Population Ageing, Labour Market Rigidity and Corporate Innovation: Evidence from China

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ABSTRACT

Population ageing leads to labour scarcity and labour market rigidity. Contrary to supply-side economists' belief that labour market rigidity tends to suppress firm innovation, we provide novel evidence of a positive relationship between population ageing and firm innovation in China. This enhancement effect is greater for firms with higher labour costs, consistent with the argument that labour scarcity encourages labour-saving innovation in response to demographic shifts. In addition, the observed positive effect is particularly pronounced for state-owned enterprises, which are widely acknowledged to be overstaffed with older workers, and firms in industries that pursue Schumpeter-II innovation and engage in more intense research and development. In addition, population ageing helps firms to generate more exploitative (vs. exploratory) innovation. Overall, our findings suggest that firms facing population ageing can adapt their strategies to innovate successfully.

JEL Classification: J11, J13, J21, O31

Keywords: Population ageing; Labour scarcity; Labour market rigidity; Innovation

1. Introduction

Numerous studies published in the last decade investigate the determinants of corporate innovation. They focus on a wide array of firm-level factors, such as managerial compensation, firing flexibility, firms' decision to go public, private equity/venture capital involvement, institutional ownership, anti-takeover provisions, conglomerate structure and chief executive officers' personal attributes. [1] Despite their significance, however, the macro-level determinants of corporate innovation are largely overlooked. Our study contributes to the literature by examining whether and how population ageing affects firm-level innovation. This topic is of interest to both academics and practitioners because of the vital role played by technological advancement in maintaining corporate and national competitiveness under the global trend of population ageing.

Virtually every country worldwide is experiencing growth in the number and proportion of older persons in its population, with implications for almost every sector of society.[2] A shrinking working-age population causes labour market shortages, commonly referred to as labour scarcity. Workforce ageing resulting from population ageing is expected to increase labour market rigidity, because older workers have less job mobility than younger workers. However, the effects of these labour market challenges on firm innovation remain unclear.

First, according to endogenous growth models, labour scarcity inhibits the growth of labour productivity and, principally, total factor productivity, which is the key factor influencing long-term technological innovation (e.g., Maestas et al., 2016; Gordon, 2016). However, recent developments in automation, having brought both labour-replacing and labour-enhancing technologies to address the problem of labour scarcity, present a strong

[1] See, for example, Baranchuk et al. (2014), Bernstein (2015), Chemmanur et al. (2014), Aghion et al. (2013), Atanassov (2013), Seru (2014), Galasso and Simcoe (2011), and Hirshleifer et al. (2012).
[2] According to data from the United Nations' *World Population Prospects: The 2019 Revision*, by 2050, one in six people in the world will be aged over 65 (16%), up from one in 11 in 2019 (9%), and one in four persons living in Europe and North America will be aged 65 or above.

rebuttal to this argument (e.g., Frey and Osborne, 2017; Autor et al., 2003; Acemoglu and Restrepo, 2017). Empirical evidence also shows that countries facing rapid ageing lead the way in adopting automation technologies in response to demographic shifts (Acemoglu and Restrepo, 2021). Second, the age-related demographic changes associated with an older workforce may lead to labour market rigidity. While some advocates of structural labour market reforms suggest that less labour flexibility hampers firm innovation (e.g., Bassanini et al., 2009; Tressel and Scarpetta, 2004; Bartelsman et al., 2016), a growing body of literature argues the opposite. Taking a Schumpeterian viewpoint, the latter studies note that labour rigidity can enhance the accumulation of knowledge from experience (e.g., Wachsen and Blind, 2016; Hoxha and Kleinknecht, 2020; Kleinknecht, 2021).

Our study investigates the impact of population ageing on corporate innovation, contingent on the aforementioned labour market challenges. In line with Hicks' (1963) analytical framework, we hypothesise that labour scarcity induces superior innovation performance when firms face higher labour costs. Inspired by Breschi et al. (2000) and Hoxha and Kleinknecht (2020), we also conjecture that greater labour market rigidity, characterised by longer job tenure and more stable positions for employees, yields better innovation outcomes for firms.

We test our hypotheses using a large sample of Chinese listed firms spanning 2004–2017. First, the exogenous imposition of China's Family Planning Programme (also known as one-child policy), launched in the 1970s, shifted age demographics by reducing the overall fertility rate. Second, China's enormous size and diversity forced its political leaders to regulate fertility on a provincial basis to accommodate local conditions, leading to significant province-level variations in the degree of population ageing (Short and Zhai, 1998). By and large, regions with stricter family planning policy implementation are more likely to suffer from population ageing. Moreover, China is currently the second largest economy in the world, and its ageing population poses a major threat to its future economic growth.[3]

Using a hand-collected dataset of patent applications that are eventually granted, we document that population ageing enhances corporate innovation, consistent with the notion that firms facing future labour scarcity challenges are prompted to engage more actively in innovation.[4] We also find, consistent with our predictions, that the enhancement effect of ageing on innovation is more pronounced for firms with higher labour costs; firms operating within an innovation regime that is more dependent on knowledge accumulation; state-owned (vs. non-state owned) firms; and firms with higher research and development (R&D) intensity. We also find that population ageing helps firms generate more exploitative (vs. exploratory) innovation, consistent with the notion that older workers are more likely to contribute their accumulated knowledge and experience to firms' innovation.

A novel contribution of our paper is its finding that the relationship between ageing and firm innovation is conditional on the interaction between firms and the labour market. Few studies examine the link between demographic characteristics and firm level innovation performance. We help to fill this gap by linking population ageing and firm innovation via labour market dynamics. Of particular interest is that we explore whether firms are prepared for the associated challenges; for example, we examine firms' capacity to make the relevant adjustments to their innovation strategies given that population ageing decreases labour force participation and increases the age of an average employee, thereby raising concerns about the future slowing of corporate growth.

[3] By 2050, 330 million Chinese people will be aged over 65. See https://time.com/5523805/china-ageing-population-working-age/.

[4] Japan is a typical example. Roughly 25% of Japan's population is currently over the age of 65, and this demographic is expected to comprise 40% of the country's population by 2060. This makes Japan one of the world's oldest societies. However, Japan is also one of the most innovative countries in the world. Many Japanese firms treat the country's ageing society as a business opportunity to spur the development of new technologies. See https://www.theglobeandmail.com/globe-investor/retirement/retire-planning/how-japan-is-coping-with-a-rapidly-aging-population/article27259703/.

The remainder of this paper is structured as follows. Section 2 describes the conceptual framework and hypothesis development. Section 3 discusses our sample and data. Sections 4 and 5 present the results of our baseline and exploratory analyses, respectively. In the final section, we discuss our main findings and elaborate on their implications.

2. Conceptual Framework and Hypothesis Development

2.1 Population ageing, labour scarcity and innovation

The rapid ageing of a population is widely considered detrimental to economic growth. Hansen (1939) views developed economies as being afflicted by secular stagnation, partly because of their ageing populations. Gordon (2016) identifies demographic change as the first 'headwind' of slowed economic growth, as an ageing population reduces labour force participation and productivity.

According to endogenous growth models, a basic question concerns the relationship between factor endowments and technology: the scarcity of labour and high factor prices resulting from population ageing inhibit technological progress and slow economic growth. Maestas et al. (2016) find that a 10% increase in the percentage of the population aged over 60 decreases the growth rate of GDP per capita by 5.5%. Two thirds of this reduction is due to slower growth in workers' labour productivity across the age distribution, and one third arises from slower labour force growth. Similarly, Lindh and Malmberg (1999) and Feyrer (2007) investigate the relationship between demographics and aggregate productivity or growth and find evidence that the fraction of the population over the age of 50 contributes negatively to GDP per capita.

However, recent developments in automation cast doubt on the adverse impact of population ageing on innovation. Acemoglu and Restrepo (2018) document that a scarcity of younger and middle-aged workers triggers the adoption of robots (and other automation technologies), which subsequently increases aggregate output, notwithstanding the reduced labour input. Acemoglu (2010) and Acemoglu and Restrepo (2017) show that labour scarcity encourages technological advancements if the technologies involved are highly labour-saving. Moreover, countries experiencing more rapid ageing are at the forefront of industrial robot adoption.

Neoclassical economic theory offers explanations for the above seemingly counterintuitive findings. In his pioneering work on the substitution of capital for labour, *The Theory of Wages*, Hicks was one of the first economists to argue that 'a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind – directed to economizing the use of a factor which has become relatively expensive' (1963, p.124). Similarly, the well-known hypothesis in economic history proposed by Habakkuk (1962) claims that technological development progressed more rapidly in the United States than in Britain in the 19th century because of labour scarcity in the former, which acted as a powerful inducement for mechanisation, the adoption of labour-saving technologies and innovation more broadly. In a similar vein, Allen (2009) argues that the relatively high wages received by workers in 18th-century Britain were the main driver of the Industrial Revolution. Samuelson (1965) similarly argues that higher wage rates and steady capital/labour ratio growth may induce innovation in the long run by prompting the greater adoption of labour-augmenting or labour-saving inventions.

Therefore, although the ageing of the labour force reduces the supply of available workers, it does not necessarily inhibit innovation. Instead, population ageing may motivate firms to engage more intensively in innovation, based on the following rationale. An ageing population forces firms to confront the challenges of future labour scarcity and consequently higher labour costs, prompting them to consider various innovative approaches and engage more actively in innovation in preparation for an ageing society. We therefore propose the following hypothesis:

Hypothesis 1 **(H1)**: Firms with higher labour costs generate better innovation outcomes under increased population ageing.

2.2 Population ageing, labour market rigidity and innovation

Population ageing directly impacts the demographic composition of firms' employees. Faced with an ageing workforce, a company's personnel structure will inevitably change. As cognitive capabilities (e.g., intelligence, creativity, reasoning and memory) are expected to diminish later in life, older employees may be less able to identify and absorb new knowledge (Leibold and Voelpel, 2007; Meyer, 2011). Most studies on innovative performance at the individual level suggest that the capacity to generate economically relevant, novel achievements follows a curvilinear, inversely U-shaped functional form with respect to age, with most inventions being produced by individuals between the ages of 35 and 50, depending on the domain (e.g., Jones, 2010; Frosch, 2011).

However, growing evidence suggests that an ageing workforce does not necessarily threaten companies' innovativeness and that its consequences might depend on a company's predominant innovation regime. In particular, changes in the demographic structure of a company's workforce lead to changes in aggregate human capital in the form of knowledge accumulated from experience. To determine whether firms' innovative competences are path-dependent on the historical accumulation of knowledge, studies distinguish between Schumpeter-I and Schumpeter-II innovation models (Breschi et al., 2000; Wachsen and Blind, 2016; Hoxha and Kleinknecht, 2020). In a broad range of classical industries, a firm's innovative competencies depend not only on its present R&D activities but also on the knowledge it has accumulated over time (i.e., Schumpeter-II innovation). Some of this knowledge is firm-specific and tacit – in other words, it is 'embodied' in people (Polanyi, 2009). The 'worker-embodied' knowledge tends to be weakly documented or codified and needs to be transferred through personal interaction. With this type of knowledge, a high degree of personnel turnover can be disadvantageous for the accumulation of knowledge from experience. In contrast, personnel turnover may not be a problem for firms in industries that rely heavily on generally available knowledge (i.e., Schumpeter-I innovation).

As older employees are unlikely to change jobs as frequently as younger employees, an ageing workforce is characterized by longer job tenure and more stable positions for employees (labour market rigidity), which are favourable for Schumpeter-II innovation because they enhance the accumulation of knowledge from experience. This is evidenced by Kleinknecht et al. (2014) and Wachsen and Blind (2016), who demonstrate that personnel flexibility is negatively related to innovation in industries that are dependent on knowledge accumulation. Although some advocates of structural labour market reform suggest that greater labour market flexibility enhances innovation (Bassanini et al., 2009; Tressel and Scarpetta, 2004; Bartelsman et al., 2016), the impact of employee turnover in a sector may differ according to the dominant innovation model.

***Hypothesis 2* (H2)**: Firms operating in an innovation regime that is more dependent on knowledge accumulated from experience generate better innovation outcomes under increased population ageing.

Specifically, in transitional economies such as China's, governments often use state-owned enterprises (SOEs) to achieve non-financial objectives and finance the resulting social burdens, such as labour redundancy.[5] As a consequence, SOEs are less likely than their non-SOE counterparts to lay off unproductive older employees in response to the ageing problem, which leads to a high degree of overstaffing in SOEs (Yin, 2001; Dong and Putterman, 2003). According to the Schumpeterian view, if we expect labour market rigidity to create strong

[5] For example, Hu Xiaoyi, Director of the Social Security Department in China's Ministry of Labor, said of the number of redundant employees, 'Most people tend to think that about 20 percent of the workers and employees in SOEs are surplus labor; that is 15 million' (Broadman, 1996, p. 125).

incentives for innovation, this effect should be more pronounced for SOEs than for non-SOEs, as the former exhibit more rigidity. Therefore, we put forward the following hypothesis:

***Hypothesis 3* (H3)**: SOEs produce better innovation outcomes than non-SOEs under increased population ageing.

2.3 Population ageing, R&D labour intensity and innovation

Beyond the aforementioned labour market challenges, classical research on corporate innovation focuses on the key factors leading to successful innovation, including firms' R&D strategies and managerial risk-taking (Ahuja and Katila, 2001; Nerkar and Roberts, 2004). R&D employees, such as scientists, are considered critical to the success of innovation, as this line of research views innovation as a result of knowledge management processes, and knowledge is embedded mainly in key R&D workers (Collins and Smith, 2006; Yanadori and Cui, 2013). We therefore discuss how population ageing affects innovation specifically via the functioning of R&D workers.

R&D workers possess technical skills and problem-solving abilities that constitute important inputs for the production of inventions. Technological change requires R&D employees to adjust to new equipment, procedures and environments and continuously enhance their job-related skills (Hedge et al., 2006). Given that R&D employees are key to the generation of new inventions, it is important for them to work in a suitable and sustainable environment.

Labour market rigidity resulting from population ageing creates a more stable work environment for R&D employees, which enhances their innovation performance. First, long job tenures make firm-specific training more attractive to R&D employees because of the prospect of staying longer at the firm (Bassanini and Ernst, 2002). Otherwise, they may only be interested in general training that will improve their employability in the external labour market. Second, long job tenures increase the loyalty and commitment of highly skilled workers, making it less likely that technological knowledge and trade secrets will be leaked to competitors; this decreases the problem of Pigouvian externalities. Third, more stable positions encourage employees to engage in riskier projects. Acharya et al. (2013) argue that under easier firing conditions, employees are less likely to engage in risky innovation projects, as they fear that they may be fired in the case of failure. Overall, the labour rigidity stemming from population ageing increases employees' trust in and commitment and loyalty to their firms, which enhances the knowledge management of R&D workers and may ultimately result in better innovation performance.

***Hypothesis 4* (H4)**: Firms with more R&D workers produce better innovation outcomes under increased population ageing.

3. Methods

3.1 Sample selection

We start with all public firms listed on the Shanghai and Shenzhen stock exchanges over the 2004–2017 period. Information on patent grants is hand-collected from the State Intellectual Property Office of China (SIPO). The ageing index and other regional variables are manually collected from the relevant *Chinese Statistical Yearbooks*. We obtain firm-level financial and accounting information from the CSMAR database and annual reports. All firm-level employee information is manually collected from the firms' annual reports. We exclude financial and utility firms as well as observations with missing values. We ultimately compile a total of 27,942 firm-year observations.

3.2 Variables

3.2.1 Measuring innovation

We follow the literature (e.g., Seru, 2014; Lerner et al., 2011; Fang et al., 2014) in using a firm's patenting outcomes to measure its innovation.[6] For each patent, the SIPO provides the patent application date, application identification, publication identification, granting date and patent identification, along with its inventors and the applying institution(s). As there is often a delay (a maximum of three years) between a patent's application year and the year in which it is granted, we manually check whether and when a patent application has been granted by extracting the patent applications filed by the sample firms, including those filed by their subsidiaries, from the SIPO database. This back-and-forth search method enables us to construct a precise measure of each firm's innovative outcomes.

According to the Patent Law of China, three types of patents may be granted: *invention* patents are granted for technological innovations that are new and inventive relative to existing technology and possess practical applicability; *utility model* patents are granted for new technical solutions related to the shape and/or structure of an object; and *design* patents are granted for original designs related to the shape, pattern or colour of an object, or a combination thereof. In general, the level of innovativeness required for a utility model or design patent is not as high as for an invention patent. Thus, following Zheng et al. (2018), to distinguish between ground-breaking innovations and incremental technological advancement, we construct our innovation measure on the basis of invention patents. As a proxy for a firm's innovation performance, we use *Patents_invention*, defined as the number of invention patent applications filed by the firm in a given year that are eventually granted. To address skewness

[6] Previous studies use R&D expenditure to measure innovation. However, R&D expenditure is only one observable input and fails to capture innovation output. Our results are qualitatively unchanged when we use R&D expenditure as a robustness check to measure firms' innovation. See Column (4) of Appendix Table I.

in our empirical analysis, we use the natural logarithm of *Patents_invention* plus one, denoted as *LnPatents_invention*, as our main dependent variable.

3.2.2 Measuring population ageing

According to a worldwide definition, ageing population refers to the group that is older than 65 (United Nations, 2019; European Central Bank, 2018).[7] Thus, our independent variable of primary interest, population ageing (*Ageing*), is measured as the percentage of the total labour force comprised of older people (i.e., people older than 65) in a province in a given year.

3.2.3 Conditioning variables

We measure firms' labour costs using two variables: *Wages* denotes the industry-adjusted (adjusted by the industry median) average wage across all employees in a firm by year and *No. of employees/PPE* denotes the industry-adjusted (adjusted by the industry median) number of employees divided by the sum of fixed assets and construction in progress multiplied by 1,000.

To gauge the extent to which a firm's innovation regime is dependent on accumulated knowledge, we follow Peneder's (2010) classification of 'cumulativeness of knowledge' (see Column *CuType* in Peneder's [2010] Table 5, p. 331).[8] We define *Knowledge_cum* as a dummy variable that equals one if a firm belongs to an industry with high knowledge cumulativeness and zero otherwise (medium and low knowledge cumulativeness).[9] In addition, *SOE* is a dummy variable that equals one when a firm is a state-owned enterprise and zero otherwise.

[7] See the *World Population Prospects: The 2019 Revision* published by the United Nations (https://www.un.org/development/desa/publications/world-population-prospects-2019-highlights.html) and the *2018 Ageing Report* published by the European Central Bank (https://www.ecb.europa.eu/pub/economic-bulletin/focus/2018/html/ecb.ebbox201804_04.en.html).
[8] In unreported results, we calculate the within sector self-citation rate to measure the extent to which a given company builds on innovations developed by other companies in the same sector. The industry classifications are based on the guidelines of the China Securities Regulatory Commission. The results are qualitatively the same.
[9] According to Peneder (2010), industries with high cumulativeness include chemicals; basic metals; machinery, nec.; electrical equipment, nec.; communication technology; precision instruments; motor vehicle parts; financial intermediation; insurance and pension funding; computer services; research and development; and other business services.

We measure a firm's R&D labour intensity using *High_edu employees%* and *R&D employees%*. Specifically, *High_edu employees%* denotes the industry-adjusted (adjusted by the industry median) number of highly educated employees (employees with a master's degree or above) as a percentage of the total number of employees. *R&D employees%* denotes the industry-adjusted (adjusted by the industry median) number of R&D employees (employees who are likely to be engaged in R&D-related tasks) as a percentage of the total number of employees.

3.2.4 Control variables

Following the innovation literature (He and Tian, 2013; Aghion et al., 2013; Fang et al., 2014; Seru, 2014; Brav et al., 2018), we control for a vector of firm and regional characteristics that may affect a firm's innovation performance.

The control variables include firm size (*Size*), measured by the natural logarithm of a firm's total assets; profitability (*ROA*), measured by a firm's return on assets; leverage (*Leverage*), measured by a firm's total debts divided by its total assets; growth opportunities (*TobinQ*), measured by a firm's market-to-book ratio; tangibility of assets (*Tangibility*), measured by the net value of a firm's fixed assets divided by its total assets; investment in fixed assets (*CAPX*), measured by a firm's capital expenditure scaled by its total assets; investment in innovation (*R&D*), measured by a firm's R&D expenses scaled by its total sales; ownership concentration (*TOP*), measured by the shareholding percentage of a firm's largest shareholder; institutional ownership (*INST*), measured by the aggregate percentage of a firm's institutional holdings; analyst following (*Analyst*), measured by the natural logarithm of the number of analysts following a firm plus one; firm age (*FirmAge*), measured by the natural logarithm of the number of years a firm has been listed plus one; regional economic development level (*LnGDP*), measured by the natural logarithm of the GDP of the province in which a firm is headquartered; and regional economic growth (*GGDP*), measured by the annual growth rate of the GDP of the province in which a firm is headquartered.

3.5 Descriptive statistics

To minimise the effects of outliers, we winsorize all of the continuous variables at the top and bottom 1%. Table 1 provides summary statistics for the main variables used in this study. On average, a firm in our final sample has 5.823 invention patents granted annually, which is consistent with previous studies (Zheng et al., 2018; Chen et al., 2020). *Ageing* has a mean value of 0.133 and a median value of 0.132. Table 1 also reports summary statistics for the moderator and control variables, which are largely comparable with previous studies (e.g., Guo et al., 2016; Zheng et al., 2018; Chen et al., 2020).

<Insert Table 1 about here>

4. Empirical Results

4.1 Model specification

To empirically test our hypotheses, we estimate the following equation:

$$\begin{aligned} LnPatents_{invention_{i,t+1}} = \beta_0 + \beta_1 Ageing_{j,t} + \beta_2 Conditioning\ Vars_{i,t} \\ + \beta_3 Aging_{j,t} \times\ Conditioning\ Vars_{i,t} + \sum_{p=1}^{m} \beta_p Controls_{i,t} \\ + \sum Year +\ \sum Firm + \epsilon_{i,t} \qquad (1) \end{aligned}$$

where subscript i indicates the firm, t indicates time and j indicates the region. The dependent variable, *LnPatents_invention*, is measured as the natural logarithm of the number of invention patent applications that are eventually granted plus one. The primary independent variable, *Ageing*, is measured as the percentage of older people (i.e., over 65) in the total labour force in the province in which the focal firm is headquartered. To test our hypotheses, we interact the conditioning variables with *Ageing*. The interaction term indicates how the ageing–innovation relationship is contingent on the variables pertaining to labour market challenges, such as labour scarcity and labour market rigidity.

All of the control variables are lagged by one year. We include year fixed effects to account for intertemporal variations that may affect the relationship between ageing and innovation and firm fixed effects to control for omitted firm characteristics that are constant over time.[10] Because *Ageing* is a province-level variable, the standard errors are clustered by province.[11]

4.2 Main results

Column (1) of Table 2 reports the baseline regression results for the impact of ageing on innovation. On average, there is a significantly positive association between ageing and innovation (coefficient for *Ageing* = 2.135, *t*-stat = 3.66). This effect is not only statistically significant but also economically sizable. A one standard deviation increase in the ageing index leads to an increase in the number of invention patents of 1.59, accounting for approximately 27% of the sample mean number of patents. Overall, the results suggest that population ageing generally enhances corporate innovation.

<Insert Table 2 about here>

Our hypotheses are premised on a positive relationship between population ageing and innovation outcomes. Column (1) of Table 2 provides evidence consistent with this premise, providing fertile ground for further testing our hypotheses. H1 posits that the enhancement effect of ageing on innovation is more pronounced in the presence of higher labour costs.

[10] In unreported results, we replace firm fixed effects with industry and province fixed effects, and the results remain qualitatively unchanged.
[11] We thank the two anonymous reviewers for this suggestion.

Columns (2) and (3) of Table 2 report the regression results for the effect of labour costs on the ageing–innovation relationship and show that the coefficients on the interaction terms (*Wages* × *Ageing* and *No. of employees/PPE* × *Ageing*) are both significantly positive. These results are consistent with H1, i.e., that population ageing imposes greater pressure to innovate on firms that face more labour scarcity.

H2 predicts a positive impact of knowledge cumulativeness on the ageing–innovation relationship. As shown in Column (4) of Table 2, the coefficient of *Knowledge_cum* × *Ageing* is 1.718 and is statistically significant at the 1% level. This is consistent with the expectation that firms operating within an innovation regime that requires more historically accumulated knowledge produce better innovation outcomes under increased population ageing.

In addition, as shown in Column (5) of Table 2, we find that the coefficient on the interaction term between *SOE* and *Ageing* is positive (coefficient for *SOE* × *Ageing* = 2.812, *t*-stat = 2.46, confirming our H3 that SOEs (vs. non-SOEs) are more likely to actively engage in innovation in response to population ageing.

Lastly, the results in Columns (6) and (7) enable us to confirm H4: firms with higher R&D labour intensity exhibit more desirable innovation outcomes under increased population ageing. We measure firms' R&D labour intensity using *High_edu employees%* and *R&D employees%*, and the coefficients on the interaction terms are 0.300 (*t*-stat = 2.60) and 0.091 (*t*-stat = 2.93), respectively.

4.3 Identification strategy

In our study, concerns about reverse causality are minimal because firm-level innovation outputs are unlikely to drive the regional population ageing trend. However, it is possible that corporate innovation and the regional ageing process are endogenously determined by time-varying omitted variables. To address these endogeneity concerns, we use two-stage least squares (2SLS) estimation as an identification strategy. Our instrumental variables (IVs) are selected based on two historical events in China: the Great Chinese Famine and the implementation of the Family Planning Programme. We elaborate on these two events, discuss the results of the 2SLS regressions and validate our IVs in the following subsections.

4.3.1 The Great Chinese Famine

The Great Chinese Famine, which occurred between 1959 and 1961, had profound demographic consequences for China. Widespread starvation and a significant overall reduction in calorie intake during the famine had a devastating impact on the health of the population and led to a huge reduction in the fertility rate and a sharp increase in the mortality rate. In 1957, China's reported crude birth rate was 34.0 per 1,000 people and its total fertility rate was 6.4 children per woman. These figures had plummeted to 18.2 per 1,000 people and 3.3 children per woman by 1961 (Yao and Yin, 1994; Yao, 1999). The officially reported crude death rate rose from 10.8 per 1,000 in 1957 to 25.4 per 1,000 in 1960 (Huang and Liu, 1995). In many regions, the reported crude death rate reached more than 100 per 1,000 people.

These three years of natural disasters led to regional variations in birth and death rates because of marked regional variations in the severity of starvation. Given the historical and exogenous nature of this event, we use the regional-level crude and net birth rates as IVs for our key variable *Ageing*. *Crude birth rate* is measured as each province's average birth rate between 1959 and 1961. *Net birth rate* is measured as each province's average birth rate less its average death rate over the same period. Both IVs should be negatively related to the regional population ageing index but not directly associated with firm-level innovation performance.

4.3.2 Family planning policy

The exogenous imposition of China's Family Planning Program, launched in the 1970s, shifted the ageing demographic by reducing the overall fertility rate. By and large, regions with stricter implementation of the family planning policy are more likely to suffer from population ageing. Therefore, we use a province's family planning policy permissiveness as the instrument for population ageing. According to Gu et al. (2007), Chinese provinces can be divided into four categories in terms of their family planning policy permissiveness.[12] Following this classification system, we construct a categorical variable, *Planning_policy*, as our IV. The value of *Planning_policy* ranges from 1 to 4, with higher values indicating more stringent fertility control enforcement. *Planning_policy* may directly affect a region's age composition without directly impacting corporate innovation.

4.3.3 Instrumental variable estimation results

Columns (1), (3) and (5) in Panel A of Table 3 present the results of the first-stage regressions in which the dependent variable is the ageing index by province. As *Ageing* and the IVs are all at the province-year level, we do not include firm-level control variables in the regressions. Consistent with our prediction, the reported coefficients for the instruments *Crude birth rate* and *Net birth rate* are significantly negative, suggesting that a lower birth rate leads to a higher degree of population ageing, and the reported coefficient for the instrument *Planning_policy* is significantly positive at the 1% level, suggesting that more rigid family planning policy enforcement leads to a higher degree of population ageing. The Cragg–Donald Wald F-statistics are 24.11, 21.27 and 24.63, rejecting the null hypothesis that the IVs are weak (Cragg and Donald, 1993). Columns (2), (4) and (6) in Panel A of Table 3 present the second-

[12] Category 1 (the group with the most stringent policies) includes Shanghai, Jiangsu, Beijing, Tianjin, Sichuan and Chongqing; Category 2 includes Liaoning, Heilongjiang, Guangdong, Jilin, Shandong, Jiangxi, Hubei, Zhejiang, Anhui and Fujian; Category 3 includes Henan, Shanxi, Guangxi, Gansu, Hubei, Inner Mongolia and Guizhou; and Category 4 (the group with the most lenient policies) includes Yunnan, Qinghai, Ningxia, Hainan and Xinjiang.

stage regression results for which the dependent variable is *LnPatents_invention*. The coefficient estimates for the instrumented *Ageing* are positive and statistically significant. Overall, the IV results reveal a similar pattern to the baseline results.

<Insert Table 3 about here>

4.3.4 Validity of the instrumental variables

A key criterion for the exclusion assumption of a valid IV is that it has no direct impact on the dependent variable. Its indirect impact, if any, should only be channelled through the endogenous independent variable. Our IVs may not satisfy this criterion because they may affect firm innovation via paths other than population ageing. Take *Planning_policy* as an example. The strictness of the implementation of the one-child policy may have affected not only the level of ageing but also the level of human capital investment in a region (e.g., parents with fewer children may have invested more in each child's education). To the extent that human capital stock affects innovation performance, the exclusion restriction of *Planning_policy* as an IV may be violated. Similarly, the changes in birth and death rates induced by the Great Chinese Famine may have influenced innovation through channels other than population ageing. For instance, the malnourishment induced by the Great Chinese Famine might have lowered local people's educational attainment and thereby reducing their innovation performance.

To empirically test the validity of our IVs, we use the following two approaches. First, we follow Atanasov and Black (2021) and perform a pretreatment balance test by regressing the shock-based IVs on various province-level characteristics as measured before the shocks (i.e., the Great Chinese Famine and the implementation of the one-child policy). The province-level variables used in the regression include the historical averages of GDP (*LnGDP_ave5* and *LnGDP_ave3*), GDP per capita (*LnGDPP_ave5* and *LnGDPP_ave3*), population density

(*LnPopulation_ave 5* and *LnPopulation_ave 3*) and net birth rate (*NetBirthRate_ave5* and *NetBirthRate_ave3*) over the 5- and 3-year periods before the shocks. The pretreatment balance test results are reported in Panel B of Table 3.[13] Across all of the model specifications, we document no pretreatment trends on the instruments, as evidenced by the insignificant core covariates. These results give us more confidence in our IVs.

Second, we test the IV independence assumption following Kedagni and Mourifie (2020). This approach is designed to assess the validity of IVs for discrete treatment, but unrestricted outcome and instruments, by combining a sample splitting procedure and an inference method for intersection bounds. Panel C of Table 3 reports the confidence intervals of the tests at three significance levels (1%, 5% and 10%) for partitions at 20% (P_y^{20}), 40% (P_y^{40}), 60% (P_y^{60}) and 80% (P_y^{80}), respectively. According to Kedagni and Mourifie (2020), if the lower bound of a confidence interval is negative, then the null hypothesis (the IV meets the independence assumption and is thus valid) cannot be rejected. Our results show that the lower bounds of the confidence intervals for all three IVs are negative, supporting their validity.

We do not consider the IV approach a perfect way to address endogeneity. Nevertheless, these results can collectively be viewed as further corroboration, if not definitive evidence, of the validity of our hypotheses.

4.4 Robustness checks

4.4.1 Alternative model specifications

In our baseline model, we consider only the number of successful applications for invention patents as a proxy for innovation activities. Many firm-year observations have a value of zero for the number of patents. Given this concern, we model the data-generation

[13] Due to historical reasons, the number of observations for Columns (1)-(4) is 28 as Hainan, Chongqing and Tibet are not included. Similarly, the number of observations for Columns (5)-(6) is 29 as Hainan and Chongqing are not included.

process using a Poisson model. Although Poisson regression is appropriate for modelling count data, our data may be over-dispersed and thus violate the basic assumption of the Poisson estimator – that the variance of the count variable should equal its conditional mean. Therefore, we also apply a negative binomial regression model, which is a generalised form of Poisson regression that incorporates individual unobserved effects into the conditional mean (Hausman et al., 1984).[14] The results reported in Columns (1) and (2) of Appendix Table I show that our inferences remain unchanged under these alternative model specifications.

4.4.2. Alternative measures of innovation and ageing

The nature and duration of innovation varies between industries. For example, the innovation process is naturally longer and riskier in the pharmaceutical industry than in the software development industry (Fang et al., 2014). To control for such heterogeneity across industries, we use *LnPatents_adjusted* as the dependent variable, defined as the natural logarithm of one plus the industry-adjusted (adjusted by the industry median) number of invention patent applications that are eventually granted. We also measure innovation intensity with the variable *LnR&D*, which is computed as the natural logarithm of R&D expenses plus one. In addition, we construct a firm-level ageing proxy (*Ageing_Firm*) as the percentage of employees over the age of 50. Our main inferences remain qualitatively unchanged. However, the sample size shrinks considerably because of missing employee age information for many sample firms. The results are reported in Columns (3)–(5) of Appendix Table I. Our conclusions are unaffected by the use of these alternative measures of innovation and ageing.

4.4.3 Controlling for other omitted regional-level variables

[14] In the Poisson model, 7,878 observations are dropped because they are either singletons or separated by a fixed effect. In the negative binomial model, 303 groups (303 observations) are dropped because there is only one observation per group, and 702 groups (7,575 observations) are dropped because of all-zero outcomes.

Our baseline model features a number of firm- and region-specific characteristics. Some omitted region-level variables may nonetheless remain, including the region's average educational level (which affects labour qualifications and innovation performance), access to foreign technology and knowledge via foreign direct investment (FDI) (regions with greater access to foreign technology and know-how may have a distinct advantage in innovation) and intellectual property protection (regions with a higher level of protection are more motivated to engage in innovation). To address concerns regarding omitted variable bias, we control for a set of these regional characteristics as a robustness check.

Appendix Table II presents the robustness test results obtained when controlling for the following region-level characteristics: *R&D_Region* denotes the natural logarithm of a province's R&D expenses; *Tech_Region* denotes the natural logarithm of patent applications in a province; *FDI_Region* denotes the natural logarithm of a province's FDI; *Education_Region* denotes a province's percentage of highly educated people; and *Property_Region* denotes a province's level of intellectual property protection. Across all six model specifications, the coefficients on *Ageing* continue to be significantly positive.

5. Exploratory Analyses

5.1 The impact of ageing on innovation quality

In the main analyses, we use the number of patents granted to capture firm innovation outcomes in our empirical work. However, patent quality concerns arise, as recent studies cast doubt on whether the patent surge in China reflects true innovation. For example, Li (2012) and Dang and Motohashi (2015) show that local government patent subsidy programmes can increase patent quantity but also stimulate lower-quality patent applications. Liang (2012) suggests that the patent review process of China's SIPO may not be as thorough as that of other countries, allowing more low-quality patents to be granted. Comparing the granting practices of the United States and China, Yang (2008) finds that China appears to give preferential treatment to domestic applications, which may decrease the relative quality. Zhang and Chen (2012) determine that the value (as measured by patent renewal payments) of Chinese patents with Chinese owners is much lower than that of patents owned by foreign entities.

Data on the renewal of patents and on family size (commonly defined in the economic literature as the number of countries in which protection has been sought) have been widely used to draw inferences on the value of patents. Studies in this field exploit the fact that it is expensive to holders to maintain patent protection for an additional period of time and in additional countries. Hence it is hypothesised that the value of continuing patent protection over time and of expanding it geographically is associated with the economic importance of the invention. Therefore, to alleviate the concern that the overall number of patents granted may not be a good proxy for innovation quality, we also examine the impact of population ageing on two alternative indicators of innovation quality: *Patents_international* and *Patents_renewal*. *Patents_international* denotes the number of annual patent applications that a firm files both domestically (with China's SIPO) and internationally (with the United States Patent and Trademark Office or the European Patent Office) that are eventually granted. An average firm in our final sample has 0.118 international invention patents granted per year, which is much smaller than the number of domestic patents granted. *Patents_renewal* denotes the average renewal years of the patent portfolio filed by a firm in a year that are eventually granted. A higher value of *Patents_renewal* indicates that the innovation quality is higher. The average of *Patents_renewal* is 0.231 years.[15]

[15] A potential caveat of the variable *Patents_renewal* is that it may underestimate the average renewal years for a patent portfolio, as we obtain the renewal years for each patent using the forward approach. However, some patents are still within the protected duration by the end of our sample period, and there are many missing values for patent renewals. For a subsample with only patents that have been renewed, the average number of renewal years is approximately 4.656 years. In an unreported test, we find that the relationship still holds for the subsample.

Columns (1) and (2) of Table 4 report the regression results regarding the impact of ageing on alternative indicators of innovation quality. The positive effect of ageing on the number of international patents is statistically significant at the 10% level (the coefficient for *Ageing* = 0.666, *t*-stat = 1.88), and its positive effect on the average number of years for patent renewals is statistically significant at the 5% level (the coefficient for *Ageing* = 0.717, *t*-stat = 2.48). Thus, we find that the enhancement effect of ageing on innovation still holds with alternative measures for innovation quality.

<Insert Table 4 about here>

5.2 The impact of ageing on innovation novelty

An important aspect of our theoretical argument is that older workers contribute to firms' innovation performance by means of their accumulated knowledge and experience. Thus, how does ageing impact firms' innovation novelty? The technological knowledge base encompassed by older workers is key to a firm's choice of an exploratory or an exploitative innovation strategy (March 1991). Firms following an exploration innovation strategy seek novel technologies and approaches, whereas those following an exploitation strategy rely more on existing competencies and refine previously patented approaches (Fitzgerald et al., 2021). Therefore, we expect firms in provinces with the majority of their population over the age of 65 to generate more exploitative (vs. exploratory) innovation outcomes, as they are more likely to focus on their current areas of expertise.

We adopt the definition of an exploitative patent developed in the recent innovation literature (Custódio et al., 2019; Fitzgerald et al., 2021) to construct proxies for exploitative patents according to the extent to which a firm's new patents utilize existing versus new knowledge. A firm's existing knowledge consists of its previous patent portfolios and the set of patents that have been cited by the firm's patents filed over the past 5 years. A patent is categorised as exploitative if at least 60% of its citations are based on existing knowledge (Custódio et al., 2019). We then calculate the ratio of exploitative patents for a given firm-year as the number of exploitative patents for a given firm-year divided by the number of patents filed by the firm in that year (*Exploitative ratio*). A higher exploitative patent ratio suggests that a firm's innovation strategy relies mainly on its existing competencies. The average for *Exploitative ratio* is 0.213 in our sample.

Column (3) of Table 4 reports the regression results for the impact of ageing on innovation novelty. We document a significantly positive association between *Ageing* and *Exploitative ratio* (coefficient for *Ageing* = 0.420, *t*-stat = 3.86). This confirms our conjecture that older workers contribute to firms' innovation outcomes through their accumulated knowledge and experience, thereby generating more exploitative patents.

5.3 Measurement error in the patent data

Throughout our empirical analyses, innovation performance is proxied for by patents. However, patents may not uniformly capture innovation outcomes in every sector. A broader understanding of innovative performance encompasses firms' achievements in terms of ideas, sketches and models of new devices, products, processes and systems. Arundel and Kabla (1998) show that patents are an appropriate innovation indicator only in certain sectors/industries, namely the pharmaceutical, chemical, machinery and precision instrument sectors/industries, in which the patent propensity rates for product and process innovations are both high. Similarly, Hagedoorn and Cloodt (2003) suggest that a single indicator such as patents clearly captures the latent variable of innovative performance in high-tech industries. Therefore, if industrial activity across provinces is heterogenous and patent propensity rates are significantly higher in some provinces than others because of industrial clustering, we may underestimate the innovation outcomes in provinces with a lower patent propensity rate. This may adversely affect our findings.

Alternative indicators of innovation outcomes could be adopted to alleviate this concern. However, it is difficult to obtain granular firm-level measures for innovation other than patents and R&D expenses. To address this issue, we compare multiple province-level indicators of innovation performance in a more complex, informative and integrated way using data from the *National Enterprise Innovation Survey Yearbook* published by the National Bureau of Statistics of China. Specifically, we calculate the Pearson correlations between the total number of patents granted and other latent province-level indicators of innovation outcomes on a province-year basis; these include the total number of registered trademarks (correlation coefficient = 0.834); the total number of national or industry standards approved by relevant departments on the basis of independent R&D and intellectual property rights (correlation coefficient = 0.612); the total expenditure for developing new products (correlation coefficient = 0.811) and the total expenditure for introducing and transforming technologies (correlation coefficient = 0.476). With this limitation in mind, the evidence confirms that patents do capture firms' innovation activity to a large extent.

5.4 Measurement error in the ageing data

We measure population ageing using province-level ageing indices because we examine how macro-level population ageing affects corporate innovation. Nevertheless, we acknowledge that an ageing workforce in the labour market will eventually lead to ageing employees at the firm level. Thus, there may be a disconnection between the measurement of ageing and firm-level innovation.

To circumvent this concern, we manually collect employee age information for each sample firm from annual reports and construct a firm-level ageing index. However, it is worth noting the following two points. 1) The firm-level data on employee age are very limited, because this information is voluntarily disclosed by firms, which leads to a significant drop in the number of observations available for empirical analysis and thus substantially reduces the statistical power. 2) Because of the relatively low retirement age thresholds in China (i.e., men retire at 60 and women retire at 55), firms normally disclose employee age information in groups, such as under 30, 30–39, 40–49 and over 50. Thus, the firm-level ageing index can only be calculated as the proportion of employees over 50. However, according to the worldwide definition, an ageing population is determined in terms of the percentage of people over 65 (United Nations, 2019; The European Central Bank, 2018). These concerns make the accuracy and credibility of applying firm-level data questionable.

With these limitations in mind, we perform a robustness check using firm-level data to provide additional supporting evidence. In unreported results, we first find a strongly positive correlation between firm- and province-level ageing indices, which validates the province-level ageing measurement. Furthermore, we regress innovation outcomes on the firm-level ageing index and determine that our baseline results mostly hold despite the limitations of the ageing measurement.[16]

6. Discussion and Conclusion

Ageing populations lead to labour market scarcity and rigidity. Although previous studies on the supply-side labour market argue that labour market rigidity may hamper innovation and productivity, our paper documents novel evidence of a positive relationship between population ageing and corporate innovation.

A possible explanation for why labour scarcity may induce firm innovation is the endogenous response of technology. Technologies can be adopted specifically to perform tasks

[16] To save space, these results are not tabulated herein but are available upon request.

previously undertaken by labour. As for why an ageing workforce might promote innovation, our results suggest that labour market rigidity may be favourable for innovation for firms that follow an innovation path dependent on the accumulation of knowledge from experience. This helps explain why we observe interesting results for Chinese SOE firms, which are widely acknowledged to be overstaffed with older workers. According to the Schumpeterian view, if we expect labour market rigidity to create a strong incentive for innovation, this effect should be more pronounced for SOEs, which exhibit more rigidity than non-SOEs. This is consistent with our findings. In addition, we echo this argument by providing evidence that firms in provinces with a larger ageing population generate more exploitative (vs. exploratory) innovation outcomes, as they are more likely to focus on their current areas of expertise.

Because our paper focuses on China, external validity may be a concern. However, we believe that our findings can be generalised to other countries, especially developing countries. Most developed countries have completed what is called the ‘demographic transition’, or the transition from a mainly rural agrarian society with high fertility and mortality rates to a predominantly urban industrial society with low fertility and mortality rates. In contrast, developing countries are still undergoing this demographic transition. Policymakers, especially those in developing countries, must therefore consider how to maintain rapid economic growth alongside technological advancement, given that their countries’ demographic dividend will disappear as their populations age.

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Table 1
Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	P25	P50	P75
Dependent Variables						
Patents_invention	27,942	5.823	18.957	0.000	0.000	3.000
LnPatents_invention	27,942	0.766	1.228	0.000	0.000	1.386
Patents_international	27,942	0.118	0.593	0.000	0.000	0.000
LnPatents _international	27,942	0.057	0.263	0.000	0.000	0.000
Patents_renewal	27,942	0.231	0.599	0.000	0.000	0.000
Exploitative ratio	27,942	0.213	0.955	0.000	0.000	0.429
Main Regressors						
Ageing	27,942	0.133	0.029	0.109	0.132	0.154
Wages	27,582	0.063	0.600	-0.272	0.003	0.332
No. of employees/PPE	27,887	0.025	0.101	-0.018	-0.001	0.028
Knowledge_cum	27,942	0.253	0.435	0.000	0.000	1.000
SOE	27,942	0.505	0.500	0.000	1.000	1.000
High_edu employees%	25,786	1.373	4.204	-0.353	0.000	1.572
R&D employees%	25,786	3.281	14.298	-4.647	0.000	7.679
Instrumental Variables						
Crude birth rate	27,468	0.021	0.006	0.019	0.022	0.026
Net birth rate	27,468	0.006	0.012	0.003	0.006	0.014
Planning_policy	27,942	3.117	0.813	3.000	3.000	4.000
Control Variables						
Size	27,942	21.906	1.370	20.959	21.721	22.622
ROA	27,942	0.037	0.066	0.012	0.035	0.066
Leverage	27,942	0.476	0.232	0.304	0.473	0.629
TobinQ	27,942	2.059	1.926	0.862	1.488	2.517
Tangibility	27,942	0.247	0.179	0.105	0.213	0.358
CAPX	27,942	0.050	0.054	0.011	0.035	0.073
R&D	27,942	0.020	0.035	0.000	0.002	0.032
TOP	27,942	36.063	15.513	23.790	33.750	47.270
INST	27,942	0.061	0.097	0.005	0.029	0.076
Analyst	27,942	1.368	1.157	0.000	1.386	2.303
FirmAge	27,942	2.114	0.722	1.609	2.197	2.708
LnGDP	27,942	9.882	0.956	9.363	9.990	10.539
GGDP	27,942	0.127	0.056	0.084	0.112	0.170

Table 2
Fixed effects panel data regression results of population ageing on firm innovation, estimated separately for different interactions

	DV= *LnPatents_invention*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ageing	2.135***	2.078***	1.963***	1.713***	0.460	1.636***	1.951***
	(3.66)	(3.65)	(3.39)	(3.18)	(0.54)	(2.79)	(3.44)
Wages		-0.087**					
		(-2.28)					
Wages×Ageing		0.495**					
		(2.08)					
No. of employees/PPE			-1.016***				
			(-2.64)				
No. of employees/PPE×Ageing			9.615***				
			(2.86)				
Knowledge_cum				-0.241***			
				(-3.54)			
Knowledge_cum ×Ageing				1.718***			
				(3.73)			
SOE					-0.290**		
					(-2.10)		
SOE ×Ageing					2.812**		
					(2.46)		
High_edu employees%						-0.033**	
						(-2.13)	
High_edu employees%×Ageing						0.300***	
						(2.60)	
R&D employees%							-0.010**
							(-2.32)
R&D employees%×Ageing							0.091***
							(2.93)
Size	0.098***	0.100***	0.102***	0.098***	0.100***	0.088***	0.089***
	(4.41)	(4.71)	(4.53)	(4.41)	(4.68)	(4.55)	(4.73)
ROA	-0.000	0.009	-0.013	-0.009	0.008	-0.030	-0.043
	(-0.00)	(0.07)	(-0.10)	(-0.07)	(0.07)	(-0.24)	(-0.35)
Leverage	0.063	0.059	0.057	0.060	0.062	0.050	0.046
	(1.00)	(0.99)	(0.88)	(0.95)	(1.00)	(0.83)	(0.75)
TobinQ	-0.002	-0.001	-0.002	-0.001	-0.000	-0.008	-0.007
	(-0.24)	(-0.20)	(-0.33)	(-0.21)	(-0.05)	(-1.33)	(-1.25)
Tangibility	0.224**	0.226**	0.276**	0.220**	0.211*	0.253**	0.255**
	(2.05)	(2.20)	(2.20)	(2.00)	(1.90)	(2.39)	(2.36)

CAPX	0.270	0.273*	0.275*	0.269*	0.270*	0.274	0.272
	(1.66)	(1.79)	(1.68)	(1.67)	(1.69)	(1.66)	(1.63)
R&D	2.992***	2.986***	2.963***	2.974***	2.986***	2.917***	2.952***
	(3.30)	(3.52)	(3.34)	(3.28)	(3.34)	(3.13)	(3.12)
TOP	-0.004***	-0.005***	-0.004***	-0.004***	-0.005***	-0.004***	-0.004***
	(-4.51)	(-4.79)	(-4.43)	(-4.46)	(-4.76)	(-4.62)	(-4.66)
INST	-0.072	-0.073	-0.069	-0.070	-0.068	-0.038	-0.040
	(-0.52)	(-0.57)	(-0.50)	(-0.51)	(-0.50)	(-0.26)	(-0.28)
Analyst	0.043***	0.043***	0.042***	0.043***	0.043***	0.047***	0.047***
	(4.13)	(4.33)	(4.06)	(4.10)	(4.11)	(4.59)	(4.59)
FirmAge	0.069	0.071*	0.072	0.068	0.086*	0.102**	0.102**
	(1.58)	(1.72)	(1.66)	(1.56)	(1.89)	(2.08)	(2.08)
LnGDP	0.250	0.250	0.255	0.250	0.233	0.167	0.194
	(1.13)	(1.21)	(1.14)	(1.13)	(1.06)	(0.81)	(0.93)
GGDP	-0.208	-0.229	-0.226	-0.204	-0.185	-0.204	-0.219
	(-0.60)	(-0.68)	(-0.65)	(-0.59)	(-0.53)	(-0.60)	(-0.64)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,942	27,582	27,887	27,942	27,942	25,786	25,786
Adj. R^2	0.654	0.653	0.654	0.654	0.654	0.655	0.655

t-statistics in parentheses. Standard errors clustered by province.

*** = p<0.01; ** = p<0.05; * = p<0.10

Table 3

Instrumental variable estimation results. The IVs are *Crude birth rate*, *Net birth rate*, and *Planning_policy*, respectively.

Panel A 2SLS estimation results

	(1)	(2)	(3)	(4)	(5)	(6)
	1st stage DV= *Ageing*	2nd stage DV = *LnPatents_invention*	1st stage DV= *Ageing*	2nd stage DV = *LnPatents_invention*	1st stage DV= *Ageing*	2nd stage DV = *LnPatents_invention*
Crude birth rate	-1.441**					
	(-2.26)					
Net birth rate			-0.680***			
			(-3.16)			
Planning_policy					0.015***	
					(3.82)	
Ageing_predicted		6.954**		5.487**		2.253*
		(2.39)		(2.19)		(1.88)
Size		0.224***		0.225***		0.214***
		(8.52)		(8.57)		(8.28)
ROA		0.398*		0.390		0.427*
		(1.70)		(1.65)		(1.92)
Leverage		-0.002		-0.003		0.027
		(-0.02)		(-0.03)		(0.35)
TobinQ		0.009		0.010		0.008
		(1.03)		(1.09)		(0.87)
Tangibility		-0.084		-0.091		-0.049
		(-0.80)		(-0.85)		(-0.44)
CAPX		0.229		0.224		0.238
		(1.19)		(1.16)		(1.18)
R&D		6.089***		6.108***		5.889***
		(5.94)		(5.93)		(5.91)
TOP		-0.001		-0.001		-0.001
		(-0.80)		(-0.78)		(-1.05)
INST		0.008		0.010		-0.005
		(0.03)		(0.04)		(-0.02)
Analyst		0.147***		0.147***		0.150***
		(10.40)		(10.55)		(10.27)
FirmAge		-0.045*		-0.046*		-0.051*
		(-1.79)		(-1.86)		(-2.00)
LnGDP	0.015***	0.016	0.015***	0.048	0.002	0.095***
	(2.99)	(0.31)	(3.53)	(1.22)	(0.44)	(4.83)
GGDP	0.066*	-0.143	0.052	-0.026	0.090**	0.294
	(1.82)	(-0.38)	(1.55)	(-0.07)	(2.29)	(0.70)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	Yes	No	Yes
Observations	435	27,468	435	27,468	450	27,942
F test	24.11		21.27		24.63	
Adj. R^2	0.390	0.318	0.440	0.318	0.495	0.317

Panel B Pretreatment balance tests

	(1)	(2)	(3)	(4)	(5)	(6)
	DV = *Crude birth rate*		DV = *Net birth rate*		DV = *Planning_policy*	
LnGDP_ave5	-3.282		0.100		-4.603	
	(-0.32)		(0.00)		(-0.92)	
LnGDPP_ave5	9.667		18.696		6.571	
	(0.95)		(0.74)		(1.26)	
LnPopulation_ave5	3.645		0.390		5.110	
	(0.40)		(0.02)		(1.06)	
NetBirthRate_ave5	0.059		-0.043		-0.213	
	(0.19)		(-0.06)		(-1.52)	
LnGDP_ave3		-3.417		-3.475		-9.555
		(-0.32)		(-0.13)		(-1.35)
LnGDPP_ave3		9.065		18.184		12.259*
		(0.87)		(0.70)		(1.66)
LnPopulation_ave3		3.736		3.220		10.110
		(0.39)		(0.14)		(1.47)
NetBirthRate_ave3		0.128		0.396		-0.169
		(0.41)		(0.51)		(-1.26)
Observations	28	28	28	28	29	29
Adj. R^2	0.248	0.248	0.359	0.352	0.196	0.186

Panel C IV independence assumption tests (Kedagni and Mourifie, 2020)

Instrument variable	P_y^{20}			P_y^{40}			P_y^{60}			P_y^{80}		
	1%	*5%*	*10%*	*1%*	*5%*	*10%*	*1%*	*5%*	*10%*	*1%*	*5%*	*10%*
Crude birth rate	*[-0.356, inf)*	*[-0.340, inf)*	*[-0.332, inf)*	*[-0.320, inf)*	*[-0.307, inf)*	*[-0.300, inf)*	*[-0.302, inf)*	*[-0.285, inf)*	*[-0.276, inf)*	*[-0.328, inf)*	*[-0.315, inf)*	*[-0.309, inf)*
Net birth rate	*[-0.287, inf)*	*[-0.269, inf)*	*[-0.260, inf)*	*[-0.327, inf)*	*[-0.309, inf)*	*[-0.299, inf)*	*[-0.268, inf)*	*[-0.251, inf)*	*[-0.241, inf)*	*[-0.278, inf)*	*[-0.261, inf)*	*[-0.253, inf)*
Planning_policy	*[-0.088, inf)*	*[-0.073, inf)*	*[-0.065, inf)*	*[-0.054, inf)*	*[-0.039, inf)*	*[-0.031, inf)*	*[-0.085, inf)*	*[-0.069, inf)*	*[-0.061, inf)*	*[-0.065, inf)*	*[-0.052, inf)*	*[-0.045, inf)*

t-statistics in parentheses for Panels A and B. Standard errors clustered by province. Confidence intervals in parentheses for Panel C.
*** = p<0.01; ** = p<0.05; * = p<0.10

Table 4
Exploratory analyses: the impact of ageing on innovation quality and novelty

Variables	(1) DV = *LnPatents_international*	(2) DV = *Patents_renewal*	(3) DV = *Exploitative ratio*
Ageing	0.666*	0.717**	0.420***
	(1.88)	(2.48)	(3.86)
Size	0.017***	0.015*	0.006
	(2.93)	(1.77)	(1.40)
ROA	0.032	-0.091	0.028
	(1.08)	(-1.63)	(0.81)
Leverage	0.005	-0.053	-0.002
	(0.30)	(-1.45)	(-0.18)
TobinQ	0.002*	-0.002	-0.004**
	(1.75)	(-0.79)	(-2.35)
Tangibility	0.016	0.038	0.043**
	(0.65)	(0.96)	(2.54)
CAPX	0.058**	0.017	0.019
	(2.14)	(0.17)	(0.35)
R&D	0.268***	-0.492*	0.498***
	(3.02)	(-2.01)	(4.39)
TOP	-0.000	-0.001	-0.001***
	(-1.66)	(-1.49)	(-4.41)
INST	-0.043	0.071	-0.004
	(-1.62)	(0.95)	(-0.14)
Analyst	0.004**	0.001	0.003
	(2.67)	(0.07)	(0.99)
FirmAge	0.020**	-0.030	0.003
	(2.39)	(-1.09)	(0.26)
LnGDP	0.022	0.082	0.027
	(0.46)	(0.83)	(0.68)
GGDP	-0.059	-0.512***	-0.027
	(-0.70)	(-3.00)	(-0.34)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	27,942	27,942	27,942
Adj. R^2	0.394	0.367	0.421

t-statistics in parentheses. Standard errors clustered by province.
*** = p<0.01; ** = p<0.05; * = p<0.10

Appendix Table I

Robustness tests: Alternative estimation models and measures for ageing and innovation

	(1)	(2)	(3)	(4)	(5)
	Poisson Model	*Negative Binomial Model*	*Fixed Effects Model*	*Fixed Effects Model*	*Fixed Effects Model*
	DV = *Patents_invention*	DV = *Patents_invention*	DV = *LnPatents_adjusted*	DV = *LnR&D*	DV = *LnPatents_invention*
Ageing	4.645***	2.126***	1.241**	11.065***	
	(4.24)	(3.76)	(2.01)	(2.86)	
Ageing_Firm					1.529***
					(3.30)
Size	0.303***	0.081***	0.109***	0.586***	0.128
	(6.53)	(5.04)	(4.83)	(3.61)	(0.94)
ROA	0.908***	1.089***	0.007	-1.290*	1.024
	(2.69)	(4.55)	(0.05)	(-1.92)	(1.30)
Leverage	-0.120	-0.282***	0.075	-0.900**	0.105
	(-0.59)	(-3.36)	(1.24)	(-2.17)	(0.31)
TobinQ	0.008	-0.033***	0.006	-0.096**	-0.008
	(0.58)	(-3.65)	(0.76)	(-2.32)	(-0.32)
Tangibility	0.127	0.365***	0.090	2.451***	-0.170
	(0.54)	(3.82)	(0.84)	(3.02)	(-0.66)
CAPX	0.936***	1.221***	0.249*	-1.468	-0.934
	(2.87)	(5.38)	(1.70)	(-1.33)	(-1.55)
R&D	0.406	3.273***	0.582		2.993**
	(0.44)	(10.07)	(0.84)		(2.10)
TOP	-0.002	-0.005***	-0.002	-0.036***	-0.003
	(-0.88)	(-4.58)	(-1.65)	(-4.35)	(-0.39)
INST	0.052	0.096	-0.196	-1.171	0.433
	(0.26)	(0.72)	(-1.42)	(-1.22)	(0.83)
Analyst	0.031*	0.095***	0.053***	0.315***	0.022
	(1.83)	(6.65)	(5.17)	(3.78)	(0.78)
FirmAge	-0.073	-0.137***	-0.001	-0.592*	0.169*
	(-1.18)	(-5.73)	(-0.02)	(-1.82)	(1.87)
LnGDP	1.240**	0.250***	0.121	0.428	0.310
	(2.32)	(9.19)	(0.65)	(0.32)	(0.39)
GGDP	-0.126	0.413	0.161	-2.510	1.028
	(-0.16)	(0.96)	(0.54)	(-1.10)	(0.91)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	20,092	20,092	27,942	27,942	3,250
Adj. R^2	0.679	-	0.559	0.717	0.802

z-statistics (t-statistics) in parentheses in Columns 1-2 (3-5). Standard errors clustered by province.
*** = p<0.01; ** = p<0.05; * = p<0.10

Appendix Table II

Robustness tests: Controlling for other region-level omitted variables

	(1)	(2)	(3)	(4)	(5)	(6)
			DV= *LnPatents_invention*			
Ageing	2.269***	2.292***	2.139***	2.124***	1.913***	2.256***
	(4.27)	(4.60)	(3.94)	(3.91)	(3.46)	(4.31)
R&D_Region	0.234**					0.143*
	(2.16)					(1.87)
Tech_Region		0.233***				0.220***
		(3.55)				(3.81)
FDI_Region			0.019			-0.058
			(0.46)			(-1.47)
Education_Region				-0.153		0.153
				(-0.30)		(0.27)
Property_Region					0.004*	0.002
					(1.81)	(1.30)
Size	0.099***	0.096***	0.098***	0.098***	0.098***	0.097***
	(4.71)	(4.56)	(4.69)	(4.68)	(4.64)	(4.58)
ROA	-0.001	0.004	0.001	-0.001	0.003	0.001
	(-0.01)	(0.03)	(0.01)	(-0.01)	(0.02)	(0.00)
Leverage	0.058	0.064	0.063	0.063	0.063	0.060
	(0.99)	(1.09)	(1.06)	(1.06)	(1.05)	(1.02)
TobinQ	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002
	(-0.29)	(-0.19)	(-0.25)	(-0.27)	(-0.29)	(-0.25)
Tangibility	0.238**	0.241**	0.224**	0.224**	0.223**	0.248**
	(2.31)	(2.35)	(2.17)	(2.15)	(2.17)	(2.42)
CAPX	0.302**	0.311**	0.271*	0.271*	0.267*	0.322**
	(2.03)	(2.15)	(1.77)	(1.77)	(1.73)	(2.24)
R&D	2.963***	2.922***	2.990***	2.992***	3.000***	2.916***
	(3.52)	(3.57)	(3.50)	(3.50)	(3.50)	(3.57)
TOP	-0.005***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(-4.85)	(-4.93)	(-4.80)	(-4.84)	(-4.79)	(-4.93)
INST	-0.074	-0.081	-0.071	-0.072	-0.073	-0.086
	(-0.58)	(-0.65)	(-0.55)	(-0.56)	(-0.57)	(-0.70)
Analyst	0.042***	0.042***	0.043***	0.043***	0.043***	0.042***
	(4.29)	(4.27)	(4.39)	(4.38)	(4.38)	(4.25)
FirmAge	0.061	0.056	0.069	0.069	0.068	0.052
	(1.31)	(1.36)	(1.66)	(1.68)	(1.65)	(1.19)
LnGDP	0.037	-0.116	0.241	0.246	0.170	-0.234
	(0.20)	(-0.81)	(1.19)	(1.18)	(0.86)	(-1.49)
GGDP	-0.055	0.130	-0.219	-0.196	-0.200	0.230
	(-0.17)	(0.47)	(-0.67)	(-0.59)	(-0.63)	(0.85)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,643	27,643	27,643	27,643	27,643	27,643
Adj R^2	0.654	0.655	0.653	0.653	0.653	0.655

t-statistics in parentheses. Standard errors clustered by province.

*** = p<0.01; ** = p<0.05; * = p<0.10