacturing, and service sectors according to the Japan Standard Industrial Classification. Because of data availability constraints, we only focus on medium-level industries, as a more detailed breakdown of sectors is published every 5 years from the Population Census.[3]

3.2 | Variables and econometrics strategy

Unlike other studies that use total employment as a dependent variable, in this work, we exclusively concentrate on enterprises engaging in R&D activities. By doing so, we can limit the effect the investment in technological advances has on unemployment in a specific set of firms in the technology sectors and hence reduce the amount of noise in the data. Besides, enterprise firms comprise the highest ratio of R&D expenditure (72.4% in 2017) amongst all surveyed sectors for R&D investment (Statistics Bureau of Japan, 2019). Other surveyed sectors include not-for-profit institutions and public organizations, colleges, and universities. The R&D term comprises all costs associated with new products and services design and development during a reference year. It is important to highlight that this amount refers to each industry's contributions and excludes amortization and depreciation of prior investments, thus representing an actual flow of the current additional R&D expenditures performed within a company (Bogliacino et al., 2012).

Innovation measures: According to the Frascati Manual (OECD, 2015), innovation can be defined as the launch of new or substantially enhanced products to the market or the introduction of a new technology or considerably advanced production methods. R&D is part of various innovation-related activities, while the term 'innovation' expands to contain 'the acquisition of existing knowledge, equipment, machinery and other capital goods, marketing, training, design and software development'. However, some innovation activities, such as licencing, patent applications, manufacturing start-ups, market research – amongst others – cannot be classified as R&D. Nevertheless, previous research shows that product innovation is strongly linked to R&D expenditure (Parisi et al., 2006). Hence, the present work approximates product innovation with R&D expenditure. As noted earlier, we use the terms 'innovation' and 'R&D expenditure' interchangeably throughout this paper. We apply three measures of innovation: (i) total intramural expenditure on R&D; (ii) self-financed R&D expenditure, which comprises funds paid by the firm to public companies, organizations, private universities, overseas institutions and not-for-profit institutions; and (iii) external R&D funds received from the outside of the company (public organizations, companies, etc.). These types of R&D investments are used as explanatory variables in the following analysis. The primary technology proxy refers to the total intramural expenditure on R&D, which is employed to demystify the connection between employment and innovation. This variable captures all current R&D expenditures made in a company yearly, irrespective of the funds' source. Given that there is no available data precisely quantifying the technological advancement, our study adopts the variables related to self-financed R&D expenditure and external R&D funds to proxy technological improvements and innovation.

Both the price and production level are crucial in determining levels of employment. In the context of this paper, we use GDP per capita and inflation as proxies for both output and prices (Feldmann, 2013). We obtain data on real GDP growth rates and inflation rates from Japan's National Accounts and the Federal Reserve Bank of St Louis (2019), respectively. Consistent with Okun (1970) law, most empirical studies suggest that GDP changes are positively correlated with employment changes, implying that unemployment rates decline when GDP increases (e.g., Attfield & Silverstone, 1997; Blázquez-Fernández et al., 2018; Zanin, 2014).

Relevant macroeconomic factors are also added to the specification to explain any industrial and related economic effects, which may drive employment levels. These control variables include the gross fixed capital formation as a percentage of GDP (*gfcfg*) and population growth (*popg*).

Gross fixed capital formation constitutes a substantial element of domestic investment and accelerates economic growth. Therefore, in our work, we expect a positive and significant association between this variable and employment. Similar studies in the literature often adopt the gross fixed capital formation (as a fraction of GDP) to examine the extent to which investment affects employment (Piva & Vivarelli, 2018; Van Roy et al., 2018). In addition, based on the traditional Phillips curve, we anticipate a positive association between inflation, which is typically represented by the Consumer Price Index, and our dependent variable (level of employment). Gross fixed capital formation and population growth are obtained from the World Bank and the Population Estimates databases (monthly and yearly published), respectively.

To better explain the variation in the dependent variable, at a second stage, we incorporate specific supply-side factors as control variables into our analysis. More specifically, following the approach of Autor et al. (2003), we investigate the gender distribution of employees within each industry by including the total percentage of male workers. Moreover, we consider the ageing population and labour force in Japan by embodying the average *age* (nationally) in the econometric models. We extract the data for age and gender from the Labour Force Survey of Japan (2018). Although the present study accounts for several critical employment determinants in the econometric analysis, it is essential to clarify that there might exist other omitted variables playing an important role in explaining the employment trends in Japan. Data limitations prevent us from including other factors in the regression that may also drive the level of employment. For example, the missing cases for the higher education variable, which reflects the acquisition of human capital, correspond to a large proportion of our sample. Such unobserved characteristics may be correlated with both R&D spending and job creation, thus biasing our estimates of interest. The model is given by the following equation:

$$\begin{aligned} emp_{it} = {} & \alpha_i + \beta_1 rnd_{it} + \beta_2 gdpg_{it} + \beta_3 inf_{it} + \beta_4 popg_{it} \\ & + \beta_5 gfcfg_{it} + \beta_6 male_{it} + \beta_7 age_{it} + \beta_8 agesq_{it} + \beta_9 rnd \\ & * male_{it} + u_{it} \end{aligned} \tag{5}$$

where *emp* is the employment in business enterprise *i* and year *t*; *rnd* represents the research & development expenditure (as a proxy for innovation), *gdpg* is the GDP growth; *inf* is the inflation rate; *popg* denotes the population growth; *gfcfg* is the gross fixed capital formation as a percentage of GDP (a predictor of investment); *male* represents a dummy variable capturing the impact of gender on employment; and *age* is the average age of the labour force.

Note we allow two forms of non-linearity in the specification (5). The first form captures the nonlinear effect of age on employment. Much of the related literature, such as Rosenzweig (1976), Clark et al. (1996), Schwartz and Kleiner (1999), van Ours and Stoeldraijer (2011), De Lange et al. (2021) (amongst others) suggest that age has a nonlinear effect on labour market outcomes. One common approach to capture this nonlinearity is to add the quadratic effect of age on employment, which is captured by the additional term *agesq*. In general, we expect age to have a decreasing marginal effect (i.e., diminishing effect on employment), suggesting an inverted U-shaped relationship between age and employment. We formally test this relationship using the *U* test pioneered by Lind and Mehlum (2010).

The second form of nonlinearity captures the gender effect of innovation on employment. Recent literature, including Díaz-García et al. (2013), Teruel and Segarra-Blasco (2017), Na and Shin (2019) and Bednar et al. (2021), suggest the presence of gender differential in innovation. In other words, the effect of innovation may not be the same across both genders. Thus, we include the interaction term *rnd*male* in the model to assess whether the impact R&D spending has on employment relates to the average proportion of male employees in each industry, conditional on the other observed variables.

Based on comparative studies in the literature alluded to in Section 2, all the variables above are known to affect employment and are proven to be significant in explaining employment trends in other countries. To evaluate the robustness of our results, in separate models, we employ the R&D received (*rnd_rf*) and the self-financed R&D (*rnd_sf*) variables as a proxy for innovation (in place of the main *rnd* variable).

3.3 | Data statistical properties

Table A1 reports a summary of key statistics for the set of explanatory and control variables used in Equation (5). Measures of employment and capital levels are expressed in natural logarithms to reduce any skewness. The macroeconomic and supply-side control variables are reported in percentages.

Table A2 reports the correlation coefficients of all variables in the model. Unsurprisingly, there is a positive and strong statistical correlation between all measures of innovation that capture the technological investment. Therefore, we include these variables in different regression specifications, one at a time. Moreover, we find a notable relationship between age and specific variables (such as population growth and inflation rate). However, there are no significant concerns regarding the correlation between the explanatory variables.[4]

4 | RESULTS

4.1 | Aggregate effect of R&D on employment

Tables 1 and 2 report results of (i) the specification involving only macroeconomic factors, and (ii) the specification that extends the former with additional supply-side factors, respectively. For robustness and consistency purposes, we employ three alternative measures of technology innovation. We also estimate the specifications using pooled OLS, FE and RE models.

In general, the results reveal a positive and statistically significant effect of all three-innovation variables on employment, suggesting that R&D investment is linked to job creation. The impact of the intramural R&D expenditure is more considerable in the pooled model (column 1) than in the FE (column 2) and RE (column 3) regressions. According to the specification tests (including the poolability and Hausman tests), we find that the RE model is preferred, both in terms of efficiency and consistency. Thus, we focus on the findings from the RE model.

Table 1 shows that, on average, a 1% increase in intramural R&D expenditure increases employment by 0.35% (column 3), keeping all else equal. The effect of self-financed R&D on employment is similar, standing at 0.36% (column 5 of Table 1). The latter accords well with the findings of Fukao et al. (2017). In contrast, the impact of R&D activities funded by organizations and institutions outside of the company on job creation is much smaller (0.02%) and is only marginally significant at the 10% level. This implies that firms possibly exploit the external R&D funding for improving their processes (rather than developing new products), which does not necessarily lead to job openings. As alluded to in Section 2, process-oriented expenditures are often associated with labour-saving effects in the literature.

Examining the coefficients of the macroeconomic variables results in some interesting findings. Specifically, GDP growth has a positive relationship with labour demand when looking at the intramural R&D expenditure, but is statistically insignificant in other models. Similarly, improving the proportion of gross fixed capital

TABLE 1 Relationship between employment and R&D expenditure: Models with macroeconomic variables

Variable	1	2	3	4	5
rnd_exp	0.494***	0.321***	0.346***		
rnd_rf				0.022*	
rnd_sf					0.356***
gdpg	0.004	0.002	0.003	−0.004	0.002
inf	−0.018**	−0.019**	−0.018**	−0.020**	−0.020***
popg	0.167	0.252**	0.240**	0.305***	0.343***
gfcfg	0.041***	0.044***	0.043***	0.049***	0.039***
Constant	−2.087***	−0.151	−0.421	8.630***	−0.455***
R^2	0.60	0.96	0.55	0.09	0.61
F-test	157.92***	364.22***	50.04***	9.35***	45.23***
Hausman test	0.00	0.00	0.00		
LR test	620.24***				
Breusch_Pagan LM			748.06***		850.27***
Pesaran LM			6.77***		9.91***
Pesaran CD			5.67***		4.77***
Observations	528	528	528	479	513

Note: (***), (**) and (*) refer to the 1%, 5% and 10% significance levels, respectively. 1: Pooled regression, 2: Fixed- effects regression, 3: Random-effects regression, 4: Random-effects regression when R&D received is used to approximate innovation, 5: Random-effects regression when self-financed R&D is employed to approximate innovation.

TABLE 2 Relationship between employment and R&D expenditure: Extended models

Variable	1	2	3	4	5	6
rnd_exp	0.497***	0.321***	0.344***			0.515***
rnd_rf				0.025*		
rnd_sf					0.357***	
gdpg	0.004	0.001	0.002	−0.003	0.001	0.0001
inf	−0.017**	−0.019**	−0.019**	−0.020**	−0.019***	−0.018
popg	0.186	0.325**	0.306**	0.360***	0.332***	0.281*
gfcfg	0.037***	0.040***	0.039***	0.045***	0.037***	0.036**
male	−0.006**	−0.004	−0.004	−0.003	−0.004	0.016
age	0.003	−0.008	0.007	0.011	−0.001	0.006
rnd_exp ∗ *male*						−0.002
Constant	−1.777***	−0.114***	−0.362***	2.950***	−0.153	−1.855
R^2	0.60	0.97	0.55	0.09	0.61	0.55
F-test	113.03***	345.42***	35.85***	6.73***	32.20***	32.88***
Hausman test		0.000				
LR test	648.71***					
Breusch_Pagan LM	752.54***				864.04***	786.56***
Pesaran LM	6.91***				10.34***	7.96***
Pesaran CD	5.29***				4.68***	5.14***
Observations	528	528	528	479	513	528

Note: (***), (**) and (*) refer to the 1%, 5% and 10% significance levels, respectively. 1: Pooled regression, 2: Fixed-effects regression, 3: Random-effects regression, 4: Random-effects regression when R&D received is used to approximate innovation, 5: Random-effects regression when self-financed R&D is employed to approximate innovation and 6: Random-effects regression including the interaction term '*rnd_exp*male*'.

formation in the GDP increases the level of employment within the firms engaging in innovation activities. Population growth is also associated with a notable boost in labour demand across all models, while inflation has a negative relationship with employment.[5]

Adding supply-side variables has a minor impact on employment and barely alters the coefficients of interest (see Table 2). The proportion of male employees in all industries and age distribution play an insignificant role.[6] Similarly, the effect of R&D expenditure on employment is not related to the average gender composition of employees in each industry, as the relevant interaction term proves statistically insignificant (see column 6 of Table 2). This suggests that the Japanese government and national policymakers should encourage and further support the participation by women in firms engaging in R&D activities, as gender is not a driving determinant of employment growth.

To summarize, R&D expenditures have a positive effect on the level of employment in Japan when examining all industries. In the following subsections, we explore heterogeneous effects in this relationship to investigate whether the results differ across sectors and levels of routine intensity.

4.2 | Impact of R&D expenditure on employment by major industry

We extend the previous analysis by exploring the variation across manufacturing and non-manufacturing sectors. The latter includes companies engaged in the service and, to a lesser extent, agricultural industries. We apply the same regression specifications defined in Section 3.2.

The model outputs shown in Tables 3 and 4 yield some interesting findings. The sign of the R&D spending on employment (for both the total intramural and the self-financed R&D spending) is as expected. Nevertheless, the size of the effect on labour demand is notably larger in the manufacturing sector. Specifically, the impact of a 10% increase in intramural R&D expenditure on employment ranges from 4% to 4.2% (depending on the specification) for an average medium-level firm operating in the manufacturing sector (columns 1 and 4 of Table 3) and between 2.7% and 3.4% for the non-manufacturing sector (Table 4). Furthermore, the impact of external R&D funds on employment is statistically significant in the manufacturing sector, whereas there is no effect in the non-manufacturing sector (columns 2 and 5). These

TABLE 3 Relationship between employment and R&D expenditure: Manufacturing sector

Variable	1	2	3	4	5	6
rnd_exp	0.404***			0.418***		
rnd_rf		0.102***			0.104***	
rnd_sf			0.402***			0.417***
gdpg	−0.0004	−0.004	0.0003	−0.006**	−0.009***	−0.006**
inf	−0.016	−0.015	−0.017	−0.018*	−0.016	−0.019*
popg	0.293***	0.254***	0.314***	0.280***	0.348***	0.272***
gfcfg	0.026***	0.032***	0.025***	−0.001	0.015	−0.001
male				−0.067***	−0.036**	−0.069***
age				1.758***	0.782	1.821***
agesq				−0.017***	−0.008	−0.018***
Constant	−0.604	3.399***	−0.597	−39.858***	−13.733	−41.248
R^2	0.70	0.25	0.70	0.71	0.25	0.71
F-test	24.82***	12.92***	24.96***	18.28***	9.76***	18.30***
Hausman test	0.00	0.00	0.00	0.00	0.00	
LR test	303.01***			306.89***		
Breusch_Pagan LM	136.98***	242.09***	245.10***	255.77***	231.65***	256.65***
Pesaran LM	3.57***	3.84***	4.01***	4.58***	3.28***	4.63***
Pesaran CD	0.57	0.68	2.82***	2.38**	0.52	2.20**
U test				0.09*	0.30	0.07*
Observations	304	302	304	304	302	304

Note: (***), (**) and (*) refer to the 1%, 5% and 10% significance levels, respectively. All models are estimated using the random-effects approach. Models 1 to 3 include macroeconomic variables, while regressions 4 to 6 contain both macroeconomic and supply-side variables. Regressions 1 and 4 use R&D spending to approximate innovation, while models 2 & 5 use R&D received and models 3 & 6 use self-financed R&D for the same purpose. U-Test tests the null of monotone or U-shape against the alternative of inverse U-shape.

findings suggest that technological progress creates jobs faster in the manufacturing sector. It could also imply that manufacturing firms direct their R&D capital to product innovation, leading to an increased demand for labour relative to firms operating in the non-manufacturing sector.

Surprisingly, economic growth has an adverse effect on employment in the manufacturing sector (extended models). This could be elucidated by the fact that Japan's economic growth has declined over the last three decades, resulting in economic stagnation. Therefore, to revitalize its economy, the country continued to spend a high proportion of its GDP on technological development, even during the global economic crisis of 2008–2009.[7] As a result, employment in companies undertaking substantial R&D activities experiences an upward trend, irrespective of the evolution of the GDP growth rate. In contrast, economic growth has an insignificant effect on the firms operating in the non-manufacturing sector. In a similar vein, inflation is negatively correlated with employment. This relationship is more pronounced in the non-manufacturing sector, where a decline in employment occurs in the presence of higher inflation rates. On the other hand, domestic investment (*gfcfg*) positively affects job creation more prominently in the non-manufacturing sector. Similarly, population growth drives employment expansion, especially in the manufacturing industries.

Furthermore, we provide evidence that gender distribution has a statistically significant and negative effect on employment, particularly in the manufacturing industry. Despite its small magnitude, the effect of gender is more significant when modelling the total intramural R&D expenditure (column 4 of Table 4).

A common practice in empirical research is using age as a proxy for experience. This approach works well, especially in a male-dominated society, like Japan. Men usually take less family responsibility and do not get hit by fertility choice directly. Therefore, compared with women, there are fewer factors which influence a man's labour force participation decision. The results presented here show that, as expected, age has a statistically significant diminishing effect on employment in the manufacturing industry, reflected by the negative sign of

TABLE 4 Relationship between employment and R&D expenditure: Non-manufacturing sector

Variable	1	2	3	4	5	6
rnd_exp	0.273***			0.336***		
rnd_rf		−0.004			−0.006	
rnd_sf			0.304***			0.304***
gdpg	0.008	−0.002	−0.013	−0.002	−0.002	−0.008
inf	−0.054**	−0.050***	−0.068***	−0.038	−0.048***	−0.053**
popg	0.021	0.015	0.018	0.027	0.023	0.021
gfcfg	0.089***	0.100***	0.092***	0.057***	0.095***	0.087***
male				−0.034***	0.017**	0.008
age				−0.024	−0.079*	−0.069***
agesq				0.0001	0.001	0.205
Constant	−0.369***	1.718***	−1.255*	2.994***	2.739*	−2.861
R^2	0.29	0.10	0.38	0.34	0.11	0.38
F-test	16.96***	1.153	14.21***	14.87***	2.87**	10.09***
Hausman test	0.000	0.00	0.00	0.00	0.00	0.00
LR test	249.16***			277.68***		
Breusch_Pagan LM	136.90***		118.36***	144.20***		121.67***
Pesaran LM	3.40***		2.03**	3.94***		2.27***
Pesaran CD	1.53		0.593	1.54		0.75
U test				0.00***	0.45	0.34
Observations	210	177	200	208	175	198

Note: (***), (**) and (*) refer to the 1%, 5% and 10% significance levels, respectively. Non-manufacturing sectors include the agriculture and service sectors. All models are estimated using the random-effects approach. Models 1 to 3 include macroeconomic variables, while regressions 4 to 6 contain both macroeconomic and supply-side variables. Models 1 & 4 use R&D spending to approximate innovation, while models 2 & 5 adopt R&D received, and regressions 3 & 6 use self-financed R&D for the same purpose.

the quadratic term of age. Furthermore, the reported *U*-test fails to reject the alternative hypothesis of the inverse U shape (Tables 3 and 4). Therefore, age has indeed a diminishing effect, which conforms with economic theory and much of the empirical literature.

We also experimented with including the product term '*rnd_exp*male*' in the models presented in Tables 3–5. The effect is, however, found to be statistically insignificant. This implies that, on average, the impact the R&D investment has on employment does not depend on the gender composition of employees in the industries with a medium proportion of routine procedures, and in both the manufacturing and non-manufacturing sectors.

4.3 | Effect of R&D expenditure on employment by routine-intensity level

Industries having a high share of routine tasks are more likely to experience the substitution effect (i.e., the replacement of the workforce by technology), resulting in employment contraction (Goos & Manning, 2007). The variable measuring the intensity of the routine proxies the ease with which a task can be repeatedly completed, where machines could substitute the workforce by accomplishing the same tasks using programming codes (Marcolin et al., 2016).

By categorizing industries based on their routine intensity, we can compare the employment trends and observe how technological advancement affects the labour demand in sectors with different susceptibility to automation. We are particularly interested in exploring how employment reacts to technology innovation in medium- and high-level routine intensity industries. In the previous subsection, we examined heterogeneous patterns of the R&D expenditure on demand for labour by classifying firms into manufacturing and non-manufacturing sectors. However, the manufacturing sector, which is the largest and fastest-growing segment in Japan, comprises a broad range of industries with varying routine intensities. Therefore, in this subsection, we adopt the approach of Autor et al. (2003) by grouping the industries according to their routine intensity scores. All industries that belong in the manufacturing sector fall

TABLE 5 Relationship between employment and R&D expenditure: Medium routine-intensity level

Variable	1	2	3	4	5	6
rnd_exp	0.298***			0.292***		
rnd_rf		0.036*			0.036*	
rnd_sf			0.442***			0.437***
gdpg	−0.002	−0.005	−0.006	−0.003	−0.006	−0.006*
inf	−0.030***	−0.030	−0.034***	−0.030**	−0.031*	−0.034**
popg	0.114	0.185	0.173**	0.192*	0.252	0.201**
gfcfg	0.059***	0.060***	0.046***	0.054***	0.055***	0.042***
male				−0.004	−0.005	−0.005
age				0.009	−0.009	0.005
Constant	−0.198***	3.012***	−1.606***	−0.156***	3.045***	−1.330**
R^2	0.56	0.12	0.72	0.55	0.13	0.72
F-test	18.82***	6.74***	28.06***	13.67***	5.05***	19.61***
Hausman test	0.000			0.000		
LR test	284.74***			314.56***		
Breusch_Pagan LM	183.91***	165.29***	170.72***	188.90***	170.30***	179.50***
Pesaran LM	4.13***	2.92***	3.27***	4.45***	3.25***	3.84***
Pesaran CD	1.53	0.71	1.31	1.55	0.76	1.34
Observations	256	241	251	256	241	251

Note: (***), (**) and (*) refer to the 1%, 5% and 10% significance levels, respectively. All models are estimated using the random-effects approach. Models 1 to 3 include macroeconomic variables, while regressions 4 to 6 contain both macroeconomic and supply-side variables. Regressions 1 and 4 use R&D spending to approximate innovation, while models 2 & 5 adopt R&D received and regressions 3 & 6 use self-financed R&D for the same purpose.

into the medium and high levels of routine intensity. Hence, we only present the results that refer to these two levels of routine intensity (medium and high). We classify the sectors according to the industry-level routine intensity indicator proposed by the OECD. The results discussed below are based on the same regression function presented in Section 3.2.

Tables 5 and 6 report the results relating to the medium routine- and high routine-intensity industries, respectively. The effect innovation has on employment is more extensive in the high routine-intensity sectors, such as the 'Food, Beverages & Tobacco', 'Transport & Telecom' and 'Chemicals' industries. Specifically, if an average company operating in those sectors raises its intramural R&D expenditure by 10%, then employment is expected to increase by 3.9% (columns 1 and 4 in Table 6). The corresponding boost in employment for medium routine-intensity firms (with activities in sectors such as the 'Basic & Fabricated Metals' and 'Electrical equipment') on average is at around 2.9%–3.0% (Table 5). Consequently, the advent of new technologies and innovation in sectors heavily based on routine skills is associated with notable growth in employment. These findings contrast the results of Ikenaga and Kambayashi (2016), who argue that innovation substitutes for high-routine jobs, based on occupational-level data of the Japanese labour market.

The other two measures of innovation that are utilized throughout this study (self-financed R&D spending and R&D funds received) also positively affect employment across both levels of routine-intensity. It is noteworthy that, unlike the other two innovation measures, the effect of the self-financed R&D expenditure is slightly higher amongst firms operating in the medium routine-intensity industries compared to the ones with a high proportion of least-skilled jobs.

Interestingly, some key macroeconomic variables have a diverse impact on employment across industries, depending on the level of their routine-intensity. Economic growth is positively linked with job gains in the high routine-intensity industries. However, as in the case of our findings concerning the manufacturing firms in Section 4.2, the effect of this variable is (marginally) negative when looking at the industries characterized by a medium level of routine tasks. Likewise, in line with our findings in the previous subsection, inflation reduces employment, and this pattern is more pronounced within the medium routine-intensity sectors. As discussed earlier, this picture probably reflects the structural issues faced by the Japanese economy over previous decades, which have

TABLE 6 Relationship between employment and R&D expenditure: High routine-intensity level

Variable	1	2	3	4	5	6	7
rnd_exp	0.387***			0.390***			1.384***
rnd_rf		0.054**			0.053**		
rnd_sf			0.415***			0.427***	
gdpg	0.017**	0.014**	0.019***	0.021**	0.016**	0.024***	0.021**
inf	−0.012	−0.008	−0.018	−0.020	−0.023	−0.029**	−0.022
popg	0.3664	0.325	0.397*	0.397	0.516*	0.327	0.350
gfcfg	0.030***	0.050***	0.043***	0.056*	0.073***	0.073***	0.057**
male				0.032***	0.035	0.040**	0.187***
age				−0.013	0.009	0.014	−0.011
rnd_exp ∗ male							0.013**
Constant	−0.614	3.035*	−1.282***	−2.943	−0.429***	−4.324***	−14.637***
R^2	0.66	0.09	0.66	0.68	0.10	0.69	0.72
F-test	20.57***	3.44***	20.57***	23.14***	2.73**	16.13***	20.72***
Hausman test	0.000			0.000			
LR test	211.77***			197.59***			
Breusch_Pagan LM	131.08***	144.90***	143.04***	119.18***	130.06***	128.37***	127.35
Pesaran LM	5.66***	6.87***	6.71***	4.63***	6.58***	5.43***	5.34
Pesaran CD	4.46***	3.45***	3.02***	5.59***	4.36***	5.98***	5.09
Observations	192	174	187	192	174	187	192

Note: (***), (**) and (*) refer to the 1%, 5% and 10% significance levels, respectively. All models are estimated using the random-effects approach. Models 1 to 3 include macroeconomic variables, while regressions 4 to 6 contain both macroeconomic and supply-side variables. Models 1, 4, & 7 use R&D spending to approximate innovation, while models 2 & 5 use R&D received, and models 3 and 6 use self-financed R&D for the same purpose. Regression 7 also includes the interaction term '*rnd_exp*male*'.

resulted in slow growth rates. As expected, the level of domestic investment (*gfcfg*) is a significant determinant of job creation in both groups of industries, while population growth also increases the employment level.

On the contrary, the gender distribution and the average age profile of employees matter little in the industries of medium routine-intensity, whereas the impact of gender on employment is more considerable in industries with a high proportion of routine procedures. Most intriguingly, the interaction term '*rnd_exp*male*' is statistically significant and positively correlated with employment only in the high routine-intensity industries (column 7 of Table 6). This means that, within the industries with a high level of routine tasks, the effect of R&D spending on job creation is more prominent amongst firms employing a higher proportion of male workers, keeping all else equal.

5 | CONCLUSION AND POLICY IMPLICATIONS

This research utilizes a panel dataset of Japanese industry sectors for the years 2002–2017 to study the relationship between R&D expenditure and employment. This paper's key findings reveal a substantial employment-creating impact of innovation, thus supporting the compensation theory, which suggests that the positive effects of innovation outweigh the potential employment losses caused by technological advancement.

It may be more realistic to expect that the technological strategies of companies differ across industries and according to their average proportion of routine procedures. Therefore, in our analysis, we consider two sectors (manufacturing and non-manufacturing) and a distinction of business enterprises based on their level of routine intensity. Indeed, the results show heterogeneous effects of the determinants of employment growth, confirming that innovation is a complex phenomenon. In contrast to other existing studies (Autor et al., 2003; David, 2017; Goos & Manning, 2007; Ikenaga & Kambayashi, 2016), we establish a positive relationship between R&D spending and job creation across all sectors.

However, manufacturing firms are the most favoured by innovation activities, as our findings indicate that a 10% increase in total intramural R&D investments boosts employment in this industry by 4.2%. It becomes evident that the technological strategies of the manufacturing companies that display high R&D intensity aim at developing new products and services to maintain or improve their competitiveness in the Japanese and global markets. Although Japan experienced growth of economic activities in the service industries, the manufacturing sector remained the largest over the period of our analysis.

For the first time, we use capital variables from the Japanese R&D Survey, which brings considerable advantages in relation to the coverage and the representativeness of the Japanese business enterprises. We link this data to variables from other sources, such as the World Bank database and the Labour Force Survey of Japan. In doing so, we give full consideration to crucial factors that shape the demand for labour, including macroeconomic and supply-side determinants. We show that raising the percentage of the gross fixed capital formation in the GDP improves employment opportunities, particularly in the non-manufacturing industry. We can, therefore, infer that domestic investments play a vital role in boosting employment, and their impact is more noticeable in the companies operating in the services and agricultural sectors. Moreover, we show that population growth is associated with a significant increase in the demand for labour across all models. This becomes more meaningful when considering that Japan is witnessing a period of population decline.

Our results, however, need to be interpreted with caution because of some limitations. We exclude companies that do not engage in R&D because there is no annual employment data for applying a more detailed breakdown of industries. Therefore, our findings do not fully portray the relationship between the explanatory variables (including innovation) and employment in Japan. Furthermore, because of data constraints, the set of control variables lacks other factors (such as the proportion of employees with a higher education degree across sectors, productivity, and other industry characteristics) that may be associated with both job creation and innovation. Hence, our paper does not discern causality on the effect of R&D expenditure on employment.

The results of this study deliver some useful insights for industrial policy related to innovation. In this context, Japanese policymakers should focus on increasing the proportion of innovative companies in the economy, particularly in the manufacturing and high routine-intensity industries, where innovation is associated with high-employment gains. This, according to our analysis, will improve employment levels. Within these sectors, we find that the negative effect of inflation on employment is negligible or insignificant. This ties in well with the monetary policies initiated by the Bank of Japan, targeting to strengthen the economy by reducing unemployment levels while pushing the inflation rate up. Hence, introducing additional funding schemes and other incentives for undertaking R&D activities in the manufacturing industry could contribute to meeting these national targets. Moreover, our findings show that gender plays a limited role in how innovation influences employment. For example, while innovation does not differ across genders overall, male-driven innovation appears to have a stronger effect on employment than female-driven innovation in high-routine intensity tasks. This may suggest the presence of gender differentials, which could be reduced by attracting more females to the process of innovation in firms with high-routine intensity tasks.

Given the COVID-19 pandemic, the Japanese government has recently provided economic incentives to Japanese companies to decrease their dependency on China as a manufacturing base (offshoring) by relocating the production of their goods back to Japan (Reynolds & Urabe, 2020). Although the literature suggests that the trade in routine tasks (foreign outsourcing) increases the labour demand for non-routine tasks in developed countries, this impact on job creation is much weaker than that of technological advancement on employment (Reijnders & de Vries, 2018). Therefore, switching the manufacturing from China (the largest trading partner of the country) back to Japan is likely to increase the demand for routine tasks, thus possibly reducing to a small extent the level to which innovation impacts the demand for workers within the high routine-intensity industries.

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DATA AVAILABILITY STATEMENT

Data of the manuscript are available in Mendeley (see https://data.mendeley.com/datasets/jn7d2yh8hb/3).

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ENDNOTES

[1] Readers are referred to Section 3.2 for a detailed discussion.

[2] For further details, see Van Reenen (1997), Bogliacino et al. (2012) and Fukao et al. (2017).

[3] The data used in this paper are available in Mendeley via this link: https://data.mendeley.com/datasets/jn7d2yh8hb/3.

[4] We also apply panel unit root tests on all variables, which strongly reject the unit root hypothesis. Results are available upon request.

[5] The issue could be because inflation is repeated across all firms and therefore it is not showing the true effect.

[6] The point that merits a little more discussion is the addition of the squared term of age (*agesq*). By including *agesq* in the extended models, we find that the influence of *inflation* and *gfcfg* on employment diminishes and becomes statistically insignificant, whereas the impact of age becomes statistically significant.

[7] We ran a separate regression by including a dummy variable capturing the effect of the 2008–2009 financial crisis. The sign and size of coefficients remain the same.

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APPENDIX A

TABLE A1 Descriptive statistics

Variable	Mean	SD	Min	Max
emp	4.584	1.226	1.163	6.790
rnd_exp	11.537	1.916	5.704	14.935
rnd_rf	8.674	2.235	0.000	13.545
rnd_sf	11.659	1.793	5.992	15.206
gdpg	0.906	1.644	−3.400	3.300
inf	0.129	0.927	−1.353	2.762
popg	−0.029	0.119	−0.189	0.163
gfcfg	0.001	4.274	−13.096	5.620
male	69.897	8.423	44.643	100.000
age	48.699	1.576	47.029	52.247

TABLE A2 Correlation matrix of the independent variables

Variable	*rnd_exp*	*rnd_sf*	*rnd_rf*	*gdpg*	*inf*	*popg*	*gfcfg*	*male*	*age*
rnd_exp	1.00								
rnd_sf	0.96	1.00							
rnd_rf	0.71	0.60	1.00						
gdpg	0.001	0.01	0.001	1.00					
inf	0.01	0.02	−0.02	−0.26	1.00				
popg	−0.01	−0.02	0.03	0.01	−0.34	1.00			
gfcfg	0.004	−0.009	0.009	0.003	0.27	0.51	1.00		
male	−0.09	−0.05	0.03	−0.01	0.05	−0.11	−0.10	1.00	
age	0.01	0.02	−0.04	0.07	0.36	−0.82	−0.25	0.09	1.00