Aging in a Dual Economy: Urban Aging, Massive Migration, and Agricultural Development*

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Abstract

We examine the effect of urban aging on technology adoption in a dual economy. To guide empirical work, we present a simple model where aging in one sector influences technology adoption in both through an induced reallocation of labor between sectors. We test the predictions of the model by using unique data from China and find no evidence that urban aging has led to an increase in industrial automation. We examine the mechanism and provide evidence that prefectures with more rapid aging as destinations of migration have a larger inflow of rural migrants that may have discouraged firms' incentive to automate. These findings suggest that industrial automation has received a limited boost from demographic changes in the urban sector. Instead, we find that the exodus of rural labor induced by urban aging has accelerated a shift toward capital-intensive agriculture in the rural sector. These findings highlight how aging generates uneven effects on technology adoption across sectors in a dual economy.

Keywords: Aging, Technology Adoption, Dual Economy, Migration, Agricultural Mechanization
JEL codes: J11, J23, J61, O15, O33, Q16

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1 Introduction

Growth in elderly populations may pressure economies by reducing savings, innovation, and aggregate demand and pose a large challenge to economic growth (Hansen, 1939; Thornton, 2001; Baldwin and Teulings, 2014; Lee, 2014; Gordon, 2016). However, by pushing up labor costs, it may also encourage the faster adoption of certain technologies, particularly those that are complementary to unskilled labor. A long-standing hypothesis posits that labor scarcity spurs the adoption of labor-saving technologies and innovation (Basu and Weil, 1998; Acemoglu, 2010; Hornbeck and Naidu, 2014). While the recent literature has argued that industrial automation has received a large boost from demographic changes in developed countries (e.g., Irmen, 2021; Zhang, Palivos and Liu, 2022; Acemoglu and Restrepo, 2022), the local effect of population aging on technology adoption depends on whether local aging induces a simultaneous reallocation of labor across regions or sectors. The sectoral and geographic reallocation of labor, especially that of young low-skilled workers, represents a potential introduction of substitutes for labor-saving technologies and thus has important implications for understanding sector-specific technology effects from demographic changes and the further consequences for economic growth for an economy characterized by a large rural population.

In this article, we examine the effect of urban aging on technology adoption in a dual economy, especially emphasizing the induced adjustment of labor across sectors and regions. Theoretically, if urban aging induces a large exodus of young or middle-aged workers from agriculture, rural households may increasingly adopt machinery and equipment to substitute manual labor toward the mechanization of farming. As a result of the acceleration of rural labor flowing into the urban sector, urban firms may not necessarily benefit from responding to local changes in demographics by replacing production tasks that have been previously performed by workers with industrial robots or other automation technologies in the urban sector. Eventually, urban aging may generate heterogeneous effects on the adoption of labor-saving technologies in the rural and urban sectors. Thus, while existing literature focuses on the *aggregate* effect of population aging on technology adoption, we instead examine the *heterogeneous* effects of aging on technology adoption across sectors in a dual economy.

To guide our empirical work, we build a simple model describing a small two-sector open economy, where middle-aged workers endowed with physical aptitude substitute machines. The model predicts that urban aging's effect on industrial automation is ambiguous, as rural labor is reallocated to the urban sector following the change in urban demographics. However, if machines (or old workers) and middle-aged workers are strong substitutes in agricultural production, urban aging may accelerate the out-migration of middle-aged workers and cause rural households to automate farming instead. Thus, an important takeaway of our model is that the effect of urban aging on technology adoption depends on the equilibrium reallocation of labor and urban aging can accelerate agricultural mechanization. To test the predictions from the model, we construct a measure of expected local urban aging as instrumental variables (IV) of observed local aging and construct a measure of rural households' exposure to the population aging of the whole urban sector, and estimate the effects of urban aging on industrial automation, migration, and agricultural mechanization in China as a dual economy.

We use China as a "laboratory" because it provides an excellent setting to explore the technological implications of urban aging. With its controversial fertility control policies and sustained increases in average life expectancy, that is, from 66 in 1978 to 77 in 2020, China has stepped into an aging society since 1999,[1] when its urbanization rate remained at a low level of less than 37%. By the end of 2015, the share of the population aged 60 years old and above reached 17.3% of the country's total population, making China the largest country in the world in terms of the elderly population.[2] Therefore, we choose the period from 2000 to 2015 to examine how changes in demographic structure affect the sector-specific adoption of technologies in a dual economy.

We assemble a unique and longitudinal dataset from multiple sources. The first dataset is firm-level data from the Annual Survey of Industrial Firms (ASIF) and China's Customs. We complement the ASIF and Customs data with data on robot adoption from the International Federation of Robotics (IFR) at the industry level. We use these data and detailed employment shares computed from China's censuses and mini-censuses to construct three different measures of industrial technology adoption across Chinese prefectures: the adoption of industrial robots, the capital-labor ratio, and the value of imported machinery and equipment. Then, these measures are matched with local aging and migration flows that are constructed from four rounds of population censuses and mini-censuses, which represent the most comprehensive demographic information on age, education, and migration in China. Furthermore, we use the National Fixed Point Survey (NFS) data that contain detailed information on machinery and equipment that are adopted in agricultural production in China. The assembled comprehensive data thus allow us to separately estimate the effects of urban aging on industrial automation and agricultural mechanization and examine the role of rural-to-urban migration in shaping the sector-specific technology effects of urban aging. By highlighting the heterogeneous effects of aging on technology adoption across sectors, our analysis complements a growing literature that focuses on the aggregate effect of population aging on technology adoption (e.g., Acemoglu and Restrepo, 2022).

We start by highlighting key facts regarding rapid aging in China and the driving forces behind the demographic changes, and discussing the ongoing rural-to-urban migration that represents one of the greatest internal migrations of people in history. Then, we estimate the effects of urban aging on industrial automation and find little evidence that supports a positive association. To construct a causality, we employ an IV strategy by using lagged demographic structures and various at-birth fertility policies to predict urban aging as our instruments. The ordinary least squares (OLS) and IV estimations produce similar results, suggesting that demographic change is not a key factor to the rise of industrial robots in China. We also use the adoption of machinery and equipment, which is less innovative in automation, as alternative measures of technology adoption, given that China falls relatively behind the world's technology frontiers. Again, we find little evidence that firms in regions undergoing more rapid urban aging adopt more capital to replace labor or import more machinery and equipment from the rest of the world than firms in other regions. Such findings indicate that demographic change plays a limited role in boosting industrial automation in developing countries like China, standing in sharp contrast to recent literature that finds that demographic changes substantially contribute to the development and adoption of industrial automation in developed countries, most notably the United States, Japan, Germany, and South Korea.[3]

Understanding the mechanism underlying the difference in the technological implications of ag-

[1] Data source: https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=CN

[2] We calculate the number based on the 2015 population census. The China National Committee on Aging (CNCA) projected that the figure of the elderly population is expected to peak at 487 million, or 35% of the country's population in 2050.

[3] For example, Acemoglu and Restrepo (2022) argue theoretically and document empirically that population aging leads to greater adoption of industrial robots in the United States.

ing between China and major developed countries motivates the subsequent analysis of migration within China. By analyzing bilateral migration flows, we show that a larger number of workers have moved into urban areas that are undergoing rapid aging whereas aging in the prefecture of origin that sends migrants has reduced the outflow of its local workers. The effect we estimate is sizable. A one standard deviation increase in urban aging at the destination increases the inflow of workers aged between 21 and 55 by 25.32% into the destination prefecture. The migratory response to destination aging is more pronounced for workers who are young, unskilled, and from rural areas. This finding is consistent with the insight generated by the literature on directed technological change (e.g., Acemoglu, 2002, 2007, 2010) which suggests that an increase in the supply of a factor induces a change in technology that is biased toward that factor. Thus, a migration-induced increase in the supply of young labor discourages the adoption of labor-saving technologies, including automation. These findings also indicate that the induced reallocation of labor across sectors following urban aging in a dual economy may attenuate the potential positive effect of urban aging on industrial automation.

Having found evidence of the sizeable out-migration of rural workers pulled by urban aging, we test the third prediction derived from our model: the aging-induced exodus of rural labor accelerates agricultural mechanization. For each rural part of a prefecture that sends migrants, we construct a measure of the region's exposure to urban aging by using aging at destinations weighted by local migration shares to each destination city. The migration shares computed from migration flows in 2000, which is the initial year of the period we study, reflect a rural region's exposure to the urban sector's aging through migration networks fixed in the initial year. Through the lens of a stable migration network, we estimate the effect of urban aging on agricultural mechanization for rural households in the originating prefectures that send migrants. We find that rural regions that are exposed to higher urban aging have experienced a larger increase in the adoption of agricultural machinery relative to other regions. The results suggest that urban aging induces an exodus of rural labor and accelerates a shift of agricultural production toward mechanization in rural China.

Overall, our results suggest that the technological implication of urban aging depends not only on the direct change in the supply of the local working-age population but also on the indirect equilibrium reallocation of labor across sectors and regions. Our findings are consistent with at least two nonmutually exclusive consequences of aging. First, urban labor scarcity and high wages spur industrial automation, which in turn relieves local demand for labor, reflecting empirically an increase in industrial automation instead of the inflow of middle-aged workers. Second, when the migration effect dominates, rural sectors that are indirectly hit may experience a large exodus of middle-aged workers flowing into cities, which would otherwise accelerate agricultural mechanization. Our evidence for China is more consistent with the latter channel that leaves an ambiguous effect of urban aging on industrial automation.

Our study contributes to three strands of the literature. First, our results are related to studies that seek to identify the costs and benefits of aging (Hansen, 1939; Baldwin and Teulings, 2014; Gordon, 2016; Irmen, 2021; Zhang, Palivos and Liu, 2022; Acemoglu and Restrepo, 2022; Jones, 2022). Much recent emphasis of the literature has been put on the role of automation technologies, such as industrial robots, one of the most promising technologies that are currently being developed and deployed in facilitating economic development (Prettner and Strulik, 2017; Abeliansky and Prettner, 2017; Graetz and Michaels, 2018; Cravino, Levchenko and Rojas, 2022; Acemoglu and Restrepo, 2022). Theoretically, automation allows firms to substitute capital (machines) in a range of tasks that were previously performed by some specific types of labor. Thus, population aging, which can spur the introduction of new automation and increase productivity, has the potential to foster economic growth. However, we find that urban aging accelerates the shift of rural labor into the urban sector, and the acceleration attenuates the potential positive impact of the increasing scarcity of the urban working-age population on industrial automation. Our findings on the impact of urban aging in a dual economy generate new insights relative to the previous research that has examined the cases of developed countries that have only one sector and typically no (internal) rural migrants to replenish the urban workforce when the urban population ages rapidly. Moreover, in highlighting the differential arrival of skill-specific migrants driven by urban aging, we contrast with a growing literature that seeks to assess how plants' automation adoption responds to increases in the relative supply of low-skill labor (e.g., Lewis, 2011; Wang, Milner and Scheffel, 2021).

We add to a large body of literature that characterizes the process of structural change where rural workers migrate to the nonagricultural sector for employment. Understanding the forces behind labor reallocation is particularly important given that labor productivity outside agriculture is higher than that in agriculture in most countries; thus, a reallocation of labor into the urban sector can increase aggregate productivity and drive the development of the economy (Foster and Rosenzweig, 2004). A body of growing literature has analyzed the forces that drive the sectoral reallocation of labor (Meng, 2012; Meng et al., 2014; Munshi and Rosenzweig, 2016; Bodvarsson, Hou and Shen, 2016; Lu, Xie and Xu, 2016; Colas and Ge, 2019; Cai, 2020; Bustos, Garber and Ponticelli, 2020; Dustmann, Fasani, Meng and Minale, 2020; Gai, Guo, Li, Shi and Zhu, 2021; Foster and Zhou, 2022). We contribute to this literature by analyzing how urban aging results in the joint adjustment of technology adoption and the labor movement.

We also contribute to the strand of literature that examines various shocks that spur agricultural development. Examples of the factors include the caloric intake of farmers in Sierra Leone (Strauss, 1986), market-oriented reforms (Lin, 1992), the accumulation of human capital (Foster and Rosenzweig, 1995), the adoption of high-yielding varieties during the Green Revolution in India (Foster and Rosenzweig, 2007), the genetically engineered soybean seeds adopted in Brazil (Bustos, Caprettini and Ponticelli, 2016), and labor market liberalization (Foster and Zhou, 2022). We differ from existing studies by analyzing the contribution of urban aging to agricultural mechanization due to a mechanism of rural out-migration. Moreover, the empirical application of the gravity equation, which contributes to explaining China's bilateral migration flows, provides new demographic insights into China's ongoing mass migration.

The rest of the paper is organized as follows. Section 2 describes several key facts regarding population aging in China. Section 3 introduces our illustrative model and the testable predictions. Section 4 discusses our data and measurement of major variables. Section 5 presents our empirical strategies and results on the effects of urban aging on technology adoption in the urban sector. Section 6 empirically examines the effects of urban aging on migration. Section 7 discusses the effects in the agricultural sector. Section 8 provides the conclusion of this study.

2 Population Aging in China

In this section, we highlight several salient facts regarding population aging in China. First, we discuss the changes in fertility and life expectancy, both of which contribute to a rapid increase in population aging between 2000 and 2015 in China. Second, we discuss China's rural-urban divide and internal migration, which can substantially affect the allocation of labor across sectors and regions. Third, we discuss the variations in aging between rural and urban China and across geographic regions.

2.1 Changes in fertility and life expectancy

Since the 1970s, the Chinese government has encouraged its citizens to have fewer children because of the belief that curbing population growth is essential to economic development. In the 1970s, China first initiated a population control policy named "Later (marriage), Longer (spacing between births), Fewer (children)." Then, in 1980, the notorious one-child policy (OCP) was implemented (Zhang, 2017; Chen and Fang, 2021). The population control policies, which promoted late marriage, delayed childbearing, and fewer children, drastically shifted China's demographic structure (Zhang, 2017). Partly as a result of family planning policies, the total fertility rate (TFR) has declined dramatically since 1970, as shown in Figure 1. By 2015, the TFR had reached 1.7, whereas the number was as high as 5.7 children per woman in 1970 when China's fertility policy was just initiated. From 1979 to 2015, China also saw its life expectancy increase sharply from 66 in 1979 to 76 years in 2015.[4] These benefits were mainly a result of improved healthcare access.

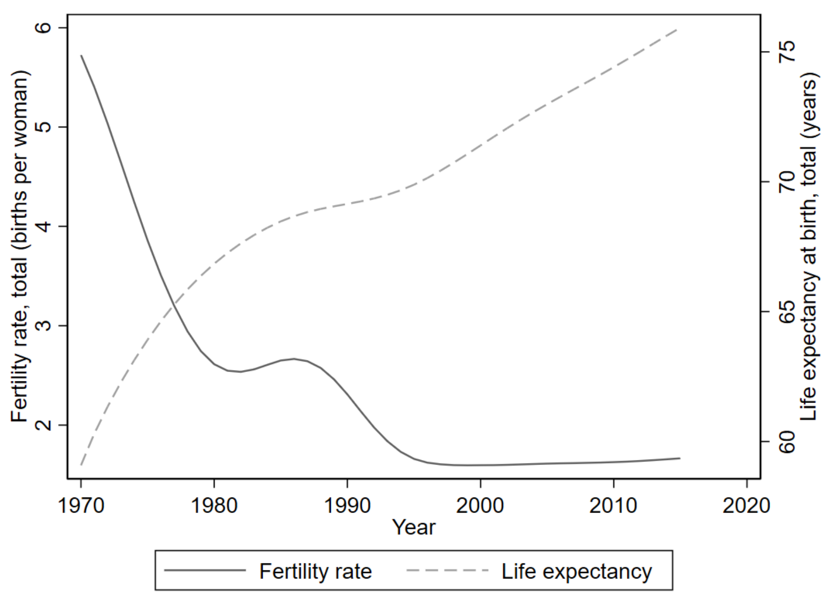


Figure 1: Fertility rate and life expectancy in China, 1970 to 2015

Note: This figure displays the annual fertility rate and life expectancy for China from 1970 to 2015. Data source: World Bank.

Greater life expectancy, combined with decades of declining fertility, contributed to a rapid change in demographic structure in China. Figure 2 shows the evolution of China's population aging measured as the ratio of the population aged 56 and above to those aged 21–55. As shown, the proportion of the population aged 56 and above was approximately 26.1% in 2000 but increased to 36.2% in 2015. Given the acceleration of aging starting in approximately 2000, the subsequent

[4]Data source: https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=CN

analysis of this study focuses mainly on the period from 2000 to 2015 to examine the various consequences of aging in China.[5]

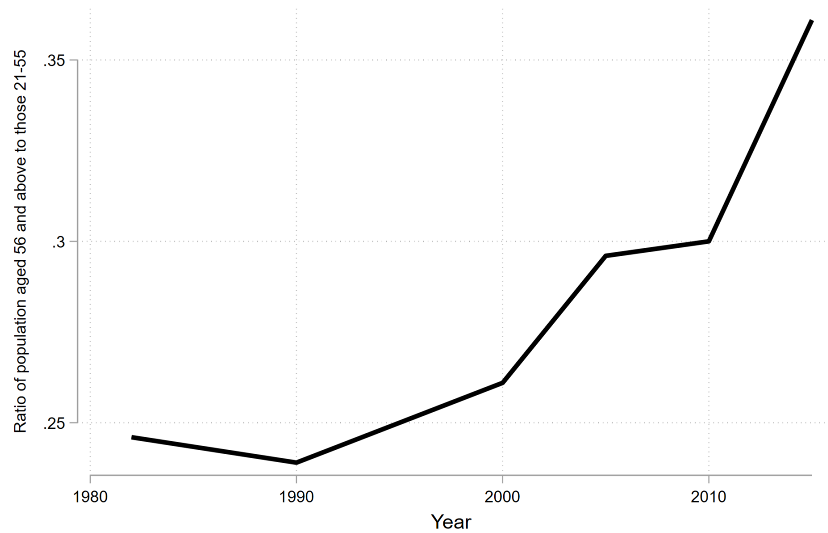


Figure 2: Evolution of population aging in China

Note: Population aging is measured by the ratio of the older population aged 56 and above to the younger population aged 21-55. Data sources: Population censuses and surveys between 1982 and 2015.

2.2 Rural-urban divide and rural-urban migration

While China has undergone rapid urbanization and economic development since 1978, China's economy is still characterized by a large population living in rural areas and substantial labor movement between rural and urban sectors. According to the data from the 2015 mini-census of the population, more than 44% of Chinese residents still lived in rural areas in 2015. This distribution is a result of China's uneven development that has split China into two economies: the rural sector and the urban sector. In contrast to the spectacular growth in urban China, rural areas saw only moderate growth since China instituted economic reforms under the "reform and open" policy in 1978 (Meng, 2000). The difference in growth is reflected at least in part by the large difference in productivity and wages between rural and urban areas (Benjamin, Brandt, Giles, Wang et al., 2008; Cheng, Hu and Li, 2020). The substantial disparity in wages between rural and urban sectors is a major force behind China's rural-to-urban migration, which represents one of the greatest internal migrations of people in history.

However, China's internal migration is restricted largely by its household registration system, a sophisticated system of residency rights known as the hukou system (Giles, Meng, Xue and Zhao, 2021; Sieg, Yoon and Zhang, 2023). The hukou system was initially devised to record migration in the 1950s and eventually evolved into a system that controlled and hindered population movements under China's planning economy (Chan, 2012). Starting in the mid-1980s, the system was gradually loosened in response to China's economic reform, which increased the demand for rural labor in cities as the urban sector continued to expand. After China's World Trade Organization (WTO)

[5] China has conducted a regular national census every 10 years since 1990, and the only census conducted in the 1980s was the 1982 census, which has no information on the hukou status.

accession in 2001, cities' demand for rural labor continued to expand, triggering an increase in the favorable treatment of migrants from central and local governments (Tian, 2022). As a result, China has witnessed substantial and rising labor migrations across regions and sectors since 2001 (Facchini, Liu, Mayda and Zhou, 2019).

2.3 Hukou-based measure of population aging

Before defining the relevant aging measures used in this study, it is important to have a clear understanding of the hukou system in China. Chinese hukou is a permit that is similar to an internal passport issued by the Chinese government. Although the current hukou system no longer directly restricts labor mobility, individuals without local hukou–those who live or work in a residential location other than their hukou registration place (hujidi)–are not fully eligible for various local social services and welfare, such as public education, health insurance, retirement allowances, unemployment insurance, maternity benefits, work insurance, and housing funds (Chen and Feng, 2013; Kuhn and Shen, 2015). By tying hukou with access to local services and welfare, hukou still has the function of regulating internal migration; thus, most migrants in China are members of a floating population, which refers to individuals who reside in a region (prefecture or province) without local hukou (Meng et al., 2014; Zhong, 2018).

Since our interest is to analyze the consequence of changes in the age structure of the local population, we use hukou-based (instead of residence-based) populations to define aging. Hukou-based aging represents a region's age structure of the local population before its population moves away from the region or other regions' population moves into the region influenced by the relative aging between the regions. Hence, this aging definition allows us to estimate the effect of local aging on sector-specific technology adoptions by linking the local population that is officially registered in a region to the local adoption of technology. Furthermore, depending on whether the hukou type (leibie) of each individual is categorized as "rural" or "urban" (hukou) residents, we distinguish between "rural" and "urban" aging by using hukou-based "rural" or "urban" populations. More precisely:

> Urban aging is computed by using the hukou-based urban population who are officially categorized as local urban hukou residents. Rural aging is similarly computed by using the hukou-based rural population who are categorized officially as local rural hukou residents. For any individual, the information on the individual's registration address and hukou type can be obtained from the census data under the question on each individual's hukou type ("rural" or "urban"). We focus on demographic changes related to aging, and the main measure of rural and urban aging is the ratio of the population above 56 to those aged between 21 and 55.[6] The choice of 55 years of age as the cutoff is motivated by the patterns of substitution between robots and workers, as documented in Acemoglu and Restrepo (2022).[7]

To illustrate the importance of migration for understanding sector-specific aging and its effects, which will be estimated subsequently, we plot sector-specific aging before and after migration. To

[6] Middle-aged workers (between 21 and 55) have a comparative advantage in manual tasks that require physical activity and dexterity and are thus more prone to automation than those who are older (56 and older). See Acemoglu and Restrepo (2022) for evidence on age-specific job specialization.

[7] Our main results remain robust if we use 50 as the cutoff.

this end, we first plot hukou-based demographic composition separately for rural and urban populations in Figure 3. Hukou-based aging captures the workforce (defined as those 16 years old or older) that is specific to a sector (rural or urban) before workers have moved across sectors. Thus, it is akin to the sector-specific age structures of the workforce before cross-sector migration. As shown, China's urban population is rapidly aging, while the rural population aging is also increasing at a fast pace, with a larger proportion of workers being older than 46 years old by 2015.

Furthermore, to show the postmigration aging in each sector, we plot employment-based aging, which refers to the age distribution of workers who are employed in the agricultural sector and those employed in the nonagricultural sectors separately in Figure 4.[8] As shown in Panel A, where we show the age proportions of workers who are employed in the nonagricultural sector, the proportion of young workers aged between 16–25 and 26–35 decreased from 27% to 15% and from 34% to 31% between 1990 and 2015, respectively. The proportion of workers aged 36–45 increased from 23% in 1990 to 28% in 2015. Over time, the proportion of workers aged 46–55 increased significantly. However, the proportion of older workers aged 56 and above remained low and was less than 6% in 2015 for the nonagricultural sector.

In Panel B of Figure 4, we plot the age proportions of workers who are employed in the agricultural sector. As shown, agricultural employment has experienced much more rapid aging than nonagricultural employment after rural-to-urban migration is considered, suggesting that young residents with rural hukou disproportionately migrate to and work in the nonagricultural sector. More specifically, the proportion of young workers aged 16–25 in the primary sector dropped drastically from 33% in 1990 to 8% in 2015, whereas the proportions of older workers aged 46–55 and 56 and above increased significantly. By 2015, more than 50% of the agriculture workers were at least 45 years old, and 27% of them were 56 years old or above.

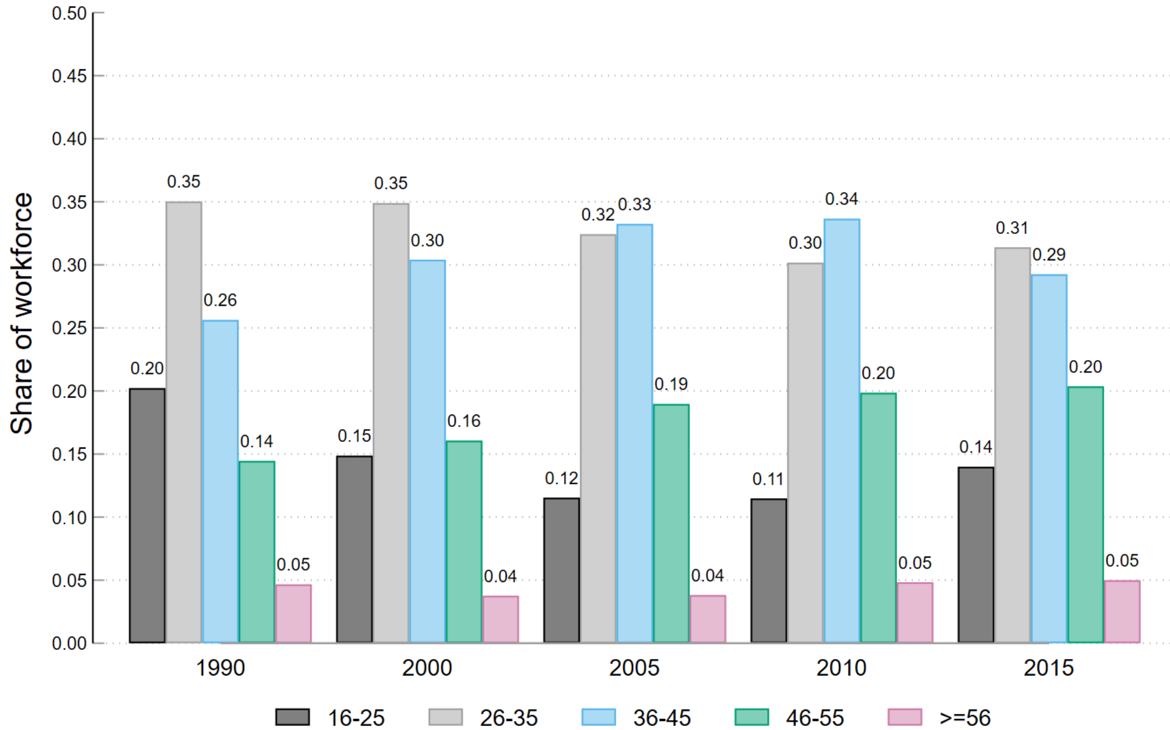
Overall, the employment-based pattern suggests a much older composition of age structures for workers who are employed in the agricultural sector relative to the nonagricultural sector, which highlights the disproportionate out-migration of young workers (relative to older ones) from rural areas to urban areas. As analyzed theoretically and empirically below, the disproportionate movement of young workers between sectors has been affected substantially by urban aging.

2.4 Geographic variations in aging

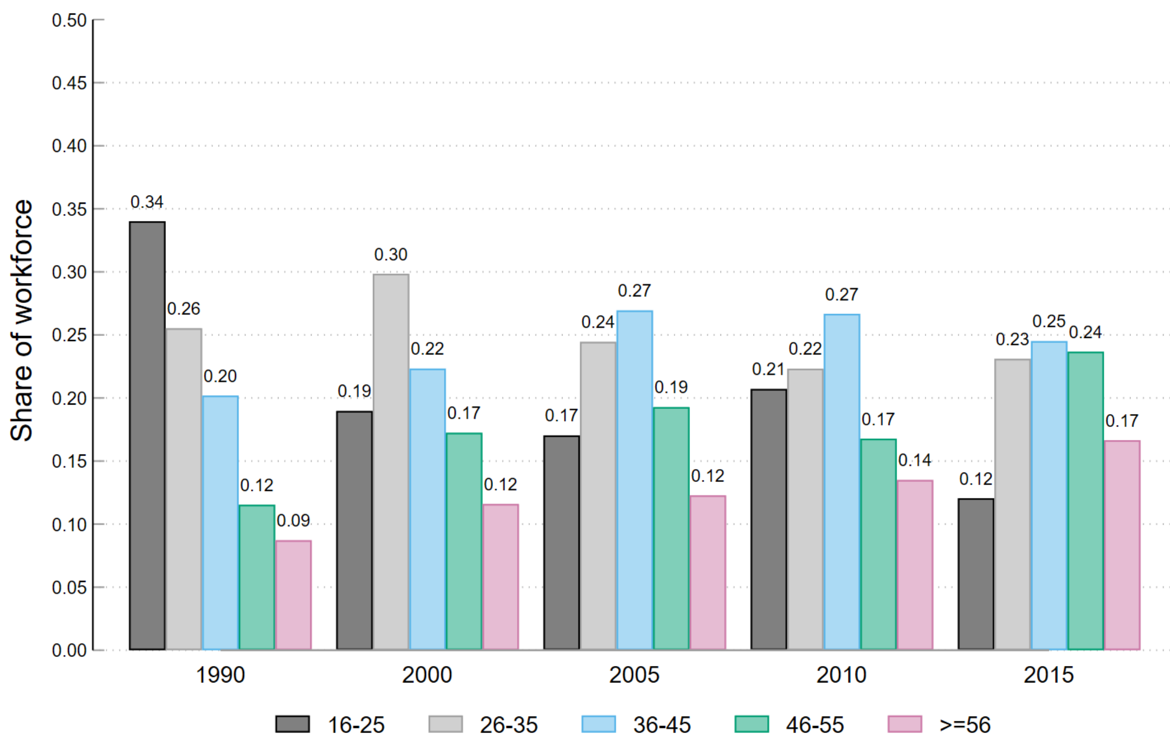
Population aging in China is also characterized by varying degrees of intensity across different regions. In Table A.1 in Appendix A, we present the geographic variations in population aging across 31 Chinese provincial-level administrative divisions, which include 22 provinces, four municipalities (Beijing, Tianjin, Shanghai, and Chongqing), and five autonomous regions (Guangxi, Inner Mongolia, Ningxia, Xinjiang, and Tibet). We measure provincial population aging by the province-level ratio of the older (56 years old and above) to the younger (between 21 and 55 years old) population with hukou registered in the administrative divisions.

The population age structure varies significantly across provinces in all years, as shown in Table

[8] We group agriculture, fishing, and forestry together to represent the agricultural sector. The remaining industries are grouped as nonagricultural, which consists of mining, manufacturing, electricity, gas and water, construction, wholesale and retail trade, hotels and restaurants, transportation, storage and communications, financial services and insurance, real estate and business services, and other services. Next, we restrict the sample only to those who are employed in one of the industries mentioned above. Given that the rural population may migrate to the urban sector and then become a worker employed in the nonagricultural sector, and thus the rural hukou population may also work in the nonagricultural sector, the employment-based aging in Figure 4 reflects the postmigration sector-specific age structure.



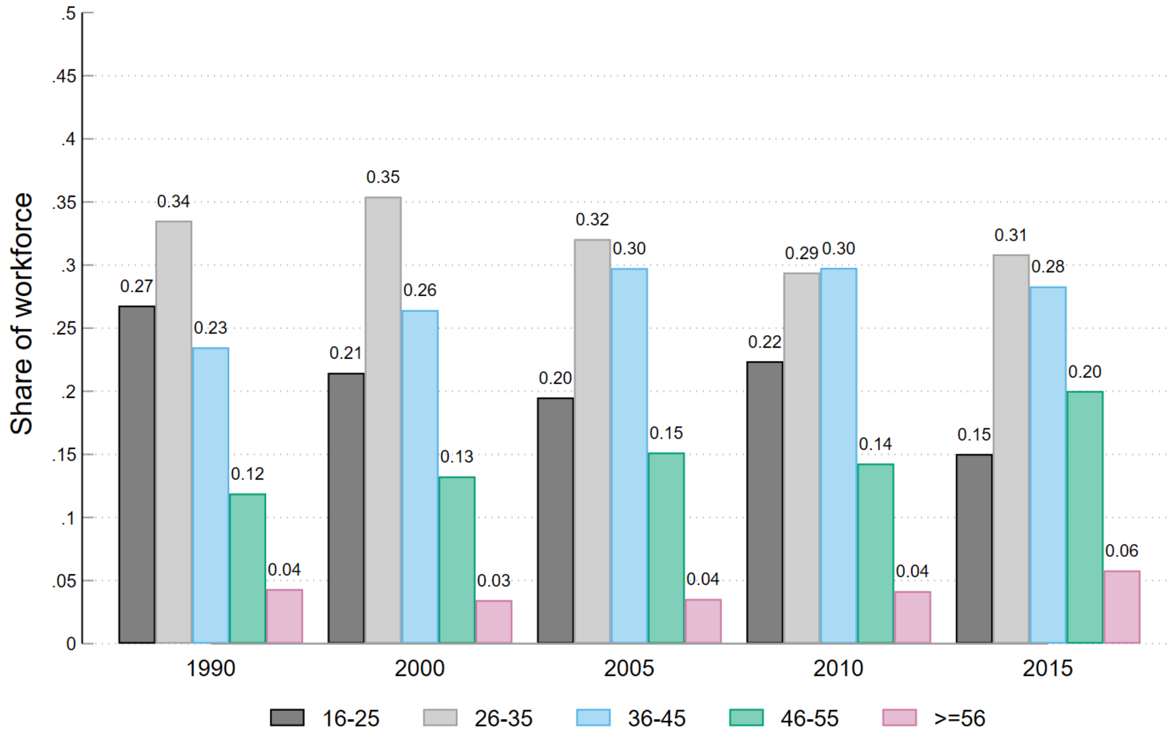
(a) Panel A: Urban hukou workforce



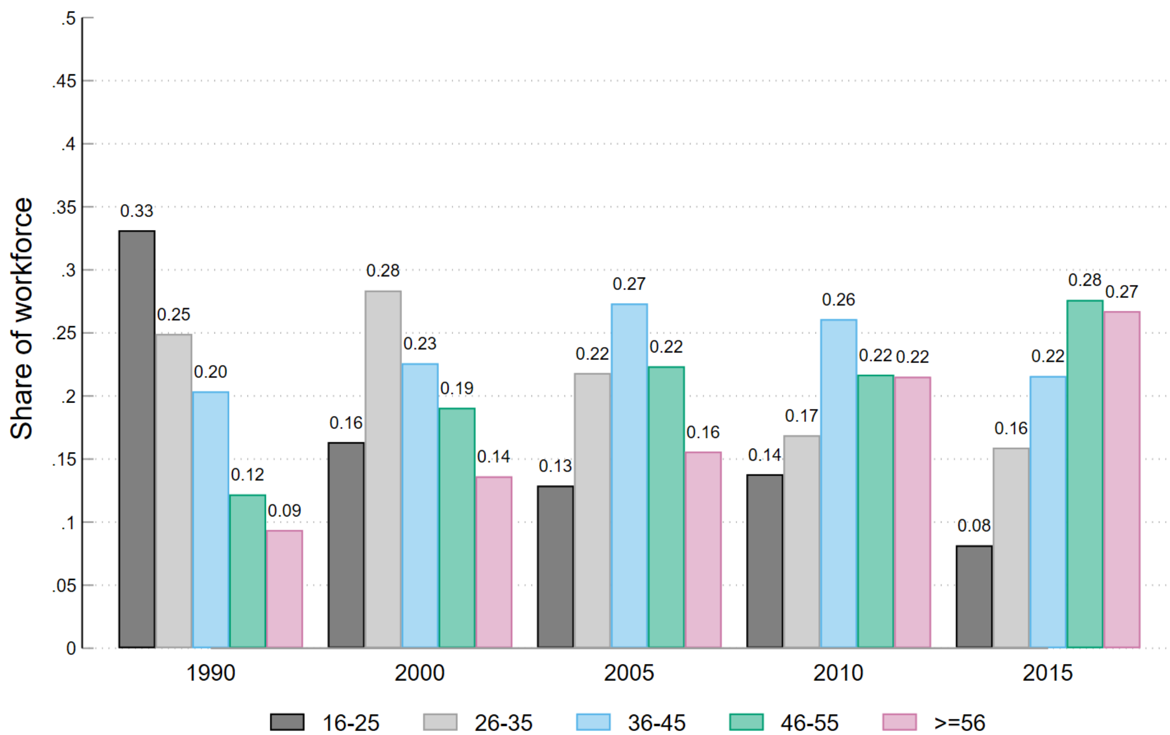
(b) Panel B: Rural hukou workforce

Figure 3: Age distribution of the workforce by hukou type in China, 1990-2015

Data source: 1982-2015 Chinese censuses and mini-censuses.



(a) Panel A: Nonagricultural sector



(b) Panel B: Agricultural sector

Figure 4: Age distribution of the workforce by sectors in China, 1990-2015

Data source: 1982-2015 Chinese censuses and mini-censuses.

A.1. In 2000, Ningxia and Heilongjiang had the lowest old-young ratios of 0.204 and 0.205, respectively, and Shanghai had the highest old-young ratio of 0.388. Between 2000 and 2015, almost all provinces experienced an increase in the old-young ratio. However, the speed of population aging varied significantly across provinces. For example, Liaoning and Guizhou had a similar old-young ratio in 2000 (0.264 and 0.251). Liaoning became one of the most rapidly aging provinces with an old-young ratio of 0.487 in 2015, whereas Guizhou experienced aging at a lower speed between 2000 and 2015 and the ratio stood at 0.266 in 2015. Moreover, over time, we observe more variations in population aging across Chinese provinces.

In our empirical analysis, we treat Chinese prefectures as the local labor markets and use the prefecture as the unit of observation. A prefecture is an administrative division that ranks below a province and above a county in China's administrative structure. For each prefecture, we compute the prefecture's urban aging by using the prefecture's hukou-based urban population. We also compute each prefecture's rural aging by using the prefecture's hukou-based rural population.

Figure 5a shows the geographic variations in population aging across Chinese prefectures in 2000. The old-young ratio varies from less than 0.1 to 0.4 across prefectures. In terms of spatial distribution, prefectures in the coastal areas appear to have an older population than those in the western part of China. Figure 5b further shows the change in geographic variations of population aging between 2000 and 2015. Over the period, the change in old-young ratio varies from –0.08 to 0.38, and North China, especially the northeast part of China, appears to have experienced a larger increase in aging compared with other parts of China.

3 Conceptual Framework

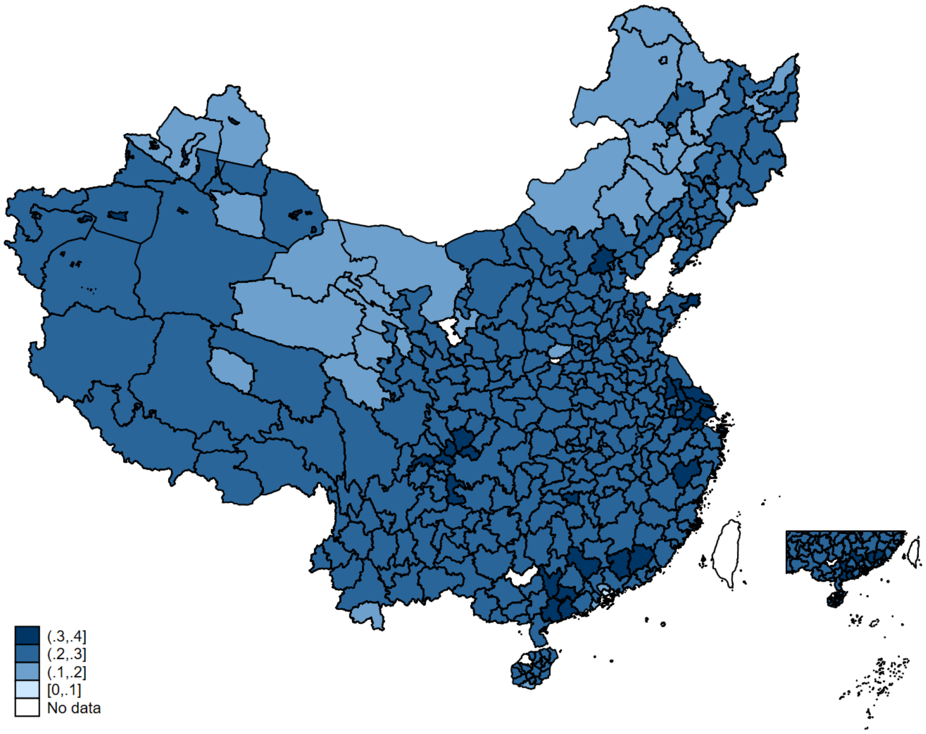
This section presents an illustrative model. We present the model by first considering a small open economy with one sector that is conceptually close to the economy of developed countries (relative to a dual economy). Next, we extend the model to a dual economy characterized by two sectors. Our two-sector model derives three predictions that guide the subsequent empirical analyses of the effects of urban aging on industrial automation, migration, and agricultural mechanization in the rest of the article.

3.1 Aging in a one-sector economy

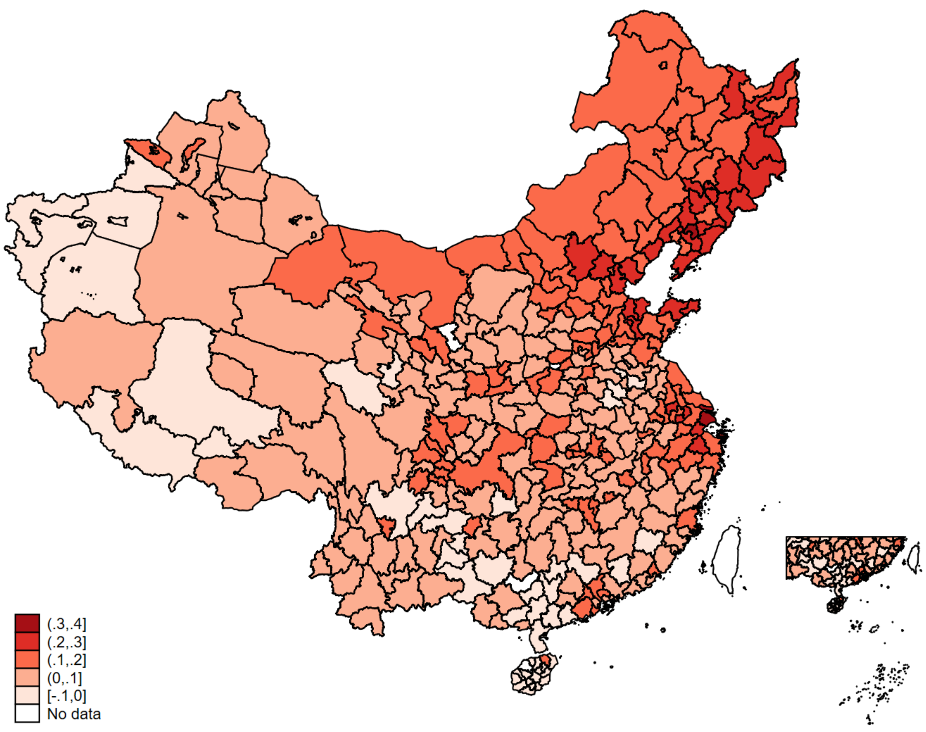
We first consider a small open economy with one sector. The economy produces a numeraire good Q by using three inputs: middle-aged workers (L), older workers (S), and machines (M) through the following production function:

$$Q = z(A_L L + M)^{\alpha} S^{1-\alpha}. \tag{3.1}$$

Following Acemoglu and Restrepo (2022), we impose the assumption that middle-aged workers fully specialize in production inputs and older workers fully specialize in service inputs. The exponent α, $0 < \alpha < 1$, designates the importance of production inputs relative to service inputs in the production function. We assume that middle-aged workers and machines are perfect substitutes and A_L designates the productivity of middle-aged workers relative to machines. In addition, the parameter z captures Hicks-neutral technical change.



(a) Population aging across Chinese prefectures in 2000



(b) Change in population aging between 2000 and 2015

Figure 5: Population aging and its change

Data source: 2000 population census and 2015 mini-census of the population of China.

We denote the (inelastic) supply of middle-aged workers by $\bar{L}$ and the supply of older workers by $\bar{S}$. Profit maximization implies that the value of the marginal product of machines must equal the rental price of machines (r). This condition and the labor market clearing conditions determine the equilibrium adoption of machines,

$$M^* = (\frac{z\alpha}{r})^{\frac{1}{1-\alpha}}\bar{S} - A_L\bar{L}. \tag{3.2}$$

Next, we assess the response of the adoption of machines (including automation) to aging. Wages are determined by the marginal products of labor. As the number of older workers increases or the number of middle-aged workers decreases, the wage for middle-aged workers rises, whereas that for older workers declines. Given that the machine's rental price, r, is determined in the international market and middle-aged workers and machines are perfect substitutes, substituting middle-aged workers with machines would be cheaper when the demographic structure becomes older. From equation 3.2, we immediately have

$$\frac{\partial M^*}{\partial \bar{S}} > 0, \text{ and } \frac{\partial M^*}{\partial \bar{L}} < 0. \tag{3.3}$$

That is, an increase in the supply of older workers or a decrease in the supply of middle-aged workers leads to a greater adoption of automation technologies.

3.2 Aging in a dual economy

We next extend the model to a two-sector economy, where sector j is either urban (U) or rural (R). The sector-specific production function is given by

$$Q^j = z^j(A_L^j L^j + M^j)^\alpha (S^j)^{1-\alpha}. \tag{3.4}$$

We normalize the product price in the rural sector to one and let the product price in the urban sector be P^U. Given China's urban-biased policy (Yang, 2003), we assume that $P^U > 1$. In addition, technological development and labor productivity are at higher levels in the urban sector (Park, 2008), and thus we have $z^U > z^R$ and $A_L^U > A_L^R$.

Given the differences in product prices and labor productivity, urban wages are higher than rural wages. Thus, rural workers have incentives to migrate to the urban sector. However, if the migration cost is prohibitively high and there is no labor mobility between the two sectors, the equilibrium adoption of machines in each sector will only depend on sector-specific productivity parameters and labor supplies. Therefore,

$$M^{*j} = (\frac{z^j\alpha}{r})^{\frac{1}{1-\alpha}}\bar{S}^j - A_L^j\bar{L}^j, \tag{3.5}$$

which is exactly the same as that in the one-sector model. In this case, aging in a sector leads to greater adoption of automation technologies in the sector but has no effect on automation in the other sector.

When migration restrictions are relaxed, rural workers move to the urban sector for higher wages. The migration literature finds that younger workers have a much higher migration propensity (Cortina and Taran, 2014; Foster and Zhou, 2022). For simplicity but without loss of generality, we assume that only middle-aged workers migrate. The labor market equilibrium conditions are as follows:

$$S^U = \bar{S}^U, \text{ and } S^R = \bar{S}^R \tag{3.6}$$

$$L^U + L^R = \bar{L}^U + \bar{L}^R, \tag{3.7}$$

where superscripts U and R represent rural and urban sectors, respectively. If no migration cost exists, rural middle-aged workers will migrate to the urban sector until the marginal value products of labor equalize across the two sectors. Therefore, the optimal labor allocation of middle-aged workers is determined by

$$P^U \frac{\partial Q^U}{\partial L^U} = \frac{\partial Q^R}{\partial L^R}. \tag{3.8}$$

A large body of literature shows that capital investment is lumpy (e.g., Winberry, 2021). In the short run, the sector-specific adoption of machines is determined by equation 3.5. We plug in the levels of the machines in both sectors in equation 3.8 and derive the total number of middle-aged workers in the urban sector at equilibrium.

$$L^{*U} = \bar{L}^U + (\theta - 1)(\frac{\alpha}{r})^{\frac{1}{1-\alpha}}[\frac{A_L^U}{\bar{S}^U(z^U)^{\frac{1}{1-\alpha}}} + \frac{\theta A_L^R}{\bar{S}^R(z^R)^{\frac{1}{1-\alpha}}}]^{-1}, \tag{3.9}$$

where

$$\theta = (\frac{P^U A_L^U}{A_L^R})^{\frac{1}{1-\alpha}} > 1. \tag{3.10}$$

Therefore, there is a positive flow of rural migrants into the urban sector,

$$L^{*U} > \bar{L}^U. \tag{3.11}$$

The equilibrium number of middle-aged workers in the rural sector is determined by the labor market equilibrium condition and is equal to

$$L^{*R} = \bar{L}^U + \bar{L}^R - L^{*U} < \bar{L}^R. \tag{3.12}$$

With this model, we can derive the following testable predictions.

Prediction 1: Urban aging leads to more rural-to-urban migration.

From equation 3.9, it is straightforward to show that

$$\frac{\partial(L^{*U} - \bar{L}^U)}{\partial \bar{S}^U} > 0. \tag{3.13}$$

Urban aging leads to a rise in middle-aged workers' wages in the urban sector, which attracts more rural-to-urban migration.

Prediction 2: Urban aging's effect on urban automation is ambiguous.

After the labor market adjustment, the optimal adoption of the machine is determined by

$$M^{*j} = (\frac{z^j \alpha}{r})^{\frac{1}{1-\alpha}} \bar{S}^j - A_L^j L^{*j}. \tag{3.14}$$

Therefore, urban aging has a direct effect on urban automation through the supply of older workers and an indirect effect on urban automation through labor migration.

$$\frac{\partial M^{*U}}{\partial \bar{S}^U} = (\frac{z^U \alpha}{r})^{\frac{1}{1-\alpha}} - A_L^U \frac{\partial L^{*U}}{\partial \bar{S}^U}. \tag{3.15}$$

Urban aging itself would lead to more automation, which is similar to the effect in the one-sector model. However, the inflow of rural middle-aged workers in response to urban aging can lead to less automation. Therefore, the overall effect is ambiguous.

Prediction 3: Urban aging leads to more rural automation.

The effect of urban aging on rural machine adoption is determined by:

$$\frac{\partial M^{*R}}{\partial \bar{S}^U} = -A_L^R \frac{\partial L^{*R}}{\partial \bar{S}^U} > 0. \tag{3.16}$$

As urban aging attracts rural middle-aged workers to move to the urban sector, the loss of rural middle-aged workers promotes rural automation.

4 Data Sources and Measurements

In this section, we discuss the datasets used in the article and how we construct our measures on aging, industrial automation, and agricultural mechanization. We also introduce the differences between hukou-based population aging and resident-based population aging.

4.1 Population census and definition for aging

The main demographic data are from the population censuses and mini-censuses of China. Every 10 years since 1990, China's National Bureau of Statistics (NBS) has conducted a population census. We use microlevel censuses from 1990, 2000, and 2010 and the 1% National Population Surveys from 2005 and 2015, which are nationally representative surveys that are widely known as mini-censuses. Specifically, we have access to a 1% sample of the 1990 census, a 0.95% sample of the 2000 census, a 20% sample of the 2005 population survey, a 0.35% sample of the 2010 census, and a 9.4% sample of the 2015 population survey. These data are well suited to describing broad country-wide patterns for population and workforce aging, changes across sectors and regions, and various prefecture-to-prefecture migration flows constructed according to migrants' hukou statuses, age groups, and educational levels in China.

Our definition of aging is the ratio of the older population (56 and older) to the middle-aged population (between 21 and 55) throughout the article. The choice of 55 years of age as the cutoff is motivated by the substitution patterns between robots and workers as discussed in Acemoglu and Restrepo (2022). We construct the aging variables by using the population censuses and mini-censuses of China. For each prefecture, our computation on local population aging is based on hukou instead of individuals' residential prefecture, as discussed in Section 2.3. This is mainly because each person in China is assigned to a unique administrative unit as his/her official "permanent" residence under the hukou system, and thus, the hukou-based age structure is a more suitable measure of local labor supply relative to the age structure measured from the population living in a region, which includes local residents and temporary migrants. Hence, our hukou-based measure of population aging should be interpreted as a measure of local demographic structures before migration.

4.2 Data and measurements on industrial automation

We use three sources of data to measure industrial automation in China: data on the use of industrial robots from the IFR, data on the capital-labor ratio by industrial firms from ASIF, and data on imports of robots and other types of machinery and equipment from China's customs.

First, we use data on robot adoption from the IFR, which compiles information on robots by surveying global robot suppliers. The IFR data, which have covered 50 countries since 1993, consist of counts of robot installation and operational stock by industry, country, and year. For China, the IFR has collected country-level data since 1999 and reported industry-specific data after 2006. The industry-level data cover six broad nonmanufacturing industries: agriculture, forestry, and fishing; mining; utilities; construction; education, research and development; and services. Within manufacturing, the IFR covers 13 disaggregated industries: food and beverages; textiles (including apparel); wood and furniture; paper and printing; plastics, chemicals, and pharmaceuticals; glass and nonmetals; basic metals; metal products; metal machinery; electronics; automotive; other vehicles; and miscellaneous manufacturing (e.g., production of jewelry and toys).

Our robot data from the IFR are reported at the industry level, and there are 19 Chinese industries in our IFR sample. Using the data, we construct the prefecture-level adoption of industrial robots as a measure of industrial automation in China. In doing so, we exploit the variation in the distribution of industrial employment in the initial year across industries and the variation in the penetration of robots across industries. Specifically, the prefecture-level penetration of industrial robots is constructed as the summarized interaction of the initial industry employment intensity and the changes in the adoption of industrial robots at the industry level. Formally:

$$\Delta Robot\,adoption_p = \sum_{i \in \Phi} \left(\frac{Emp_{pi}^{initial}}{\sum_i Emp_{pi}^{initial}} \frac{\Delta\, Robot\,adoption_i}{\sum_p Emp_{pi}^{initial}} \right), \tag{4.1}$$

where $Emp_{pi}^{initial}$ is the total number of workers employed in industry i in prefecture p in the initial year (in one thousand workers per unit). Φ refers to the set that includes all IFR industries. We calculate three five-year-interval changes in the adoption of industrial robots over the 2000–2005, 2005–2010, and 2010–2015 periods. The choices of initial years are 2000, 2005, and 2010 for the periods, respectively. We also compute a long interval change in the adoption of industrial robots over the 2000–2015 period, and use the year 2000 as the initial year for the period to compute the total number of workers employed in industry i in prefecture p. $\Delta\, Robot\,adoption_i$ is the change in the total number of industrial robots in use in industry i over a period. Given that our robot data from IFR start in 2006, we use the changes in the total number of industrial robots between 2006 and

2010 as a proxy to calculate the $\Delta Robot\,adoption_i$ over the 2005–2010 period. Moreover, since almost no robots were in use in 2000, we use the level of the total number of industrial robots in 2006 and 2015 as a proxy for the $\Delta Robot\,adoption_i$ over the 2000–2005 and 2000–2015 periods. Hence, for each period of 2000–2005, 2005–2010, 2010–2015, and 2000–2015, we construct a measure of the change in the adoption of industrial robots per thousand workers over the period.

Second, we use the ASIF data to calculate the average capital-labor ratio of industrial firms for each Chinese prefecture. The ASIF data provide the most comprehensive and representative firm-level dataset covering all industrial firms that are above the designated size in China. The data were collected by the National Bureau of Statistics of China, which includes all state-owned firms and nonstate firms with sales exceeding 5 million RMB.[9] These firms contribute to the majority of China's industrial sales, employment, exports, and value added (Brandt, Van Biesebroeck and Zhang, 2014). The dataset contains detailed information on each firm's industry affiliation and location, firm ownership, capital structure, assets and debts, various dimensions of output, such as sales value and profits, and various dimensions of input, such as employment and wages. It is used to calculate matrices in the national income account (e.g., GDP) and major statistics published in China's Statistical Yearbooks.

In the present literature, capital deepening is often used as a measure of technological change (e.g., Krusell, Ohanian, Ríos-Rull and Violante, 2000). The ASIF covers a wide range of industrial industries. Therefore, we aggregate the firm-level data to the level of the prefecture to compute a prefecture's capital-labor ratio as a proxy for local industrial investment in traditional technology. We compute the variables for 2000, 2005, 2010, and 2015. Among them, we use the 2009 ASIF as a proxy for that in 2010 due to data limitation.[10]

Finally, we complement the ASIF data with information on the imports of machinery and equipment from the trade statistics obtained from China's customs. The customs data consist of records of the universe of exports and imports through China's customs at the product level. We focus on firms' imports of products of machinery and equipment in 2000, 2005, 2010, and 2015. According to China's product classifications under the Harmonized System (HS) two-digit level, these products are classified into Chapter 84 and include nuclear reactors, boilers, machinery, and mechanical appliances. Our customs data include detailed information on importers' firm names, addresses, and telephone numbers, thus enabling us to aggregate the firm-level data to the prefecture level. We compute the changes in the values of imported machinery and equipment per worker in a logarithm and merge the import variables with the variables on aging and others. Hence, we use the average changes in the prefecture-level value of imported machinery and equipment per worker as an alternative measure of industrial automation in China.

4.3 Data and measurements on agricultural mechanization

Our measure of agricultural mechanization is the adoption of machinery and equipment per mu in agricultural production.[11] We use three variables to measure agricultural mechanization: log power of agricultural machines per mu, log number of agricultural machines per mu, and machin-

[9] At the exchange rate of 8.27 RMB per USD (between January 1997 and July 2005), this amount is equivalent to approximately 600,000 USD.

[10] We have access to the ASIF data ranging from 1998 to 2015. However, the 2010 data has no information on firms' identification numbers and addresses and thus we use the 2009 data as a proxy for the 2010. Our estimates remain robust if we drop the year 2010.

[11] Mu is a Chinese unit of land measurement, which is equivalent to 0.165 acres or 666.5 square meters.

ery quality defined as the ratio of the total mechanical power to the total number of machines. We calculate these variables by using the NFS. The nationally representative NFS is an annual survey that has been conducted by the Research Center of Rural Economy of the Chinese Ministry of Agriculture since 1986. We use the rounds in 2000, 2005, 2010, and 2015 to construct panel data, which allow an investigation of agricultural mechanization by focusing on (almost) the same households over time. Finally, we aggregate the nationally representative household-level data to the prefecture level as a measure of local average agricultural mechanization. Benjamin, Brandt and Giles (2005) provide a discussion of the NFS data in greater detail. Appendix B provides summary statistics of the main variables in our empirical analysis.

4.4 Additional data sources

We use several other data sources to obtain control variables. Variables on firm characteristics include the average firm age, average sale value, interest payment, and the share of state-owned enterprises (SOEs) at the prefecture level, and they are constructed from the ASIF data. Prefecture characteristics include GDP per capita, local average wage,[12] sex ratio, urbanization rates, and the skill composition of the local workforce. Among them, GDP per capita and local average wage are from China City Statistical Yearbooks, and the remaining three variables are constructed from the population censuses and mini-censuses of China. We also use variables on lagged age structures and fertility policy to predict aging. Lagged age structure variables are constructed using population censuses and mini-censuses. The fertility policy variables from Ebenstein (2010) include at-birth fines for extra births, the amount of a one-child bonus, punishment for higher-order births, and policy rules for fertility (the number of free-of-fine children allowed for each couple in a province).

5 Urban Aging and Industrial Automation

In this section, we examine the effects of urban aging on industrial automation, which are measured by three different variables. The three variables include the adoption of industrial robots, the capital-labor ratio, and the value of imported machinery and equipment. Overall, we find little evidence supporting a positive association between urban aging and industrial automation.

5.1 Empirical framework: OLS specification

Middle-aged workers (between 21 and 55 years old) have a comparative advantage in manual tasks that require physical activity and dexterity and are thus more prone to automation than older workers (56 years old and above) (Acemoglu and Restrepo, 2022). To test the impact of urban aging on industrial automation, we estimate the following regression model that relates industrial automation to the aging of the urban population across Chinese prefectures:

$$\Delta Y_p = \beta_1 \Delta Urban\ aging_p + \gamma_1 \Delta \mathbf{Z_p^{firm}} + \gamma_2 \Delta \mathbf{Z_p^{pref}} + \epsilon_p. \tag{5.1}$$

[12] We use the average wage of workers employed in the public sector as a proxy for local wage. To our best knowledge, this wage is the only annual wage at the prefecture level that is available in China.

Here, ΔY_p is the change in industrial automation in prefecture p over a period, which is measured by three variables: change in the number of industrial robots (per thousand workers), change in capital-labor ratio in log, and change in the value of imported machinery and equipment in log. We first estimate the long first differences model for the whole interval between 2000 and 2015. Next, we stack the five-year equivalent first differences for the three periods, namely, 2000 to 2005, 2005 to 2010, and 2010 to 2015, and pool all the five-year differences together to fit the model. $\Delta Urban\ aging_p$ is the change in the ratio of the hukou-based older urban population (aged 56 or above) to the urban middle-aged population (aged between 21 and 55) over a corresponding period. We control for the prefecture-level average changes in firm characteristics and average changes in prefecture characteristics in vectors $\Delta \mathbf{Z}_\mathbf{p}^\mathbf{firm}$ and $\Delta \mathbf{Z}_\mathbf{p}^\mathbf{pref}$ over corresponding periods. We cluster standard errors at the level of the prefecture in all stacked differences regressions. ϵ_p is the error term.

While the first differences, firm controls, and prefecture controls alleviate some concerns about omitted variable bias, they cannot completely eliminate endogeneity. In the next subsection, we discuss the potential concerns about endogeneity and how we construct the expected urban aging as an IV to address the potential concerns.

5.2 Instrument construction

The main threat to the validity of our analysis is the issue of omitted variables, which may contaminate our identification. First, our measure of urban aging may proxy for other concurrent factors, such as the skill composition of the local workforce, the sex composition of the local population, or urbanization rates. Our main specifications already include local changes in the average skill composition of the workforce, changes in the average sex composition of the population, and changes in the average urbanization rates. We also include the local average wage to account for labor costs. Moreover, we control for the changes in GDP per capita (in log), which can absorb local shocks to demand. To address the omitted variables concern from heterogeneous firms further, we include the changes in average firm age, average sale value, interest payment, and the share of SOEs.

However, there may still be some variables that are difficult to observe and are out of our control. For example, the observed population aging in urban China may be correlated with local productivity shocks.[13] In this case, the OLS estimate of how increased urban aging affects China's industrial automation may overstate the true impact if local technology adoption and demographic changes are positively correlated with unobserved shocks to local changes in productivity. To identify the causal effect of demographic changes on the adoption of automation technologies, we employ an IV strategy that accounts for the potential endogeneity of local urban aging.

Our IV strategy relies on relatively exogenous determinants of demographic structures to predict a region's hukou-based observed aging. China provides a helpful setting where its controversial fertility control policies lasted for more than three decades and dramatically altered demographic structures exogenously (Huang, Lei and Zhao, 2016; Zhang, 2017; Huang, Lei and Sun, 2021). China has implemented stringent fertility policies to control its population since the 1970s. However, these policies vary across provinces and across rural and urban areas. For example, rural households in 17 provinces were permitted to have a second child if their first child was a girl, whereas in some other provinces, such as Hainan and Guangdong, residents in rural regions were allowed to have two children regardless of the sex of the first. In urban areas of some provinces, couples were allowed to

[13]Imagine that local productivity shocks affect the proportion of local middle-aged workers through permanent migration.

have a second child if both parents were the only children of their parents themselves; but in most other cases they were restricted to one child (Zhang, 2017).

To achieve population control, China's central government introduced an incentive system that rewarded couples who observed the policies and penalized those who did not. Families with out-of-planning births would be imposed heavy at-birth fines, which were euphemistically called "social service expenditures." The fines, depending on the region, varied from approximately 370 to 12,800 Yuan (many times the average annual income for most Chinese).[14] If couples failed to pay a fine, the child could not be registered in the national household system, which entailed that they did not exist legally and thus would not have access to social services, such as public education. Moreover, couples adhering to fertility policies could receive various bonuses and premiums. For example, parents who had only one child would receive a "one-child glory certificate," which entitled them to economic benefits, such as an extra month's salary every year until the child was 14. They also had access to priority in school enrollment and new housing for urban households with family members working in the public sector.

Fertility policies vary across Chinese provinces and across rural and urban areas, allowing us to predict the local cohort size of future working-age populations. Ebenstein (2010) provides a detailed discussion of the construction of the policy variables, including at-birth fines for extra births, amount of one-child bonus, premium punishments to higher-order births, and policy rules for fertility (the number of free-of-fine children allowed for each couple in a province).[15] Specifically, we use the fertility policy variables and the hukou-based age structure of the local population five years ago to predict urban aging as our instrument, as discussed below.

We use various at-birth fertility policies and lagged demographic structures to predict local aging for the urban population, rural population, and prefecture population, and use the predicted aging as the IVs of the corresponding observed local aging variables to address the potential concern about endogeneity. Specifically, to construct the IVs, we estimate the following zero-stage equation by regressing the variables of observed urban, rural, and prefecture aging separately on a set of corresponding at-birth fertility policies variables and lagged demographic structure variables.[16] The inclusion of demographic structures from five years ago in our prediction, which represents the mechanical prediction of population aging, can help absorb the changes in aging from permanent migration (i.e., the inflow or outflow of migrants with a hukou change) and mortality-induced changes in local aging over the past five years, both of which may be correlated with local technology adoption and other outcome variables of interest. Formally, our zero-stage equation for predicting aging is as follows:

$$Y_{pt} = \beta_0 + \beta_1 Age\ structure_{p,t-5} + \mathbf{\Gamma X_{prov,t-20}} + \epsilon_{pt}. \tag{5.2}$$

Here, Y_{pt} is the observed local urban aging, rural aging, or prefecture aging, which are defined as the corresponding ratio of the urban, rural, or the whole prefecture population aged 56 and above to those aged between 21 and 55 in prefecture p at year t, respectively. $Age\ structure_{p,t-5}$

[14] See a discussion on the history of the One Child Policy and its impact on China from https://factsanddetails.com/china/cat4/sub15/item128.html.

[15] According to Ebenstein (2010), the enforcement of China's One Child Policy includes three variations: one-child policy, two-child policy, and one-and-a-half child policy. The "one-and-a-half child" policy refers to provinces with the policy that rural couples were permitted to have two children if the first was a girl.

[16] Although the zero-stage strategy is not necessary to construct and use our instrument, it is intuitively helpful for understanding the sources of the variation of our instrument. Additionally, we are not the first study to use such a strategy for constructing IV and see Dreher and Langlotz (2020) for a similar approach.

is the corresponding ratio of the population aged 51 and above to those aged between 16 and 50 constructed by using population censuses or mini-censuses conducted in year $t-5$.[17] $\mathbf{\Gamma X_{porv,t-20}}$ is a vector of province-level characteristics on China's fertility policies in province *prov* at year $t-20$. The fertility policies, which were taken from Ebenstein (2010), include at-birth fines for extra births, amount of one-child bonus, premium punishments to higher-order births, and policy rules for fertility (the number of free-of-fine children allowed for each couple in a province).

Table 1: Zero-stage OLS estimates: Effects of lagged age structure and fertility policy on aging

Dependent Var.:	Rural aging	Urban aging	Prefecture aging
	(1)	(2)	(3)
lagged rural age structure	0.699***		
	(0.023)		
lagged urban age structure		0.284***	
		(0.047)	
lagged prefecture age structure			0.664***
			(0.022)
premium punishments to higher-order births	0.016***	0.031***	0.013***
	(0.004)	(0.005)	(0.004)
at-birth fines for extra births	0.016***	0.007**	0.009***
	(0.002)	(0.003)	(0.002)
amount of one-child bonus	0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
policy rules for fertility	-0.046***	-0.066***	-0.042***
	(0.008)	(0.009)	(0.007)
Observations	1331	1331	1331
R^2	0.670	0.331	0.680

Notes: OLS estimates are reported. The dependent variables are observed urban aging (the ratio of the urban population aged 56 and above to those aged between 21 and 55), observed rural aging (the ratio of the rural population aged 56 and above to those aged between 21 and 55), and observed prefecture aging (the ratio of the prefecture population aged 56 and above to those aged between 21 and 55) in Columns 1-3, respectively. Lagged age structures for rural, urban, and prefecture populations are respectively defined as the ratio of rural, urban, and prefecture aging of five years ago (the corresponding populations above 51 to those aged between 16 and 50 in year $t-5$), and these variables are constructed from population censuses and mini censuses. At-birth fines for extra births, amount of one-child bonus, premium punishments to higher-order births, and policy rules for fertility are province-level variables on fertility policy from Ebenstein (2010). The regressions use data from four rounds of population censuses and mini-censuses in 2000, 2005, 2010, and 2015. * p<0.1; ** p<0.05; *** p<0.01.

Estimates of the zero-stage equation 5.2 are reported in Table 1. Columns 1–3 use different outcome variables to estimate the effects of the hukou-based local age structures five years ago and the fertility policies twenty years ago on observed rural aging, urban aging, and prefecture aging, respectively. In all three columns, we find that rural, urban, and prefecture aging are positively associated with the age structure variables of five years ago, as expected. We also find that these aging variables are associated with most of the fertility policies of twenty years ago. With these estimated coefficients in hand, we calculate the predicted rural, urban, and prefecture aging for each prefecture in a year. Then, we use the predicted aging to calculate the predicted changes in population aging over various periods as our IVs, that is, local changes in expected aging. In the next subsection, we use the IVs to estimate the effects of urban aging on local technology adoption. The identifying assumption for the IV estimates below is that the expected aging affects industrial automation mainly through the channel of observed population aging instead of others.

[17] Hence, we use the age structures in 2000, 2005, and 2010 to predict the aging variables for 2005, 2010, and 2015, respectively. However, for 2000, we use the age structure of 1990, i.e., the ratio of the population aged 46 and above to those aged between 11 and 45 for prediction because mini-census data from 1995 are not available.

5.3 Estimation results

We now turn to the estimates of the effect of urban aging on industrial automation. China is becoming the world's leading buyer of robots. Therefore, our empirical analysis begins with estimating the effect of urban aging on the adoption of industrial robots across Chinese prefectures. Table 2 presents initial estimates of the relationship between changes in urban aging and changes in industrial automation when the outcome variable is the prefecture-level changes in industrial robots, as discussed in Section 4.2. Using the (almost) full sample of 296 prefectures and weighting each observation by the number of individuals the prefecture represents, we fit the models of equation 5.1. We estimate the long first differences model for the whole long interval between 2000 and 2015 and present the results in Panel A of Table 2. The fifteen-year-difference model is equivalent to a fixed effects regression with data from 2000 and 2015.

In Panel B of Table 2, we stack the five-year equivalent first differences for the three periods, namely, 2000–2005, 2005–2010, and 2010–2015, and include separate time dummies for each five-year interval.[18] The five-year-specific models are similar to a four-period fixed effects model with slightly less restrictive assumptions made on the error term, as discussed in Wooldridge (2010).[19] Additionally, the vectors $\Delta \mathbf{Z}_{\mathbf{p}}^{\mathbf{firm}}$ and $\Delta \mathbf{Z}_{\mathbf{p}}^{\mathbf{pref}}$ represent a set of controls for local firms' changes in average age, average sale value, and interest payment, and a set of prefectures' changes in GDP per capita in log, the local average wage in log, sex ratio, urbanization rates, and the skill composition of the local workforce, respectively. Standard errors are clustered at the prefecture level in stacked first differences models to account for spatial correlations across prefectures in all estimates.

In each panel, the first two columns are for the IV estimate of equation 5.1 by instrumenting the changes in observed urban aging with the changes in expected urban aging at the prefecture level. The following two columns provide the reduced form (RF) estimates from regressing the changes in the stock of industrial robots per thousand workers directly on the instrument. As shown, changes in urban aging in the local labor market are negatively associated with the changes in the adoption of industrial robots, while the effects are less precisely estimated in Panel B. The first stages of the IV are highly significant (the F-statistic is larger than 13 in each column). The estimated negative association appears to be robust either for the long first differences over the whole period of 2000–2015 or for the stacked five-year first differences models. However, the latter tend to be less precisely estimated. This finding is in contrast to the evidence presented in Acemoglu and Restrepo (2022), who find that population aging leads to greater adoption of robots in the United States. One potential explanation for the discrepancy is that Chinese firms still rely on conventional automation technologies, such as machinery and equipment, and below we test the conjecture.

To examine whether a firm's technology adoption beyond robots is associated with urban aging, we use the ratio of fixed capital to the number of employed workers as a measure of technology adoption. The capital-labor ratio variable at the prefecture level is constructed by using the ASIF data, as discussed in Section 4.2. Table 3 displays estimates of the relationship between changes in urban aging and changes in the local average capital-labor ratio across Chinese prefectures. Similar to Table 2, Panel A and Panel B of Table 3 provide first differences estimates for 2000–2015 and stacked five-year first differences estimates, respectively. In each panel, the first two columns are for

[18] Our results remain stable if we drop the time dummies.

[19] Estimating a five-year equivalent first differences model of Equation 5.1 would be more efficient if the errors were a random walk. Meanwhile, estimating a fixed-effects model of the same equation requires the assumption that the errors are serially uncorrelated. See Wooldridge (2010) for a discussion. Additionally, our results are similar in either case.

Table 2: Effect of urban aging on the adoption of industrial robots

	IV estimates		RF estimates	
	(1)	(2)	(3)	(4)
Panel A, 2000–2015 simple first differences				
Dependent var.: changes in the stock of industrial robots per thousand workers				
Change in urban ageing	-0.010***	-0.010***		
	(0.004)	(0.004)		
Change in expected urban ageing			-0.011***	-0.011***
			(0.004)	(0.004)
Change in average firm characteristics	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	13.667	13.667		
R^2			0.045	0.045
N	296	296	296	296
Panel B, 2000–2015 stacked first differences				
Dependent var.: changes in the stock of industrial robots per thousand workers in every five-year interval				
Change in urban ageing in every five-year interval	-0.170	-0.170		
	(0.163)	(0.163)		
Change in expected urban ageing in every five-year interval			-0.232	-0.232
			(0.215)	(0.215)
Change in average firm characteristics	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	19.956	19.956		
R^2			0.005	0.005
N	885	885	885	885

Notes: 2SLS and RF regressions. The table presents IV estimates, and reduced form (RF) results from regressing the change in outcome variable directly on the changes in expected urban aging (i.e., our instrument). Urban aging is defined as the ratio of the urban population aged 56 and above to those aged between 21 and 55. Our instruments are the fifteen-year changes in expected urban aging over the 2000–2015 period in Panel A, and five-year changes in expected urban aging in Panel B. In all Panels, the dependent variable is the changes in the stock of industrial robots per thousand workers. The changes are defined as the changes in the ratio of the stock of industrial robots normalized by industrial employment in 2000 for the 2000–2015 period and the 2000–2005 period, 2005 for the 2005–2010 period, and 2010 for the 2010–2015 period. Firm characteristics include the average firm age, average sale value, interest payment, and the share of SOEs at the prefecture level. Prefecture characteristics include GDP per capita in log, the local average wage in log, sex ratio, urbanization, and the skill composition of the local workforce. Regressions are weighted by cell population. Standard errors are clustered at the prefecture level and reported in parentheses. *p <0.1, ** p <0.05, *** p <0.01.

the IV estimate, which is obtained by instrumenting the changes in observed urban aging with the changes in expected urban aging, as discussed in Section 5.1. The following two columns are for the RF results from regressing the changes in the capital-labor ratio in log directly on the instrument. As shown, though the coefficients tend to be positive for the IV estimates in Panel A, they become negative for the RF estimates in Panel B, and in all columns, the coefficients are statistically insignificant. These results further confirm the previous finding that industrial automation has received a limited boost from demographic changes in China.

Table 3: Effect of urban aging on capital-labor ratio

	IV estimates		RF estimates	
	(1)	(2)	(3)	(4)
Panel A, 2000–2015 simple first differences				
Dependent var.: changes in capital-labor ratio between 2000 and 2015 in log				
Change in urban aging between 2000 and 2015	0.011	0.011		
	(0.011)	(0.011)		
Change in expected urban aging between 2000 and 2015			0.009	0.009
			(0.009)	(0.009)
Change in average firm characteristics	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	13.397	13.397		
R^2			0.0004	0.0004
N	286	286	286	286
Panel B, 2000–2015 stacked first differences				
Dependent var.: changes in capital-labor ratio in every five-year interval in log				
Change in urban aging in every five-year interval	-0.048	-0.048		
	(0.092)	(0.092)		
Change in expected urban in every five-year interval			-0.040	-0.040
			(0.075)	(0.075)
Change in average firm characteristics	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	19.427	19.427		
R^2			0.002	0.002
N	920	920	920	920

Notes: 2SLS and RF regressions. The table presents IV estimates, and reduced form (RF) results from regressing the changes in outcome variable directly on the changes in expected urban aging (i.e., our instruments). Urban aging is defined as the ratio of the urban population aged 56 and above to those aged between 21 and 55. Our instruments are the fifteen-year changes in expected urban aging over the 2000–2015 period in Panel A, and five-year changes in expected urban aging in Panel B. The dependent variable is the changes in the capital-labor ratio in log at the prefecture level. Firm characteristics include the average firm age, average sale value, interest payment, and the share of SOEs at the prefecture level. Prefecture characteristics include GDP per capita in log, the local average wage in log, sex ratio, urbanization, and the skill composition of the local workforce. Regressions are weighted by cell population. Standard errors are clustered at the prefecture level and reported in parentheses. *p <0.1, ** p <0.05, *** p <0.01.

A major source of machinery and equipment is the global market. This source may be particularly important for China, where technology lags behind the world frontier of machinery production from 2000–2015. Thus, we also exploit local imports of machinery and equipment from the rest of the world as an alternative measure of automation to further explore the effect of the changes in urban aging on the changes in technology adoption. As discussed in Section 4.2, we use China's customs data to extract all import records on machinery and equipment, which are classified into Chapter 84 according to China's product classifications under the HS. Next, we aggregate these firm-level imports to the level of the prefecture and compute local average changes in the values of imported machinery and equipment per worker in log form. Finally, we use the average changes in the machinery and equipment imported as the outcome variable to repeat the Table 3 estimates.

Table 4 displays the estimated effect of the changes in urban aging on changes in the average value of imported machinery and equipment per worker in log. Similar to Table 2 and Table 3, Panel A and Panel B of Table 4 provide the first differences estimates for 2000–2015 and the stacked five-year first differences estimates, respectively. In each panel, Columns 1–2 are for the IV estimates, and the following two columns are for the RF estimates, which are obtained by regressing the changes in the average value of imported machinery and equipment per worker in log directly on the instrument. These results show that the effects of the changes in urban aging in the local labor market on the changes in imported machinery and equipment per worker by local firms are less precisely estimated in all columns, though the effects appear to be positive. Overall, we find little evidence that supports a positive and significant association between changes in local aging and changes in imported machinery and equipment by local industrial firms from 2000–2015.

Table 4: Effect of urban aging on imports of machinery and equipment

	IV estimates		RF estimates	
	(1)	(2)	(3)	(4)
Panel A, 2000–2015 simple first differences				
Dependent var.: changes in values of import of machinery and equipment between 2000–2015 in log				
Change in urban aging between 2000 and 2015	3.770	3.770		
	(2.744)	(2.744)		
Change in expected urban aging between 2000 and 2015			3.853	3.853
			(2.896)	(2.896)
Change in average firm characteristics	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	9.407	9.407		
R^2	0.026	0.026	0.007	0.007
N	202	202	202	202
Panel B, 2000–2015 stacked first differences				
Dependent var.: changes in the values of imported machinery and equipment in every five-year interval in log				
Change in urban aging in every five-year interval	2.338	2.338		
	(3.023)	(3.023)		
Change in expected urban aging in every five-year interval			2.888	2.888
			(3.607)	(3.607)
Change in average firm characteristics	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	11.978	11.978		
R^2	0.041	0.041	0.011	0.011
N	527	527	527	527

Notes: 2SLS and RF regressions. The table presents IV estimates, and reduced form (RF) results from regressing the changes in outcome variables directly on the changes in expected aging (i.e., our instruments). Urban aging is defined as the ratio of the urban population aged 56 and above to those aged between 21 and 55. Our instruments are the fifteen-year changes in expected urban aging over the 2000–2015 period in Panel A, and five-year changes in expected urban aging in Panel B. The dependent variable is the changes in values of import of machinery and equipment per worker in log at the prefecture level. Firm characteristics include the average firm age, average sale value, interest payment, and the share of SOEs at the prefecture level. Prefecture characteristics include GDP per capita in log, the local average wage in log, sex ratio, urbanization, and the skill composition of the local workforce. Regressions are weighted by cell population. Standard errors are clustered at the prefecture level and reported in parentheses. *p <0.1, ** p <0.05, *** p <0.01.

One major concern regarding the effect of population aging on the Chinese economy is the end of cheap labor, which can increase labor costs for firms (Li, Li, Wu and Xiong, 2012). However, we find no evidence that an increasing urban ratio of older to younger workers is associated with greater adoption of industrial automation across Chinese prefectures, either the adoption of industrial robots or more conventional technologies as measured by the capital-labor ratio of industrial firms or the imported machinery and equipment from the rest of the world.

To further explore whether the responses of technology adoption to urban aging vary by geography. In Appendix C, we examine the effects of urban aging on industrial automation across East, Central, and West China, respectively.[20] In doing so, we still use the changes in the stock of industrial robots per thousand workers, the changes in the capital-labor ratio in log, and the changes in the values of imported machinery and equipment per worker in log to measure industrial automation. Then, we repeat the stacked five-year first differences estimates for each region.[21] Table C.1 presents the IV estimates by instrumenting the five-year changes in observed urban aging by the changes in expected urban aging in every five-year interval.

Indicative evidence suggests that the effects of urban aging on the capital-labor ratio and the imports of machinery and equipment are positive but statistically insignificant in the coastal (east) provinces, whereas the effects on industrial robots are negative and insignificant. In contrast, in the inland (central and west) provinces, the estimated effects are negative in most columns. Overall, these cross-region results are consistent with our previous finding that industrial automation has received a limited boost from demographic changes in urban China.[22]

Overall, these results are consistent with our model from which we derive the prediction that urban aging's effect on nonagricultural automation is ambiguous in a dual economy, and thus, the effect is an empirical issue. However, our empirical finding is different from the cross-country evidence presented in Acemoglu and Restrepo (2022), who argue theoretically and document empirically that aging leads to a greater adoption of robots in developed countries, most notably the United States, Japan, Germany, and South Korea. Understanding the potential mechanism that leads to the discrepancy between China and major developed countries is one of the major contributions of this work. One potential explanation is that labor still remains cheaper than robots in China compared with developed countries. Therefore, Chinese firms have less incentive to replace labor with robots or other more conventional technology as the population ages quickly. The relative advantage of labor over robots and other technologies may reflect a positive effect of urban aging on induced inflows of middle-aged workers into the urban areas, as rationalized in our model in Section 3. We will empirically test the prediction in the next section.

6 Urban Aging and Bilateral Migration Flows

In this section, we examine how demographic changes at the originating prefecture and the destination prefecture affect bilateral migration flows. We also explore a series of heterogeneous effects that, as discussed below, shed light on important characteristics that are associated with migrants' response to population aging at the prefecture of destination and at the originating prefecture that is sending migrants. To estimate a causal effect, we follow the previous IV strategy to construct predicted population aging as our IV and employ a simple reduced-form gravity equation of migration, which is similar to the gravity model that is widely used in the international trade literature (Krugman, 1980; Yu, 2010). Migrations from an originating prefecture to a destination prefecture at a given time depend on (i) a push factor, which causes migrants to leave the prefecture of origin, and (ii) a pull factor, which causes migrants to move into that prefecture of destination.

[20] East China includes 10 provinces and municipalities: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Central China consists of 9 provinces: Heilongjiang, Jilin, Liaoning, Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. West China contains the remaining 12 provinces and municipalities: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

[21] We find also no evidence that urban aging significantly increased local industrial automation across regions if we estimate a simple first differences model over the 2000–2015 period.

[22] Note that our instruments are weak in some columns in Table C.1 and therefore the evidence should be interpreted with caution.

Formally, to evaluate how aging at the destination prefecture and sending prefecture affects the prefecture-to-prefecture migration flows, we estimate the following gravity equation of migration:

$$lnMigrant_{pqt} = \beta_0 + \beta_1 Aging\_dest_{qt} + \beta_2 Aging\_orig_{pt} + \gamma_1 \mathbf{Z_{pt}} + \gamma_2 \mathbf{Z_{qt}} + \delta_{pq} + \eta_t + \epsilon_{pqt}, \quad (6.1)$$

where p and q represent prefecture-level origin and destination of migration flows and t represents the year. $lnMigrant_{pqt}$ is the number of workers moving from prefecture p to prefecture q in year t in log, which is constructed by using data from the population censuses and mini-censuses. Our key independent variables are aging in the destination prefecture, $Aging\_dest_{qt}$, and aging in the originating prefecture, $Aging\_orig_{pt}$. Given that cities are major destinations of migration in China (Chan, 2013), we use urban aging as a measure of destination aging, which is defined as the ratio of the hukou-based urban population aged 56 and above to those aged 21–55 of the destination prefecture. Aging at the originating prefecture is defined as the ratio of the population aged 56 and above to those aged 21–55 by using the whole population in a prefecture of origin.

To guard against a wide range of possible confounding factors besides demographic changes, we control for origin-specific push factors. These factors include GDP per capita in log, the local average wage in log, the sex ratio of the local population (the ratio of males to females), urbanization rates (the ratio of urban population to total population), and the skill composition of local workforce (the ratio of workers with high school education and below to those with education above high school). Similarly, we also control for destination-specific pull factors by using five similar variables constructed by using population at the destination prefecture. $\mathbf{Z_{pt}}$ and $\mathbf{Z_{qt}}$ represent the five control variables at the sending and destination prefectures, respectively, in equation 6.1. We include the destination-origin fixed effects and year-fixed effects in all specifications. ϵ_{pqt} is the error term.

Table 5 reports the results from estimating equation 6.1. Column 1 shows the total impact of aging on bilateral migration flows using the log number of total migrants aged between 21 and 55 from prefecture p to prefecture q as the dependent variable. We focus on the migrants aged 21–55 because they, as middle-aged workers, have a comparative advantage in manual tasks that require physical activity and dexterity; thus, they are more prone to automation than those who are older (aged 56 and above), as documented in Acemoglu and Restrepo (2022). Columns 2–4 consider specific subgroups (migrants aged 12–30, 31–40, and 41–55). All estimates suggest that an increase in destination aging is associated with an increase in the number of migrants that flow into the prefecture, though estimates in some columns are less precise. However, the estimates for aging in the prefecture of origin tend to be less precise and not consistent in sign.

The estimated impact of destination aging on migration flows is most pronounced for the migrants aged 21–30, suggesting that younger migrants are more responsive to changes in the demographic structures of the destination. Moreover, the first stages of the IV estimates are highly significant, with the F-statistic being 236.14 in Table 5, relieving the concern of weak IV. The estimates are also sizable in magnitude. Focusing on our estimates in Column 1, everything else equal, one unit increase in urban aging is associated with a 3.12 percentage point increase in the log number of total migrants. With the average urban aging at the destination increasing by 0.09 from 2000 to 2015, prefectures facing the average increase in population aging experienced a 0.281 increase in the log number of total workers moving into the prefecture of destination, which represents a 16.32% increase in the average migration flows over the 2000–2015 period.

In Columns 5-8 of Table 5 we report RF estimates by regressing the log number of migrants in each age category directly on the instrument. Notably, in Columns 5–8, the variables for urban aging in the destination prefecture have the expected signs. However, they are smaller in magnitude possibly because of less variation in those expected urban aging variables. Increases in urban aging at the destination have a positive (and significant, except Column 8) impact on the inflow of migrants. The larger the increase in population aging at the destination is, the higher the increase in migrants moving into the prefecture will be. The estimated positive relationship is consistent with the IV estimates reported in Columns 1–4 of Table 5. A little surprisingly, aging in the prefecture of origin also tends to increase the outflow of migrants. However, the estimated coefficients are not significant in some columns and will become negative when we separately estimate the effects by the rural-urban divide as reported in Table 6.

Taken together, these estimates suggest that population aging at the destination substantially increases the inflow of migrants into the region, and push factors from the origin aging tend to be statistically less important in explaining migration flows. If automation technologies (such as robots) are strongly labor saving, the arrival of migrants will discourage the adoption of the technologies, even though increased labor scarcity induced by urban aging theoretically encourages automation. Our results suggest that the former effect dominates the latter, and thus, we find little evidence of an increase in industrial automation induced by urban aging in China.

Table 5: Effect of aging on bilateral migration flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV estimates				RF estimates			
	Age 21-55	21-30	31-40	41-55	Age 21-55	21-30	31-40	41-55
Urban aging at destination	3.120***	5.975***	3.082	2.135				
	(0.586)	(1.680)	(2.034)	(1.693)				
Prefecture aging at origin	1.442	-0.770	6.794***	2.325				
	(1.006)	(2.917)	(1.749)	(1.640)				
Expected urban aging at destination					0.837***	1.542***	0.919*	0.596
					(0.144)	(0.419)	(0.517)	(0.435)
Expected prefecture aging at origin					1.075*	0.062	4.096***	1.491
					(0.626)	(1.456)	(1.377)	(0.908)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-origin-pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-stat, $1^{st} Stage$	236.140	236.140	236.140	236.140				
R^2					0.486	0.070	0.080	0.135
N	54376	54376	54376	54376	56025	56025	56025	56025

Notes: 2SLS and RF regressions. The table presents IV estimates, and reduced form (RF) results from regressing the outcome variable directly on our instruments. Urban (prefecture) aging is defined as the ratio of the hukou-based urban (prefecture) population aged 56 and above to those aged between 21 and 55. Our instrument for urban aging at destination is the expected urban aging at destination and the instrument is constructed from equation 5.2. Similarly, our instrument for urban aging at origin is the expected urban aging at origin and the instrument is also constructed from equation 5.2. In Columns 1 and 4, the dependent variables are the log number of migrants aged between 21-55 plus one in a year. In Columns 2-4 and 5-8, the dependent variables are the log number of migrants aged between 21-30, 31-40, and 41-55, plus one, respectively. Control variables include GDP per capita in log, the local average wage in log, sex ratio, urbanization, and the skill composition of the local workforce at both the sending prefectures and the destination prefectures. Regressions are weighted by cell population. Standard errors are clustered at the prefecture level and reported in parentheses. *p <0.1, ** p <0.05, *** p <0.01.

Next, we examine whether aging has a differential effect depending on the hukou type of migrants (rural vs. urban hukou) and/or education levels of migrants (middle school and below vs. high school vs. college and above education). The heterogeneous analysis will shed light on whether the changes in internal migration we observe are driven mainly by certain types of migrants and, if so, of which types. We start by examining the heterogeneous effects on migrants by differentiating the hukou types of migrants. In doing so, we estimate a modified equation 6.1 by replacing the outcome variable of interest, $lnMigrant_{pqt}$, with the log number of rural and urban migrants, separately, from prefecture p to prefecture q at year t. When estimating the effect of aging on rural migration, we use the hukou-based rural population to compute origin aging (instead of the whole population in a prefecture). Similarly, we use the hukou-based urban population to construct the variable of origin aging and to estimate the effects of aging on urban migration. Moreover, no matter which type of migrants we try to estimate the effect of aging on, we always use urban aging as a measure of destination aging because cities are the major destinations of internal migration in China.

Table 6 presents the estimates for rural and urban migration separately. As shown in Column 1, although the inflows of rural and urban workers significantly increase with faster aging at the destination, the estimated effect of destination aging on the total inflow of rural migrants tends to be more pronounced than that of urban migrants, with estimated coefficients of 7.690 and 3.911, respectively. Columns 2-4 repeat the estimate of Column 1 of Table 6 but use more detailed categories of migrants by age groups (21–30, 31–40, and 41–55) as the outcome variables. These estimates further confirm the finding that destination aging spurs the inflow of rural and urban middle-aged workers into the prefecture. Meanwhile, rural workers tend to be more responsive to destination aging than urban migrants in almost all intervals of age.

We now turn to examine whether aging has a differential effect depending on the education levels of migrants. In doing so, we divide migrants into three categories of education (below high school, high school, and college and above education). Then, we re-estimate equation 6.1 by replacing the log number of bilateral migration flows with migration flows of the three types of education levels. As shown, the estimates for total migrants (those aged 21–55) in Columns 1 and 5 of Table 7 are the same as those in Table 5.

In Column 2 of Table 7, we start by focusing on migrants with only middle school and below education. In the following two columns, we focus on migrants with a high school education and those with a college education and above. In Columns 5–8, we estimate an RF specification by directly regressing the outcome variables of interest on our instruments to test the robustness of our results. Overall, destination aging induces a greater inflow of workers into the destination for those with various educational levels, while the estimates for those with the highest education levels are statistically insignificant. Notably, the effects of destination aging on the inflow of workers decline substantially as the education levels of migrants increase, suggesting that lower-skilled workers are more responsive to destination aging than high-skilled workers. Similar to previous results, the estimates on origin aging are not consistent in sign and are statistically insignificant in most columns.

Taken together, the results presented in Tables 5-7 suggest that destination aging increases the inflow of workers and that the effects are more pronounced for workers who have relatively low skills and come mainly from rural areas. Low-skilled and young workers are widely believed to be close substitutes for labor-saving technologies, such as robots and more conventional technologies. The accelerated arrival of these low-skilled and young rural workers following rapid urban aging may have attenuated the potential positive impact of urban aging on industrial automation. Thus, this evidence highlights the importance of induced change in rural-to-urban migration in shaping the effects of urban aging on industrial automation in a dual economy.

Table 6: Effect of aging on bilateral migration flows by rural-urban divide

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV estimates				RF estimates			
	Age 21-55	21-30	31-40	41-55	Age 21-55	21-30	31-40	41-55
Panel A. Dependent var.: the log number of migrants with agricultural hukou								
Urban aging at destination	7.690***	10.621***	1.212	3.791*				
	(1.936)	(2.167)	(2.383)	(2.050)				
Rural aging at origin	-2.780	-6.083	6.131	1.824				
	(4.071)	(4.043)	(4.305)	(2.925)				
Expected urban aging at destination					1.932***	2.611***	0.474	1.035**
					(0.459)	(0.520)	(0.595)	(0.518)
Expected rural aging at origin					-0.370	-1.252	2.105*	0.868
					(1.332)	(1.277)	(1.258)	(0.912)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-origin-pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-stat, $1^{st} Stage$	156.212	156.212	156.212	156.212				
R^2					0.155	0.137	0.117	0.148
N	54347	54347	54347	54347	56010	56010	56010	56010
Panel B. Dependent var.: the log number of migrants with nonagricultural hukou								
Urban aging at destination	3.911**	6.243***	2.526	-2.530				
	(1.721)	(2.051)	(1.648)	(1.622)				
Urban aging at origin	-2.836	-2.705	-2.136	-3.287*				
	(1.990)	(1.646)	(1.978)	(1.696)				
Expected urban aging at destination					0.966**	1.580***	0.618	-0.731*
					(0.452)	(0.543)	(0.440)	(0.439)
Expected urban aging at origin					-1.437	-1.301*	-1.094	-1.862
					(1.071)	(0.785)	(0.948)	(1.288)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-origin-pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-stat, $1^{st} Stage$	246.469	246.469	246.469	246.469				
R^2					0.074	0.054	0.041	0.063
N	54283	54283	54283	54283	55963	55963	55963	55963

Notes: 2SLS and RF regressions. The table presents IV estimates, and reduced form (RF) results from regressing the outcome variable directly on our instruments. Urban (rural) aging is defined as the ratio of the hukou-based urban (rural) population aged 56 and above to those aged between 21 and 55. In Panel A, our instrument for urban aging at destination is the expected urban aging at destination and the instrument is constructed from equation 5.2. The instrument for rural aging at origin is the expected rural aging at origin and it is also constructed from equation 5.2. In Panel B, the instrument for urban aging at destination is still the expected urban aging as the one used in Panel A, and the instrument for urban aging at origin is the expected urban aging at origin that is constructed from equation 5.2. In Panel A, the dependent variable is the log number of rural migrants aged between 21-55 plus one in a year in Columns 1 and 4, and in Columns 2-4 and 3-8 of Panel A, the dependent variables are the log number of the migrants aged between 21-30, 31-40, and 41-55, plus one, respectively. In Panel B, we calculate similar outcome variables but using urban migrants. Control variables include GDP per capita in log, local average wage in log, sex ratio, urbanization, and the skill composition of the local workforce at both the sending prefectures and the destination prefectures. Regressions are weighted by cell population. Standard errors are clustered at the prefecture level and reported in parentheses. *p <0.1, ** p <0.05, *** p <0.01

Table 7: Effect of aging on bilateral migration flows by education levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV estimates				RF estimates			
	All migrants	Middle school and below	High-school	College and above	All migrants	Middle school and below	High-school	College and above
Urban aging at destination	3.120***	7.612***	5.173**	1.065				
	(0.586)	(1.459)	(2.069)	(2.184)				
Prefecture aging at origin	1.442	0.705	-1.648	0.648				
	(1.006)	(2.593)	(1.839)	(1.796)				
Expected urban aging at destination					0.837***	1.993***	1.318**	0.288
					(0.144)	(0.383)	(0.514)	(0.566)
Expected prefecture aging at origin					1.075*	1.032	-0.501	0.455
					(0.626)	(1.386)	(0.876)	(1.050)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-stat, $1^{st} Stage$	236.140	236.140	236.140	236.140				
R^2					0.486	0.078	0.051	0.115
N	54376	54376	54376	54376	56025	56025	56025	56025

Notes: 2SLS and RF regressions. The table presents IV estimates, and reduced form (RF) results from regressing the outcome variable directly on our instruments. Urban (prefecture) aging is defined as the ratio of the hukou-based urban (prefecture) population aged 56 and above to those aged between 21 and 55. Our instrument for urban aging at destination is the expected urban aging at destination and the instrument is constructed from equation 5.2. Similarly, our instrument for urban aging at origin is the expected urban aging at origin and the instrument is also constructed from equation 5.2. In Columns 1 and 4, the dependent variable is the log number of migrants aged between 21-55 plus one in a year. In Columns 2-4 and 5-8, the dependent variables are the log number of migrants aged between 21-55 and with different education levels plus one: those with middle school, high school, and college and above education. Control variables include GDP per capita in log, the local average wage in log, sex ratio, urbanization, and the skill composition of the local workforce at both the sending prefectures and the destination prefectures. Regressions are weighted by cell population. Standard errors are clustered at the prefecture level and reported in parentheses. *p <0.1, ** p <0.05, *** p <0.01.

7 Beyond the Urban Sector: Urban Aging and Agricultural Development

The previous sections provide a range of evidence that urban aging accelerates the outflow of rural workers. Through the channel of induced movement of labor across sectors, urban aging may also affect the adoption of agricultural machinery and equipment, which is a substitute for manual labor. In what follows we construct a measure of rural households' exposure to urban aging and estimate the effect of urban aging on agricultural mechanization in China.

To investigate the effect of urban aging on agricultural mechanization, we estimate the following specification:

$$Y_{pt} = \beta_0 + \beta_1 Urban\ aging_{pt}^{weighted} + \beta_2 Rural\ aging_{pt} + \alpha \mathbf{Z_{pt}} + \delta_p + \eta_t + \gamma_{prov,t} + \epsilon_{pt}, \tag{7.1}$$

where p, t, and $prov$ represent prefecture, year, and province, respectively. Y_{pt} is the outcome variable on agricultural mechanization in prefecture p at year t and is measured by the total power of agricultural machines per mu in log and the total number of agricultural machines per mu in log.[23] We also use the average quality of agricultural machines (defined as the ratio of the total power over the total number of agricultural machines) as an alternative measure for agricultural mechanization. $Rural\ aging_{pt}$ denotes local rural aging, which is defined as the ratio of the hukou-based local rural population aged 56 and above to those aged 21–55 in a prefecture. $\mathbf{Z_{pt}}$ is a vector of prefecture characteristics that vary with time. It includes GDP per capita in log, the local average wage in log, sex ratio, urbanization rates, and the skill composition of the local workforce. We also include prefecture-fixed effects, year-fixed effects, and province-by-year fixed effects in all specifications.

Our key right-hand side variable is a weighted index that measures local rural households' exposure to urban aging, which is defined as:

$$Urban\ aging_{pt}^{weighted} = \sum_q \frac{Migrant_{pq2000}}{\sum_q Migrant_{pq2000}} (Urban\ aging_{qt}), \tag{7.2}$$

where $Migrant_{pq2000}$ represents the number of migrants that moved to prefecture q from prefecture p in 2000, which is the initial year of our study period. Our main measure of rural households' exposure to urban aging in prefecture p depends on the intensity of urban aging (ratio of the urban population aged 56 and above to those aged 21–55) at destination q, to which local rural workers migrate, and the shares of prefecture p's migration to prefecture q in 2000. Furthermore, to address the potential endogeneity, we use the following equation to construct our IV for $Urban\ aging_{pt}^{weighted}$:

$$Urban\ aging^{weighted}\_IV_{pt} = \sum_q \frac{Migrant_{pq2000}}{\sum_q Migrant_{pq2000}} (Expected\ urban\ aging_{qt}), \tag{7.3}$$

where $Expected\ urban\ aging_{qt}$ is estimated by using equation 5.2. Other variables are the same as those in Equation 7.2.

[23] Agricultural machines include various tractors, modern harvesters, planters, trailers, and others.

Panel A of Table 8 presents the IV results, which are obtained by instrumenting a rural region's exposure to destination aging ($Urban\ aging_{pt}^{weighted}$) with $Urban\ aging^{weighted}\_IV_{pt}$ from equation 7.3. Column 1 presents the estimated changes in the log power of agricultural machines per mu from estimating 7.1 and controlling for a battery of fixed effects. As shown, the adoption of agricultural machinery and equipment in total power increased significantly as rural workers moved out of the agricultural sector, which was accelerated by urban aging. Column 2 reports the estimated changes in the log number of agricultural machines per mu. These estimates suggest that rural regions exposed to larger urban aging experienced a larger increase in the total number of agricultural machines in log in 2000–2015. In Column 3, we report estimated changes in the quality of adopted agricultural machines. The estimates reflect an upgrading of the quality of machinery and equipment that were adopted in the agricultural sector following a larger exposure to urban aging in China.

Panel B of Table 8 further reports RF estimates by regressing agricultural mechanization directly on our instrument. These estimates produce results that are similar to those of Panel A. Overall, these results suggest that rural households in a prefecture that is exposed to larger urban aging have experienced a larger increase in shifting toward capital-intensive agriculture. In contrast, local rural aging appears to have a positive but insignificant impact on agricultural mechanization.

Table 8: Effect of urban aging on agriculture mechanization

	(1)	(2)	(3)
Panel A: IV estimates	total power of agr. machine in log	total number of agr. machine in log	machine quality
Destination-based urban aging	61.349**	34.802**	26.547**
	(24.870)	(15.069)	(12.996)
Local rural aging	1.846	1.300	0.546
	(1.979)	(1.404)	(1.595)
Control variables	Yes	Yes	Yes
Prefecture fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province-by-year fixed effects	Yes	Yes	Yes
K-P F-stat, 1^{st}	20.213	20.213	20.213
N	682	682	682
Panel B: RF estimates			
Destination-based expected urban aging	45.943***	26.062**	19.880*
	(16.561)	(10.995)	(10.150)
Local rural aging	1.860	1.309	0.552
	(2.413)	(1.862)	(2.048)
Control variables	Yes	Yes	Yes
Prefecture fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province-by-year fixed effects	Yes	Yes	Yes
R^2	0.819	0.834	0.778
N	715	715	715

Notes: 2SLS and RF regressions. The table presents IV estimates, and reduced form (RF) results from regressing the outcome variable directly on our instruments. Urban (rural) aging is defined as the ratio of hukou-based urban population aged 56 and above to those aged between 21 and 55. Our instrument for destination-based weighted aging is the destination-based weighted expected aging that is constructed by weighting the expected urban aging at the destination prefectures by migration shares of the prefecture of origin in the initial year. In Columns 1-3, the dependent variables are the log power of the agricultural machines, the log number of agricultural machines, and machine quality which is defined as the ratio of total power to the total number. Control variables include GDP per capita in log, the local average wage in log, sex ratio, urbanization, and the skill composition of the local workforce. Regressions are weighted by cell population. Standard errors are clustered at the prefecture level and reported in parentheses. *p <0.1, ** p <0.05, *** p <0.01.

8 Final Remarks

The population in developing countries is aging rapidly and is expected to accelerate in the coming decades, posing an enormous challenge to the prospect of economic development. In this article, we examine the technological implications of urban aging in China as a dual economy, especially emphasizing the equilibrium labor allocation across sectors and regions. We present a simple model that describes a small two-sector open economy that produces three testable predictions to illustrate theoretically how urban aging affects the adoption of labor-saving technology across sectors, including industrial automation and agricultural mechanization, in a dual economy.

To test the predictions, we assemble a unique dataset. With high-quality microdata, we construct three different measures of industrial automation to investigate the effect of urban aging on industrial automation in China spanning 2000–2015. Based on the measures of the adoption of industrial robots, the capital-labor ratio, and the value of imported machinery and equipment from the rest of the world, we find little evidence that urban aging increases industrial automation. These results appear in contrast to recent evidence that demographic changes substantially contribute to the development and adoption of industrial automation in developed countries, most notably the United States, Japan, Germany, and South Korea.

To understand the differences, we exploit a gravity model of migration to examine the effect of aging at destination and originating prefectures on shaping bilateral migration flows. We find that aging at the destination increases the inflow of middle-aged workers while the estimated impact of origin aging tend to be noisy. We also find that the migratory response to destination aging is most pronounced for workers who are close substitutes for labor-saving technologies relative to others. Lastly, we test our third prediction from our model, which posits that urban aging accelerates agricultural modernization. We construct a measure of rural households' exposure to urban aging and provide prediction-consistent evidence that urban aging encourages the faster adoption of agricultural mechanization in China.

These findings take an important step toward understanding how demographic changes affect the adoption of technology in a dual economy, where middle-aged workers are becoming increasingly scarce but a large rural population, including middle-aged workers, still works with low-productivity agriculture. Our findings imply that urban aging accelerates the reallocation of rural labor to the urban sector and thus encourages agricultural mechanization. Our findings also imply that the migration impacts attenuate the potentially positive effect of urban aging on industrial automation. Overall, our findings underscore the uneven effects of population aging on technology adoption across sectors in a dual economy.

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Appendices for Online Publication Only

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A Change in Aging across Provinces in China

Table A.1: Change in aging across provinces in China, 2000–2015

Province/Municipality	2000	2005	2010	2015
Beijing	0.3257	0.3639	0.3920	0.5288
Tianjing	0.2868	0.3344	0.3813	0.5153
Hebei	0.2490	0.2773	0.3071	0.3966
Shanxi	0.2393	0.2461	0.2889	0.3451
Neimenggu	0.2129	0.2435	0.2627	0.3505
Liaoning	0.2638	0.3049	0.3538	0.4872
Jilin	0.2134	0.2602	0.3031	0.4141
Heilongjiang	0.2052	0.2547	0.2912	0.4004
Shanghai	0.3881	0.4554	0.5423	0.7604
Jiangsu	0.3006	0.3256	0.3685	0.4376
Zhejiang	0.2874	0.3660	0.3677	0.4328
Anhui	0.2688	0.3110	0.2871	0.3096
Fujian	0.2462	0.2882	0.2616	0.3089
Jiangxi	0.2330	0.2673	0.2407	0.3053
Shandong	0.2698	0.3115	0.3335	0.4264
Henan	0.2472	0.2609	0.2712	0.3220
Hubei	0.2459	0.2911	0.2819	0.3458
Hunan	0.2690	0.2940	0.3005	0.3466
Guangdong	0.2771	0.3175	0.2662	0.3157
Guangxi	0.2763	0.2865	0.2542	0.2870
Hainan	0.2704	0.2677	0.2524	0.2803
Chongqing	0.3128	0.3745	0.3647	0.3991
Sichuan	0.2790	0.3605	0.3453	0.3723
Guizhou	0.2506	0.3022	0.2538	0.2655
Yunnan	0.2394	0.2603	0.2542	0.2755
Xizang	0.2305	0.2613	0.1903	0.2148
Shaanxi	0.2500	0.2899	0.2872	0.3351
Gansu	0.2304	0.2671	0.2790	0.3030
Qinghai	0.2079	0.2237	0.2355	0.2503
Ningxia	0.2035	0.2070	0.2291	0.2621
Xinjiang	0.2248	0.2524	0.2296	0.2505

Notes: Population aging is measured by the ratio of the older population aged 56 and above to the younger population aged 21-55. Data sources: Population censuses and surveys between 2000 and 2015.

B Summary Statistics of Main Variables

Table B.1: Summary statistics of main variables

	Obs	Mean	SD	Min	Max
Panel A. Aging variables					
Urban aging	56,025	0.300	0.082	0.050	0.629
Rural aging	56,025	0.207	0.081	0.020	0.551
Prefecture aging	56,025	0.293	0.096	0.017	0.716
Panel B. Industrial automation variables					
Change in stock of industrial robots per thousand workers	885	0.007	0.130	0	3.880
Change in capital-labor ratio in every five-year interval in log	920	0.005	0.075	-0.570	1.532
Change in values of import of machinery and equipment in every five-year interval in log	527	5.918	1.988	-1.586	11.605
Panel C. Rural mechanization variables					
Log power of agricultural machine	723	5.548	1.606	0.219	12.641
Log number of agricultural machine	723	3.990	1.363	-0.372	10.859
Machine quality	735	1.581	1.249	-2.996	7.721
Panel D. Prefecture-to-prefecture Migration Flows					
Log number of migrants aged between 21-55	56,025	7.095	1.488	4.666	13.547
Log number of migrants aged between 21-30	56,025	5.391	2.992	0	12.637
Log number of migrants aged between 31-40	56,025	4.166	3.419	0	12.557
Log number of migrants aged between 41-55	56,025	3.326	3.455	0	12.474

C Heterogeneous Effect of Urban Aging on Industrial Automation across Regions

Table C.1: Heterogeneous effect of urban aging on industrial automation across regions

	Industrial robots		Capital-labor ratio		Imports of machinery and equipmen	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: East China					
Change in urban aging in every five-year interval	-0.426	-0.426	0.037	0.037	4.268	4.268
	(0.482)	(0.482)	(0.056)	(0.056)	(6.301)	(6.301)
Change in average firm characteristics	No	Yes	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	4.247	4.247	0.795	0.795	3.393	3.393
N	252	252	250	250	187	187
	Panel B: Central China					
Change in urban aging in every five-year interval	-0.020**	-0.020**	-0.003*	-0.003*	-0.665	-0.665
	(0.008)	(0.008)	(0.002)	(0.002)	(3.399)	(3.399)
Change in average firm characteristics	No	Yes	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	24.278	24.278	24.629	24.629	25.531	25.531
N	345	345	352	352	218	218
	Panel C: West China					
Change in urban aging in every five-year interval	-0.020**	-0.020**	-0.284	-0.284	52.568	52.568
	(0.008)	(0.008)	(0.548)	(0.548)	(121.714)	(121.714)
Change in average firm characteristics	No	Yes	No	Yes	No	Yes
Change in prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes
K-P F-stat, 1^{st}	19.996	19.996	11.897	11.897	0.147	0.147
N	288	288	318	318	122	122

Notes: The table presents 2SLS estimates. Urban aging is defined as the ratio of the urban population aged 56 and above to those aged between 21 and 55. Our instruments are the five-year changes in expected urban aging in each panel. Dependent variables are the changes in the stock of industrial robots per thousand workers for Columns 1–2, the changes in the capital-labor ratio in log for Columns 3–4, and the changes in the values of imported machinery and equipment per worker in log for Columns 3–4. Panels A, B, and C present results using prefectures from East China, Central China, and West China, respectively. Firm characteristics include the average firm age, average sale value, interest payment, and the share of SOEs at the prefecture level. Prefecture characteristics include GDP per capita in log, the local average wage in log, sex ratio, urbanization, and the skill composition of the local workforce. Regressions are weighted by cell population. Standard errors are clustered at the prefecture level and reported in parentheses. *p <0.1, ** p <0.05, *** p <0.01.