Demographics and Automation*

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Abstract

We argue theoretically and document empirically that aging leads to greater (industrial) automation, and in particular, to more intensive use and development of robots. Using US data, we document that robots substitute for middle-aged workers (those between the ages of 21 and 55). We show that demographic change—measured by an increase in the ratio of older to middle-aged workers—is associated with greater adoption of robots and other automation technologies across countries and with more robotics-related activities across US commuting zones. We also provide evidence of more rapid development of automation technologies in countries undergoing greater demographic change. Our directed technological change model predicts that the induced adoption of automation technology should be more pronounced in industries that rely more on middle-aged workers and those that present greater opportunities for automation. Both of these predictions receive support from country-industry variation in the adoption of robots. Our model also implies that the productivity implications of aging are ambiguous when technology responds to demographic change, but we should expect productivity to increase and the labor share to decline relatively in industries that are more amenable to automation, and this is indeed the pattern we find in the data.

Keywords: aging, automation, demographic change, economic growth, directed technological change, productivity, robots, tasks, technology.

JEL Classification: J11, J23, J24, O33, O47, O57.

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1 Introduction

Automation and robotics technologies are poised to transform the nature of production and work (e.g., Brynjolfsson and McAfee, 2012, Ford, 2016), and have already changed many aspects of modern manufacturing (e.g., Graetz and Michaels, 2018, Acemoglu and Restrepo, 2018c). The most common narrative sees automation as the natural next step in the technological developments based on the silicon chip (Brynjolfsson and McAfee, 2012). Though there is undoubtedly some truth to this narrative, we argue that it ignores another powerful driver of automation: demographic change. Indeed, automation technologies have made much greater inroads in countries with more rapidly aging populations. For example, the number of industrial robots per thousand of industrial workers in the US stands at 9.14 in 2014, while the same number is considerably higher in countries undergoing rapid demographic change, such as Japan (14.20), Germany (16.95) and South Korea (20.14).[1] Similarly, the United States lags behind Germany and Japan in the production of robots—a single major producer of industrial robots is headquartered in the United States, compared to six in each of Germany and Japan (Leigh and Kraft, 2018).

In this paper, we advance the hypothesis that the development and adoption of robots and other industrial automation technologies have received a big boost from demographic changes in several countries, most notably Germany, Japan and South Korea. In fact, demographic factors alone account for close to a half of the cross-country variation in the adoption of robots and other automation technologies. This is not because of differential demand for automation in the service sector in countries undergoing rapid aging—our focus is on the manufacturing sector and industrial automation (thus excluding the emerging applications of artificial intelligence). Rather, we document that this pattern reflects the response of firms to the relative scarcity of middle-aged workers, who typically perform manual production tasks and are being replaced by robots and industrial automation technologies. Moreover, we show that automation technologies developed in rapidly-aging countries are then exported to others, so that demographic change impacts automation throughout the world.

We start with a simple model of technology adoption and innovation to clarify how demographic change affects incentives to develop and use automation technologies. Two types of workers, *middle-aged* and *older*, are allocated across different tasks and industries. Middle-aged workers have a comparative advantage in production tasks, which require physical activity and dexterity, while older workers specialize in nonproduction services. Firms can invest resources to automate and substitute machines for labor in production tasks, and will have stronger incentives to automate when the middle-aged wage is greater. Using this framework, we show that demographic changes that reduce the ratio of middle-aged to older workers generate a powerful incentive for the adoption and development of automation technologies. This effect is particularly pronounced in industries that rely more on middle-aged workers and those that have greater technological opportunities for automation. Aging-induced automation can also undo some of the adverse economic consequences of

[1] Industrial employment, from the ILO, comprises employment in manufacturing, mining, construction and utilities, which are the sectors currently adopting industrial robots.

demographic change, and we show that in countries experiencing rapid aging, relative productivity increases in sectors with greater technological opportunities for automation.

The bulk of the paper investigates these predictions empirically, focusing on industrial robots as well as other automation technologies. Our results point to a sizable impact of aging on the adoption of robots and other automation technologies. We first use country-level data on the stock of robots per thousand workers between 1993 and 2014 from that International Federation of Robotics (IFR) to investigate the effects of aging on the adoption of robots. Our main specifications focus on long differences, where our left-hand side variable is the change in the number of robots relative to industrial employment between 1993 and 2014. Our results indicate that countries undergoing more rapid aging—measured as an increase in the ratio of workers above 56 to those between 21 and 55—invest more in robotics. The effects we estimate are quantitatively large. Aging alone explains between 40% and 65% of the cross-country variation in the adoption of industrial robots. A 10 percentage point increase in our aging variable is associated with 0.9 more robots per thousand workers—compared to the average increase of 3 robots per thousand workers observed during this period. This magnitude suggests for instance that if the United States had the same demographic trends as Germany, the gap in robotics between the two countries would be 25% smaller.

We conduct several robustness checks. First, the relationship between demographics and the adoption of robots is unchanged when we control for differential trends across countries. For example, they are hardly affected when we control for differential trends by initial GDP per capita, schooling, population level, robot density, capital output ratio, the size of the manufacturing sector, and unionization rates. Second, because immigration may be correlated with economic trends, we verify our baseline results using an instrumental-variables (IV) strategy exploiting past birth rates and cohort sizes which strongly predict aging and are unlikely to be correlated with subsequent automation decisions through other channels. These estimates are very similar to the ordinary least squares (OLS) estimates. Third, we obtain similar results in specifications that stack two 10-year differences together and include linear time trends to control for any other differential changes across countries. Fourth, we show that it is not past but current and future demographic changes that predict the adoption of robots. Finally, we also confirm these results using an alternative estimate of investment in robotics: imports of industrial robots obtained from bilateral trade data.

The effects of demographic change on technology are not confined to robotics. Using bilateral trade data, we show a similar relationship between aging and a number of other automation technologies (such as numerically controlled machines, automatic welding machines, automatic machine tools, weaving and knitting machines, and various dedicated industrial machines). Also reassuring for our overall interpretation, that the patterns we are uncovering are related to the substitution of automation technology for middle-aged workers in production tasks, we verify that there is no relationship for technologies that appear more broadly labor-augmenting (such as manual machine tools and non-automatic machines as well as computers).

The relationship between demographics and automation is not confined to the adoption margin either. Using data on exports of automation technologies and patents, we provide evidence that countries undergoing more rapid demographic change are developing and exporting more automation technologies. Once again reassuringly, there is no similar relationship between demographic change and exports or patents for other types of technologies. Our export results also show that automation technologies developed in rapidly-aging countries are spreading to the rest of the world.

We further estimate the effects of aging on the adoption of robots at the commuting zone level in the US. Though we do not have measures of investments in robots for commuting zones, we use Leigh and Kraft's (2018) data on the location of robot integrators as a proxy for robotics-related activity. Because integrators specialize in installing, reprogramming and maintaining industrial robots, their presence indicates the adoption of robots in the area. Using this measure, we document a strong relationship between demographic change and the adoption of robots across US local labor markets.

We then move to investigate the mechanisms underlying the cross-country and cross-commuting zone association between aging and automation technologies. We first document that, consistent with our theoretical approach, automation is directly substituting for production/blue-color workers, which are disproportionately middle-aged. For example, automation is associated with sharp declines in the share of production workers in an industry and with share of production wages in total costs. Most directly, we establish that the adoption of robots across commuting zones is associated with lower wages and employment of middle-aged workers, but not of older workers.

We next turn to the prediction of the directed technological change approach that the effects of demographic change should be particularly pronounced in industries that rely more on middle-aged workers and that present greater opportunities for automation. Using industry-level data from the IFR, we find robust support for these predictions as well.

Finally, we investigate the implications for aging on labor productivity. Consistent with our theoretical expectations, we find a positive impact of demographic change on labor productivity in industries that are most amenable to automation. We also verify that these are the same industries experiencing the most pronounced declines in the labor share—a telltale sign of significant automation in these industries (Acemoglu and Restrepo, 2018b).

Our paper is related to a few literatures. The first is a literature estimating the implications of automation on labor markets. Early work (e.g., Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Michaels, Natraj and Van Reenen, 2014; Autor and Dorn, 2013; Gregory, Salomons and Zierahn, 2016) provides evidence suggesting that automation of routine jobs has been associated with wage inequality and decline of middle-skill occupations. More recently, Graetz and Michaels (2018) and Acemoglu and Restrepo (2018c) estimate the effects of the adoption of robotics technology on employment and wages (and in the former case, also on productivity). Our work differs from these papers since, rather than the implications of automation, we focus on it's determinants.

Second, a growing literature emphasizes the potential costs of demographic change, in some cases seeing this as a major disruptive factor that will bring slow economic growth (e.g., Gordon, 2016) and potentially other macroeconomic problems such as an aggregate demand-induced secular stagnation (see the essays in Baldwin and Teulings, 2014). We differ from this literature by focusing on the effects of demographic changes on automation—an issue that does not seem to have received much attention in this literature (and here we follow our short paper, Acemoglu and Restrepo, 2017, which pointed out that despite these concerns, there is no negative relationship between aging and GDP growth, and suggested that this might be because of the effects of aging on technology adoption, but did not present any evidence on this linkage, nor did it develop the theoretical implications of demographic change on technology adoption and productivity). A few works focusing on the effects of demographic change on factor prices (e.g., Poterba, 2001, Krueger and Ludwig, 2007) and human capital (e.g., Ludwig, Schelkle and Vogel, 2012) are also related, but we are not aware of any papers studying the impact of aging on technology, except the independent and simultaneous work by Abeliansky and Prettner (2017). There are several differences between our work and this paper. These authors focus on the effect of the slowdown of population growth—rather than age composition—on different types of capital, one of which corresponds to automation (without any directed technological change). They also do not consider the industry-level variation. We show that the effects we estimate are not driven by the level of population or its slower growth, thus distinguishing our results from theirs.

Third, our work is related to the literature on technology adoption. Within this literature, most closely linked to our conceptual approach is Zeira's (1998) paper which develops a model of economic growth based on the substitution of capital for labor, but does not explore the implications of demographic change on technology adoption. A few recent papers that study the implications of factor prices on technology adoption are related to our work as well. Manuelli and Seshadri (2010) use a calibrated model to show that stagnant wages mitigated the adoption of tractors before 1940. Clemens et al. (2018) find that the exclusion of Mexican *braceros*—temporary agricultural workers—induced farms to adopt mechanic harvesters and switch to crops with greater potential for mechanization, while Lewis (2011) shows that in US metropolitan areas receiving fewer low-skill immigrants between 1980 and 1990, equipment and fabricated metal plants adopted more automation technologies.

Finally, our conceptual approach builds on the directed technological change literature (e.g., Acemoglu, 1998, 2002). Our model is a mixture of the setup in Acemoglu (2007, 2010), which develops a general framework for the study of directed innovation and technology adoption, with the task-based framework of Acemoglu and Restrepo (2018a,b), Acemoglu and Autor (2011) and Zeira (1998). One contribution of the theory part of our paper is to develop a flexible model with multiple sectors and heterogeneous labor, and analyze the effects of demographic changes on technology without the specific functional form restrictions (such as constant elasticity of substitution and factor-augmenting technologies) as in the early literature or the supermodularity assumptions as in Acemoglu (2007, 2010). Existing empirical works on directed technological change (e.g., Finkelstein, 2004, Acemoglu and Linn, 2005, Hanlon, 2016) do not focus on demographic changes. Acemoglu and Linn (2005) and Costinot, Donaldson, Kyle and Williams (2017) exploit demographic changes as a source of variation, but this is in the context of the demand for different types of pharmaceuticals rather than for technology adoption.

The rest of the paper is organized as follows. We introduce our model of directed technology adoption in the next section. Section 3 presents our data sources. Section 4 presents our cross-country evidence on the effect of demographic change on the adoption of robots and other automation technologies. Section 5 provides evidence on the impact of demographic change on innovation and development of automation technologies. Section 6 investigates the relationship between demographics and robots across US commuting zones. Section 7 investigates the mechanisms at the root of the effect of aging on automation technologies. We first demonstrate that (industrial) automation technologies are indeed used predominantly to automate tasks performed by middle-aged workers. Next we show that, consistent with our theory, the effects of demographic change on the adoption of robotics technology are most pronounced in industries that rely more on middle-aged workers and in those with greater opportunities for automation. Finally, we show that the relationship between demographic change and productivity and the labor share at the industry level is also consistent with our theoretical framework. Section 8 concludes, while the (online) Appendix contains proofs omitted from the text and additional data details and empirical results.

2 Directed Technology Adoption

In this section, we introduce a tractable model of directed technology adoption with multiple sectors and heterogeneous labor, which enables us to derive the main implications of demographic change on automation technologies. In our model, industries employ middle-aged workers, older workers and machines to perform tasks necessary for production, and *technology monopolists* invest in the development of new technologies that automate production tasks performed by middle-aged workers.[2] Our objective for presenting this model is threefold. First, it clarifies the critical feature of automation—as technologies that enable the substitution of machines for tasks previously performed by labor. Second, it establishes our main conceptual argument—that demographic change leads to the adoption and innovation of automation technologies. It also demonstrates that this result is rooted in a natural complementarity between automation technologies and the prices of the factors being replaced, in this case middle-aged workers previously specializing in manual production tasks. Finally, it generates additional predictions that clarify the mechanism via which these effects work, which we then investigate in our empirical work.

2.1 The Environment

The economy produces a numeraire good Y by combining the output of a continuum of industries (or varieties) through a CES aggregator:

$$Y = \left(\int_{i\in\mathcal{I}} Y(i)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}, \text{ with } \sigma > 1. \tag{1}$$

[2] In our model, there is directed technological change (investment by technology monopolists in developing different types of technologies) and endogenous adoption of these technologies. We emphasize both margins since our focus is not just on the development but also on the adoption of the robotics technologies.

Here $Y(i)$ is the net output of industry i and $\mathcal{I}$ denotes the set of industries.

In each industry, gross output is produced by combining production tasks, service or support (non-production) tasks, and intermediates that embody the state of technology (in particular automation) for this industry:

$$Y^g(i) = \frac{\eta^{-\eta}}{1-\eta}\left[X(i)^{\alpha(i)}S(i)^{1-\alpha(i)}\right]^{\eta} q(\theta(i))^{1-\eta}. \tag{2}$$

Firms first combine production inputs, $X(i)$, with service inputs, $S(i)$.[3] The exponent $\alpha(i) \in (\underline{\alpha}, \overline{\alpha})$, with $0 < \underline{\alpha} < \overline{\alpha} < 1$, designates the importance of production inputs relative to service inputs in the production function of industry i. The aggregate of these two inputs is then combined with unit elasticity with the quantity of intermediates for this industry, $q(\theta(i))$. The term $\theta(i)$ designates the extent of automation embedded in the intermediates that firms purchase. Finally, $1-\eta \in (0,1)$ is the share of intermediates required for production.[4]

Production inputs, $X(i)$, are an aggregate of a unit measure of industry-specific tasks,

$$X(i) = \left(\int_0^1 X(i,z)^{\frac{\zeta-1}{\zeta}} dz\right)^{\frac{\zeta}{\zeta-1}},$$

where ζ is the elasticity of substitution between tasks.

Following Acemoglu and Restrepo (2018a,b), we model automation as the substitution of machines for labor in the production of tasks. Each production task $X(i,z)$ is produced either by labor or machines,

$$X(i,z) = \begin{cases} A(i)l(i,z) + m(i,z) & \text{if } z \in [0, \theta(i)] \\ A(i)l(i,z) & \text{if } z \in (\theta(i), 1], \end{cases}$$

where $l(i,z)$ denotes the amount of production labor employed in task z in industry i, and $m(i,z)$ denotes machines used in industry i to produce task z. In addition, $A(i)$ corresponds to the productivity of labor relative to machines in tasks in industry i. Labor and machines are perfect substitutes in (technologically) automated tasks (those with $z \le \theta(i)$ in industry i). An increase in $\theta(i)$ extends the set of tasks where machines can substitute for labor and hence corresponds to an advance in automation technology for industry i.

Intermediates for industry i embedding automation technology $\theta(i)$, denoted by $q(\theta(i))$, are supplied by a technology monopolist that owns the intellectual property rights over these technologies. This technology monopolist produces each unit of $q(\theta(i))$ using $1-\eta$ units of industry i's output.[5] The net output in industry i is then obtained by subtracting the total cost of intermediates,

[3] It is straightforward to extend this production function to have non-unitary elasticity of substitution between $X(i)$ and $S(i)$, but we opted for the Cobb-Douglas specification for simplicity.

[4] The assumption that $\sigma > 1$ is for simplicity. The model can be extended to cover the case with $\sigma < 1$ if we make two modifications to our baseline setup: (i) introduce limit pricing rather than monopoly pricing by technology monopolists; (ii) change equation (2) so that the elasticity of substitution between intermediates and the aggregate of production inputs, $X(i)^{\alpha(i)}S(i)^{1-\alpha(i)}$, is less than one.

[5] This formulation, linking the cost of intermediates to industry i to that industry's output, is convenient, because it avoids any relative price effects that would have been present if other inputs had been used for producing intermediates.

$(1-\eta)q(\theta(i))$, from the gross output of the industry:

$$Y(i) = Y^g(i) - (1-\eta)q(\theta(i)). \tag{3}$$

There are two types of workers: middle-aged workers and older workers. We simplify the analysis throughout the paper by imposing:

Assumption 1 *Middle-aged workers fully specialize in production inputs. Older worker fully specialize in service inputs.*

This assumption introduces the comparative advantage of middle-aged workers for production tasks. It is meant to capture not the differences in education or other types of general skills between middle-aged and older workers, but their relative abilities to perform manual tasks (which require physical activity and dexterity) and non-manual tasks. Put differently, middle-aged workers have a comparative advantage in production work because of its physical requirements. This structure of comparative advantage is also consistent with the fact that industrial automation technologies are designed to automate tasks that are typically performed by blue-collar workers (Ayres et al., 1987, Groover et al. 1986). It is further supported by the empirical evidence we present in Section 7.1. In reality, of course, worker productivity in manual tasks declines slowly with age, but we simplify the analysis by limiting ourselves to a world with two types of workers for simplicity (and extending the model to a setup with a smooth comparative advantage schedule is conceptually straightforward but notationally cumbersome).

We denote the total (inelastic) supply of middle-aged workers by L. For older workers, we assume that each produces one unit of service tasks, which implies that $S(i)$ is also the total employment of older workers in sector i, and thus with a slight abuse of notation, we also denote the (inelastic) supply of older workers by S. We denote the wage of middle-aged workers by W, the wage of older workers by V, and the total supply of machines by M. Market clearing requires the demand for each factor to be equal to its supply, or more explicitly,

$$L = L^d = \int_{i\in\mathcal{I}}\int_0^1 l(i,z)dzdi, \quad M = M^d = \int_{i\in\mathcal{I}}\int_0^1 m(i,z)dzdi, \text{ and } S = S^d = \int_{i\in\mathcal{I}} s(i)di,$$

where the last equality in each expression defines the demand for that factor. Finally, we assume that machines are supplied at an exogenously fixed rental price P.

2.2 Equilibrium with Exogenous Technology

Denote the set of technologies adopted across all industries by $\Theta = \{\theta(i)\}_{i\in\mathcal{I}}$. We first characterize the equilibrium with exogenous technology, where the set of technologies, Θ, is taken as given. An *equilibrium with exogenous technology* is defined as an allocation in which all industries choose the profit-maximizing levels of employment of middle-aged workers, employment of older workers, machines and intermediates, all technology monopolists set profit-maximizing prices for their intermediates, and the markets for middle-aged workers, older workers and machines clear.

Let $P_{Y(i)}$ denote the price of output in industry i, and $p(\theta(i))$ be the price of the intermediate for industry i that embodies technology $\theta(i)$. The demand for $q(\theta(i))$ is given by:

$$q(\theta(i)) = \frac{1}{\eta} X(i)^{\alpha(i)} S(i)^{1-\alpha(i)} \left(\frac{p(\theta(i)))}{P_Y(i)} \right)^{-\frac{1}{\eta}}. \tag{4}$$

Faced with this demand curve with elasticity $1/\eta$, the technology monopolist for industry i will set a profit-maximizing price that is a constant markup of $1/(1-\eta)$ over marginal cost. Given our normalization of the marginal cost of intermediate production to $1-\eta$ units of the industry's product, the profit-maximizing price is $p(\theta(i)) = P_Y(i)$. Substituting this price into (4), and using (2) and (3), we derive the net output of industry i as

$$Y(i) = \frac{2-\eta}{1-\eta} X(i)^{\alpha(i)} S(i)^{1-\alpha(i)}.$$

The Cobb-Douglas production technology in equation (2) then implies

$$P_Y(i) = \lambda(i) P_X(i)^{\alpha(i)} V^{1-\alpha(i)},$$

where $P_X(i)$ denotes the price of $X(i)$, and $\lambda(i) = (1-\eta)\alpha(i)^{-\alpha(i)}(1-\alpha(i))^{\alpha(i)-1}$.

We next turn to the decision to adopt existing automation technologies. This decision depends on the cost savings from automation, which are in turn determined by factor prices. Let $\pi(i)$ denote the cost savings from automation in industry i, meaning the percent decline in costs when a task is produced by machines rather than labor:

$$\pi(i) = \frac{1}{1-\zeta} \left[1 - \left(\frac{A(i)P}{W} \right)^{1-\zeta} \right]. \tag{5}$$

When $\frac{W}{A(i)} > P$, the effective cost of producing with labor in industry i, $\frac{W}{A(i)}$, is greater than the cost of using a machine, P, and as a result, $\pi(i) > 0$. Conversely, when $\frac{W}{A(i)} < P$, it is more expensive to produce with machines in industry i and firms do not adopt the automation technologies because it would raise their cost. Therefore, available automation technologies will be adopted if $\pi(i) > 0$.

We can then summarize automation decisions by defining an *automation threshold*, $\theta^A(i)$,

$$\theta^A(i) = \begin{cases} \theta(i) & \text{if } \pi(i) > 0 \\ 0 & \text{if } \pi(i) \leq 0, \end{cases} \tag{6}$$

where we are assuming without loss of any generality that when indifferent, firms do not switch to machines. Equation (6) highlights a key point in our model: firms adopt existing automation technologies when the effective wage of middle-aged workers is high.

Using the threshold $\theta^A(i)$, we can express the price of $X(i)$ as

$$P_{X(i)} = \left(\theta^A(i) P^{1-\zeta} + (1-\theta^A(i)(i)) \left(\frac{W}{A(i)} \right)^{1-\zeta} \right)^{1-\zeta}, \tag{7}$$

and the share of middle-aged labor in the production of $X(i)$ as:[6]

$$s_L(i) = (1-\theta^A(i)) \left(\frac{W}{A(i)P_X(i)} \right)^{1-\zeta} \in [0,1] \tag{8}$$

Using the above expressions for prices and the share of labor in $X(i)$, we can derive the demand for factors of production in the economy as

$$L^d = \frac{Y}{(2-\eta)W} \int_{i\in\mathcal{I}} \lambda(i)^{1-\sigma} P_Y(i)^{1-\sigma} \alpha(i) s_L(i) di \tag{9}$$

$$M^d = \frac{Y}{(2-\eta)P} \int_{i\in\mathcal{I}} \lambda(i)^{1-\sigma} P_Y(i)^{1-\sigma} \alpha(i)(1-s_L(i)) di \tag{10}$$

$$S^d = \frac{Y}{(2-\eta)V} \int_{i\in\mathcal{I}} \lambda(i)^{1-\sigma} P_Y(i)^{1-\sigma} (1-\alpha(i)) di. \tag{11}$$

The next proposition establishes the existence and uniqueness of the equilibrium and characterizes it. In what follows, we let $\phi = \frac{S}{L+S}$ denote the share of older workers in the population, and think of aging as an increase in ϕ.

Proposition 1

1. *An equilibrium with exogenous technology always exists and is unique. The equilibrium levels of middle-aged and older wages, W and V are the unique solutions $\{W^E(\phi;\Theta), V^E(\phi,\Theta)\}$ to the system of equations given by: the* ideal price index condition,

$$1 = \left(\int_{i\in\mathcal{I}} \lambda(i)^{1-\sigma} P_Y(i)^{1-\sigma} di \right)^{\frac{1}{1-\sigma}}, \tag{12}$$

and the relative demand for workers,

$$\frac{1-\phi}{\phi} = \frac{V}{W} \frac{\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma} \alpha(i) s_L(i) di}{\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma} (1-\alpha(i)) di.} \tag{13}$$

Aggregate output and machinery per worker, $\{y^E(\phi;\Theta), m^E(\phi,\Theta)\}$, can be then computed using $\{W^E(\phi;\Theta), V^E(\phi,\Theta)\}$.

2. *The middle-aged wage $W^E(\phi,\Theta)$ is increasing in ϕ, and the older worker wage $V^E(\phi,\Theta)$ is decreasing in ϕ. On the other hand, ϕ has an ambiguous impact on output per capita $y^E(\phi,\Theta)$.*

Like all other proofs, the proof of Proposition 1 is provided in the Appendix.

Panel A of Figure 1 depicts the characterization of the equilibrium with exogenous technology. Let $C(W,V,P)$ denote the cost of producing one unit of the final good, which is given by the right-hand side of equation (12). The equilibrium wages, W^E and V^E, are then given by the tangency

[6]Let $L(i) = \int_0^1 l(i,s) ds di$ and $M(i) = \int_0^1 m(i,s) ds di$ denote the amounts of middle-aged labor and machines employed in industry i, respectively. Then total production in industry i can be written as

$$X(i) = \left(\theta^A(i)^{\frac{1}{\zeta}} M(i)^{\frac{\zeta-1}{\zeta}} + (1-\theta^A(i))^{\frac{1}{\zeta}} L(i)^{\frac{\zeta-1}{\zeta}} \right)^{\frac{\zeta}{\zeta-1}}.$$

Thus as highlighted in (7), an increase in $\theta(i)$ (and hence $\theta^A(i)$) makes the production of $X(i)$ less labor intensive.

of the isocost curve $C(W,V,P)=1$ (condition (12)) with a line of slope $-\frac{1-\phi}{\phi}$ (at which point we have $\frac{\partial C(W,V,P)/\partial W}{\partial C(W,V,P)/\partial V}=\frac{1-\phi}{\phi}$, which is condition (13)). Aging—an increase in ϕ—raises W^E and lowers V^E along the convex isocost curve $C(W,V,P)=1$, as shown in Panel A.

Proposition 1 also shows that aging has an ambiguous effect on aggregate output per worker. In particular, in the Appendix we show that

$$\frac{1}{2-\eta}y^E_\phi(\phi,\Theta)=V^E(\phi,\Theta)-W^E(\phi,\Theta)+P\cdot m^E_\phi(\phi,\Theta). \tag{14}$$

This expression clarifies that the effect of aging on aggregate output depends on the wage of middle-aged workers relative to the wage of older workers. In particular, if $V^E<W^E$, there will be a negative effect on productivity (though m^E_ϕ can be positive, offsetting this effect). Existing evidence (e.g., Murphy and Welch, 1990) suggests that earnings peak when workers are in their 40s, which in our model implies $V<W$, and thus creates a tendency for aging to reduce productivity. This negative effect echoes the concerns raised by Gordon (2016) on the potential for slower growth in the next several decades because of demographic change.

The next proposition shows how demographic change affects the adoption of existing automation technologies. For this proposition and for what follows, we denote by $\mathcal{I}^+(\phi,\Theta)$ the set of industries where $\pi(i)>0$ and new automation technologies are all adopted.

Proposition 2 *The set $\mathcal{I}^+(\phi,\Theta)$ satisfies the following properties:*

- *For $\phi\leq\phi'$ we have $\mathcal{I}^+(\phi,\Theta)\subseteq\mathcal{I}^+(\phi',\Theta)$.*
- *There exists a positive threshold $\widetilde{\phi}<\infty$ (independent of the $\theta(i)$'s), such that for $\phi<\widetilde{\phi}$, the set $\mathcal{I}^+(\phi,\Theta)$ has measure zero. For $\phi>\widetilde{\phi}$, the set $\mathcal{I}^+(\phi,\Theta)$ has positive measure.*

The proposition shows that aging encourages the adoption of existing automation technologies. The intuition is similar to models of technology adoption building on Zeira (1998) and works through the effect of higher wages on incentives to adopt automation technologies. For $\phi<\widetilde{\phi}$, there is no adoption of automation technologies because middle-aged workers are abundant and thus cheap. When $\phi>\widetilde{\phi}$, the middle-aged wage is sufficiently high that automation becomes profitable.

What is the effect of automation on factor prices? As in Acemoglu and Restrepo (2018a), this is determined by two competing forces. On the one hand, we have a *displacement effect*—when automation technologies are adopted, they squeeze middle-aged workers into fewer tasks, reducing the demand for middle-aged labor. On the other hand, we have a *productivity effect*—when automation technologies are adopted, they allow industries to reduce their costs and expand output, raising the demand for middle-aged workers in non-automated tasks. When $\pi(i)$ is small (but positive), the productivity effect is weak; available automation technologies will be adopted in industry i, generating the displacement effect, but only a minimal productivity effect. This reasoning implies that there exists a threshold $\overline{\pi}>0$ such that, when new automation technologies are introduced in industry i with $\pi(i)\in(0,\overline{\pi})$, the displacement effect dominates the productivity effect, and automation reduces wages.[7] This result is stated and some of its implications are developed in the next proposition, where for simplicity we consider marginal changes in automation technologies, denoted by $\{d\theta(i)\}_{i\in\mathcal{I}}$ (with $d\theta(i) \geq 0$).

Proposition 3 *Suppose new automation technologies $\{d\theta(i)\}_{i\in\mathcal{I}}$ become available. Then:*

- *New automation technologies are not adopted when $\phi < \widetilde{\phi}$, and are adopted in industries in $\mathcal{I}^+(\phi,\Theta)$ when $\phi > \widetilde{\phi}$.*
- *There exists a threshold $\overline{\phi}(\Theta) > \widetilde{\phi}$ such that, if $\widetilde{\phi} < \phi < \overline{\phi}(\Theta)$, then $\pi(i) < \overline{\pi}$ for* almost all *industries. In this region, if $d\theta(i) > 0$ for a (positive measure) subset of $\mathcal{I}^+(\phi,\Theta)$, the wage of middle-aged workers declines and the wage of older workers increases.*

Panel B of Figure 1 illustrates the comparative statics presented in this proposition. The displacement effect corresponds to a clockwise rotation of the isocost curve $C(W,V,P)=1$ around the equilibrium point, reducing W and increasing V. The productivity effect corresponds to an outward shift of the isocost curve, increasing both wages.[8]

2.3 Equilibrium with Endogenous Technology

Our analysis so far took the available automation technologies, $\Theta = \{\theta(i)\}_{i\in\mathcal{I}}$, as given. We now endogenize these technologies using an approach similar to Acemoglu (2007, 2010).

For industry i, there is a single technology monopolist who can develop new automation technologies and sell the intermediates embodying them—the $q(\theta(i))$'s—to firms in that industry. Developing an automation technology $\theta(i)$ costs the monopolists $\frac{1-\eta}{2-\eta}P_Y(i)Y(i)\cdot C_i(\theta(i))$ units of the final good, where $C_i(\cdot)$ is an increasing and convex function that varies across industries. The specification imposes that the cost of introducing innovations is proportional to $\frac{1-\eta}{2-\eta}P_Y(i)Y(i)$, which is adopted to simplify the algebra.

Equation (4) shows that the monopolist in industry i earns profits $\frac{1-\eta}{2-\eta}P_Y(i)Y(i)$. Using the fact that $Y(i) = P_Y(i)^{-\sigma}Y$, we can write the *net* profits from developing automation technology $\theta(i)$ as $\frac{1-\eta}{2-\eta}P_Y(i)^{1-\sigma}Y(1-C_i(\theta(i)))$. Moreover, because monopolists, like their industries, are infinitesimal, they take wages and aggregate output, Y, as given. We can then write the profit-maximizing problem of the technology monopolist for industry i in logs as

$$\max_{\theta(i)\in[0,1]} \pi^M(i) = (1-\sigma)\alpha(i)\ln\left(\theta^A(i)P^{1-\zeta} + (1-\theta^A(i))\left(\frac{W}{A(i)}\right)^{1-\zeta}\right) + \ln(1-C_i(\theta(i))) \quad (15)$$

This expression clarifies that monopolists have an incentive to develop automation technologies that reduce $P_X(i)$, which translates into greater profits for them. We further simplify the analysis

[7] This discussion also highlights the critical difference between automation technologies and the more familiar factor-augmenting technologies (see Acemoglu and Restrepo, 2018c, for more details). This distinction will play an important role in shaping the incentives for the adoption and development of automation technologies as well.

[8] Although the impact of automation on middle-aged wages is ambiguous when $\phi < \overline{\phi}(\Theta)$, it is straightforward to see that automation still reduces the demand for middle-aged workers relative to older workers in industries adopting the automation technologies. For example, if $\theta(i)$ increases in a single industry with $\pi(i) > 0$, $L(i)/S(i)$ declines in that industry.

by assuming that the cost function $C_i(\cdot)$ takes the form

$$C_i(\theta(i)) = 1 - (1 - H(\theta(i)))^{\frac{1}{\rho(i)}},$$

where H is an increasing and convex function that satisfies $H'(0) = 0$, $\lim_{x \to 1} H(x) = 1$, and $h(x) \geq 1/(1-x)$, where $h(x) = H'(x)/(1 - H(x))$. The last assumption strengthens convexity and ensures that (15) has a unique solution. The exponent $\rho(i) > 0$ represents heterogeneity across industries in the technological possibilities for automation; a higher $\rho(i)$ characterizes industries in which, due to engineering reasons, monopolists can more easily develop new automation technologies.

Given the convexity assumptions on H, the maximization problem in equation (15) yields a unique technology choice for each industry, $\theta_i^R(W)$, which depends only on parameters and the middle-aged wage, W. We define the mapping $\Theta^R(W) = \{\theta_i^R(W)\}_{i \in \mathcal{I}}$ from the middle-aged wage to the equilibrium technology choices.

We define an *equilibrium with endogenous technology* as an allocation where technology choices $\Theta^R(W)$ maximize (15), and given technology choices $\Theta^R(W)$, Proposition 1 applies. From this proposition, technology choices Θ determine factor prices, and in particular, the middle-age wage W as $W^E(\phi, \Theta)$. Thus, an equilibrium corresponds to a middle-aged wage, W^*, that is a solution to the following fixed point problem,

$$W^* = W^E(\phi, \Theta^R(W^*)). \tag{16}$$

To study this fixed point problem, we first characterize the behavior of the equilibrium technology choice $\theta_i^R(W)$ for industry i.

Lemma 1

1. *The maximization problem in equation (15) exhibits increasing differences in W and $\theta(i)$. Thus, $\theta_i^R(W)$ is nondecreasing in W.*

2. *If $\theta_i^R(W) > 0$, then $\pi(i) > 0$.*

The key result in this lemma is that the technology monopolists face stronger incentives to develop new automation technologies when the middle-aged wage, W, is higher.[9] Economically, this is the case because automation allows firms to substitute machines for middle-aged labor, and when this labor is more expensive, automation is more profitable.

The second part of the lemma shows that, in an equilibrium with endogenous technology in which $\theta^A(i) > 0$, we always have $\pi(i) > 0$. Thus, monopolists only introduce technologies that will be immediately adopted, and in an equilibrium with endogenous technology, we always have

[9] In the Appendix we show that equilibrium technology satisfies the complementary slackness condition,

$$h(\theta_i^R(W)) \geq (\sigma - 1)\alpha(i)\rho(i)\frac{s_L(i)}{1 - \theta_i^R(W)}\pi(i), \tag{17}$$

and $\theta_i^R(W) \geq 0$, and that a greater W leads to higher cost savings from automation, $\pi(i)$. It is this property that implies the maximization problem of monopolists exhibits increasing differences in W and $\theta(i)$.

$\theta^A(i) = \theta(i)$. An immediate corollary is that any comparative static result that applies to the innovation margin $\theta(i)$ also applies to the adoption margin $\theta^A(i)$.

PROPOSITION 4 *For any $\phi \in (0,1)$, there exists an equilibrium with endogenous technology. In such equilibrium the middle-aged wage, W^*, satisfies the fixed point condition in equation (16). Each fixed point W^* defines a unique set of technology choices $\Theta^* = \{\theta_i^*\}_{i \in \mathcal{I}}$ given by $\Theta^* = \Theta^R(W^*)$.*

To illustrate this proposition, suppose that the mapping $W^E(\phi, \Theta^R(W))$ is decreasing in W.[10] In this case, automation decisions across industries are strategic substitutes—because more automation in one industry reduces the middle-aged wage and discourages automation in other industries. Consequently, the equilibrium with endogenous technology is unique as in Panel A of Figure 2.

In general, $W^E(\phi, \Theta^R(W))$ need not be decreasing in W, because strong productivity gains from automation could make the middle-aged wage increasing in automation. In this case, we could have multiple equilibria, as automation in one sector increases the wage W and creates incentives for further automation in other sectors. Nevertheless, there are still well-defined *least* and *greatest* equilibria as shown in Figure 2, determined by the smallest and largest equilibrium values of the wage W that solve the fixed point problem in equation (16). The Appendix shows that, in the least and the greatest equilibrium, the mapping $W^E(\phi, \Theta^R(W))$ cuts the 45 degree line from above (as shown in Panel B of Figure 2). Then we have

PROPOSITION 5 *In the least and the greatest equilibrium, an increase in ϕ—aging—increases the equilibrium wage W^*, expands the set of automation technologies Θ^*, and expands the set of industries that adopt automation technologies $\mathcal{I}^+(\phi, \Theta^*)$.*

This proposition provides one of our main results: aging always encourages the development and use of automation technologies, and this is regardless of whether automation has a positive or negative effect on the middle-aged wage and whether or not there are multiple equilibria (if there are multiple equilibria, it applies for the relevant equilibria, which are those with the least and greatest values of the middle-aged wage). Intuitively, machines compete against middle-aged workers, and a greater scarcity of these workers always increases the relative profitability of automation.

Finally, the next proposition shows how the response of technology to aging varies by industry.

PROPOSITION 6 *In the least and the greatest equilibrium, θ_i^* exhibits increasing differences in ϕ and $\alpha(i)$, and ϕ and $\rho(i)$.*

This proposition thus implies that aging—an increase in ϕ—should have a more pronounced impact on automation in industries that rely more heavily on middle-aged workers (i.e., those with high $\alpha(i)$) and that present greater technological opportunities for automation (i.e., those with high $\rho(i)$). In our empirical work, we will investigate both implications.

[10]The Appendix shows that a sufficient condition for this mapping to be decreasing is $\widetilde{\phi} < \phi < \overline{\phi}(\Theta = (\{0\}_{i \in \mathcal{I}}))$ (so that the productivity gains from automation are positive for some industries but still smaller than $\overline{\pi}$). In this case, the mapping $W^E(\phi, \Theta^R(W))$ is constant for $W \leq \widetilde{W}$ and decreasing for $W > \widetilde{W}$ (here, $\widetilde{W}$ is the largest wage such that $\widetilde{W} < \widetilde{A}(i)P$ for almost all $i \in \mathcal{I}$). Note also that for $\phi \leq \widetilde{\phi}$ the unique equilibrium involves $\theta(i)^* = 0$.

2.4 Implications for Productivity

With endogenous technology, aging creates a positive effect via the response of automation, and we next show that as a result, when the workforce is aging, productivity in industries with greater opportunities for automation tends to increase relative to others.

PROPOSITION 7 *In the least and the greatest equilibrium, equilibrium output in industry i, $Y^*(i)$, exhibits increasing differences in ϕ and $\rho(i)$.*

From Proposition 6, the endogenous response of technology is stronger in industries with greater $\alpha(i)$ and greater $\rho(i)$, which implies that industries that have greater opportunities for automation (a large $\rho(i)$) increase their relative performance in aging economies, and for the same reason, these industries will also experience a greater decline in their labor share (recall from footnote 6 that automation makes industry production less labor-intensive). But there are no unambiguous results for industries that rely more heavily on middle-aged workers (i.e., those with high $\alpha(i)$). This is because, on the one hand, these industries are more exposed to the increase in wages, and on the other hand, as a result of this, they also have greater incentives to automate their production process, increasing productivity.

Propositions 1 and 7 highlight that the aggregate productivity implications of aging will be ambiguous in the presence of endogenous developments of automation technologies, and as a result, demographic change may not have as significant negative effects on GDP once technology adjusts.

2.5 Extensions

In the Appendix, we consider two extensions of this framework. First, we endogenize the industry-level labor-augmenting technology, $A(i)$. In this case, demographic change impacts technology not just by encouraging automation but also by directly influencing the productivity of middle-aged labor in the production tasks it performs. We show that the effect of aging on the endogenous choice of $A(i)$ is ambiguous. By increasing the share of middle-aged workers in value added (when $\zeta < 1$), aging encourages the development of labor-augmenting technologies. But it also fosters automation and thus reduces the set of tasks performed by middle-aged workers, making labor-augmenting technologies less profitable. In our empirical work, we will indeed find that there are no positive effects of aging on non-automation technologies.

Second and more importantly, we establish a link between rapid aging in some countries and the adoption of automation technologies throughout the world. We do this by considering an extension of our model to a global economy with multiple countries, where some of them are experiencing more rapid aging and thus are ahead of others in the development of automation technologies. In this setup, we show that there will be imports and exports of automation technologies (as in our empirical work), and advances in automation technologies in one country are later adopted in another country and can lead to a decline in the wages of middle-aged workers in the adopting country.

3 Data and Trends

In this section, we present our data sources and show some of the most salient trends in our data. The Appendix contains additional description and details.

3.1 Cross-Country Data

We focus on demographic changes related to aging, and measure them by the change in the ratio of older workers (56 and older) to middle-aged workers (between 21 and 55). The cutoff of 55 years of age is motivated by the patterns of substitution between robots and workers we document in the next section. We obtained the demographic variables from the United Nations (UN) data, which measure population by age and also provide a forecast of these variables up to 2050. As Figure 3 shows, both our entire world sample and the OECD have experienced significant aging starting around 1990—a trend that is expected to continue into the future. Aging is much faster in Germany and South Korea and is slower in the United States than the OECD average. We use the change in the ratio of older to middle-aged workers between 1990 and its expected level in 2025 as our baseline measure of aging. This latter choice is motivated by the fact that investments in robotics and automation technologies are forward looking. The IFR estimates the average life-span of a robot to be about 12 years, so investments in robots in the 2010s should take into account demographic change until at least 2025. In our empirical exercises, we instrument aging using crude birth rates between 1950 and 1985, which we also obtained from UN data.

We use four sources of data to measure the adoption and development of robots and other automation technologies across countries: data on the use of robots from the IFR; data on imports of robots and other types of machinery from Comtrade; data on exports of robots and other types of machinery also from Comtrade; and patents by different countries filed at the USPTO.

The IFR provides data on the stock of robots and new robot installations by industry, country and year. The data are compiled by surveying global robot suppliers. Table A1 in the Appendix provides the list of countries covered by the IFR.[11] In our cross-country analysis we use the change in the stock of robots divided by industrial employment as our dependent variable. The denominator is constructed using employment data for 1990 from the International Labour Organization (ILO). To account for differences in hours worked, we normalize the stock of robots using full-time equivalent industrial workers (as described in footnote 1). The resulting measure of the stock of robots per thousand industrial workers covers 52 countries between 1993 and 2014, and is illustrated in Figure 3. The figure underscores the pattern we noted in the Introduction—that Germany and South Korea are considerably ahead of the United States in terms of the adoption of robotics technology. Panel A of Table A2 in the Appendix provides summary statistics separately for all the countries in our sample, for OECD countries, and for rapidly-aging countries (above the median in terms of expected aging between 1990 and 2025) and slowly-aging countries. In our full sample, the number

[11] Although the IFR also reports numbers for Japan and Russia, the data for these countries underwent major reclassifications. For instance, the IFR used to count *dedicated machinery* as part of the stock of industrial robots in Japan, but starting in 2000, stopped doing so, making the numbers reported for Japan not comparable over time. We thus exclude both countries from our analysis.

of robots per thousand workers increased from 0.72 in 1993 to 3.79 in 2014.

We complement the IFR data with estimates of robot imports and exports from the bilateral trade statistics obtained from Comtrade. When using the data on robot imports, we exclude Japan, which mostly uses domestically produced robots (the other major producer, Germany, also has significant imports; see Leigh and Kraft, 2018). In addition, to account for entrepôt trade, we remove re-exports of robots and keep only countries whose imports of robots net of re-exports are positive. Likewise, when analyzing the export data, we keep only countries whose exports of robots (without including re-exports) are positive. The resulting data cover 131 countries importing robots between 1996 and 2015, and 105 countries exporting robots between 1996 and 2015.[12] We also use the Comtrade data to compute imports and exports of other intermediates related to industrial automation. Panel B of Table A2 provides summary statistics for the Comtrade data.

Finally, we use data on robotics-related patents granted by the USPTO to assignees based in each country between 1990 and 2015. We focus on patents in the USPTO 901 class, which comprises technologies related to industrial robots, and patents that reference the 901 class. The Appendix describes these data and our construction of other proxies for robotics-related patents, including measures that search for robotics-related words in patent abstracts, and measures based on citation patterns. We exclude countries with no robotics-related patents and focus on 69 countries (31 of them in the OECD) that patented in robotics-related classes. Panel C of Table A2 shows that the average number of robotics-related patents received by a country in our sample is 718, while the same number is about twice as large for the OECD and for rapidly-aging countries.

We also use data on GDP per capita, population and average years of schooling obtained from version 9.0 of the Penn World Tables (Feenstra, Inklaar and Timmer, 2015), and data on manufacturing value added in 1990 from UNIDO.

3.2 Data on Robot Integrators

For US labor markets we do not have data on the adoption or use of robots. Instead, we proxy robotics-related activities in a commuting zone using a dichotomous measure of whether it houses robot integrators, obtained from Leigh and Kraft (2018).[13] Integrators install, program and maintain robots, and tend to locate close to their customers.

For commuting zones, we measure aging by the change in the ratio of older to middle-aged workers between 1990 and 2015, obtained from the NBER Survey of Epidemiology and End Results

[12] Industrial robots are counted under the HS6 code 847950. Because this category was introduced in 1996, it is only possible to track international trade of industrial robots after this date. For the remaining types of equipment used in our empirical analysis, we compute imports and exports going back to 1990.

There are several reasons why there is a relatively large number of countries exporting robots. First, some exporting firms may use ports located in different countries to send their robots (for example, German and Belgium robot producers can export from Luxembourg). Second, there are likely some classification errors by custom authorities. Finally, some countries may sell used inventory. All of these add measurement error to this variable, but should not bias our results. In the exports data, Nigeria is a massive outlier, with a share of robotic exports two orders of magnitudes greater than other countries, which is almost certainly a mistake in the data. We thus exclude Nigeria from regressions for industrial robots, though because we focus on weighted regressions the results are very similar even if it is included.

[13] Commuting zones, defined in Tolbert and Sizer (1996), are groupings of counties approximating local labor markets. We use 722 commuting zones covering the entire US continental territory (this excludes Alaska and Hawaii).

dataset (we do not have forecasts of aging at the commuting-zone level). We also use various demographic and economic characteristics of commuting zones in 1990, obtained from the NHGIS at the county level (Manson et al., 2017), and data on *exposure to robots* from Acemoglu and Restrepo (2018a) to measure the local effects of robots.

3.3 Industry Data

In addition to the country-level data, the IFR reports data on robot installations by year separately for 19 industries in 50 of the countries in our sample, including 13 industries at the three-digit level within manufacturing and six non-manufacturing industries at the two-digit level. As Table A1 in the Appendix shows, these data are not available in every year for every country-industry pair, so in our analysis, we focus on an unbalanced panel of annual data rather than long differences. Table A3 summarizes the industry-level data. For each industry, we report the average number of robot installations per thousand workers, using two possible denominators. The first one uses the ILO data described above, while the second uses data from EUKLEMS, which provides the 1995 employment levels for all 19 industries used in our analysis, but only covers 21 of the countries in our sample (Jägger, 2016).[14] In the Appendix, we further use the UNIDO dataset for an additional robustness check and describe these data there.

From the EUKLEMS data, we also obtain information on value added per worker (in real dollars) and the change in the share of labor in value added. These outcomes are available only between 1995 and 2007, and cover all 19 industries included in the IFR data. The third and fourth columns of Table A3 summarize these data.

To explore whether aging has heterogeneous impacts on different industries, we construct industry-level measures of reliance on middle-aged workers, and opportunities for automation. We measure an industry's reliance on middle-aged workers with the ratio of middle-aged to older workers, computed from the 1990 US Census data. Heavy manufacturing industries, construction and utilities have significantly greater reliance on middle-aged workers. We use two proxies for the opportunities for automation (focusing in particular on robots). The first is the "replaceability" index constructed by Graetz and Michaels (2018), which is derived from data on the share of hours spent by workers in the United States on tasks that can be performed by industrial robots. The replaceability index is strongly correlated with robot adoption and explains 22% of the total variation in the installation of robots across industries. The second measure is a dummy variable for automobiles, electronics, metal machinery, and chemicals, plastics and pharmaceuticals, which are are singled out by a recent report by the Boston Consulting Group (BCG, 2015) as having the greatest technological opportunities for the use of robots, based on the type of tasks that workers perform on the job. The data presented in Table A2 confirm that these are among the industries experiencing the fastest growth in the adoption of robots. Figure A1 in the Appendix summarizes the industry heterogeneity in their reliance on middle-aged workers and replaceability index.

[14]We use employment levels in 1995 to normalize the number of robot installations because the data are missing for many countries before then. We also focus on the growth in value added per worker and the labor share between 1995 and 2007 because post-2007 data disaggregated by industry are unavailable for many countries in our sample.

4 Demographic Change and Automation

In this section, we present our main cross-country results, which show a robust positive association between aging and the adoption of automation technologies.

4.1 Main Results

Our main specification relates the adoption of robots to the aging of the population in a country:

$$\frac{\Delta R_c}{L_c} = \beta \text{Aging}_c + \Gamma X_{c,1990} + \varepsilon_c. \tag{18}$$

Here $\frac{\Delta R_c}{L_c}$ is the (annualized) *change* in the stock of robots between 1993 and 2014 in country c normalized by industrial employment (in thousands) in 1990 from the ILO. We keep the denominator fixed in 1990 to avoid endogenous changes in employment impacting our left-hand side variable. Aging_c is the expected *change* between 1990 and 2025 in the ratio of older workers (who are above the age of 56) to middle-aged workers (between the ages of 21 and 55).[15] As described in Section 3, we use UN population forecasts to measure aging. Finally, the vector $X_{c,1990}$ includes covariates and ε_c is an heteroscedastic error term. We present both unweighted specifications and regressions weighted by manufacturing value added in 1990, which are useful because robots and the industrial automation technologies that guide our model are used much more intensively in manufacturing than in other sectors.

Panel A of Table 1 presents our unweighted OLS estimates of equation (18). Columns 1-3 are for the full sample of 52 countries. Column 1 controls for dummies for East Asia and the Pacific, South Asia, Middle East and North Africa, Africa, Eastern Europe and Central Asia, Latin America and the Caribbean, and OECD countries to account for regional trends. Column 2 adds the 1993 values of log GDP per capita, log population, average schooling and the ratio of middle-aged and older workers as covariates; these variables control for differential trends depending on initial levels of economic development and demographic characteristics. Column 3 also includes the stock of industrial robots per thousand workers and the log of manufacturing value added in 1990 as controls, and thus allows for the possibility that countries with more robots or a larger manufacturing sector at the beginning of the sample may adopt robots at differential rates. Columns 4-6 present the same specifications for the 30 countries in the OECD sample.

In all six columns of Panel A, we find that aging—an increase in the ratio of older to middle-aged workers—is associated with the adoption of more robots. All estimates are statistically significant and quantitatively sizable. The specification in column 1 has a R^2 of 0.47 (and the partial R^2 of aging alone is close to 0.40 in column 3 as noted in the Introduction). In the specification with all the controls in column 3, the coefficient estimate on aging is 0.57 (s.e.=0.24). This implies that a 20 percentage point increase in our aging variable, which is roughly the difference between Germany

[15] The relative employment rates of workers of different age groups in blue-collar and white-collar occupations documented in Section 7.1 motivate the use of 55 years of age as our baseline cutoff to define older and middle-aged workers. Table A4 in the Appendix shows that our results are robust to different ways of classifying middle-aged and older workers.

and the United States (0.5 vs. 0.28, respectively), leads to an increase of 0.11 robots per thousand workers per year. This adds up to two additional robots per thousand workers over our sample period, which accounts for 25% of the Germany-US difference in the adoption of robots.

Figure 4 depicts the relationship between demographic change and the number of robots per thousand workers in the full sample of countries and in the OECD (using the models estimated in columns 2 and 5 in Table 1). Even though South Korea is an outlier, Table A5 in the Appendix presents several strategies to show that the relationship between aging and adoption of robots is not driven by outliers.

Panel B presents instrumental-variables (IV) models. Our IV models are motivated by the concern that changes in labor markets that influence the adoption of robots may also affect migration (and even mortality) patterns, which would bias our OLS estimates. To address this concern, we instrument expected aging between 1990 and 2025 using the average birth rates over each five-year interval from 1950-1954 to 1980-1984. These birth rates satisfy the requisite exogeneity assumption since past changes in birth rates are unlikely to be driven by contemporaneous wages or technologies, and also explain a large portion of the variation in aging across countries (in column 1, the first stage F-statistic is 25.2). The IV estimates of the effect of demographic change on the adoption of robots are slightly larger than their OLS counterparts.[16]

One potential concern with our IV estimates is that our first-stage is borderline weak in the OECD sample. We address this concern in two ways. First, Panel B reports the p-value of the Anderson-Rubin test for the coefficient β being equal to zero. Second, Panel C reports estimates where we use a single instrument computed as the percent decline in birth rates from 1960 to 1985. Using this single instrument we estimate a similar effect of aging on the adoption of robots, but now the first-stage F-statistic is above 14 in all columns.

Panels D and E present OLS and IV estimates from regressions weighted by manufacturing value added in 1990. The estimates are larger and more precise than their counterparts in Panels A and B. Correspondingly, the estimates become quantitatively more important than before. With the IV estimate in column 3, the differential demographic trends of Germany and the United States explain about half of the difference in the adoption of robots between the two countries.

In Table 1 we focused on a parsimonious specification with the change in the ratio of older to middle-aged population as our main explanatory variable. In Table A6 in the Appendix we justify this specification by showing that, when included separately, the change in the log population of middle-aged workers has a negative impact on the adoption of robots, while the change in the log population of older workers has a positive impact of a similar magnitude. In line with these findings, Table A7 further shows that, once we control for our measure of aging, there is no relationship between the change in population and the adoption of robots. Thus the patterns we are reporting are all about the relative size of middle-aged and older cohorts.[17]

[16] In all tables, when we have more than one instrument, we report the $p-$value from Hansen's overidentification test. Except for a few marginal Instances, in most cases this test does not reject the joint validity of our instruments.

[17] These results are the basis of our claim in the Introduction that we do not find a robust relationship between the level or change in population and automation (which contrasts with the results in Abeliansky and Prettner, 2017).

4.2 Past vs. Expected Aging, Robustness and Additional Results

In this subsection we show that *past* demographic changes do not predict the adoption of robotics technology, and then document the robustness of the results in Table 1 to a range of variations.

In Panel A of Table 2, we include aging between 1950 and 1990 as an additional explanatory variable. Past demographic changes should have no impact on the adoption of robotics technology after 1990, unless countries that have adopted more robots since 1993 were on different demographic trends before the 1990s. The results in Panel A confirm the lack of such differential trends, bolstering our confidence in the interpretation presented so far. Panel B goes one step further and looks at the relationship between aging between 1950 and 1990 and the adoption of robots after 1993 without controlling for expected aging. This is a more demanding specification because correlation between past aging and our main aging variable could bias our estimates. Nevertheless, with the exception of the estimate in column 3 which is marginally significant at 10%, we see no systematic and significant relationship between past aging and the adoption of robots between 1993 and 2014. Table A8 in the Appendix reports similar findings using weighted specifications.

Panel C of Table 2 investigates the question of whether it is contemporaneous demographic change or the expectation of future aging that is more strongly associated with the adoption of robots. We simultaneously include aging between 1990 and 2015—the contemporaneous demographic change—and expected aging between 2015 and 2025. The results are not as precise as before, since contemporaneous and expected aging are highly correlated. Nevertheless, both aging variables are positively associated with the adoption of robots. In no specification can we reject the null hypothesis that contemporaneous and expected aging have the same impact on robot adoption. These results support our choice of focusing on expected aging between 1990 and 2025 as our main explanatory variable.[18]

We have so far reported estimates from long-differences specifications, focusing on the change in the stock of robots between 1993 and 2014. This is a transparent specification, especially in view of the evidence that it is not just contemporaneous but future demographic changes that are impacting the adoption of robots. However, long differences fail to exploit covariation between the timing of aging and the adoption of robots within subperiods. To utilize this source of variation, Table 3 turns to stacked-differences specifications where for a country we include two observations on the left-hand side: the change in the stock of robots between 1993 and 2005 and between 2005 and 2014. We then regress these changes on aging between 1990 and 2005 and between 2005 and 2015, respectively. To ease the comparison with our previous estimates, we re-scale the coefficients so that they are directly comparable to the estimates in Table 1. Panel A presents our OLS estimates. Columns 1 and 4 give our most parsimonious model where we only control for region and period dummies. Columns 2 and 5 include all the country level covariates as controls (baseline values of log GDP per capita, log population, average schooling, ratio of older to middle-aged workers,

[18] Table A9 in the Appendix demonstrates that our results are very similar if we use aging between 1990 and 2015 in our main specifications. In addition, Table A10 presents the cross-sectional (level) relationship between demographic structure (the ratio of older to middle-aged workers) and the stock of robots, and shows that countries with an older workforce use significantly more robots.

stock of industrial robots per thousand workers and the log of manufacturing value added). Panel B presents the corresponding IV estimates, while Panels C and D report results from weighted regressions. The estimates confirm the results in Table 1. In columns 3 and 6, we go one step further and include linear country trends. These specifications only exploit the differential rate at which demographic change proceeds and additional robots are adopted in the two subperiods for each country. Remarkably, the estimates in these demanding specifications are similar to our baseline estimates, and statistically significant at 10% or less except in Panel C.

Besides aging, our model suggests that other factors affecting the wage of production workers, such as unionization, and the wage level itself are important determinants of the adoption of robots. We explore these issues in Table A11 in the Appendix, where in addition to estimating the impact of aging on robot adoption, we control for the 1990-1995 union membership and the log of hourly wages in 1993.[19] The results support the idea that countries with greater unionization rates adopt more robots, presumably because unions raise labor costs (though we lack instruments for unionization). Quantitatively, our estimates in column 6 of Panel B imply that a 10 percentage point increase in union membership—roughly the difference between Germany and the United States—is associated with 0.04 additional robots per thousand workers per year, a magnitude that is about 40% of the quantitative effects from aging reported above. The wage level, on the other hand, has a positive point estimate, but this estimate is not robust.[20] Importantly, our point estimates for aging do not change when we control for unionization, suggesting that aging is not capturing differences in labor market institutions across countries.

Finally, we explored models for the percent increase in robots rather than the increase in the number of robots per thousand workers as in our baseline specification. In Table A12, we present estimates using either $\Delta \ln(1 + R_c)$ or $\Delta \ln R_c$ as the dependent variable. The former specification is motivated by the fact that the initial stock of robots is equal to zero for several countries. In all cases, the results are similar to our baseline estimates.

In summary, there is a robust and quantitatively large effect of aging on the adoption of industrial robots.

4.3 Other Automation Technologies

We now show a similar relation between aging and other automation technologies using Comtrade imports data. We first confirm the results presented so far using imports of industrial robots. To do so, we estimate a variant of equation (18) with the log of robot imports relative to other intermediate imports between 1996 and 2015 as the dependent variable.[21] Because these measures

[19] We use the average share of workers belonging to a union between 1990 and 1995 as our measure of unionization (from Rama and Artecona, 2002). The data on wages are from the Penn World Tables, version 9.0 (see Feenstra, Inklaar and Timmer, 2015). In addition, because wages partly reflect differences in labor productivity, in all these models we control for the log of output per worker in 1993. Because the data on union membership are only available for a subset of countries, our sample now consists of 46 countries, 30 of which are in the OECD.

[20] This might be because high wages reflect not just greater “wage push”, but also a higher marginal product of workers, or because our measure is the average wage rather than the wage of blue-collar or middle-aged workers, which are the ones that should matter in our model.

[21] Several points are worth noting. First, since imports (and later exports and patents) are flow variables, our dependent variable corresponds to the growth in the stock of these intermediates, in line with our baseline specification

are imprecise for countries with little trade and small manufacturing sectors (that tend to trade few intermediates), we focus on regressions weighted by manufacturing value added in 1990.[22]

Panels A and B of Table 4 presents our OLS and IV estimates. The table has the same structure as the previous tables, with the exception that in columns 3 and 6 we now control for the log of intermediate imports instead of the initial robot density. Moreover, because Comtrade data cover more countries, our sample now includes 130 countries, 34 of which are in the OECD (recall that these models exclude Japan). We find that aging countries tend to import more industrial robots relative to other intermediate goods. Figure 5 provides regression plots for the full sample and the OECD sample. The implied quantitative magnitudes are similar to those reported so far. The IV coefficient estimate in column 3 of Table 4, 1.82 (s.e.=0.77), implies that a 20 percentage point increase in aging, corresponding to the difference between Germany and the US, leads to a 36% increase in the imports of industrial robots relative to total intermediate imports and closes about a third of the gap between the two countries (which is comparable to the quantitative magnitudes for robot installations in our baseline estimates). Moreover, aging by itself accounts for over 20% of the cross-country variation in the imports of robots.

Figure 7 turns to imports of other equipment from the Comtrade data, and reports estimates of the IV models in columns 2 and 5 of Table 4. We provide results for three sets of imported intermediates. The first set includes intermediates related to industrial automation: dedicated machinery (including robots), numerically controlled machines, automatic machine tools, automatic welding machines, weaving and knitting machines, dedicated textile machinery, automatic conveyors, and regulating and control instruments. The second set comprises non-automated technologies used for similar industrial tasks. This set includes manual machine tools, manual welding machines, machines that are not numerically controlled, other conveyors, and other industrial machinery. Finally, we consider intermediates related to nonindustrial technologies, which should not become more profitable when the population ages—at least not through the channels we have been emphasizing. This set includes vending machines, laundry machines, agricultural machinery (including tractors) and computers.[23] The evidence in Figure 7 is consistent with the idea that aging is associated with the adoption of a range of technologies for industrial automation, and not other technologies. For the full sample of countries, aging leads to a sizable increase in the relative imports of all of our industrial automation technologies, except automatic conveyors. For the OECD, the

with the increase in robots on the left-hand side in equation (18). Second, our normalization ensures that our findings are not driven by an overall increase in imports in aging countries. Third, because data on robot imports and exports are only available between 1996 and 2015, in these models we focus on aging between 1995 and 2025, and measure all of our controls in 1995 rather than in 1993. Finally, we choose the specification with logs as the baseline because it turns out to be less sensitive to outliers, and we focus on the sample of countries with positive imports or exports of the relevant intermediates (and later patenting)—the IFR sample is defined in a similar way, as it only includes countries with positive robot installations. In Table A13 and Figures A3 and A4 in the Appendix, we show the robustness of our results to different specifications and to samples that include countries with zero imports, exports or patents.

[22]The results are similar if we use total intermediate imports (exports) as weights in our regressions.

[23]Computers are of interest in and of themselves; they are also quite distinct from automation technologies, since they are typically used to complement labor in existing tasks as well as automating a smaller subset of tasks (and this non-automating role of computers is in line with the results in Acemoglu and Restrepo, 2018a).

estimates are less precise but paint a similar picture. Reassuringly from the viewpoint of our theory, in neither sample do we find a relationship between aging and imports of technologies unrelated to automation of blue-collar jobs, including computers. The results presented in this subsection are robust to a range of checks. For example, Figures A3 and A4 in the Appendix show that they are very similar when we use $\log(1+x)$ or shares on the left-and side, and when we exclude outliers.

5 Demographic Change, Exports and Innovation

While our theory links demographic change to both the adoption and the innovation of automation technologies, the evidence so far has focused on adoption. We now turn to the effect of aging on the innovation and development of new automation technologies. We first look at export of intermediates that embody automation technologies, starting with industrial robots. New or improved varieties of specialized machinery are often exported to other countries. Motivated by this reasoning, we consider (relative) exports of automation-related intermediates as a measure of development of new and higher-quality automation technologies, and investigate whether countries that are aging rapidly increase their exports of these technologies.[24]

We start with a variant of equation (18) focusing on log robot exports relative to other intermediate exports between 1996 and 2015 as dependent variable. Similar to our strategy with imports, we weight our regressions by manufacturing value added in 1990.

Panels C and D of Table 4 present OLS and IV estimates for exports of industrial robots. These panels follow the structure of Panels A and B, except that in columns 3 and 6 we control for the log of intermediate exports instead of imports. Our sample now includes 103 countries, 35 of which are in the OECD. Because we are looking at exports, these models include Japan as well. The results robustly show that demographic change is associated with greater exports of industrial robots relative to other intermediate goods. Figure 6 depict these relationships for the full sample and the OECD sample. The IV estimate in column 3, 5.2 (s.e.=1.02), implies that a 20 percentage point increase in expected aging, corresponding to the difference between Germany and the US, doubles robotics exports, which fully closes the gap between the two countries (which is about 63%). In fact, in this case, aging by itself accounts for about 60% of the cross-country variation.

Panel B of Figure 7 turns to exports of other types of machinery, including intermediates that are unrelated to industrial automation. With the exception of regulating and control instruments, we find a strong and quantitatively sizable effect of aging on the export share of all intermediates that embody industrial automation technologies. As was the case with imports, we do not see a similar association with aging for technologies unrelated to industrial automation.

The export results are also robust to a range of different specifications. Figures A3 and A4 in the Appendix show that these results are robust when we use $\log(1+x)$ or shares on the left-and side, and when we exclude outliers (see Table A13).

The export results also provide support for our claim in the Introduction that automation

[24] Costinot, Donaldson, Kyle and Williams (2017) also look at exports as a measure of the development of new technologies, but focus on pharmaceuticals.

technologies developed in countries experiencing rapid demographic change are adopted throughout the world. Data from the IFR back this up as well. An estimated 381,000 robots were installed in 2017. Even though the majority of those were produced in and exported from Germany and Japan, only 1/6th of these were installed in these two countries. The rest were exported to over 50 countries, and more than 20 countries installed more than 1000 robots each in 2017. As a result of these exports, there are now 33 countries with more than one robot per thousand industrial workers and 17 countries with more than five robots per thousand industrial workers.

Our second measure of innovation and development of new automation technologies involves robotics-related patents, as described in Section 3. We estimate a variant of equation (18) with the log of robotics-related patents relative to other utility patents granted between 1990 and 2015 as the dependent variable. The normalization ensures that our findings are not driven by an overall increase in patenting activity at the USPTO among aging countries. As before, we focus on regressions weighted by manufacturing value added in 1990, which ensures that countries with larger manufacturing sectors and thus more patents get more weight. Panels A and B of Table 5 present our OLS and IV estimates. Our sample now includes 68 countries, 31 of which are in the OECD. The results show a strong positive association between demographic change and robotics-related patents (relative to other utility patents). Figure 8 presents these relationships visually. The IV estimate in column 6, for example, is 1.34 (s.e.=0.46) and implies that a 20 percentage point increase in expected aging, corresponding to the difference between Germany and the US, leads to a 27% increase in robotics-related patents relative to all utility patents, which is about half of the gap between the two countries. Aging by itself explains over 30% of cross-country variation in robotics-related patents.

We investigated the robustness of these results in a number of dimensions. Some of those are shown in Figure 9. To start with, the results are very similar with alternative definitions of automation patents, and reassuringly from the viewpoint of our explanation, there is no similar positive association when we look at patents related to computers, nanotechnology or pharmaceuticals. Our alternative measures of robotics-related and other automation patents are: just the 901 USPTO class (as opposed to our baseline measure which also includes all patents referring to the 901 class); patent classes that tend to cite the 901 class frequently (using two definitions); patents whose abstract contains words related to robots or to industrial robots; patents whose abstract contains words related to industrial machinery; and finally patents whose abstract contains words related to numerical control. In all these cases we find a positive association between aging and the share of patents in these classes. The remaining entries in the figure show that the relationship for computers, nanotechnology and pharmaceuticals are either zero or negative. These results bolster our interpretation that demographic change encourages the development of a specific class of technologies related to industrial automation.[25]

[25]The construction of the various patent classes is further described in the Appendix, where we also show that our main results for patents are robust when we use other functional forms or when we take into account the presence of outliers (see Table A14).

6 Demographics and Robots across US Commuting Zones

In this section, we explore the relationship between aging and the adoption of robots across US commuting zones. We use Leigh and Kraft's (2018) data on the location of robot integrators to proxy for robotics-related activity. Panel A of Table 6 reports OLS estimates of the model

$$\text{Integrators}_z = \beta \text{Aging}_z + \Gamma X_{z,1990} + \upsilon_z$$

across 722 US commuting zones indexed by z. The dependent variable Integrators_z is a dummy for whether a commuting zone has any robot integrators. Aging_z denotes the *change* in the ratio of workers above 56 to those between 21 and 55 between 1990 and 2015, and $X_{z,1990}$ is a vector of additional commuting-zone characteristics measured in 1990. As in our cross-country models for robots, we focus on unweighted regressions and present weighted ones in the Appendix. The standard errors are robust against heteroskedasticity and spatial correlation at the state level.

Because people migrate across commuting zones more commonly than across countries, the endogeneity of local age composition is a more significant issue in this case than in our cross-country analysis. To address it, in Panel B we instrument aging using the average birth rates of the commuting zone over five-year intervals from 1950-1954 to 1980-1984, while in Panel C we present an alternative IV strategy using the decline in birth rates from 1950 to 1985 as a single instrument.

All panels in this table share the same structure. Column 1 controls just for regional dummies (Midwest, Northeast, South, and West). Column 2 includes demographic characteristics of commuting zones measured in 1990—a period when the US had few industrial robots and integrators. These characteristics include log average income, log population, the urbanization rate, the initial ratio of older to middle-aged workers, and the shares of people by education, race, and gender. Column 3 includes the measure of *exposure to robots* between 1990 and 2015 from Acemoglu and Restrepo (2018a), which captures the extent to which a commuting zone specializes in industries that are prone to the adoption of robots.[26] This column also controls for the shares of employment in manufacturing, agriculture, mining, construction, and finance and real estate in 1990. Column 4 controls for other major trends affecting US labor markets—exposure to Chinese imports, offshoring, and the share of routine jobs. Finally, in column 5 we follow Acemoglu and Restrepo

[26] To construct this variable, we first define the *adjusted penetration of robots* in industry i between time t_0 and t_1,

$$APR_{i,t_0,t_1} = \frac{1}{5}\sum_j \left(m^j_{i,t_1} - m^j_{i,t_0} - g^j(i,t_0,t_1) m^j_{i,t_0} \right),$$

which is based on robot adoption trends among European countries. In particular, in this equation j indexes Denmark, Finland, France, Italy or Sweden, and $m^j_{i,t}$ denotes the number of robots in country j's industry i at time t (from the IFR data), normalized by thousand workers in 1990. The term $g^j(i,t_0,t_1)$ gives the growth rate of output of industry i during this period, so that subtracting $g^j(i,t_0,t_1)m^j_{i,t_0}$ adjusts for the fact that some industries are expanding more than others (see Acemoglu and Restrepo, 2018a). The exposure to robots of a commuting zone is then

$$\textit{Exposure to robots}_{z,t_0,t_1} = \sum_{i \in \mathcal{I}} \ell^{1970}_{zi} APR_{i,t_0,t_1},$$

where the sum runs over all the industries in the IFR data, and ℓ^{1970}_{zi} stands for the 1970 share of commuting zone z employment in industry i (computed from the 1970 Census).

(2018a) and exclude the top 1% commuting zone with the highest exposure to robots to ensure that the results are not being unduly affected by the most exposed commuting zones.

Overall, the results in this table, especially the IV estimates, suggest that integrators locate in commuting zones that are aging more rapidly as well as those with the greatest exposure to robots (as shown by Acemoglu and Restrepo, 2018a). The estimates in column 4 of Panel B imply that a 10 percentage point increase in aging—the standard deviation among US commuting zones in this period—is associated with a 8.8 percentage points increase in the probability of having an integrator (compared to an average probability of 22%).

Table A15 in the Appendix shows that our commuting zone-level results are robust across a range of specifications, for example, when we exclude outliers, weight the data by the size of the manufacturing sector in each commuting zone, or use the log of the number and the employment of integrators as the dependent variable.

Figure 10 presents binned scatter plots of the relationship between predicted aging (from the IV and single-IV first stages) and the location of integrators corresponding to the IV estimates from the specification in column 4, Panels B and C, of Table 6. In addition, Figure A7 in the Appendix presents a map of commuting zones that house robot integrators next to the predicted aging patterns across commuting zones, depicting the spatial association between these two variables.

Overall, even though the presence of integrators in an area does not fully capture the extent of industrial automation or the use and development of robotics technologies, the evidence is broadly supportive of the positive impact of aging on the adoption of robots.

7 Mechanisms

We have documented the relationship between aging and automation technologies across countries and US commuting zones. Our theory suggests that this occurs because, relative to older workers, middle-aged workers have a comparative advantage in manual production tasks, which are the ones being automated using industrial automation technologies such as robots. When this is the case, aging raises the wage of production workers and makes automation technologies more profitable, particularly in industries that rely more on middle-aged workers and those that have greater opportunities for automation. This section provides evidence to bolster our interpretation. We start by showing that automation technologies (in particular, industrial robots) substitute for production workers who are significantly more likely to be middle-aged (rather than older). We then investigate the additional industry-level predictions of our theory. Finally, we look at the implications of our theory for productivity and the labor share.

7.1 The Substitution between Robots and Workers

In this section, we provide three pieces of evidence bolstering our hypothesis that middle-aged workers specialize in production tasks that can be automated using industrial robots and related automation technologies.

Using data from the the 1990 US Census, the 2000 US Census, and the 2007 American Community Survey, we first documents how the allocation of *employed* workers across industries and occupations varies with their age. Panel A of Figure 11 plots the ratio of workers employed in blue-collar jobs relative to workers employed in white-collar and service jobs for five-year age brackets. Blue-collar jobs include production workers and machinists, and represent about 13% of US employment. White-collar jobs include clerks, accountants, secretaries and salespersons, and represent about 25% of US employment, while service jobs account for 15% of US employment. The figure shows a sharp decline in this ratio starting around age 50 (in the 2007 ACS) and age 55 (in the 1990 Census). Panel B reveals a similar picture when we look at the share of workers by age employed in industries that later became more robotized. Both figures support the presumption that, relative to their older counterparts, middle-aged workers specialize in blue-collar jobs and in industries that are more prone to the use of industrial robots. Consistent with automation technologies replacing middle-aged workers in production tasks, both figures also show a decline over time in the share of middle-aged workers employed in blue-collar jobs and in industries prone to the use of industrial robots.

Our second strategy documents that as an industry adopts more robots, the employment and wage bill shares of production workers in that industry decline. This evidence suggests that, consistent with our theoretical framework, robots replace workers in production tasks in manufacturing, which from Figure 11 tend to be the middle-aged workers. For each industry, we measure the share of wages paid to production workers employed using data from the NBER-CES Manufacturing Industry Database. Following Acemoglu and Restrepo (2018a), we use the *adjusted penetration of robots* in each industry (see footnote 26), which focuses on common technological developments driving the adoption of robots throughout the world. Figure 12 indicates that, across the 13 manufacturing industries covered by the IFR and NBER-CES, the adjusted penetration of robots is correlated with a significant decline in the employment and wage bill shares of production workers during the 1993-2007 period.

Finally, we look at the impact of automation on the wages and employment of workers by age. We follow Acemoglu and Restrepo's (2018a) approach to estimate the impact of robots across US commuting zones and use the exposure to robots (see footnote 26). We then estimate the following model for employment and wages by 10-year age group across commuting zones:

$$\Delta Y_{z,a} = \beta_a^Y \ \textit{Exposure to robots 1993 to 2007}_z \ + \epsilon_{z,a}^L,$$

where $\Delta Y_{z,a}$ is the change in the employment rate (or the wage rate) of age group a in commuting zone z between 1990 and 2007. Figure 13 presents the estimates of the coefficients for employment and wages by 10-year age groups (together with 95% confidence intervals). We report three specifications similar to those in Acemoglu and Restrepo (2018a), except that in line with the focus here all regressions are unweighted. The first one we report is the baseline specification in Acemoglu and Restrepo (2018a), which controls for Census region fixed effects, demographic differences across commuting zones, broad industry shares, the share of routine jobs and the impact of trade with

China (as in Autor, Dorn and Hanson, 2013).[27] The second specification removes the top 1% commuting zones with the highest exposure to robots, to ensure that the results are not being driven by the most exposed commuting zones. The last specification pools the data for all age groups and forces our covariates, except exposure to robots, to have the same impact on all workers.

For both employment and wages, the negative effects of industrial robot adoption concentrate on workers between the ages of 35 and 54, with mild effects on those older than 55 and no effects on those above 65.[28] The results from this strategy are our most direct evidence that, relative to older workers, middle-aged workers specialize in tasks that can be performed by, and thus are more substitutable to, industrial robots.

7.2 Industry-Level Results

A key prediction of our model is that the impact of aging should be more pronounced in industries that rely more on middle-aged workers and also in industries in which these middle-aged workers engage in tasks that can be more productively automated. This subsection explores this prediction using robot adoption data by industry and country.

Table 7 estimates regression models using IFR data on robot installations by country, industry and year, where we also interact aging with industry characteristics:

$$\begin{aligned}\frac{IR_{i,c,t}}{L_{i,c,1990}} =& \beta \text{Aging}_c + \beta_R \text{Aging}_c \times \text{Reliance on Middle-Aged Workers}_i \\ &+ \beta_P \text{Aging}_c \times \text{Opportunities for Automation}_i + \Gamma_{i,t} X_{c,1990} + \alpha_i + \delta_t + \varepsilon_{i,c,t}.\end{aligned} \tag{19}$$

In contrast to equation (18), the left-hand side variable now denotes the (annual) installation of new robots per thousand workers (still normalized by employment in 1990).[29] Aging_c is once again defined as the change in the ratio of the population above 56 to those between 21 and 55 between 1990 and 2025. We include industry and year effects, and also allow the covariates in $X_{c,1990}$ to have time-varying coefficients and affect industries differentially. Reliance on Middle-Aged Workers_i and Opportunities for Automation_i were defined in Section 3 and capture the relevant dimensions of industry heterogeneity according to our theory. Our sample for this regression covers up to 50 countries for which industry data are available, and covers the 1993-2014 period but is unbalanced since, as indicated in Table A1, data are missing for several country×industry×year combinations.[30]

[27] Specifically, we control for the 1990 levels of: log population, the share of population above 65; the shares of population with different education levels, the share of population by race and gender, and the shares of employment in manufacturing, light manufacturing, mining and construction, as well as the share of female employment in manufacturing. The variables are described in detail in Acemoglu and Restrepo (2018a).

[28] In Figure A8 in the Appendix, we report similar results by five-year age bins. In weighted regressions, the estimates for employment are similar, but we do see some significant negative wage effects for older groups as well. This might reflect the downward wage pressure exerted by displaced middle-aged workers on jobs occupied by older workers in some large commuting zones.

[29] Table A16 in the Appendix shows that if we estimate an analogue of equation (19) using yearly data on robot installation for countries, the results are similar to our baseline cross-country estimates in Table 1. The slight differences are due to the depreciation of the stock of robots (if robots did not depreciate, the two models would yield the exact same results since total installations would add up to the change in the stock of robots).

[30] In this and subsequent industry-level regressions, we weight country-industry pairs using the baseline share of employment in each industry in that country. This weighting scheme ensures that all countries receive the same

Standard errors are now robust against heteroscedasticity, and cross-industry and temporal correlation at the country level.

To normalize our left-hand side variable, we use several approaches. First, in Panels A and B we use the ILO country data to normalize robot installations by $L_{c,1990}/19$ (recall that the IFR reports data for 19 industries). This normalization allows us to use all 50 countries for which there are industry-level robots data. Second, in Panels C and D we use data for employment by industry and country from EUKLEMS, which cover all the industries in our sample for 22 countries. Finally, Table A17 in the Appendix uses data on employment by industry and country from UNIDO, which covers manufacturing industries for 44 countries.

Column 1 presents estimates of equation (19) without the interaction terms. The positive estimates for aging across all panels show that, even within a given industry, countries that are aging rapidly adopted more robots than other countries. This result confirms that our cross-country relationship between aging and the adoption of robots takes place within industries (as in our model), and does not simply reflects differences in the industry composition of aging countries.

The remaining columns include the interaction of aging with an industry reliance on middle-aged workers and opportunities for automation. In columns 2-4, Opportunity for Automation$_i$ is proxied using Graetz and Michaels's replaceability index, while in columns 5-7, it is proxied by a dummy for the industries identified by BCG (2015). The estimates in columns 2 and 5 show positive and statistically significant interactions with both variables in all panels. Those in column 2 of Panel A, for example, indicate that a 10 percentage point increase in aging leads to an increase of 0.2 ($= 2.25 \times 0.89 \times 0.1$) annual robot installations per thousand workers in an industry at the 95th percentile of reliance on middle-aged workers compared to an industry at the 5th percentile. In the plastic and chemicals industry, which is at the 95th percentile of reliance on middle-aged workers, a 10 percentage point increase in aging raises robot installations by 0.27 per thousand workers per year, while in textiles, which is at the 5th percentile, the same change leads to 0.07 more installations per thousand workers. On the other hand, a 10 percentage point increase in aging is associated with an increase of 0.23 ($= 0.35 \times 6.47 \times 0.1$) annual robot installations per thousand workers in an industry at the 95th percentile of the replaceability index compared to an industry in the 5th percentile. For instance, in the metal products industry, which is at the 95th percentile of the replaceability index, a 10 percentage point increase in aging raises robot installations by 0.27 per thousand workers per year; while in agriculture, which is at the 5th percentile, the same change leads to 0.04 more installations per thousand workers. These columns report the main effect of aging evaluated at the 95th percentile of reliance on middle-aged workers and replaceability. Evaluated at this point, the main effect of aging is 2.5 times larger than at the average industry, illustrating the quantitative importance of industry heterogeneity.

The remaining columns show that our results are robust to the inclusion of other controls. In

weight—as in our unweighted country specifications—while industry weights reflect their relative importance in each country (this is the same weighting scheme used by Graetz and Michaels, 2018).

Though not reported in our tables to save space, our covariates, $X_{c,1990}$, include region dummies, log GDP per capita, log population, average years of schooling and the ratio of older to middle-aged workers in 1990.

columns 3 and 6, we control for a measure of the baseline extent of robot use in each country-industry pair, which accounts for any unobserved industry characteristics that may be correlated with initial investments and subsequent trends in robotics and/or for mean-reversion (or other) dynamics.[31] In columns 4 and 7 we control for a full set of country fixed effects (we no longer estimate the main effect of aging in this case). In these models the interaction between aging and industry characteristics is identified solely from within-country variation. Reassuringly, the size of the interaction coefficients does not change much in either case.

Finally, Panels B and D present IV specifications. As in our cross-country analysis, we instrument aging using past birth rates, and we also include interactions of these birth rates with our measures of reliance on middle-aged workers and opportunities for automation to generate instruments for the interaction terms. The IV estimates are similar to the OLS ones. We also confirmed that past demographic changes neither have significant main effects nor interaction effects (with reliance on middle-aged workers or opportunities for automation) and further verified that these results are robust under different specifications and to excluding outliers. These results are presented in Tables A18, A19, and A20 in the Appendix.

Overall, the cross-industry patterns provide support for the theoretical predictions of our framework, and indicate that the adoption of robots responds to aging precisely in industries that rely more on middle-aged workers and that have greater opportunities for automation.

7.3 Productivity and the Labor Share

As highlighted in Section 2, the relationship between aging and industry productivity is in general ambiguous. On the one hand, demographic change might reduce the number of high-productivity middle-aged workers relative to lower-productivity older workers. On the other hand, demographic change might increase productivity because of the technology adoption it triggers. Nevertheless, because of the induced increase in automation, in aging countries industries with the greatest opportunities for automation should increase their value added per worker relative to other industries that cannot rely on automation to substitute for middle-aged workers. For the same reason, we also expect a differential negative impact of aging on the labor share in industries with the greatest opportunities for automation.

Panels A and B of Table 8 present OLS and IV estimates of a variant of equation (19) with the change in log value added per worker in industry i in country c between 1995 and 2007 as the left-hand side variable (instead of annual robot installations, so that now we have a single observation for each country-industry pair). Otherwise, the structure of Table 8 is similar to that of Table 7.[32]

Column 1 in Panel A shows a small and insignificant main effect of aging on value added per worker. A 10 percentage point increase in aging is associated with a 2.6% decline in value added

[31] Because we do not observe the stock of robots for all country-industry pairs in 1993, we follow Graetz and Michaels (2018) and impute them when missing by deflating the first observation of the stock of robots in a country-industry pair back in time using the growth rate of the stock of total robots in the country during the same period.

[32] The only difference is that, because the value added data from EUKLEMS is available for a wide range of countries starting only in 1995, we compute our aging variable to be between 1995 and 2025.

per worker (s.e.=2.2%).[33]

Of greater interest given our model predictions is the interaction between aging and opportunities for automation. Columns 2-7 show a positive interaction, indicating that as countries age, industries with greater potential for automation experience relative productivity gains. The magnitudes are sizable. The IV estimate in column 2 of Panel B shows that a 10 percentage points increase in aging causes an increase of 17.5% ($= 0.35 \times 5 \times 0.1$) in the value added per worker in an industry at the 95th percentile of the replaceability index compared to an industry at the 5th percentile. Our main effects, which are evaluated at an industry at the 95th percentile of replaceability and 5th percentile of reliance on middle-aged workers, show that aging is associated with an absolute increase in value added per worker in industries that can automate in response to aging.[34]

Finally, in Panels C and D of Table 8, we present regressions for the change in the labor share between 1995 and 2007 as outcome. Column 1 shows that, on average, industries located in countries undergoing more rapid demographic change experienced a decline in their labor share. The remaining columns show that these effects are more pronounced in industries that have greater opportunities for automation, which is consistent with the presumption that these industries are undergoing faster automation in countries with aging workforces. We also find a positive interaction between aging and reliance on middle-aged workers, which is consistent with production tasks being complements ($\zeta < 1$ in our model). The heterogeneous effects on the labor share across industries are again sizable.

Overall, consistent with our theoretical predictions, the evidence suggests that aging increases relative productivity and reduces the labor share in industries that have the greatest opportunities for automation.

8 Conclusion

Advances in robotics and other automation technologies transforming the nature of work in modern economies are often viewed as the natural next phase of the (largely exogenous) march of technology. In this paper, we argue that the adoption and development of these technologies are also receiving a powerful boost from demographic changes throughout the world and especially in a number rapidly-aging countries such as Germany, Japan and South Korea.

We show why aging should, theoretically, lead to industrial automation—because the relative scarcity of middle-aged workers with the skills to perform manual production tasks increases the value of technologies that can substitute for them. We then document that, consistent with this

[33] The point estimate for aging is more negative than what we found in Acemoglu and Restrepo (2017), where we showed that there was no negative relationship between aging and growth in GDP per capita. The difference is driven by the smaller EUKLEMS sample (22 countries). As Table A21 shows, if we estimate the analogue of this equation at the country level using GDP per capita data from the Penn World Tables, we obtain a similar point estimate, and as we increase the sample, the point estimates become positive or zero.

[34] We also find some negative estimates of the interaction between aging and reliance on middle-aged workers, but as emphasized in Section 2, our model has no tight predictions in this case, because both the direct effect (which is negative) and the technology response (which can be positive) tend to be greater for industries that rely more heavily on middle-aged workers.

theoretical perspective, countries and local US labor markets undergoing major demographic change have invested more in new robotic and automation technologies. We also provide evidence that this is because of the resulting scarcity of middle-aged workers and that industrial automation is indeed most substitutable with middle-aged workers. The effects of demographic change on investment in robots are robust and quantitatively sizable. For example, differential aging alone accounts for about 40% of the cross-country variation in investment in robotics. We also show using data on intermediate exports and patents that demographic change encourages not just the adoption of automation technologies but also their development. Furthermore, automation technologies developed in rapidly-aging countries are exported and used throughout the world.

Our directed technological change model further predicts that the effects of demographic change should be more pronounced in industries that rely more on middle-aged workers (because the scarcity of middle-aged workers will be felt more acutely in these industries) and in those that present greater technological opportunities for automation. Using the industry dimension of our data, we provide extensive support for these predictions as well.

The technology responses to aging mean that the productivity implications of demographic changes are more complex than previously recognized. In industries most amenable to automation, aging can trigger a sizable adoption of robots and as a result, lead to greater productivity. Using industry-level data, we find that the main effect of aging on productivity is ambiguous, but as in our theoretical predictions, in the presence of demographic change, industries with the greatest opportunities for automation are experiencing more rapid growth of productivity and greater declines in labor share relative to other industries.

Several questions raised in this paper call for more research. First, it is important to extend the conceptual structure presented here in a more quantitative direction to investigate whether plausible directed technology adoption and innovation responses can generate both the magnitudes of automation technologies we have documented here and a powerful effect throughout the world via exports of these technologies. Second, it would be fruitful to study the effects of aging on technology adoption and productivity using more disaggregated industry-level or firm-level data. Third, another interesting question is whether the effects of demographic change on technology adoption are being mediated through wages and whether other factors, such as differences in labor market institutions, also have direct effects on technology. Fourth, it would be interesting to study technology responses to changes in the gender composition of the workforce as well (though our data on automation technologies are too late to capture the most major changes in the developed world). Finally, motivated by industrial automation, our focus has been on the substitution of machines for middle-aged workers in production tasks (and mostly in manufacturing). Though it is well-known that with the advent of artificial intelligence, a broader set of tasks can be automated, there is currently little research on incentives for the automation of nonproduction tasks and their productivity implications.

References

Abeliansky, Ana and Klaus Prettner (2017) "Automation and Demographic Change," CEGE wp 310.

Acemoglu, Daron (1998) "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality," *Quarterly Journal of Economics,* 113(4): 1055-1089.

Acemoglu, Daron (2002) "Directed Technical Change," *Review of Economic Studies,* 69(4): 781–810.

Acemoglu, Daron (2007) "Equilibrium Bias of Technology," *Econometrica,* 75(5): 1371–1410.

Acemoglu, Daron (2010) "When Does Labor Scarcity Encourage Innovation?" *Journal of Political Economy,* 118(6): 1037–1078.

Acemoglu, Daron and David Autor (2011) "Skills, tasks and technologies: Implications for employment and earnings," *Handbook of Labor Economics*, 4: 1043–1171.

Acemoglu, Daron, and Joshua Linn (2004) "Market size in innovation: theory and evidence from the pharmaceutical industry," *The Quarterly Journal of Economics* 119(3): 1049–1090.

Acemoglu, Daron and Pascual Restrepo (2017) "Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation" *American Economic Review, P&P*, 107 (5): 174–79.

Acemoglu, Daron and Pascual Restrepo (2018a) "The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment" *American Economic Review,* forthcoming.

Acemoglu, Daron and Pascual Restrepo (2018b) "Artificial Intelligence, Automation and Work" NBER Working Paper No. 24196.

Acemoglu, Daron and Pascual Restrepo (2018c) "Robots and Jobs: Evidence from US Labor Markets" NBER Working Paper No. 23285.

Autor, David H., Frank Levy and Richard J. Murnane (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics,* 118(4): 1279–1333.

Autor, David H. and David Dorn (2013) "The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market," *American Economic Review,* 103(5): 1553–97.

Autor, David H., David Dorn, and Gordon H. Hanson (2013) "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103(6): 2121–68

Ayres, Robert U., Brautzsch, H.-U. and Mori, S. (1987) "Computer Integrated Manufacturing and Employment: Methodological Problems of Estimating the Employment Effects of CIM Application on the Macroeconomic Level," IIASA Working Paper WP-87-019.

Ayres, Robert and Steve Miller (1981) "The Impacts of Industrial Robots," Department of Engineering and Public Policy and The Robotics Institute Carnegie-Mellon University.

Baldwin, Richard and Coen Teulings (2014) *Secular Stagnation: Facts, Causes and Cures*, CEPR Press.

Boston Consulting Group (2015) "The Robotics Revolution: The Next Great Leap in Manufacturing."

Brynjolfsson, Erik and Andrew McAfee (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, W. W. Norton & Company.

Clemens, Michael A., Ethan G. Lewis and Hannah M. Postel (2018) "Immigration Restrictions as Active Labor Market Policy: Evidence from the Mexican Bracero Exclusion," *American Economic Review,* 108(6):1468–1487.

Costinot, Arnaud, Dave Donaldson, Margaret Kyle and Heidi Williams (2016) "The More We Die, The More We Sell? A Simple Test of the Home-Market Effect," NBER Working Paper No. 22538.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer (2015) "The Next Generation of the Penn World Table" *American Economic Review,* 105(10): 3150–82.

Finkelstein, Amy (2004) "Static and Dynamic Effects of Health Policy: Evidence from the Vaccine Industry," *Quarterly Journal of Economics,* 119 (2): 527–564.

Ford, Martin (2015) *The Rise of the Robots,* Basic Books, New York.

Goos, Maarten, and Alan Manning (2007) "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics,* 89(1): 118-133.

Gordon, Robert (2016) *The Rise and Fall of American Growth*, Princeton University Press, Princeton New Jersey.

Graetz, Georg and Guy Michaels (2018) "Robots at Work," *Review of Economics and Statistics,* forthcoming.

Gregory, Terry, Anna Salomons, and Ulrich Zierahn (2016) "Racing With or Against the Machine? Evidence from Europe," ZEW - Paper No. 16-053.

Groover, Mikell, Mitchell Weiss, Roger N. Nagel, and Nicholas G. Odrey (1986) *Industrial Robotics: Technology, Programming and Applications,* Mcgraw-Hill Inc.

Hanlon, Walker W. (2015) "Necessity Is the Mother of Invention: Input Supplies and Directed Technical Change," *Econometrica*, 83: 67–100.

International Federation of Robotics (2014) Wold Robotics: Industrial Robots.

Jägger, Kirsten (2016) "EU KLEMS Growth and Productivity Accounts 2016 release - Description of Methodology and General Notes."

Krueger, Dirk, and Alexander Ludwig (2007) "On the Consequences of Demographic Change for Rates of Returns to Capital, and the Distribution of Wealth and Welfare," *Journal of Monetary Economics* 54(1): 49–87.

Leigh, Nancey Green and Benjamin R. Kraft (2018) "Emerging Robotic Regions in the United States: Insights for Regional Economic Evolution." *Regional Studies* 52(6): 804?815.

Lewis, Ethan (2011) "Immigration, Skill Mix, and Capital Skill Complementarity," The Quarterly Journal of Economics 126(2): 1029–1069.

Ludwig, Alexander, Thomas Schelkle, and Edgar Vogel (2012) "Demographic Change, Human Capital and Welfare," *Review of Economic Dynamics* 15(1): 94–107.

Manuelli, Rodolfo E., and Ananth Seshadri (2014) "Frictionless Technology Diffusion: The Case of Tractors," *American Economic Review* 104(4): 1368–91.

Manson, Steven, Jonathan Schroeder, David Van Riper, and Steven Ruggles (2017) "IPUMS National Historical Geographic Information System: Version 12.0 [Database]." Minneapolis: University of Minnesota.

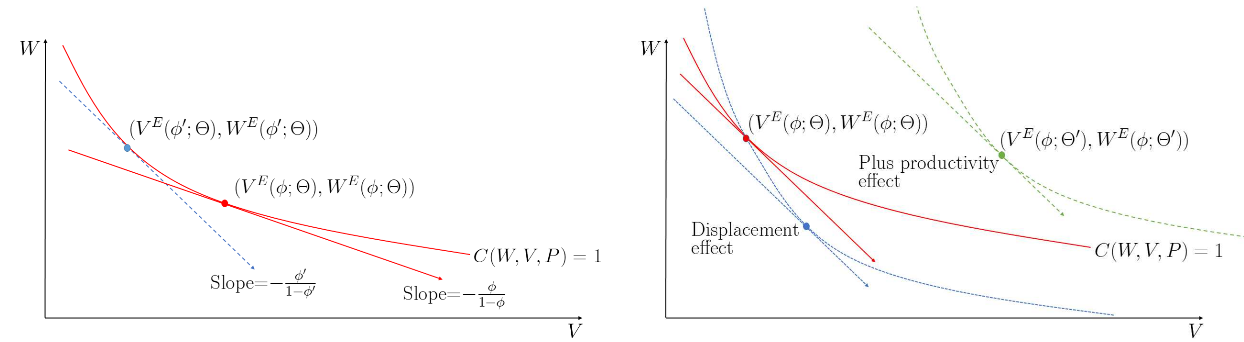
Michaels, Guy, Ashwini Natraj and John Van Reenen (2014) "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years,"*Review of Economics and Statistics,* 96(1): 60–77.

Murphy, Kevin M. and Finis Welch (1990) "Empirical Age-Earnings Profiles" *Journal of Labor Economics*, H(2), 202-229.

Poterba, James M (2001) "Demographic Structure and Asset Returns," *The Review of Economics and Statistics* 83(4): 565–584.

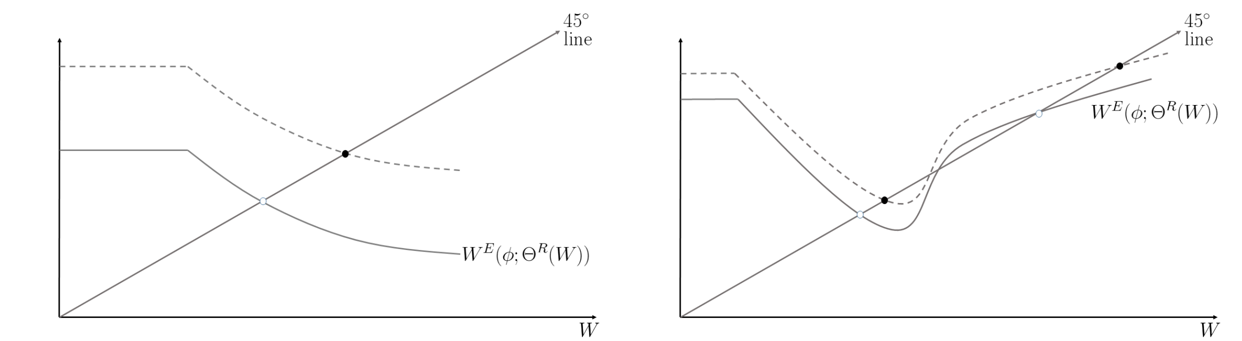
Tolbert, Charles M., and Molly Sizer (1996) "US Commuting Zones and Labor Market Areas: A 1990 Update." Economic Research Service Staff Paper 9614.

Zeira, Joseph (1998) "Workers, Machines, and Economic Growth," *Quarterly Journal of Economics,* 113(4): 1091–1117.



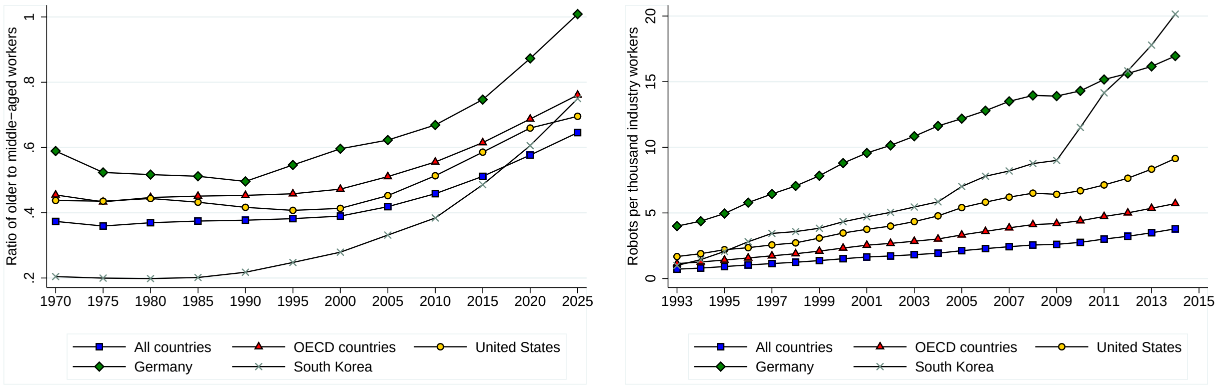
Panel A Panel B

FIGURE 1: Equilibrium wages W^E and V^E. The downward-slopping red curve is the isocost $C(W,V,1)=1$ (condition (12)). The equilibrium is given by the point of tangency between the isocost and a line with slope $-\frac{1-\phi}{\phi}$, and at this point $\frac{\partial C/\partial W}{\partial C/\partial V}=\frac{1-\phi}{\phi}$ (condition (13)). Panel B shows that automation rotates the isocost curve clockwise (displacement effect) and shifts it outwards (productivity effect).



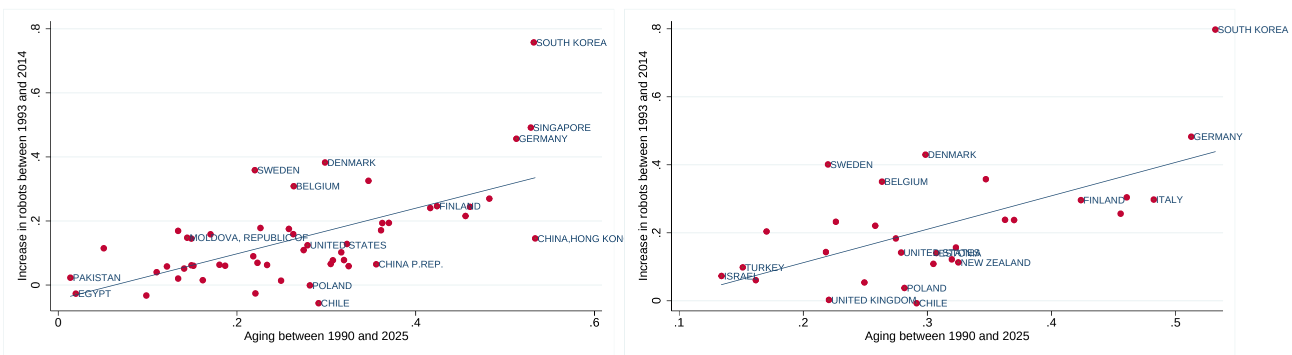
Panel A Panel B

FIGURE 2: Equilibrium middle-aged wage with endogenous technology. Panel A: unique equilibrium. Panel B: multiple equilibria. Aging shifts the mapping W^E up, and this increases the equilibrium wage in the least and the greatest equilibrium.



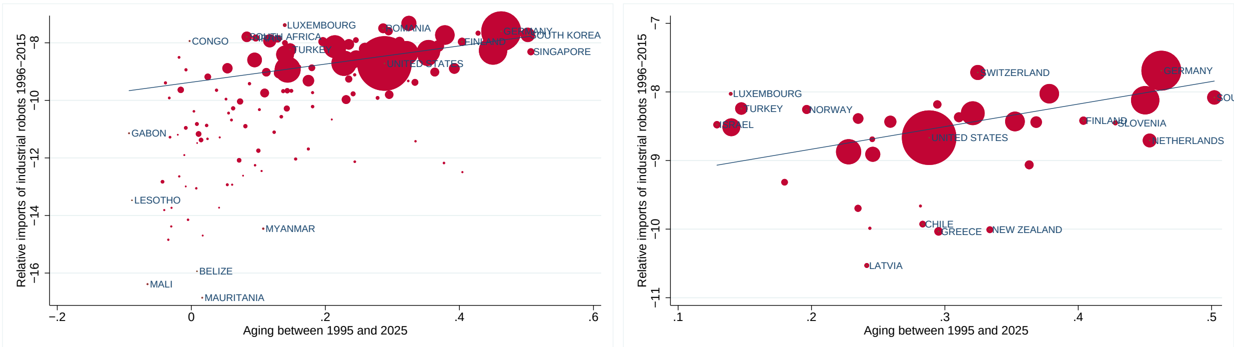
Panel A Panel B

FIGURE 3: Panel A presents trends in aging—the ratio of older (56 years of age or older) to middle-aged (between 21 and 55 years of age) workers—using data and forecasts from the UN. Panel B presents trends in robot adoption. Robot adoption is measured by the number of robots (using robot data from the IFR) normalized by thousand industrial workers in 1990 (from the ILO).



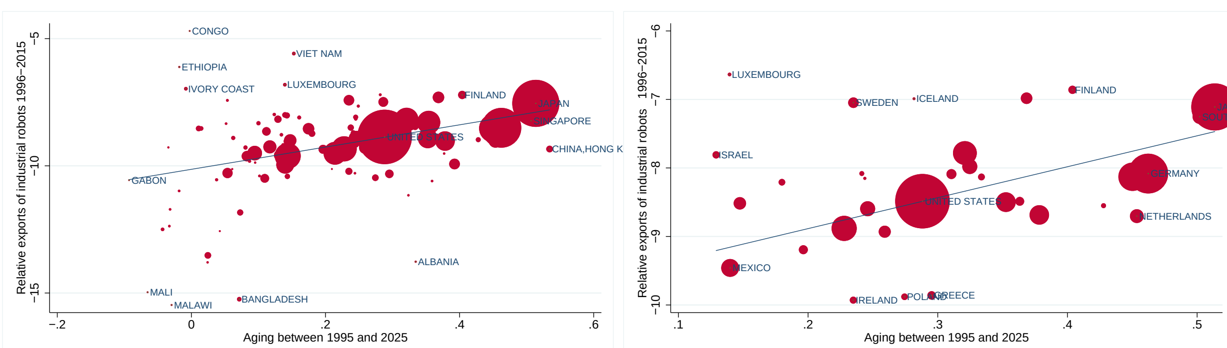
Panel A Panel B

FIGURE 4: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the increase in the number of industrial robots per thousand workers between 1993 and 2014. The plots partial out the covariates included in the regression models in columns 2 and 5 of Table 1.



Panel A Panel B

FIGURE 5: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of imports of industrial robots between 1996 and 2015 (relative to imports of intermediates). Panel A is for the full sample and Panel B is for the OECD sample. The plots partial out the covariates included in the regression models in columns 2 and 5 of Table 4. Marker size indicates manufacturing value added.



Panel A Panel B

FIGURE 6: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of exports of industrial robots between 1996 and 2015 (relative to exports of intermediates). Panel A is for the full sample and Panel B is for the OECD sample. The plots partial out the covariates included in the regression models in columns 2 and 5 of Table 4. Marker size indicates manufacturing value added.

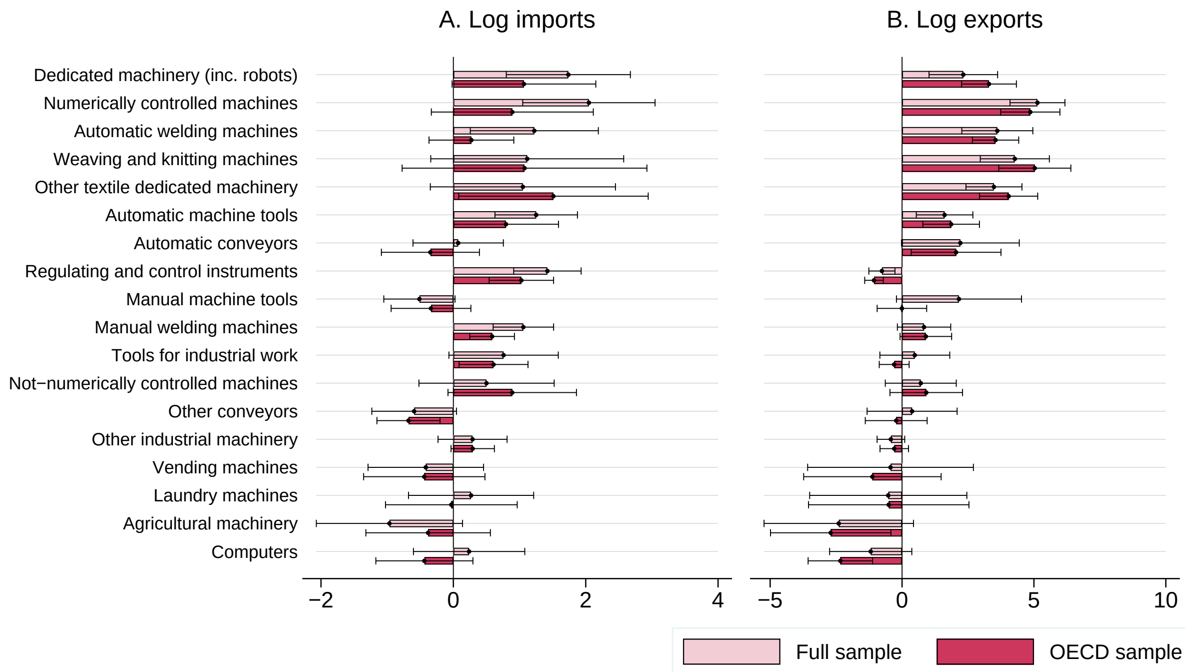
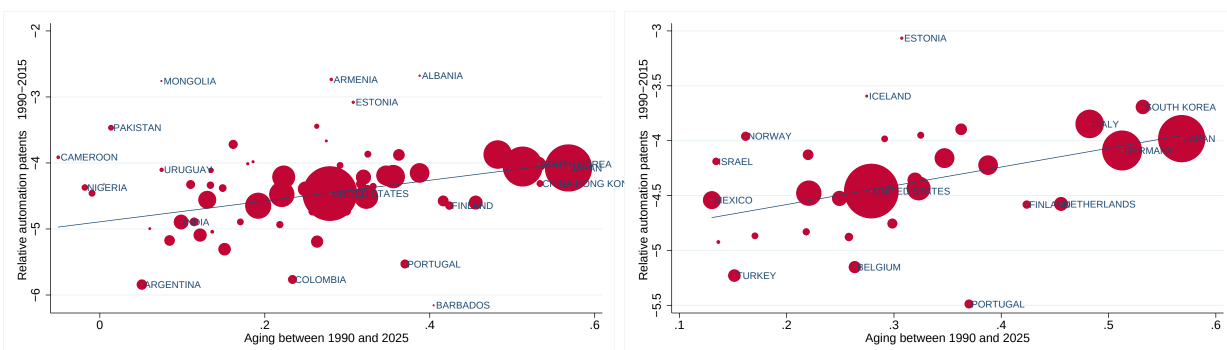


FIGURE 7: Estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of imports (Panel A) and exports (Panel B) of intermediate goods between 1990 and 2015. These outcomes are normalized by the total intermediate exports and imports, respectively, during this period. The figure presents separate estimates for the full sample of countries and for the OECD sample.



Panel A

Panel B

FIGURE 8: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of automation patents granted to a country between 1990 and 2016 (relative to total patents at the USPTO). Panel A is for the full sample and Panel B is for the OECD sample. The plots partial out the covariates included in the regression models in columns 2 and 5 of Table 5. Marker size indicates manufacturing value added.

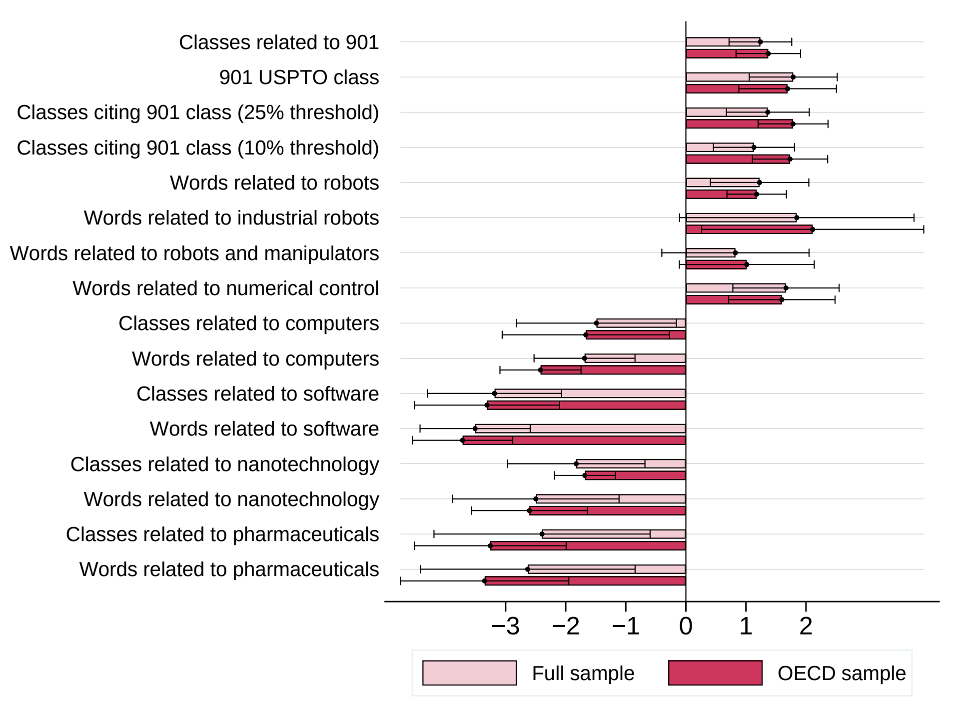
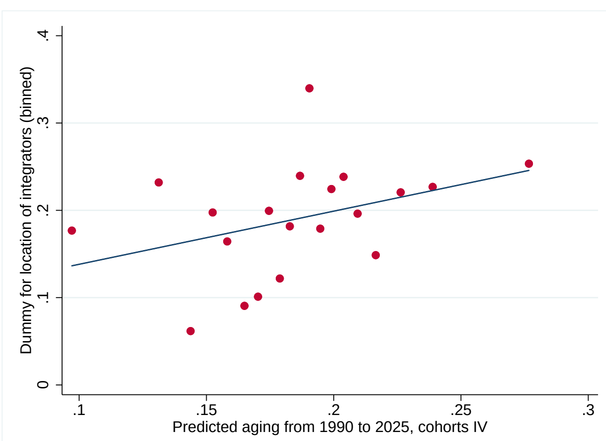
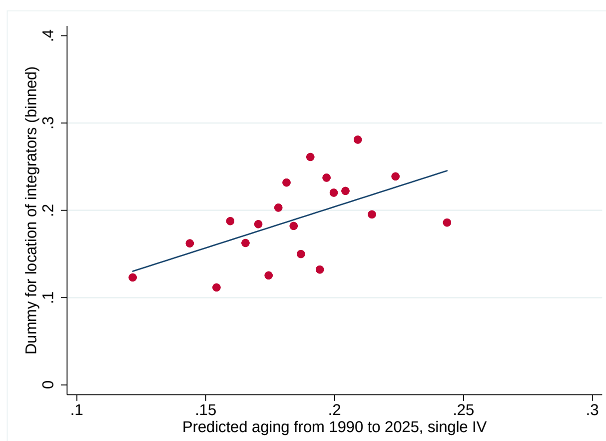


FIGURE 9: Estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of patents in the indicated category between 1990 and 2015. These outcomes are normalized by the total patents granted by the USPTO during this period. The figure presents separate estimates for the full sample of countries with patent data and for OECD countries.

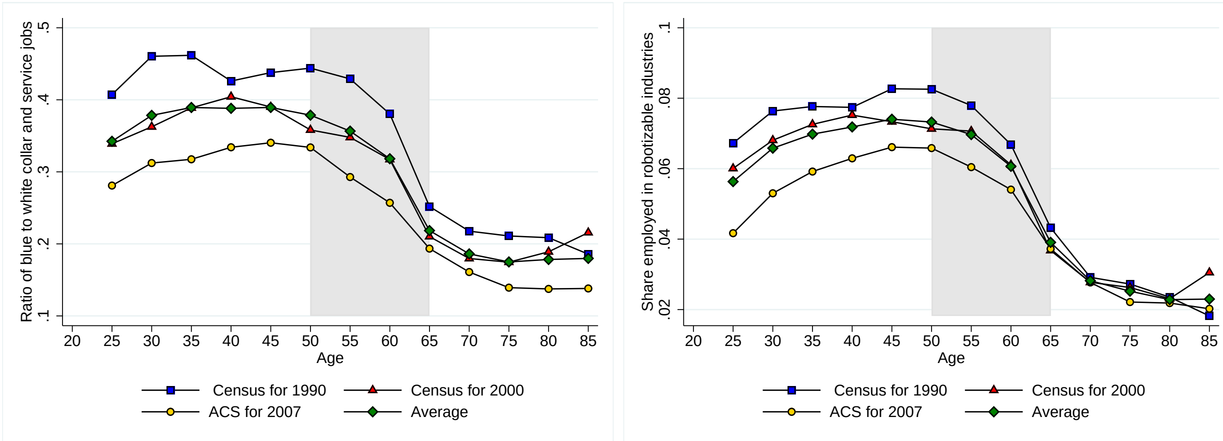


Panel A



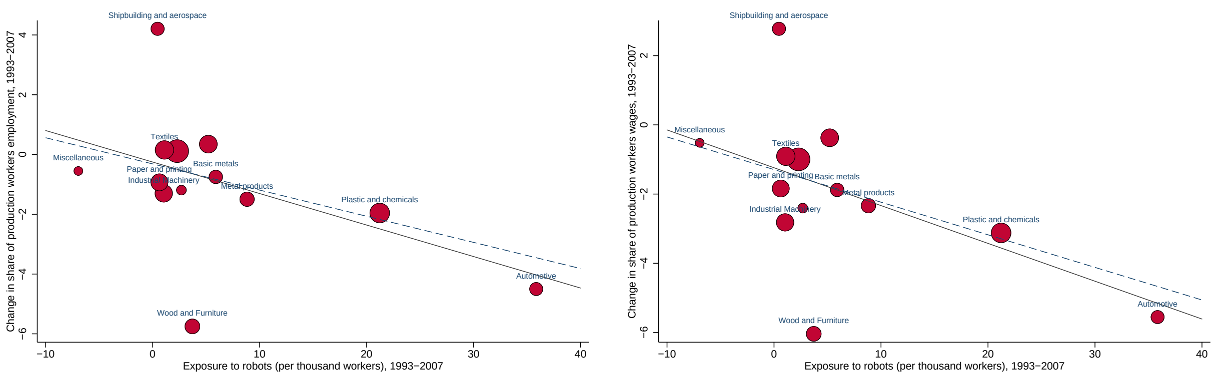
Panel B

FIGURE 10: Binned plot of the relationship between predicted aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2015) and the location of robot integrators in the US (from Leigh and Kraft, 2018). Panel A uses predicted aging based on birthrates from 1950 to 1985, and thus corresponds to the IV estimates in Table 6. Panel B uses predicted aging based on the decline in birth rates between 1950-1985, and thus corresponds to the single-IV estimates in Table 6. The plots partial out the covariates included in the regression models in column 4 in Table 6.



Panel A Panel B

FIGURE 11: For each age group, Panel A plots the ratio of the number of employees in blue-collar production jobs to the number of employees in white-collar and service jobs. For each age group, Panel B plots the share of employees working in industries with the greatest opportunities for automation (car manufacturing, electronics, metal machinery, and chemicals, plastics, and pharmaceuticals). Both figures present data from the 1990 and 2000 Censuses, the 2007 American Community Survey, and an average of these series.



Panel A Panel B

FIGURE 12: The figure presents the correlation across industries between the exposure to robots and the change between 1993 and 2007 in the share of production workers (Panel A) and the share of wages paid to production workers (Panel B) across three-digit US industries. Data from the NBER-CES Manufacturing Industry Database. Marker size indicates total employment in each industry. The dotted line is from a regression excluding the automotive industry.

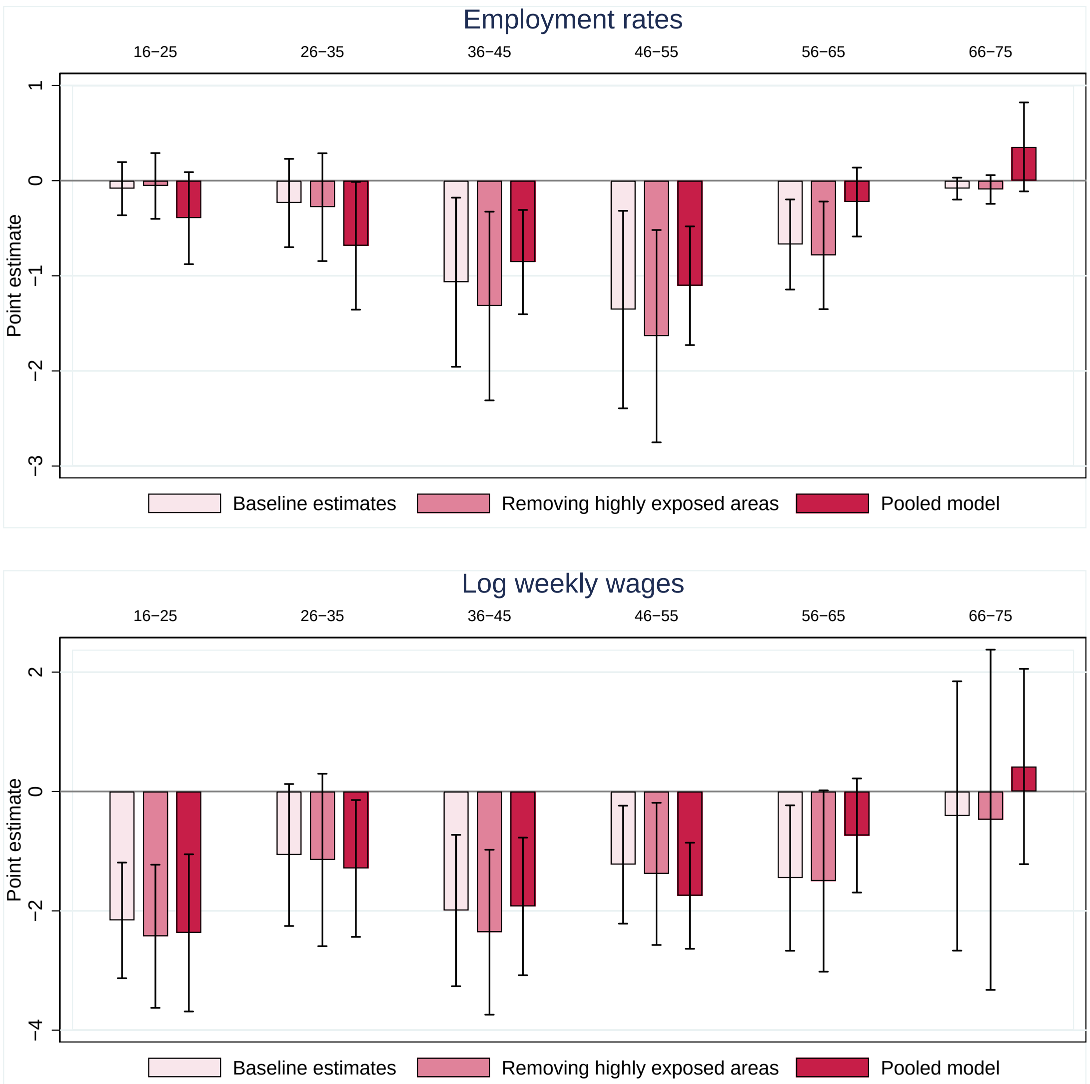


FIGURE 13: The figure presents estimates of the impact of one additional robot per thousand workers on the employment and wages of different age groups across US commuting zones. The three specifications and the data used are described in the main text and in Acemoglu and Restrepo (2018a). The spiked bars present 95% confidence intervals based on standard errors that are robust to heteroskedasticity and serial correlation within US states.

Table 1: Estimates of the impact of aging on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging between 1990 and 2025	0.769	0.712	0.567	1.117	0.983	0.711
	(0.252)	(0.237)	(0.241)	(0.366)	(0.298)	(0.311)
log of GDP per capita in 1993		0.032	-0.005		0.037	-0.112
		(0.030)	(0.050)		(0.052)	(0.081)
Robots per thousand workers in 1993			0.077			0.065
			(0.013)			(0.026)
Observations	52	52	52	30	30	30
R-squared	0.47	0.59	0.70	0.38	0.54	0.64
	Panel B. IV estimates					
Aging between 1990 and 2025	0.874	0.767	0.714	1.576	1.018	0.901
	(0.263)	(0.241)	(0.251)	(0.473)	(0.316)	(0.323)
Observations	52	52	52	30	30	30
First-stage F stat.	25.2	17.8	15.2	7.7	7.1	8.7
Overid $p-$ value	0.67	0.66	0.09	0.75	0.34	0.10
Anderson-Rubin Wald test $p-$ value	0.02	0.03	0.00	0.03	0.03	0.00
	Panel C. Single-IV estimates					
Aging between 1990 and 2025	1.011	0.831	0.637	1.622	1.265	1.051
	(0.361)	(0.329)	(0.363)	(0.555)	(0.402)	(0.494)
Observations	52	52	52	30	30	30
First-stage F stat.	32.4	27.9	19.6	14.6	29.9	17.7
	Panel D. OLS estimates weighted by manufacturing value added					
Aging between 1990 and 2025	1.054	1.185	0.829	1.185	1.336	0.936
	(0.340)	(0.196)	(0.223)	(0.361)	(0.172)	(0.288)
Observations	52	52	52	30	30	30
R-squared	0.66	0.82	0.86	0.52	0.79	0.82
	Panel E. IV estimates weighted by manufacturing value added					
Aging between 1990 and 2025	1.020	1.146	1.035	1.120	1.281	1.080
	(0.300)	(0.187)	(0.235)	(0.381)	(0.178)	(0.270)
Observations	52	52	52	30	30	30
First-stage F stat.	6.9	7.4	19.1	9.2	14.6	22.7
Overid $p-$ value	0.07	0.13	0.17	0.45	0.20	0.18
Anderson-Rubin Wald test $p-$ value	0.00	0.01	0.00	0.00	0.00	0.00
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). Aging is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panels A and D present OLS estimates. Panels B and E present IV estimates where aging is instrumented using the size of five-year birth cohorts between 1950 and 1985. Panel C presents IV estimates where aging is instrumented using the decline in birth rates between 1960 and 1980. For our IV estimates, we report the first-stage $F-$statistic. When using multiple instruments, we also report the $p-$value of Hansen's overidentification test, and the $p-$value of Anderson and Rubin's test for the coefficient on aging being zero. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. The regressions in Panels A, B and C are unweighted, while the regressions in Panels D and E are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity.

Table 2: OLS estimates of the impact of past and expected aging on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Estimates of past vs. expected aging					
Aging between 1990 and 2025	0.801	0.717	0.523	1.105	0.988	0.700
	(0.263)	(0.229)	(0.234)	(0.348)	(0.306)	(0.314)
Aging between 1950 and 1990	-0.304	-0.052	0.272	-0.243	0.192	0.392
	(0.377)	(0.329)	(0.226)	(0.436)	(0.315)	(0.293)
Observations	52	52	52	30	30	30
R-squared	0.49	0.59	0.70	0.38	0.54	0.65
	Panel B. Estimates of past aging					
Aging between 1950 and 1990	-0.098	0.226	0.583	-0.357	0.095	0.455
	(0.378)	(0.411)	(0.340)	(0.587)	(0.456)	(0.409)
Observations	52	52	52	30	30	30
R-squared	0.25	0.42	0.63	0.02	0.26	0.54
	Panel C. Estimates of current vs. future aging					
Aging between 1990 and 2015	0.694	0.524	0.431	0.861	0.688	0.555
	(0.268)	(0.288)	(0.270)	(0.366)	(0.347)	(0.358)
Aging between 2015 and 2025	0.855	0.935	0.734	1.398	1.320	0.925
	(0.442)	(0.520)	(0.557)	(0.527)	(0.564)	(0.722)
Test for equality	0.75	0.54	0.67	0.31	0.38	0.69
Observations	52	52	52	30	30	30
R-squared	0.47	0.59	0.70	0.38	0.55	0.64
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added			✓			✓

Notes: The table presents OLS estimates of the relationship between past and expected aging and the adoption of robots. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). The aging variable varies across panels: Panels A and B present estimates using the change in the ratio of workers above 56 to workers between 21 and 55 between 1950 and 1990 (from the UN Population Statistics) as an explanatory variable. Panel C separately estimates coefficients for aging between 1990 and 2015 (current aging) and between 2015 and 2025 (expected aging). We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. All regressions are unweighted, and the standard errors are robust against heteroscedasticity.

Table 3: Stacked-differences estimates of the impact of aging on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Contemporary aging	0.843	0.552	0.448	0.983	0.733	0.583
	(0.291)	(0.207)	(0.206)	(0.440)	(0.281)	(0.323)
Observations	104	104	104	60	60	60
R-squared	0.28	0.49	0.13	0.15	0.41	0.13
	Panel B. IV estimates					
Contemporary aging	1.157	0.831	0.797	1.752	1.043	1.122
	(0.401)	(0.294)	(0.473)	(0.773)	(0.412)	(0.647)
Observations	104	104	104	60	60	60
First-stage F stat.	10.4	6.1	4.1	6.6	6.1	4.2
Overid $p-$ value	0.50	0.07	0.49	0.64	0.29	0.47
Anderson-Rubin Wald test $p-$ value	0.02	0.00	0.14	0.00	0.00	0.00
	Panel C. OLS estimates weighted by manufacturing value added					
Contemporary aging	1.384	0.744	0.509	1.484	0.775	0.595
	(0.445)	(0.268)	(0.352)	(0.437)	(0.302)	(0.417)
Observations	104	104	104	60	60	60
R-squared	0.40	0.62	0.05	0.27	0.55	0.07
	Panel D. IV estimates weighted by manufacturing value added					
Contemporary aging	1.907	0.831	1.024	1.854	1.112	1.135
	(0.549)	(0.294)	(0.370)	(0.481)	(0.290)	(0.434)
Observations	104	104	104	60	60	60
First-stage F stat.	4.8	6.1	3.5	39.7	22.4	39.7
Overid $p-$ value	0.37	0.07	0.26	0.11	0.48	0.71
Anderson-Rubin Wald test $p-$ value	0.00	0.00	0.00	0.00	0.00	0.00
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added		✓	✓		✓	✓
Country trends			✓			✓

Notes: The table presents OLS and IV stacked-differences estimates of the relationship between aging and the adoption of robots for the two periods 1993-2005 and 2005-2014. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers (from the IFR) for two periods: between 1993 and 2005 and between 2005 and 2014. The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 for both periods as well (from the UN Population Statistics). Panels A and C present OLS estimates. Panels B and D present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic, the $p-$value of Hansen's overidentification test, and the $p-$value of Anderson and Rubin's test for the coefficient on aging being zero. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990, the 1993 value of robots per thousand workers, and the log of the 1990 value added in manufacturing. Columns 3 and 6 include country fixed effects. The regressions in Panels A and B are unweighted, while the regressions in Panels C and D are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity and correlation within countries.

TABLE 4: Estimates of the impact of aging on imports and exports of industrial robots.

	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: log of imports of industrial robots relative to intermediates					
	Panel A. OLS estimates					
Aging between 1995 and 2025	3.501	3.155	1.818	3.495	3.287	2.160
	(1.281)	(0.865)	(0.768)	(1.511)	(0.860)	(0.724)
Log of the GDP per capita in 1995		-0.122	-1.327		-0.406	-1.311
		(0.195)	(0.388)		(0.373)	(0.467)
Log of intermediate imports			0.161			0.220
			(0.261)			(0.318)
Observations	130	130	130	34	34	34
R-squared	0.29	0.50	0.58	0.27	0.71	0.79
	Panel B. IV estimates					
Aging between 1995 and 2025	3.266	3.197	1.969	3.268	2.883	1.691
	(1.469)	(0.902)	(0.962)	(1.727)	(0.820)	(0.806)
Log of the GDP per capita in 1995		-0.123	-1.304		-0.402	-1.383
		(0.182)	(0.402)		(0.353)	(0.419)
Log of intermediate imports			0.154			0.218
			(0.251)			(0.267)
Observations	130	130	130	34	34	34
Instruments F-stat	13.67	11.90	10.70	23.79	11.29	9.65
Overid p-value	0.16	0.71	0.68	0.32	0.12	0.04
	Dependent variable: log of exports of industrial robots relative to intermediates					
	Panel C. OLS estimates					
Aging between 1995 and 2025	6.141	4.396	4.657	6.309	4.516	4.144
	(1.048)	(0.952)	(0.985)	(1.131)	(1.147)	(1.165)
Log of the GDP per capita in 1995		0.688	0.675		0.967	0.631
		(0.246)	(0.465)		(0.404)	(0.682)
Log of intermediate exports			-0.114			-0.104
			(0.128)			(0.197)
Observations	103	103	103	35	35	35
R-squared	0.78	0.83	0.83	0.61	0.76	0.77
	Panel D. IV estimates					
Aging between 1995 and 2025	7.015	4.713	5.199	6.903	4.645	4.803
	(0.935)	(1.039)	(1.167)	(1.064)	(1.230)	(1.177)
Log of the GDP per capita in 1995		0.680	0.770		0.974	0.772
		(0.232)	(0.431)		(0.370)	(0.598)
Log of intermediate exports			-0.132			-0.123
			(0.126)			(0.177)
Observations	103	103	103	35	35	35
Instruments F-stat	11.56	13.13	15.00	36.39	19.03	12.23
Overid p-value	0.10	0.16	0.14	0.11	0.22	0.14
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and imports and exports of industrial robots. In Panels A and B, the dependent variable is the log of imports of industrial robots relative to all intermediates between 1996 and 2015 (from Comtrade). In Panels C and D, the dependent variable is the log of exports of industrial robots relative to all intermediates between 1996 and 2015 (from Comtrade). The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1995 and 2025 (from the UN Population Statistics). Panels A and C present OLS estimates. Panels B and D present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1995 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55. Columns 3 and 6 add the log of the 1990 value added in manufacturing and the log of intermediate imports (Panels A and B) or exports (Panels C and D) as additional covariates. All regressions are weighted by value added in manufacturing in 1990, and the standard errors are robust against heteroscedasticity.

Table 5: Estimates of the impact of aging on patents related to robotics.

	Dependent variable: log of robotics-related patents relative to utility patents					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging between 1990 and 2025	1.642	1.382	1.411	1.639	1.302	1.593
	(0.334)	(0.294)	(0.444)	(0.347)	(0.275)	(0.547)
Log of the GDP per capita in 1990		0.126	0.110		0.187	0.456
		(0.132)	(0.248)		(0.233)	(0.421)
Log of patents at USPTO			-0.055			-0.142
			(0.039)			(0.056)
Observations	68	68	68	31	31	31
R-squared	0.58	0.63	0.64	0.42	0.58	0.66
	Panel B. IV estimates					
Aging between 1990 and 2025	1.630	1.241	0.755	1.830	1.372	1.342
	(0.405)	(0.316)	(0.572)	(0.435)	(0.325)	(0.464)
Log of the GDP per capita in 1990		0.126	-0.128		0.196	0.338
		(0.121)	(0.258)		(0.215)	(0.361)
Log of patents at USPTO			-0.030			-0.131
			(0.039)			(0.047)
Observations	68	68	68	31	31	31
Instruments F-stat	7.11	6.13	5.03	27.39	26.14	18.63
Overid p-value	0.14	0.08	0.21	0.41	0.11	0.33
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and robotics-related patents assigned to companies and inventors from different countries by the USPTO. In both panels, the dependent variable is the log of robotics-related patents relative to all utility patents granted between 1990 and 2015 (from Patents View). The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1995 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55. Columns 3 and 6 add the log of utility patents received by each country and the log of the 1990 value added in manufacturing as additional covariates. All regressions are weighted by value added in manufacturing in 1990, and the standard errors are robust against heteroscedasticity.

Table 6: Estimates of the impact of aging on the location of robot integrators in the US.

	Dependent variable: Dummy for presence of robot integrator				
	(1)	(2)	(3)	(4)	(5)
			Panel A. OLS estimates		
Aging between 1990 and 2015	-0.087	0.143	0.142	0.141	0.170
	(0.146)	(0.090)	(0.077)	(0.079)	(0.075)
Exposure to robots			0.061	0.059	0.096
			(0.019)	(0.020)	(0.022)
Observations	722	722	722	722	712
R-squared	0.03	0.41	0.45	0.45	0.46
			Panel B. IV estimates		
Aging between 1990 and 2015	1.371	0.759	0.610	0.606	0.604
	(0.386)	(0.241)	(0.231)	(0.230)	(0.226)
Exposure to robots			0.054	0.052	0.090
			(0.020)	(0.021)	(0.021)
Observations	722	722	722	722	712
First-stage F stat.	11.4	20.6	23.1	23.9	23.3
Overid $p-$ value	0.00	1.00	0.84	0.82	0.69
			Panel C. Single-IV estimates		
Aging between 1990 and 2015	2.307	1.043	0.952	0.945	0.996
	(0.737)	(0.402)	(0.388)	(0.390)	(0.391)
Exposure to robots			0.048	0.046	0.085
			(0.022)	(0.023)	(0.022)
Observations	722	722	722	722	712
First-stage F stat.	16.4	55.0	54.6	56.4	58.8
Covariates included:					
Regional dummies	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry composition			✓	✓	✓
Other shocks				✓	✓
Excluding highly exposed commuting zone					✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the location of robot integrators across US commuting zones. In all panels, the dependent variable is a dummy for the presence of robot integrators in each US commuting zone (from Leigh and Kraft, 2018). The aging variable is the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015 (from the NBER-SEER). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Panel C presents IV estimates where the aging variable is instrumented using the decline in birth rates between 1950 and 1980. For our IV estimates, we report the first-stage $F-$statistic. When using multiple instruments, we also report the $p-$value of Hansen's overidentification test. Column 1 includes Census region dummies. Column 2 includes the 1990 values for the log of average income, the log of the population, the initial ratio of older to middle-aged workers, and the share of workers with different levels of education in each commuting zone. Column 3 includes the exposure to robots measure from Acemoglu and Restrepo (2018a) and also controls for the shares of employment in manufacturing, agriculture, mining, construction, and finance and real estate in 1990. Column 4 includes additional demographic characteristics measured in 1990, including the racial composition of commuting zones and the share of male and female employment, and controls for other shocks affecting US markets, including offshoring, trade with China and the decline of routine jobs. Finally, column 5 excludes the top 1% commuting zones with the highest exposure to robots. All regressions are unweighted, and in parenthesis we report standard errors that are robust against heteroscedasticity and correlation in the error terms within states.

TABLE 7: Estimates of the impact of aging on robot installations by country-industry pairs.

		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Installation of robots in country-industry pairs normalizing by average employment in an industry from ILO						
	Panel A. OLS estimates.						
Aging between 1990 and 2025	1.560	4.085	2.800		6.734	4.850	
	(0.439)	(1.127)	(0.882)		(1.851)	(1.537)	
Aging × reliance on middle-aged		0.886	0.627	0.628	0.264	0.182	0.183
		(0.255)	(0.218)	(0.215)	(0.090)	(0.086)	(0.085)
Aging × opportunities for automation		6.469	4.433	4.439	6.046	4.440	4.458
		(2.255)	(1.528)	(1.506)	(1.681)	(1.356)	(1.340)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
	Panel B. IV estimates.						
Aging between 1990 and 2025	1.430	3.780	2.992		6.585	5.246	
	(0.477)	(1.254)	(1.025)		(2.175)	(1.768)	
Aging × reliance on middle-aged		0.958	0.682	0.680	0.327	0.193	0.194
		(0.318)	(0.247)	(0.243)	(0.112)	(0.094)	(0.093)
Aging × opportunities for automation		4.919	4.597	4.553	5.902	4.835	4.823
		(2.228)	(1.883)	(1.863)	(1.986)	(1.594)	(1.575)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
Instruments F-stat	19.1	.	6.2	7.9	.	7.4	8.4
Overid p-value	0.86	0.32	0.46	0.38	0.17	0.15	0.07
	Dependent variable: Installation of robots in country-industry pairs normalizing by industrial employment from KLEMS						
	Panel C. OLS estimates.						
Aging between 1990 and 2025	0.787	4.598	2.471		5.180	3.455	
	(0.184)	(1.169)	(0.906)		(1.258)	(1.004)	
Aging × reliance on middle-aged		0.363	0.412	0.372	0.116	0.171	0.139
		(0.134)	(0.126)	(0.129)	(0.065)	(0.071)	(0.073)
Aging × opportunities for automation		10.300	4.335	4.716	4.665	3.019	3.070
		(2.776)	(2.143)	(2.113)	(1.159)	(0.901)	(0.885)
Observations	5833	5833	5833	5833	5833	5833	5833
Countries in sample	21	21	21	21	21	21	21
	Panel D. IV estimates.						
Aging between 1990 and 2025	0.850	4.953	3.088		5.817	4.149	
	(0.195)	(1.171)	(0.927)		(1.414)	(1.231)	
Aging × reliance on middle-aged		0.417	0.338	0.295	0.182	0.108	0.072
		(0.141)	(0.193)	(0.194)	(0.063)	(0.107)	(0.109)
Aging × opportunities for automation		10.953	6.244	6.658	5.181	3.752	3.815
		(2.666)	(2.008)	(1.966)	(1.346)	(1.089)	(1.065)
Observations	5833	5833	5833	5833	5833	5833	5833
Countries in sample	21	21	21	21	21	21	21
Instruments F-stat	32.5	65.9	130.5	20.9	57.2	89.3	19.0
Overid p-value	0.06	0.30	0.43	0.18	0.36	0.30	0.18
Covariates included:							
Baseline country covariates	✓	✓	✓	✓	✓	✓	✓
Initial robot density			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots for industry-country cells. In all panels, the dependent variable is robot installations per thousand workers in each industry-country cell for all available years between 1993 and 2014 (from the IFR). The explanatory variables include aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025); the interaction between aging and industry reliance on middle-aged workers (proxied using 1990 US Census data on the age distribution of workers in each industry); and the interaction between aging and two measures of opportunities for automation: the replaceability index from Graetz and Michaels (2018) in columns 2-4; and a measure of opportunities for the use of robots from the BCG in columns 5-7. Panels A and B use data on average employment by industry from the ILO to normalize robot installations; whereas Panels C and D use data on industrial employment from KLEMS to normalize robot installations. Panels A and C present OLS estimates. Panels B and D present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. All columns include region dummies, the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the initial robot density in 1993 for each industry-country cell as a control. All these covariates are allowed to affect industries differently. Columns 4 and 7 add a full set of country dummies. All regressions weigh industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries.

Table 8: Estimates of the impact of aging on the value added of country-industry pairs per year.

		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Change in value-added per worker between 1995 and 2007						
	Panel A. OLS estimates						
Aging between 1995 and 2025	-0.261	1.627	1.222		1.763	1.290	
	(0.224)	(0.880)	(1.005)		(0.905)	(1.075)	
Aging × reliance on middle-aged		-0.278	-0.183	-0.246	-0.288	-0.191	-0.259
		(0.202)	(0.241)	(0.218)	(0.202)	(0.245)	(0.225)
Aging × opportunities for automation		3.388	3.119	3.187	1.304	1.140	1.225
		(1.065)	(1.085)	(0.997)	(0.452)	(0.484)	(0.463)
Observations	399	399	399	399	399	399	399
Countries in sample	21	21	21	21	21	21	21
	Panel B. IV estimates						
Aging between 1995 and 2025	-0.472	2.786	2.583		2.545	2.315	
	(0.294)	(0.846)	(0.990)		(1.013)	(1.222)	
Aging × reliance on middle-aged		-0.581	-0.548	-0.549	-0.557	-0.523	-0.536
		(0.244)	(0.282)	(0.299)	(0.255)	(0.297)	(0.319)
Aging × opportunities for automation		5.011	4.962	4.458	1.579	1.532	1.468
		(1.140)	(1.016)	(1.031)	(0.353)	(0.345)	(0.386)
Observations	399	399	399	399	399	399	399
Countries in sample	21	21	21	21	21	21	21
Instruments F-stat	9.62	430.37	127.00	5.08	134.35	5.94	5.92
Overid p-value	0.25	0.40	0.51	0.36	0.36	0.35	0.35
	Dependent variable: Change in the labor share between 1995 and 2007						
	Panel A. OLS estimates						
Aging between 1995 and 2025	-0.389	-2.659	-2.673		-3.069	-3.111	
	(0.099)	(0.894)	(0.884)		(1.059)	(1.058)	
Aging × reliance on middle-aged		0.681	0.685	0.667	0.709	0.717	0.702
		(0.254)	(0.255)	(0.271)	(0.265)	(0.267)	(0.286)
Aging × opportunities for automation		-0.929	-0.939	-0.811	-0.689	-0.703	-0.665
		(0.615)	(0.580)	(0.602)	(0.291)	(0.279)	(0.306)
Observations	399	399	399	399	399	399	399
Countries in sample	21	21	21	21	21	21	21
	Panel B. IV estimates						
Aging between 1995 and 2025	-0.432	-3.529	-3.677		-4.271	-4.496	
	(0.133)	(0.903)	(1.014)		(1.192)	(1.318)	
Aging × reliance on middle-aged		1.059	1.088	1.107	1.100	1.141	1.176
		(0.302)	(0.318)	(0.353)	(0.321)	(0.336)	(0.376)
Aging × opportunities for automation		-0.347	-0.423	-0.211	-0.802	-0.868	-0.884
		(0.600)	(0.611)	(0.637)	(0.241)	(0.268)	(0.340)
Observations	399	399	399	399	399	399	399
Countries in sample	21	21	21	21	21	21	21
Instruments F-stat	9.62	430.37	127.00	5.08	134.35	5.94	5.92
Overid p-value	0.22	0.65	0.72	0.47	0.47	0.52	0.37
Covariates included:							
Baseline country covariates	✓	✓	✓	✓	✓	✓	✓
Initial value added in 1995			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and value added and the labor share for industry-country cells. In Panels A and B, the dependent variable is the change in value added per worker between 1995 and 2007 for each industry-country cell (from the KLEMS data). In Panels C and D, the dependent variable is the change in the labor share between 1995 and 2007 for each industry-country cell (from the KLEMS data). The explanatory variables include aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1995 and 2025); the interaction between aging and industry reliance on middle-aged workers (proxied using 1990 US Census data on the age distribution of workers in each industry); and the interaction between aging and two measures of opportunities for automation: the replaceability index from Graetz and Michaels (2018) in columns 2-4; and a measure of opportunities for the use of robots from the BCG in columns 5-7. Panels A and C present OLS estimates. Panels B and D present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. All columns include region dummies, the 1995 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55. All these covariates are allowed to affect industries differently. Columns 3 and 6 add the log of value added per worker in 1995 for each industry-country cell as a control. Columns 4 and 7 add a full set of country dummies. All regressions weigh industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries.

Proof of Proposition 1

1. Existence and uniqueness of the equilibrium with exogenous technology.

Recall that $C(W, V, P)$ is the cost of producing one unit of aggregate output. The Cobb-Douglas production function for $Y(i)$ in equation (2) implies that

$$P_Y(i) = (1-\eta)\eta^{\eta} \times (\alpha(i)\eta)^{-\alpha(i)\eta}((1-\alpha(i)\eta))^{-(1-\alpha(i))\eta}(1-\eta)^{-(1-\eta)}P_X(i)^{\alpha(i)\eta}V^{(1-\alpha(i))\eta}P_Y(i)^{1-\eta}.$$

Solving for $P_Y(i)$ yields the formula for $P_Y(i)$ given in the main text. Equation (1) then implies

$$C(W, V, P) = \left(\int_0^1 P_Y(i)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = \left(\int_0^1 \lambda(i)^{1-\sigma}P_X(i)^{\alpha(i)(1-\sigma)}V^{(1-\alpha(i))(1-\sigma)}\right)^{\frac{1}{1-\sigma}},$$

where $P_X(i)$ is given in equation (7) in the main text.

The demand for middle-aged workers can then be computed as

$$\begin{aligned}
L^d &= \frac{1}{W}\int_{i\in\mathcal{I}} L(i)W di \\
&= \frac{1}{W}\int_{i\in\mathcal{I}} P_X(i)X(i)s_L(i)di \\
&= \frac{1}{W}\int_{i\in\mathcal{I}} P_Y(i)Y^g(i)\eta\alpha(i)s_L(i)di \\
&= \frac{1}{W}\int_{i\in\mathcal{I}} P_Y(i)Y(i)\frac{Y^g(i)}{Y(i)}\eta\alpha(i)s_L(i)di \\
&= \frac{Y}{W}\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma}\frac{1}{\eta(2-\eta)}\eta\alpha(i)s_L(i)di \\
&= \frac{Y}{(2-\eta)W}\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma}\alpha(i)s_L(i)di \\
&= \frac{Y}{2-\eta}C_W(W, V, P).
\end{aligned}$$

This derivation uses the fact that $\eta\alpha(i)$ is the share of production inputs in the gross production of $Y(i)$, and that the ratio of $\frac{Y^g(i)}{Y(i)}$ equals $\frac{1}{\eta(2-\eta)}$. The last line arrives at a result similar to Shepherd's lemma, but now, the $2-\eta$ in the denominator accounts for the intermediate goods, $q(\theta(i))$, and the cost of producing these goods.

Likewise, the demand for older workers can be computed as

$$
\begin{aligned}
S^d &= \frac{1}{V}\int_{i\in\mathcal{I}} S(i)V\,di \\
&= \frac{1}{V}\int_{i\in\mathcal{I}} P_Y(i)Y^g(i)\eta(1-\alpha(i))di \\
&= \frac{1}{V}\int_{i\in\mathcal{I}} P_Y(i)Y(i)\frac{Y^g(i)}{Y(i)}\eta(1-\alpha(i))di \\
&= \frac{Y}{V}\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma}\frac{1}{\eta(2-\eta)}\eta(1-\alpha(i))di \\
&= \frac{Y}{(2-\eta)V}\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma}(1-\alpha(i))di \\
&= \frac{Y}{2-\eta}C_V(W,V,P).
\end{aligned}
$$

From these equations, conditions (12) and (13) can be written as

$$
\begin{aligned}
1 =& C(W^E(\phi,\Theta),V^E(\phi,\Theta),P), && \text{(A1)}\\
\frac{1-\phi}{\phi} =& \frac{C_W(W^E(\phi,\Theta),V^E(\phi,\Theta),P)}{C_V(W^E(\phi,\Theta),V^E(\phi,\Theta),P)}, && \text{(A2)}
\end{aligned}
$$

where C_W and C_V denote the partial derivatives of the cost function.

We now show that, for any $\phi \in (0,1)$ there is a unique pair $\{W^E(\phi,\Theta),V^E(\phi,\Theta)\}$ that solves (A1) and (A2). Consider the isocost $C(W,V,P)=1$. The market equilibrium occurs at a point where the tangent to this curve has slope $-\frac{\phi}{1-\phi}$ as shown in Figure 1.

Along this isocost, $C_W(W,V,P)/C_V(W,V,P)=0$ as $\frac{V}{W}\to 0$. To prove this, note that

$$
\begin{aligned}
0 \le \frac{C_W(W,V,P)}{C_V(W,V,P)} =& \frac{V}{W}\frac{\int \alpha(i)s_L(i)\lambda(i)^{1-\sigma}P_Y(i)^{1-\sigma}di}{\int(1-\alpha(i))\lambda(i)^{1-\sigma}P_Y(i)^{1-\sigma}di} \\
&\le \frac{V}{W}\frac{\overline{\alpha}}{1-\underline{\alpha}}\frac{\int \lambda(i)^{1-\sigma}P_Y(i)^{1-\sigma}di}{\int \lambda(i)^{1-\sigma}P_Y(i)^{1-\sigma}di} \\
&= \frac{V}{W}\frac{\overline{\alpha}}{1-\underline{\alpha}}. && \text{(A3)}
\end{aligned}
$$

Therefore, as $\frac{V}{W}\to 0$, $\frac{C_W(W,V,P)}{C_V(W,V,P)}\to 0$.

Likewise, along the isocost, $C_W(W,V,P)/C_V(W,V,P)=\infty$ as $\frac{V}{W}\to\infty$. To prove this, note that

$$
\begin{aligned}
\frac{C_W(W,V,P)}{C_V(W,V,P)} \ge& \frac{V}{W}\frac{\underline{\alpha}}{1-\overline{\alpha}}[\min_{i\in\mathcal{I}} s_L(i)]\frac{\int \lambda(i)^{1-\sigma}P_Y(i)^{1-\sigma}di}{\int \lambda(i)^{1-\sigma}P_Y(i)^{1-\sigma}di} \\
=& \frac{V}{W}\frac{\underline{\alpha}}{1-\overline{\alpha}}[\min_{i\in\mathcal{I}} s_L(i)]. && \text{(A4)}
\end{aligned}
$$

Since $\frac{V}{W}\to\infty$, $W\to 0$ (otherwise, we would have $V\to\infty$ and $W>0$, which would not satisfy $C(W,V,P)=1$). Because $W\to 0$, $\theta^A(i)=0$ for all tasks, which implies that $s_L(i)=1$ for all i. Therefore, as $\frac{V}{W}\to\infty$, we must have $\frac{C_W(W,V,P)}{C_V(W,V,P)}\to\infty$.

Because $C_W(W,V,P)/C_V(W,V,P) = 0$ as $\frac{V}{W} \to 0$ and $C_W(W,V,P)/C_V(W,V,P) = \infty$ as $\frac{V}{W} \to \infty$, the intermediate value theorem implies that there exists $W^E(\phi,\Theta), V^E(\phi,\Theta)$ along the isocost that satisfies equation (A2). This establishes existence.

To prove uniqueness, note that since $C(W,V,P)$ is a cost function, it is jointly concave in W, V, and P, which implies that the isocost curve $C(W,V,P) = 1$ is convex. That is, along the curve $C(W,V,P) = 1$, C_W/C_V is decreasing in W and is increasing in V. Thus, there is a unique pair $W^E(\phi,\Theta), V^E(\phi,\Theta)$ along the isocost that satisfies equation (A2).

Finally, aggregate output per worker is given by

$$y^E(\phi,\Theta) = (2-\eta)\frac{\phi}{C_V(W^E(\phi,\Theta), V^E(\phi,\Theta), P)},$$

while machinery per worker is given by

$$m^E(\phi,\Theta) = \phi\frac{C_P(W^E(\phi,\Theta), V^E(\phi,\Theta), P)}{C_V(W^E(\phi,\Theta), V^E(\phi,\Theta), P)};$$

and the threshold $\theta^A(i)$ can be computed from equation (6).■

2. Comparative statics with respect to ϕ.

Because the isocost curve $C(W,V,P) = 1$ is convex, an increase in ϕ raises $W^E(\phi,\Theta)$ and reduces $V^E(\phi,\Theta)$. To complete the proof, we derive the formula for $y^E_\phi(\phi,\Theta)$ given in the main text. The national income accounting identity implies

$$\frac{1}{2-\eta}y^E(\phi,\Theta) = \phi V^E(\phi,\Theta) + (1-\phi)W^E(\phi,\Theta) + m^E(\phi,\Theta)P, \tag{A5}$$

where the $\frac{1}{2-\eta}$ accounts for the cost of intermediate goods. Differentiating this expression with respect to ϕ, we obtain

$$\frac{1}{2-\eta}y^E_\phi(\phi,\Theta) = V^E(\phi,\Theta) - W^E(\phi,\Theta) + m^E_\phi(\phi,\Theta)P + \phi V^E_\phi(\phi,\Theta) + (1-\phi)W^E_\phi(\phi,\Theta).$$

Next differentiating $C(W,V,P) = 1$ with respect to ϕ, and recalling that $\frac{C_W}{C_V} = \frac{1-\phi}{\phi}$, we obtain $\phi V^E_\phi(\phi,\Theta) + (1-\phi)W^E_\phi(\phi,\Theta) = 0$. Substituting this into the previous expression, we obtain (14).■

Proof of Proposition 2

Part 1: Suppose that $\phi \leq \phi'$ and take an $i \in \mathcal{I}^+(\phi,\Theta)$, so that $\frac{W^E(\phi,\Theta)}{A(i)} > P$. Proposition 1 implies that $W^E(\phi,\Theta) \leq W^E(\phi',\Theta)$, and thus $\frac{W^E(\phi',\Theta)}{A(i)} > P$ and $i' \in \mathcal{I}^+(\phi', A)$, which implies that $\mathcal{I}^+(\phi,\Theta) \subseteq \mathcal{I}^+(\phi', A)$.

Part 2: Let $W^E(\phi,\Theta_0)$ denote the middle-aged wage that would result if $\theta(i) = 0$ and there were no automation technologies. Proposition 1 implies that $W^E(\phi,\Theta_0)$ is increasing in ϕ.

In addition, we have that $W^E(\phi,\Theta_0) \to 0$ when $\phi \to 0$, and $W^E(\phi, A) \to \infty$ when $\phi \to 1$. To prove the first claim, we use the inequality in equations (A3) and (A4) derived above, which implies

$$\frac{V^E(\phi,\Theta_0)}{W^E(\phi,\Theta_0)}\frac{\underline{\alpha}}{1-\overline{\alpha}}. \leq \frac{1-\phi}{\phi} \leq \frac{V^E(\phi,\Theta_0)}{W^E(\phi,\Theta_0)}\frac{\overline{\alpha}}{1-\underline{\alpha}}.$$

When $\phi \to 0$, the right-hand side of the above inequality must converge to ∞. This requires that either $W^E(\phi,\Theta_0) \to 0$ or $V^E(\phi,\Theta_0) \to \infty$. Suppose it is the latter. Then $C(W,V,P) = 1$ implies $W^E(\phi,\Theta_0) \to 0$. Thus in either case we have $W^E(\phi,\Theta_0) \to 0$ as desired.

On the other hand, when $\phi \to 1$, the left-hand side of the above inequality must converge to 0. This requires that either $W^E(\phi,\Theta_0) \to \infty$ or $V^E(\phi,\Theta_0) \to 0$. Supposed again that it is the latter. Then $C(W,V,P) = 1$ once again implies $W^E(\phi,\Theta_0) \to \infty$, and thus in either case the desired conclusion is established.

We can therefore define $\widetilde{\phi}$ as the maximum level of ϕ such that $\frac{W^E(\phi,\Theta_0)}{A(i)} \leq P$ for almost all i. For $\phi \leq \widetilde{\phi}$, we have that the unique equilibrium is given by $\theta^A(i) = 0$ for almost all i and $W^E(\phi,\Theta_0) = W^E(\phi,\Theta)$. Thus, for $\phi \leq \widetilde{\phi}$, the set $\mathcal{I}^+(\phi, A)$ has measure zero.

For $\phi > \widetilde{\phi}$, we have $W^E(\phi,\Theta) > W^E(\widetilde{\phi},\Theta) = W^E(\widetilde{\phi},\Theta_0)$. Thus, the equilibrium must involve a positive measure of industries that are adopting automation technologies. ■

Proof of Proposition 3

We start by providing a formula for $d\ln W$ following a change in technology. We then state and prove a lemma on the conditions under which automation reduces the middle-aged wage, and then we provide a proof of the proposition.

Let $\chi(i)$ denote the share of expenditure going to industry i, $\chi_L(i)$ the share of payments to middle-aged workers going to those in industry i, and $\chi_S(i)$ the share of payments to older workers going to those in industry i.

We have

$$d\theta^A(i) = \begin{cases} d\theta(i) & \text{if } i \in \mathcal{I}^+(\phi,\Theta) \\ 0 & \text{otherwise.} \end{cases}$$

Following an increase in $d\theta(i) > 0$, we have

$$d\ln P_X(i) = s_L(i) d\ln W - \frac{s_L(i)}{1-\theta^A(i)}\pi(i) d\theta^A(i).$$

Using this expression, and taking log-derivatives of the equilibrium conditions, we obtain:

- From the ideal price condition, (12):

$$\Lambda^\pi_W d\ln W + \Lambda^\pi_V d\ln V = \Pi \tag{A6}$$

where

$$\begin{aligned}
\Lambda_V^{\pi} =& \int_{i\in\mathcal{I}} \chi(i)(1-\alpha(i))di > 0,\\
\Lambda_W^{\pi} =& \int_{i\in\mathcal{I}} \chi(i)\alpha(i)s_L(i)di > 0,\\
\Pi =& \int_{i\in\mathcal{I}} \chi(i)\alpha(i)s_L(i)\pi(i)\frac{d\theta^A(i)}{1-\theta^A(i)}di \geq 0.
\end{aligned}$$

Here, $\Pi \geq 0$ denotes *the productivity gains from automation.*

- From the demand for middle-aged workers, (9):

$$\Lambda_W^L d\ln W = d\ln Y - \Lambda_V^L d\ln V + T^L - \Delta, \tag{A7}$$

where

$$\begin{aligned}
\Lambda_W^L =& \zeta + (1-\zeta)\int_{i\in\mathcal{I}} \chi_L(i)s_L(i)di + (\sigma-1)\int_{i\in\mathcal{I}} \chi_L(i)\alpha(i)s_L(i)di,\\
\Lambda_V^L =& (\sigma-1)\int_{i\in\mathcal{I}} \chi_L(i)(1-\alpha(i))di,\\
T^L =& (\sigma-1)\int_{i\in\mathcal{I}} \chi_L(i)\alpha(i)s_L(i)\pi(i)\frac{d\theta^A(i)}{1-\theta^A(i)}di,\\
\Delta =& \int_{i\in\mathcal{I}} \chi_L(i)\frac{d\theta^A(i)}{1-\theta^A(i)} - (1-\zeta)\int_{i\in\mathcal{I}} \chi_L(i)s_L(i)\pi(i)\frac{d\theta^A(i)}{1-\theta^A(i)}di.
\end{aligned}$$

Here, $\Delta > 0$ denotes the *displacement effect from automation*, which tends to reduce the demand for middle-aged workers, while T^L captures how sectoral shifts affect the demand for middle-aged workers.

- From the demand for older workers, (11):

$$\Lambda_V^S d\ln V = d\ln Y - \Lambda_W^S d\ln W + T^S, \tag{A8}$$

where

$$\begin{aligned}
\Lambda_V^S =& 1 + (\sigma-1)\int_{i\in\mathcal{I}} \chi_S(i)(1-\alpha(i))di,\\
\Lambda_W^S =& (\sigma-1)\int_{i\in\mathcal{I}} \chi_S(i)\alpha(i)s_L(i)di,\\
T^S =& (\sigma-1)\int_{i\in\mathcal{I}} \chi_S(i)\alpha(i)s_L(i)\pi(i)\frac{d\theta^A(i)}{1-\theta^A(i)}di.
\end{aligned}$$

Here, T^S captures how sectoral shifts affect the demand for middle-aged workers.

Using equations (A6), (A7) and (A8), we can solve for $d\ln W$ as:

$$d\ln W = \frac{1}{\Lambda_V^\pi(\Lambda_W^L - \Lambda_W^S) + \Lambda_W^\pi(\Lambda_V^S - \Lambda_V^L)}\left[(\Lambda_V^S - \Lambda_V^L)\Pi + \Lambda_V^\pi(T^L - T^S) - \Lambda_V^\pi\Delta\right], \tag{A9}$$

where the denominator, $\Lambda_V^\pi(\Lambda_W^L - \Lambda_W^S) + \Lambda_W^\pi(\Lambda_V^S - \Lambda_V^L)$, is always positive.[35]

LEMMA A2 *Suppose that for almost all industries*

$$\pi(i) < \overline{\pi} = \frac{1}{(\sigma-1)\overline{\alpha} + 1 - \zeta + \frac{\sigma}{1-\overline{\alpha}}\overline{\alpha}}.$$

Then $d\theta(i) > 0$ for a positive measure subset of industries in $\mathcal{I}^+(\phi,\Theta)$ leads to a lower W and a larger V.

PROOF. Equation (A9) implies that a sufficient condition to ensure that $d\ln W < 0$ is

$$\chi_L(i) > \Bigg((\sigma-1)(\chi_L(i) - \chi_S(i))\alpha(i)s_L(i) + (1-\zeta)\chi_L(i)s_L(i) + \frac{1 + (\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i) - \chi_S(i))\alpha(i)di}{\int_{i\in\mathcal{I}\chi(i)}(1-\alpha(i))di}\chi(i)\alpha(i)s_L(i)\Bigg)\pi(i)\forall i\in\mathcal{I}$$

In addition, we also have

$$\sigma > 1 + (\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i) - \chi_S(i))\alpha(i)di,$$

and

$$\frac{1}{1-\overline{\alpha}} > \frac{1}{\int_{i\in\mathcal{I}}\chi(i)(1-\alpha(i))di}.$$

A sufficient condition to ensure that $d\ln W < 0$ is

$$\chi_L(i) > \left((\sigma-1)\chi_L(i)\alpha(i)s_L(i) + (1-\zeta)\chi_L(i)s_L(i) + \frac{\sigma}{1-\overline{\alpha}}\chi(i)\alpha(i)s_L(i)\right)\pi(i)$$

for all $i\in\mathcal{I}$. This inequality is equivalent to:

$$1 > \left((\sigma-1)\alpha(i)s_L(i) + (1-\zeta)s_L(i) + \frac{\sigma}{1-\overline{\alpha}}\frac{\chi(i)\alpha(i)s_L(i)}{\chi_L(i)}\right)\pi(i).$$

[35] The fact that $\Lambda_V^\pi(\Lambda_W^L - \Lambda_W^S) + \Lambda_W^\pi(\Lambda_V^S - \Lambda_V^L) > 0$ is equivalent to $C(W,V,P)$ being strictly quasi-concave in $\{V,W\}$. In particular, $\Lambda_V^\pi(\Lambda_W^L - \Lambda_W^S) + \Lambda_W^\pi(\Lambda_V^S - \Lambda_V^L) > 0$ if and only if

$$C_{WW}C_V^2 + C_{VV}C_W^2 - 2C_{WV}C_VC_W < 0,$$

which corresponds to the determinant of the bordered Hessian of $C(W,V,P)$ with respect to V and W,

$$H = \begin{pmatrix} 0 & C_W & C_V \\ C_W & C_{WW} & C_{WV} \\ C_V & C_{WV} & C_{VV} \end{pmatrix},$$

being positive. Since $C(W,V,P)$ is strictly concave in its first two arguments, we always have $\Lambda_V^\pi(\Lambda_W^L - \Lambda_W^S) + \Lambda_W^\pi(\Lambda_V^S - \Lambda_V^L) > 0$.

Finally, because $s_L(i) \leq 1$ and

$$\frac{\chi(i)\alpha(i)s_L(i)}{\chi_L(i)} = \int_{i\in\mathcal{I}} \chi(i)\alpha(i)s_L(i)di < \overline{\alpha},$$

we obtain that a sufficient condition to ensure that $d\ln W < 0$ is given by:

$$1 > \left((\sigma-1)\overline{\alpha} + (1-\zeta) + \frac{\sigma}{1-\overline{\alpha}}\overline{\alpha}\right)\pi(i) \quad \forall i \in \mathcal{I},$$

which is equivalent to

$$\frac{1}{(\sigma-1)\overline{\alpha} + 1 - \zeta + \frac{\sigma}{1-\overline{\alpha}}\overline{\alpha}} = \overline{\pi} > \pi(i) \quad \forall i \in \mathcal{I}.$$

In addition, equation (A6) implies that automation must increase the price of at least one type of labor. Thus, when $\pi(i) < \overline{\pi}$ for almost all i, $d\ln V > 0$ and $d\ln V/W$ increases. ■

Proof of Proposition 3:

The definition of $\widetilde{\phi}$ implies that for $\phi < \widetilde{\phi}$, we have $\theta^A(i) = 0$. Therefore, changes in automation technologies do not lead to their adoption (and there is no impact on equilibrium wages). Conversely, when $\phi > \widetilde{\phi}$, new automation technologies will be adopted by all industries in $\mathcal{I}^+(\phi, \Theta)$. This completes the proof of the first part of the proposition.

Because $W^E(\phi, \Theta)$ is increasing in ϕ, cost savings from automation for industry $i \in \mathcal{I}^+(\phi, \Theta)$, $\pi(i)$, are also increasing in ϕ. Therefore, there exists a threshold $\overline{\phi}(\Theta) > \widetilde{\phi}$ such that $\pi(i) < \overline{\pi}$ for almost all industries.

This definition implies that, for $\phi \in (\widetilde{\phi}, \overline{\phi}(\Theta))$, we have $\pi(i) < \overline{\pi}$ for almost all industries. Lemma A2 then implies that automation reduces middle-aged wages and increases older worker wages. ■

Proof of Lemma 1

We first prove that the optimal technology choice $\theta_i^R(W)$ is unique and lies in $[0, 1)$.

We start by showing that every critical point of $\pi^M(i)$ is a local maximum. Suppose that we have an interior critical point, $\theta_0 > 0$. Then it satisfies the first-order condition

$$\frac{\partial \pi^M(i)}{\partial \theta(i)} = 0 \rightarrow (\sigma-1)\alpha(i)\frac{s_L(i)}{1-\theta_0}\pi(i) = \frac{1}{\rho(i)}h(\theta_0).$$

The second derivative of $\pi^M(i)$ is

$$\frac{\partial^2 \pi^M(i)}{\partial\theta(i)\partial\theta(i)} = \frac{1}{\rho(i)}\frac{h(\theta_0)}{1-\theta_0}(\zeta-1)s_L(i)\pi(i) - \frac{1}{\rho(i)}h'(\theta_0).$$

Because $(\zeta-1)s_L(i)\pi(i) < 1$, this expression is negative provided that $\frac{h'(\theta)}{h(\theta)} \geq \frac{1}{1-\theta}$. This condition is satisfied in view of the properties of the H function in the text. In particular,

$$\frac{h'(\theta)}{h(\theta)} = \frac{H''(\theta)}{H'(\theta)} + h(\theta) \geq \frac{1}{1-\theta}.$$

Thus, every critical point is a local maximum.

Now, suppose that $\pi^M(i)$ has two local maxima, θ_0 and $\theta_1 > \theta_0$. The intermediate value theorem then implies that $\pi^M(i)$ has a local minimum in (θ_0, θ_1), which contradicts the fact that any critical point of $\pi^M(i)$ is a maximum. This contradiction establishes that $\pi^M(i)$ is single peaked, and therefore has a unique global maximum. Moreover, our boundary conditions on $H(x)$ implies that $\theta_i^R(W) \in [0, 1)$. Thus, equation (17) is a necessary and sufficient condition for the global maximum.

Part 1: The cross-partial derivative of $\pi^M(i)$ with respect to $\theta(i)$ and W is

$$\frac{\partial^2 \pi^M(i)}{\partial W \partial \theta} = (\sigma-1)\alpha(i)\frac{1}{1-\theta^A(i)}\frac{\partial s_L(i)}{\partial W}\pi(i) + (\sigma-1)\alpha(i)\frac{1}{1-\theta^A(i)}s_L(i)\frac{\pi(i)}{\partial W}.$$

When $\zeta \leq 1$, the equations for $s_L(i)$ (equation (8)) and $\pi(i)$ (equation (5)) in the main text imply that $\frac{\partial s_L(i)}{\partial W} \geq 0$ and $\frac{\partial \pi(i)}{\partial W} \geq 0$.

When $\zeta > 1$, we can group terms differently and rewrite this derivative as

$$\frac{\partial^2 \pi^M(i)}{\partial W \partial \theta} = \frac{1}{W}\left((\sigma-1)\alpha(i)\frac{1}{1-\theta^A(i)}s_L(i) + (\sigma-1)\alpha(i)\left[\frac{P^{1-\zeta}}{P_X^{1-\zeta}} - \frac{(W/A)^{1-\zeta}}{P_X^{1-\zeta}}\right]s_L(i)\right) \geq 0.$$

Therefore, $\frac{\partial^2 \pi^M(i)}{\partial W \partial \theta} \geq 0$ in all cases (and this is an equality only when $\pi(i) = 0$). This implies that $\pi^M(i)$ exhibits increasing differences in W and $\theta(i)$. Increasing differences ensure that the function $\theta_i^R(W)$ is nondecreasing in W (see Topkis, 1981).

Part 2: Suppose that $\theta(i) > 0$. Then $\frac{\partial \pi^M(i)}{\partial \theta(i)} = 0$, and equation (17) holds with equality. Because $h(\theta(i)) > 0$ (recall that H is convex), we must have $\pi(i) > 0$. ■

Proof of Proposition 4

To prove the existence of an equilibrium we analyze the properties of the function $W^E(\phi, \Theta^R(W))$ when $W = 0$ and $W \to \infty$.

When $W \to 0$, we have $\pi(i) = 0$. Part 2 of Lemma 1 implies $\theta_i^R(W) = 0$. Thus, $W^E(\phi, \Theta = \{0\}_{i \in \mathcal{I}}) > 0$.

When $W \to \infty$, $\theta_i^R(W)$ converges to a finite limit (recall that $\theta_i^R(W)$ is increasing in W, and bounded above by 1). Thus, $W^E(\phi, \Theta^R(W))$ converges to a finite limit as well.

These observations imply that the curve $W^E(\phi, \Theta^R(W))$ starts above the 45 degree line and ends below it. Thus, there exists at least one solution to $W = W^E(\phi, \Theta^R(W))$, establishing the existence of an equilibrium. If there are multiple intersections, the ones with the smallest and the largest wage give the least and the greatest equilibria in view of the results in Lemma 1.

Finally, the result that given the equilibrium middle-aged wage W^*, the set of equilibrium technology choices Θ^* is uniquely defined is an immediate consequence of the fact that by definition

$\Theta^* = \Theta^R(W^*)$ and $\Theta^R(W)$ is uniquely defined from Lemma 1. ■

Recall that in the main text, we mentioned that a sufficient condition to ensure that the equilibrium is unique is $\phi < \overline{\phi}(\Theta = \{0\}_{i \in \mathcal{I}})$. We now provide a formal statement and proof of this result.

PROPOSITION A1 *1. If $\phi < \widetilde{\phi}$, the mapping $W^E(\phi, \Theta^R(W))$ is constant at $W^E(\phi, \Theta = \{0\}_{i \in \mathcal{I}})$. In this case, the unique equilibrium involves $\Theta = \{0\}_{i \in \mathcal{I}}$.*

2. If $\widetilde{\phi} < \phi < \overline{\phi}(\Theta = \{0\}_{i \in \mathcal{I}})$, the mapping $W^E(\phi, \Theta^R(W))$ is nonincreasing in W, and the equilibrium is unique.

PROOF. First suppose that $\phi < \widetilde{\phi}$. The definition of $\widetilde{\phi}$ implies that for almost all industries we will have $\pi(i) = 0$. Thus, independently of $\Theta^R(W)$, we will have that $\theta^A(i) = 0$ for almost all industries, and

$$W^E(\phi, \Theta^R(W)) = W^E(\phi, \Theta = \{0\}_{i \in \mathcal{I}}),$$

which does not depend on W. This implies that there is a unique equilibrium given by a wage $W = W^E(\phi, \Theta = \{0\}_{i \in \mathcal{I}})$. At this wage, $\pi(i) = 0$ for almost all industries. Part 2 of Lemma 1 then implies that there will be zero introduction and adoption of automation technologies.

Now suppose that $\widetilde{\phi} < \phi < \overline{\phi}(\Theta = \{0\}_{i \in \mathcal{I}})$. The definition of $\overline{\phi}(\Theta = \{0\}_{i \in \mathcal{I}})$ implies that when $\Theta = \{0\}_{i \in \mathcal{I}}$, we have that $\pi(i) < \overline{\pi}$ for almost all industries. Lemma A2 then implies that $W^E(\phi, \Theta)$ is nonincreasing in Θ around $\Theta = \{0\}_{i \in \mathcal{I}}$, which in turn implies that $W^E(\phi, \Theta^R(W))$ is nonincreasing in W around $W = 0$.

Suppose to obtain a contradiction that $W^E(\phi, \Theta^R(W))$ is increasing in W at some point. Let $W_0 > 0$ be the first point where $W^E(\phi, \Theta^R(W))$ starts increasing. Because $W^E(\phi, \Theta^R(W))$ is nonincreasing in $[0, W_0)$, we have

$$W^E(\phi, \Theta^R(W_0)) \leq W^E(\phi, \Theta^R(0)) = W^E(\phi, \Theta = \{0\}_{i \in \mathcal{I}}).$$

This inequality then implies that at W_0 we have $\pi(i) \leq \overline{\pi}$ for almost all i. Lemma A2 then implies that $W^E(\phi, \Theta^R(W))$ is nonincreasing in W around W_0, yielding a contradiction and establishing that $W^E(\phi, \Theta^R(W))$ must be nonincreasing throughout. ■

Proof of Proposition 5

Both parts of this proposition follow from Topkis's monotonicity theorem (Topkis, 1998).

In particular, Proposition 1 shows that an increase in ϕ shifts the map $W^E(\phi, \Theta^R(W))$ up (as shown in Panel A of Figure 2, which raises W^* in the least and the greatest equilibrium). Lemma A2 then shows that $\theta_i^* = \theta_i^R(W^*)$ increases for $i \in \mathcal{I}^+(\phi, \Theta^*)$, and the formula for $\pi(i)$ in equation (5) shows that the set $i \in \mathcal{I}^+(\phi, \Theta^*)$ expands. ■

Proof of Proposition 6

Recall that W^* is increasing in ϕ. Because $\theta_i^* = \theta_i^R(W^*)$, it is sufficient to show that $\theta_i^R(W^*)$ exhibits increasing differences in W^* and $\alpha(i)$, and in W^* and $\rho(i)$.

From Lemma 1, $\theta_i^R(W^*)$ satisfies the necessary and sufficient first-order condition in equation (17). Suppose first that the first-order condition in equation (17) is slack, and $\theta_i^R(W^*) = 0$. Then clearly, $\frac{d\theta_i^R(W^*)}{d\ln W^*} = 0$.

Suppose now that the first-order condition in equation (17) holds with equality. The implicit function theorem then implies that $\theta_i^R(W^*)$ is continuous and differentiable, and the derivative of $\theta_i^R(W^*)$ with respect to $\ln W^*$ is

$$\frac{d\theta_i^R(W^*)}{d\ln W^*} = \frac{(\sigma-1)\alpha(i)\rho(i)\frac{s_L(i)(1-s_L(i))}{\theta_i^*(1-\theta_i^*)}}{h'^*(i)) + h(\theta_i^*)\frac{(1-s_L(i)-\theta_i^*)}{\theta_i^*(1-\theta_i^*)}}.$$

This expression shows that the (semi-)elasticity of θ_i^* with respect to middle-aged wages is

$$\Gamma(\alpha(i)\rho(i)) = \begin{cases} \dfrac{(\sigma-1)\alpha(i)\rho(i)s_L(i)(1-s_L(i))}{h'^*(i))\theta_i^*(1-\theta_i^*) + h(\theta_i^*)(1-s_L(i)-\theta_i^*)} d\ln W^* > 0 & \text{if } \theta_i^* > 0 \\ 0 & \text{otherwise.} \end{cases}.$$

The desired result then follows by observing that aging only impacts automation decisions through the change in middle-age wages, W^*, and that the (semi-)elasticity of $\theta_i^R(W)$ with respect to W, $\Gamma(\alpha(i)\rho(i))$, is nondecreasing in $\alpha(i)\rho(i)$.[36] ■

Proof of Proposition 7

We have $Y^*(i) = P_Y^*(i)^{-\sigma} Y^*$. Taking a log-derivative of this expression we obtain

$$\begin{aligned}\frac{d\ln Y^*(i)}{d\phi} =& \frac{d\ln Y^*}{d\phi} - \sigma\alpha(i)s_L(i)\frac{d\ln W^*}{d\phi} - \sigma(1-\alpha(i))\frac{d\ln V^*}{d\phi} \\ &+ \sigma\alpha(i)\frac{s_L(i)}{1-\theta_i^*}\pi(i)\Gamma(\alpha(i)\rho(i))\frac{d\ln W^*}{d\phi}.\end{aligned}$$

The term $\sigma\alpha(i)\frac{s_L(i)}{1-\theta(i)}\pi(i)\Gamma(\alpha(i)\rho(i))\frac{d\ln W^*}{d\phi}$ captures the productivity benefits to industry i arising from the endogenous response of automation. Because of the term $\Gamma(\alpha(i)\rho(i))$, theses productivity benefits are larger for industries with a larger $\rho(i)$, which implies that aging raises output in industries with a greater $\rho(i)$ relative industries with lower $\rho(i)$. ■.

Extensions

Endogenous development of labor-augmenting technologies: We now sketch a version of our model in which monopolists also invest in labor-augmenting technologies $A(i)$. The main

[36]Note that the denominator in our formula for $\Gamma(\alpha(i)\rho(i))$ is a transformed version of the negative of the second-order condition for $\theta_i^R(W^*)$, and is thus positive.

difference is that now, the monopolist problem is given by:

$$\max_{\theta(i),A(i)} \pi^M(i) = (1-\sigma)\alpha(i)\ln\left(\theta^A(i)P^{1-\zeta} + (1-\theta^A(i))\left(\frac{W}{A(i)}\right)^{1-\zeta}\right) + \frac{1}{\rho(i)}\ln(1-H(\theta(i))) + \frac{1}{\upsilon(i)}\ln(1-G(A(i))) \text{ for all } i\in\mathcal{I},$$

where G is a cost function satisfying the same restrictions as H.

The first-order condition for $A(i)$ is given by:

$$g(A(i)) = \frac{1}{A(i)}(\sigma-1)\upsilon(i)\alpha(i)s_L(i).$$

This first-order condition shows that the effect of aging on $A(i)$ is ambiguous when $\zeta < 1$. On the one hand, aging raises W and hence the labor share $s_L(i)$. But on the other hand, aging fosters automation, reducing $s_L(i)$.

Instead, when $\zeta \geq 1$, one can show that the maximization problem in equation (15) exhibits increasing differences in $W, \theta(i)$, and $-A(i)$. This implies that aging will reduce the development of labor-augmenting technologies but will increase the development of automation technologies.

Multiple countries: We now sketch a version of our model that incorporates multiple countries. Our main objective is to show how, in the presence of multiple countries experiencing differential demographic changes, some will develop more automation technologies and export those to others. These generate imports and exports of automation technologies and motivate our empirical work. This extension also undergirds our claim that demographic change in one country will lead to the adoption of automation technologies in the rest of the world.

Suppose that there are two countries: U—the US—and J—Japan (or Germany). We use superscripts to distinguish variables related to these two countries, with ϕ^U and ϕ^J denoting aging in country U and in country J, respectively.

Relative to our main model, the only difference is that we now assume that country U can "import" part of the automation technologies from the more advanced country J, and as a result, in the tasks it is importing technologies, automation becomes easier for the technology monopolists in country U. We capture this by positing:

$$\rho^U(i) = \rho(i;\theta^J(i))$$
$$\rho^J(i) = \rho(i),$$

where $\rho(i;\theta^J(i))$ is increasing in $\theta^J(i)$. This captures in a simple way the idea that advances in automation technologies in country J, that is, increases in $\theta^J(i)$, generate opportunities for automation in country U and for imports and exports of technologies.

It is straightforward to establish that an equilibrium with endogenous technology exists in this global economy. In particular, Proposition 4 establishes that an equilibrium exists for country J, and taking as given the equilibrium value of Θ^{J^*}, another application of this proposition characterizes the equilibrium in country U. Let us also define the greatest (least) equilibrium in this case as the equilibrium with the highest (lowest) level of automation in each country (these are also the equilibria with the largest (smallest) values of the middle-aged wage in country J, but not necessarily in country U as we will see next).

The following proposition summarizes the results from this extension:

PROPOSITION A2 *Assume that $\phi^J > \tilde{\phi}^J$ and $\overline{\phi}^U(\Theta = \{0\}_{i\in\mathcal{I}}) > \phi^U > \tilde{\phi}^U$. Then there exist well-defined greatest and least equilibria. In the least or the greatest equilibrium, an increase in ϕ^J:*

1. *increases the middle-aged wage W^{J^*}, increases automation technologies $\{\theta^{J^*}(i)\}_{i\in\mathcal{I}^+(\phi^J,\Theta^{J^*})}$, and expands the set of industries that adopt automation $\mathcal{I}^+(\phi^J,\Theta^{J^*})$ in country J;*
2. *increases automation technologies $\theta^{U^*}(i)$ in a positive subset of industries and reduces the middle-aged wage W^{U^*} in country U.*

PROOF. The existence of greatest and least equilibria follow from applying Proposition 4 in the main text. In particular, from this proposition we can characterize the equilibrium with endogenous technology in country J in isolation, which leads to the existence of a least and greatest equilibrium for this country. Then applying Proposition A1 to country U we can see immediately that the least equilibrium in country J will lead to a unique equilibrium with the lowest possible level of automation in country U, and likewise for the greatest equilibrium.

The comparative statics for country J follows from applying Proposition 5 in the main text.

The comparative statics for country U follows from observing that aging in J results in an increase in $\rho(i;\theta^{J^*})$ for all i. The first-order condition for a monopolist in country U is now:

$$h(\theta_i^R(W)) \geq (\sigma-1)\rho(i;\theta^{J^*}(i))\alpha(i)\frac{s_L^U(i)}{1-\theta_i^R(W)}\pi^U(i),$$

with equality if $\theta_i^R(W) > 0$. As a result, when $\theta^{J^*}(i)$ increases, the optimal choice of technology in country U, $\theta_i^R(W)$, shifts up for any given wage level. Because we have assumed that $\overline{\phi}^U(\Theta = \{0\}_{i\in\mathcal{I}}) > \phi^U > \tilde{\phi}^U$, country U is in the region in which automation reduces W. This implies that for U, the mapping $W^E(\phi^U, \Theta^R(W))$ shifts down, bringing down the equilibrium wage, but increasing automation in a positive measure of industries. ■

The most important results contained in this proposition are the following. First, advances in automation technologies in country J are "exported" to or "imported" by country U. Second and as a result of the first, aging in country J induces greater automation not just in its own economy but also in the economy of country U as we claim the text.

Additional References

Donald M. Topkis (1998) *Supermodularity and Complementarity*, Princeton University Press.

Appendix: Data Description

This Appendix describes in detail some of the sources of data used in our analysis.

Comtrade data

As explained in the text, we complement the IFR data with estimates of robot imports and exports from the bilateral trade statistics obtained from Comtrade.

We focus on trade in *intermediate goods*, defined as products whose two-digit HS code is given by 82 (Tools), 84 (Mechanical machinery and appliances), 85 (Electrical machinery and equipment), 87 (Tractors and work trucks), and 90 (Instruments and apparatus). We partitioned all intermediates into the categories reported in Figures 7, A3, and A4. We defined the categories using the HS-2012 classification, and mapped them to the HS-1992 classification using the crosswalks available at https://unstats.un.org/unsd/trade/classifications/. The 1992 classification allows us to track our categories consistently over time and compute the total value of imports and exports of intermediates between 1990 and 2016 in constant 2007 dollars.

The categories used in the paper are defined as follows:

- *Industrial robots:* This category includes industrial robots. It is defined by the six-digit HS code 847950. This category was introduced to the HS-1996 classification, and so we only compute data on imports of robots between 1996 and 2016.
- *Dedicated machinery (including robots):* This category includes machinery and mechanical appliances with individual functions. It is defined by the six-digit HS code 847989. This category was introduced in the HS-1992 classification. It is a superset of industrial robots and in addition to industrial robots, it contains dedicated (automatic) machinery. It can be tracked consistently over time between 1990 and 2016.
- *Numerically controlled machines:* For a wide class of metal-working machines (lathes, milling machines), the HS classification distinguishes "numerically controlled" vintages from "other than numerically controlled" vintages. Based on this distinction we create two separate categories: *numerically controlled machines* and *not-numerically controlled machines*. Both can be tracked consistently over time between 1990 and 2016.
- *Machine tools:* For a wide class of machine tools (six-digit HS codes 845600 to 851519), the HS classification distinguishes those that are for "working with hands" from the rest. Based on this distinction we create two separate categories: *automatic machine tools* and *manual machine tools*. Both can be tracked consistently over time between 1990 and 2016.
- *Tools for industrial work:* This category includes tools (not machines or machine tools) used in industrial applications. It is defined by the six-digit HS codes between 820200 and 821299. This category can be tracked consistently over time between 1990 and 2016.
- *Welding machines:* For welding machines (six-digit HS codes 851521 to 851590), the HS classification distinguishes those that are automatic from those that are not. Based on this distinction we create two separate categories: *automatic welding machines* and *manual welding machines*. Both can be tracked consistently over time between 1990 and 2016.

- *Weaving and knitting machines:* This category includes weaving and knitting machines used in the textile industry. It is defined by the six-digit HS codes 844600-844699 (weaving machines) and 844700-844799 (knitting machines). We grouped the remaining dedicated machinery used in textiles (six-digit HS codes 844400-845399) into *Other textile dedicated machinery.* Both can be tracked consistently over time between 1990 and 2016.

- *Conveyors*: For conveyors (six-digit HS codes 842511-842839), the HS classification distinguishes those that are "continuous action" and therefore automatic from other machinery that transfer or move materials with human operation (like work trucks). Based on this distinction we create two separate categories: *automatic conveyors* and *other conveyors*. Both can be tracked consistently over time between 1990 and 2016.

- *Regulating and control instruments*: This category includes instruments typically used for control applications in manufacturing (six-digit HS codes 902500-903299). These intermediates can be tracked consistently over time between 1990 and 2016.

- *Other industrial machinery*: This is defined as a residual category that includes all industrial machinery that were not otherwise classified as related (or unrelated) to industrial automation.

- *Vending machines:* This category includes vending machines and their parts. It is defined by the six-digit HS codes 847621-847690. This category can be tracked consistently over time between 1990 and 2016.

- *Laundry machines:* This category includes laundry machines and their parts. It is defined by the six-digit HS codes 845100-845199. This category can be tracked consistently over time between 1990 and 2016.

- *Agricultural machinery:* This category includes agricultural machinery (six-digit HS codes 843200-843799) and tractors (six-digit HS codes 843200-843799). This category can be tracked consistently over time between 1990 and 2016.

- *Computers:* This category includes computers and their parts. It is defined by the six-digit HS codes 847100-847199. This category can be tracked consistently over time between 1990 and 2016.

As a final check on the Comtrade data on robot imports and exports, we explore the relationship between robot imports and robot use from the IFR. This measure of the change in the value of imports of industrial robots is highly correlated with our IFR measure of the change in the stock of robots per thousand workers, both in levels and in logs, as shown in Figure A6. In the level specification, the bivariate regression coefficient is 48,722 (standard error=11,873). This coefficient is reasonable in view of the fact that the cost of a typical robot ranges between $50,000 and $100,000 (This excludes the costs of installation and programming, which often add about $300,000 to the cost of a robot, but since these services are typically provided by local integrators, they do not show up in import statistics).

USPTO patent data

Finally, we use data on robotics-related patents granted by the USPTO between 1990 and 2015, and allocate them across countries according to the last recorded location of the assignee of the patent. The assignee of the patent is the company, foundation, partnership, holding company or individual that owns the patent. The latter could be an "independent inventor", meaning that the assignee is the same person as the inventor of the patent. In a small fraction of cases (about 3% of our sample), patents have multiple assignees, and we allocate them proportionately to the countries of all of the assignees.

We use several measures of robotics-related patents. First, we use patents in the USPTO class 901, which includes inventions related to industrial robots. This category is labeled as *901 USPTO class* in our figures. We then construct a category containing patents in classes referenced by the 901 class. These classes contain technologies that are related to robotics, even if the patent itself is not for a different type of robot. This category is labeled as *Classes related to 901* in our figures, and it is the category we use in our baseline estimates for patents.

We also used patent citations to define classes related to industrial robots. We created two categories, one including all classes with at least 25% of their citations referencing class 901, and another one including all classes with at least 10% of their citations referencing class 901.

In another approach, we used the words in the abstracts of patents to define robotics-related patents. In a first category, labeled *words related to robots*, we count patents including the words "robot." In the category *words related to industrial robots*, we count patents including the words "robot" and "industrial." The category *words related to robots and manipulators* expands the previous one by also including patents with the the words "robot arm" and "robot machine" or "robot manipulator." Finally, the category *words related to numerical control* includes patents whose abstracts include the words "numeric" and "control." When computing these categories, we exclude patents related to prosthetic arms, which tend to share several of the same keywords.

We also counted patents related to computers, software, nanotechnology, and pharmaceuticals. For computers, we have *classes related to computers*, which includes the USPTO classes 708, 709, 710, 711, 712, 713, 718 and 719, and *words related to computers*, which includes patents whose abstract includes the word "computer." For software, we have *classes related to software*, which includes the USPTO classes 717, and *words related to software*, which includes patents whose asbtract includes the words "software." For nanotechnology, we have *classes related to nanotechnology*, which includes the USPTO class 977, and *words related to nanotechnology*, which includes patents whose abstract includes the words "nano" and "technology." For pharmaceuticals, we have *classes related to pharmaceuticals*, which includes the USPTO classes 514 and 424, and *words related to pharmaceuticals*, which includes patents whose asbtract includes the words "pharma."

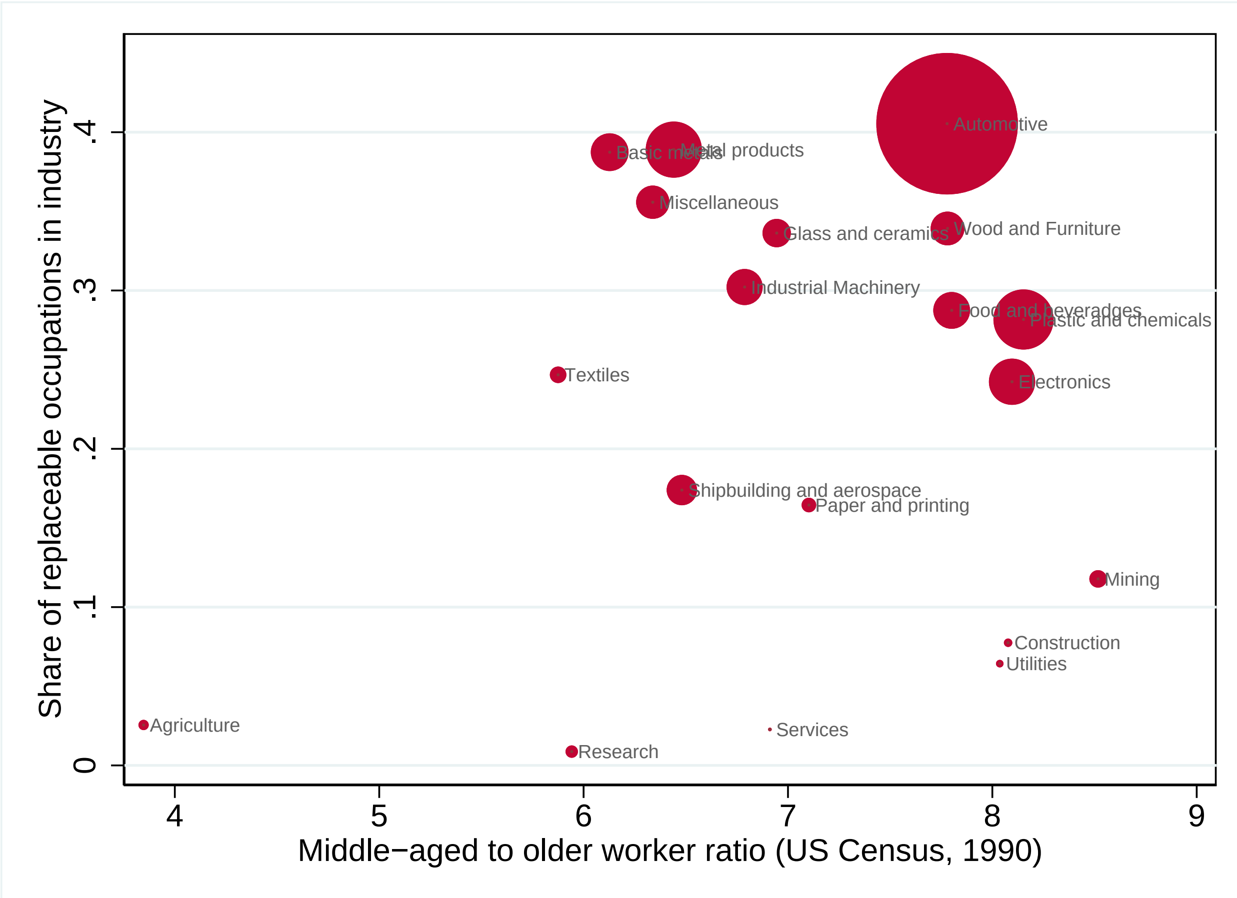
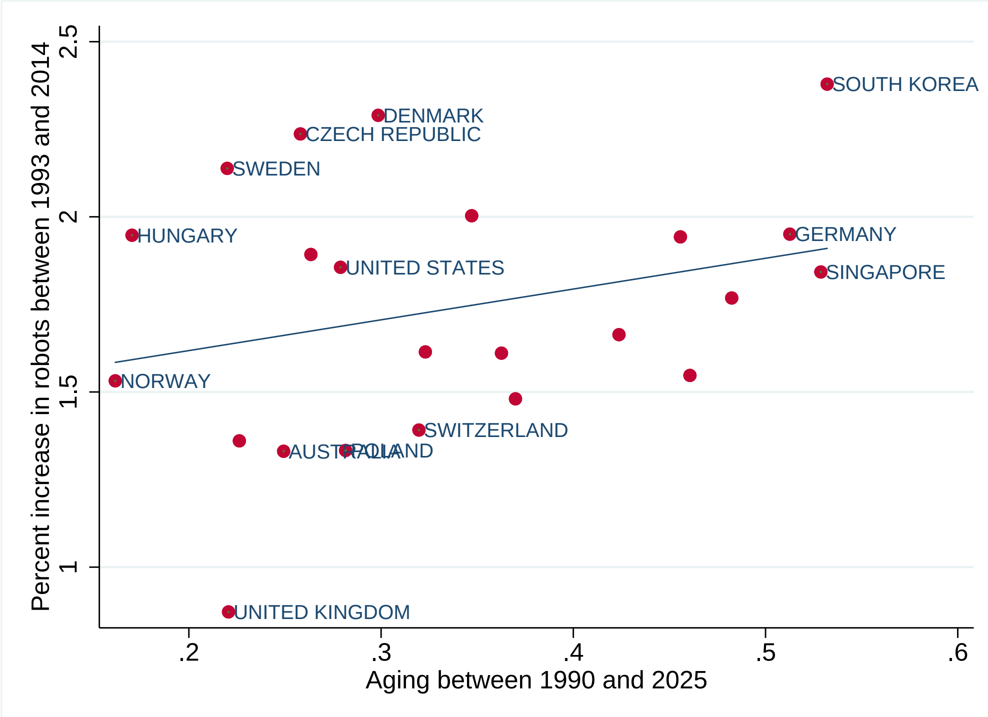


Figure A1: The figure plots industries according to their reliance on middle-aged workers (horizontal axis) and their share of replaceable jobs (vertical axis). The size of the markers indicate the average robot installations per thousand workers by industry over the 1993-2014 period.



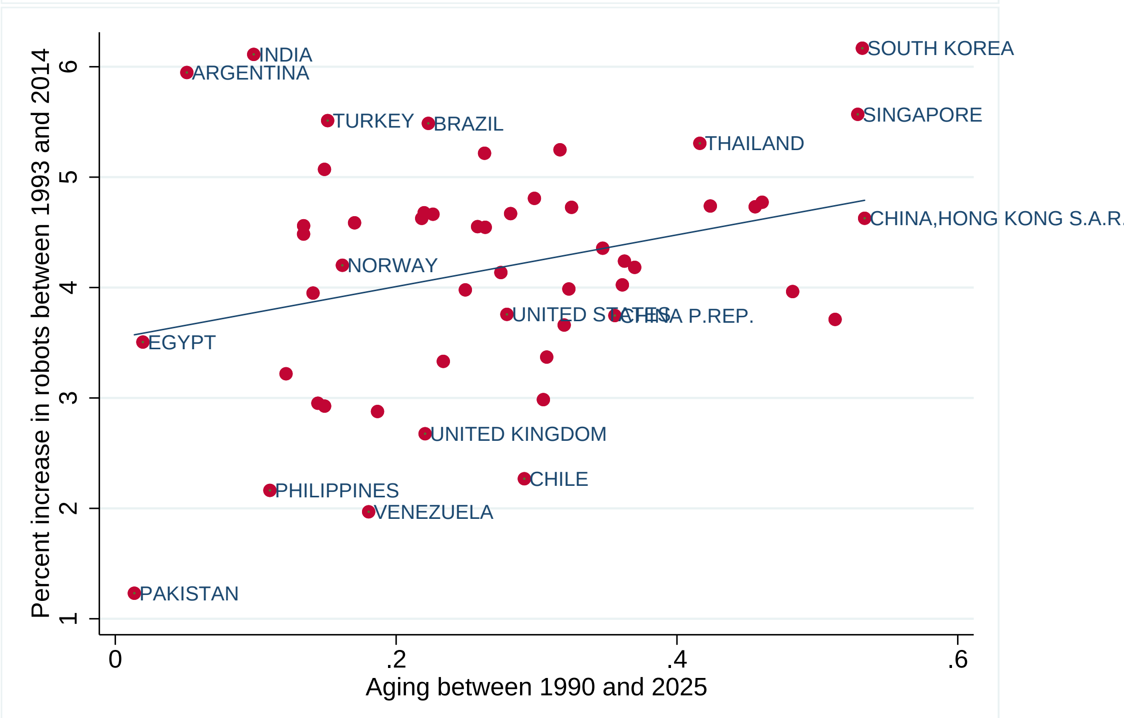


FIGURE A2: Residual plots of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the increase in the number of industrial robots per thousand workers between 1993 and 2014. The plots partial out the covariates included in the regression models in columns 2 and 5 of Table A12.

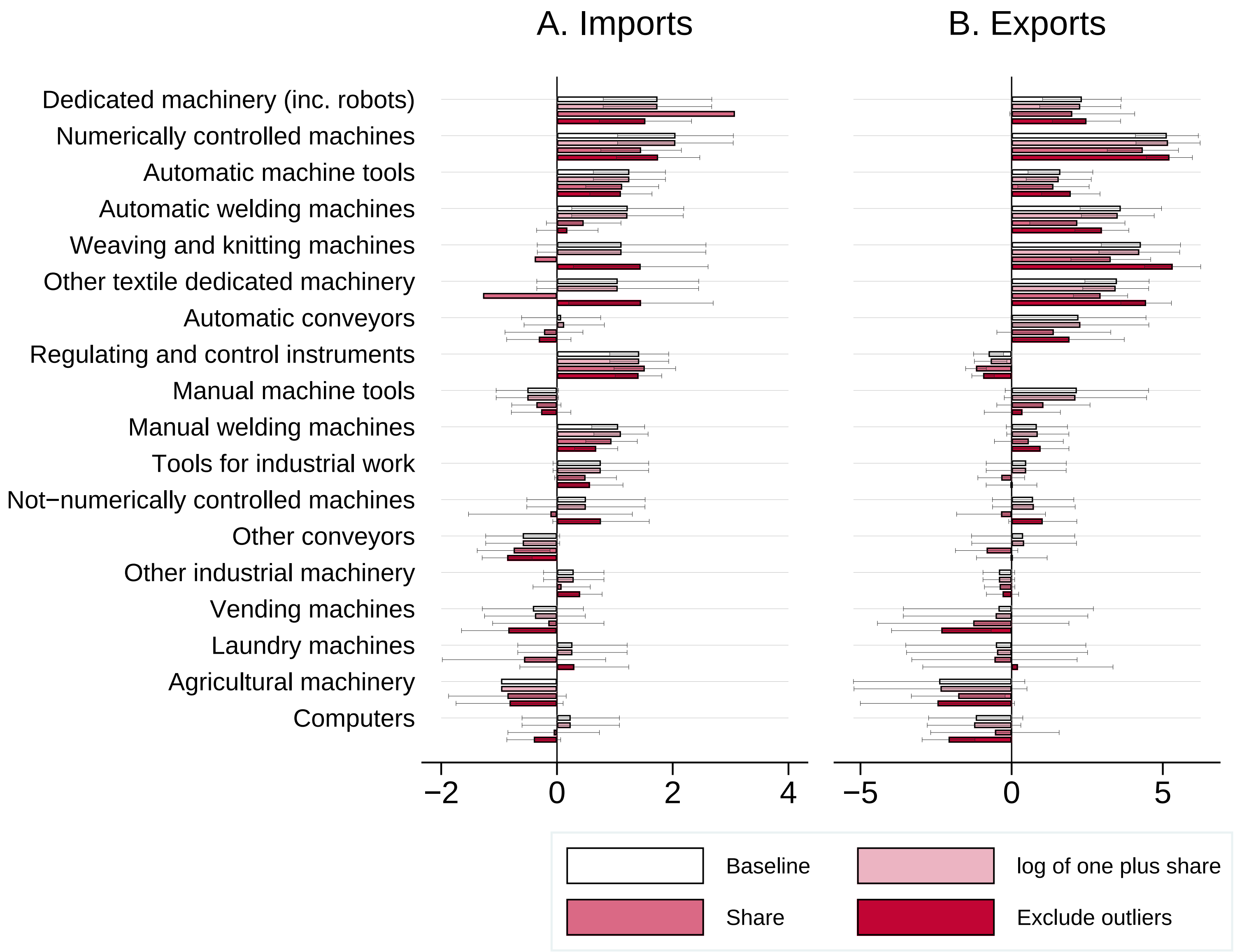


FIGURE A3: Estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and exports (left panel) and imports (right panel) of different intermediate goods between 1990 and 2015. These outcomes are normalized by the total intermediate exports and imports, respectively, during this period. The figure presents several estimates, including our baseline, a specification using the log of one plus the imports (or exports) of industrial robots per million dollars of intermediate goods imported (exported), a specification using the share of robot imports (or exports), and a version of our baseline specification where we exclude outliers manually (observations with a standardized residual outside the ±1.96 range).

FIGURE A4: OECD estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and exports (left panel) and imports (right panel) of different intermediate goods between 1990 and 2015. These outcomes are normalized by the total intermediate exports and imports, respectively, during this period. The figure presents several estimates, including our baseline, a specification using the log of one plus the imports (or exports) of industrial robots per million dollars of intermediate goods imported (exported), a specification using the share of robot imports (or exports), and a version of our baseline specification where we exclude outliers manually (observations with a standardized residual outside the ±1.96 range).

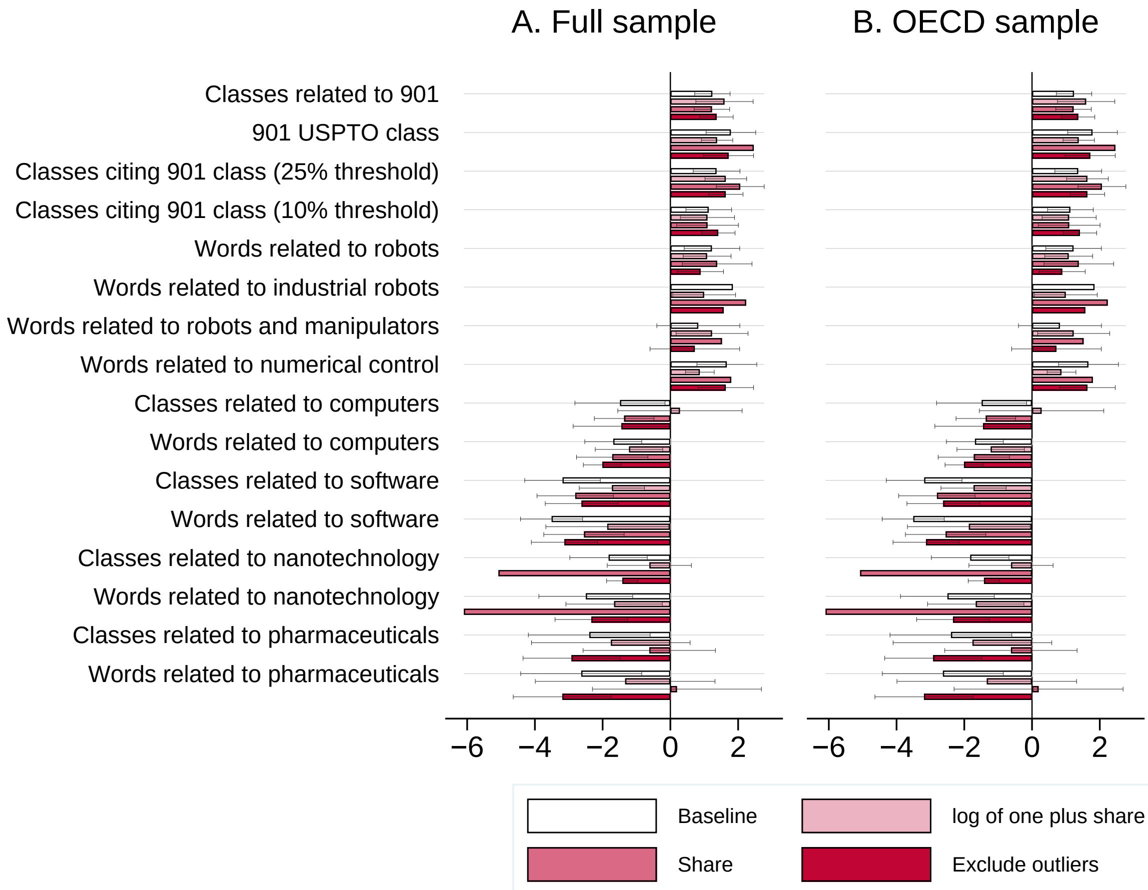


FIGURE A5: Estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of patents with different characteristics between 1990 and 2015. These outcomes are normalized by the total patents granted by the USPTO during this period. The figure presents several estimates, including our baseline, a specification using the log of one plus the imports (or exports) of industrial robots per million dollars of intermediate goods imported (exported), a specification using the share of robot imports (or exports), and a version of our baseline specification where we exclude outliers manually (observations with a standardized residual outside the ±1.96 range).

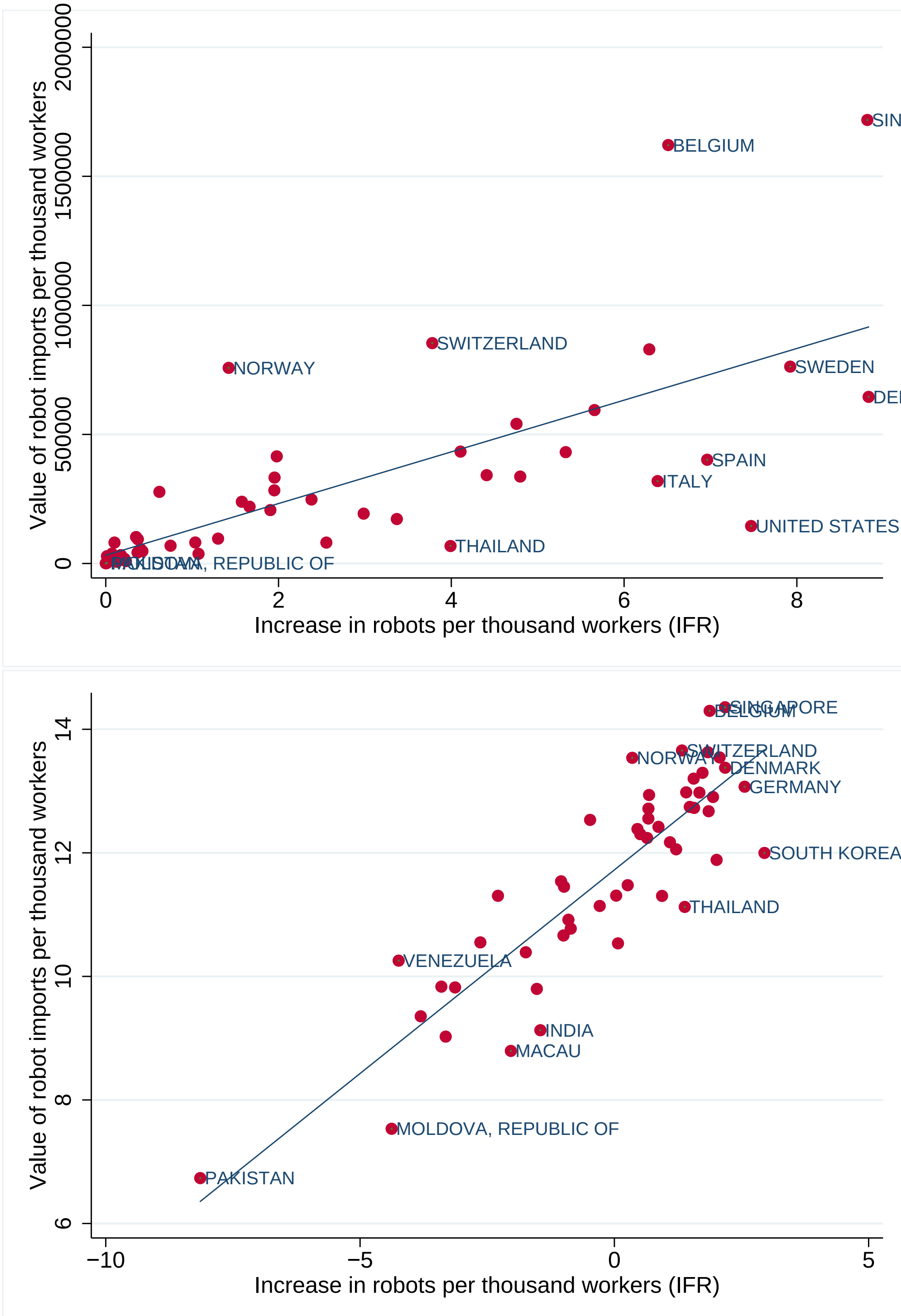
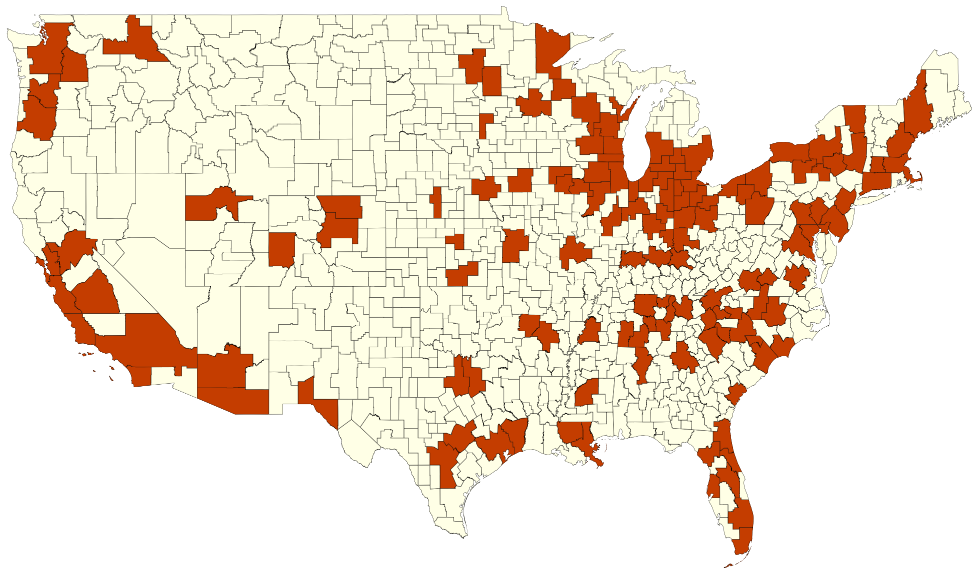
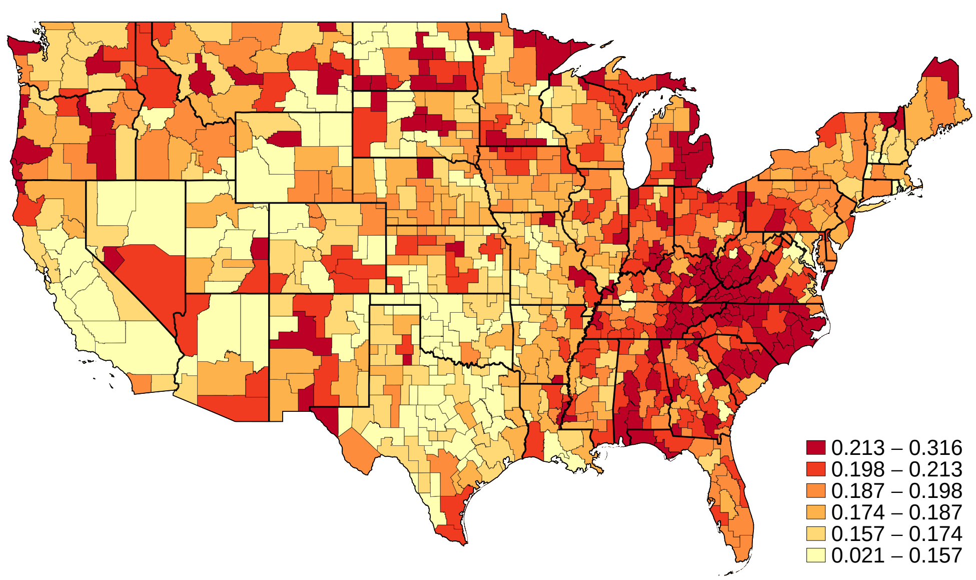


FIGURE A6: Scatter plots of the relationship between imports of robots per thousand workers (in 2007 dollars, from Comtrade) and the increase in the number of industrial robots per thousand workers between 1993 and 2014, both in levels and in logs.



Panel A



Panel B

FIGURE A7: The maps present the location of commuting zones that house robot integrators (Panel A) and predicted aging across commuting zones based on birthrates from 1950 to 1985 (Panel B).

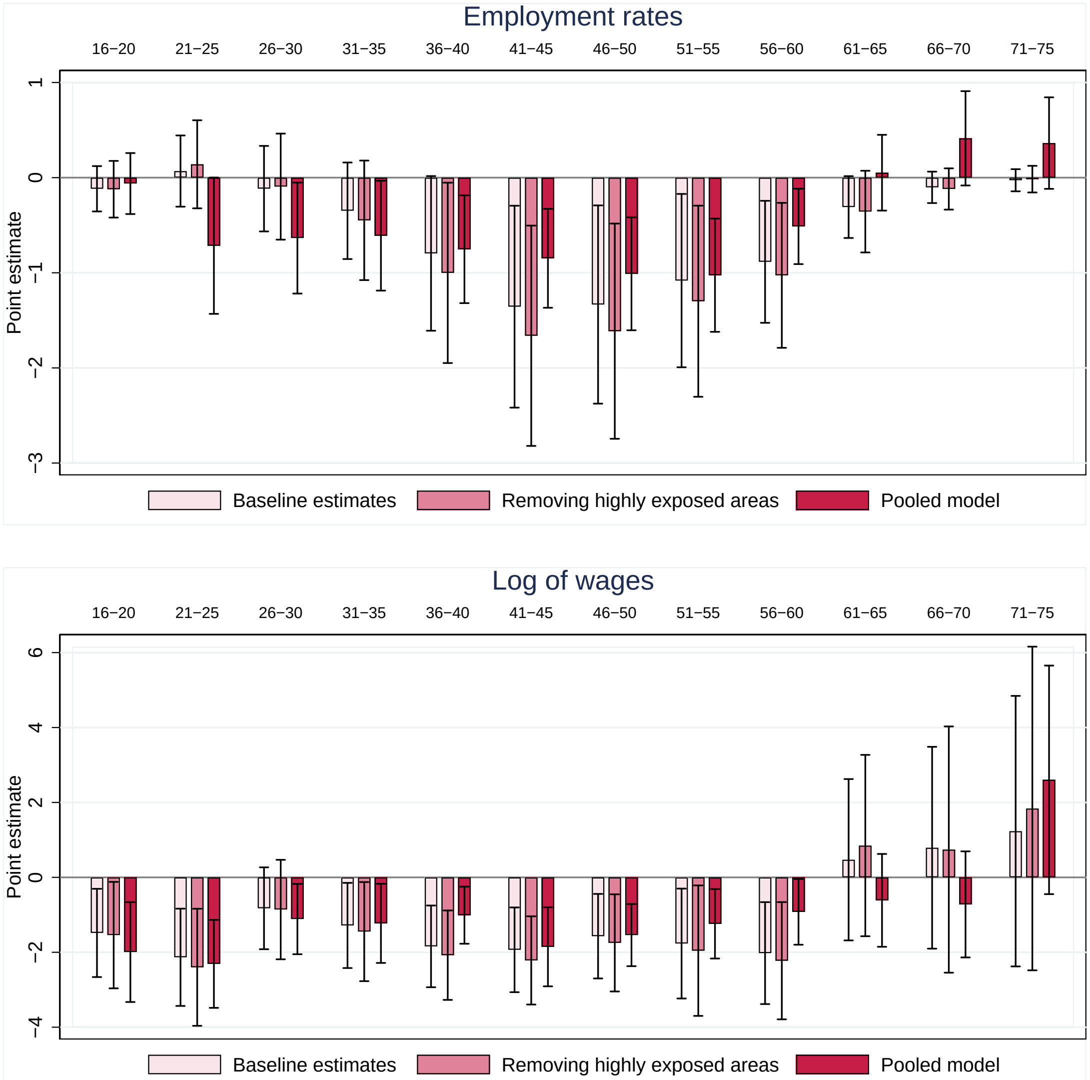


FIGURE A8: The figure presents estimates of the impact of one additional robot per thousand workers on the employment and wages of people in different age groups. These estimates are computed by exploiting differences in the exposure to robots across US commuting zones. The three specifications and the data used are described in the main text and in Acemoglu and Restrepo (2018a).

Table A1: Set of countries in our sample and availability of robot installations by industry.

OECD sample		Other countries	
Country name	*Industry data since*	*Country name*	*Industry data since*
Australia	2006	Argentina	2004
Austria	2003	Brazil	2004
Belgium	2004	Bulgaria	2006
Chile	2006	China	2006
Czech Republic	2004	Colombia	2007
Denmark	1996	Egypt	2005
Estonia	2004	Hong Kong	2006
Finland	1993	India	2006
France	1993	Indonesia	2006
Germany	1993	Malaysia	2006
Greece	2006	Moldova	2010
Hungary	2004	Morocco	2005
Iceland	2006	Peru	2006
Ireland	2006	Philippines	2006
Israel	2005	Romania	2004
Italy	1993	Singapore	2005
Netherlands	2004	Thailand	2005
New Zealand	2006	Ukraine	2004
Norway	1993	Venezuela	2007
Poland	2004	Vietnam	2005
Portugal	2004		
Rep. of Korea	2001	Countries with no industry data	
Slovakia	2004	Pakistan	.
Slovenia	2005	Macau	.
Spain	1993		
Sweden	1993		
Switzerland	2004		
Turkey	2005		
United Kingdom	1993		
United States	2004		

Notes: The table presents a list of the countries in our sample as well as the years for which industry-level data are available from the IFR.

Table A2: Summary statistics for countries

	All countries	OECD	Rapidly-aging countries	Slowly-aging countries
Panel A: IFR data.				
Robots per thousand workers in 2014	3.79	5.71	5.76	1.81
	(4.60)	(4.83)	(5.29)	(2.64)
Robots per thousand workers in 1993	0.72	1.14	1.09	0.34
	(1.13)	(1.22)	(1.24)	(0.87)
Annualized increase between 1993 and 2014	0.15	0.22	0.22	0.07
	(0.18)	(0.19)	(0.21)	(0.09)
Ratio of older to middle-aged workers	0.38	0.45	0.41	0.34
in 1990	(0.13)	(0.09)	(0.12)	(0.14)
Change in older to middle-aged workers	0.27	0.31	0.37	0.16
between 1990 and 2025	(0.13)	(0.11)	(0.09)	(0.07)
Change in older to middle-aged workers	0.13	0.16	0.19	0.08
between 1990 and 2015	(0.08)	(0.06)	(0.05)	(0.08)
Value added in manufacturing 1990	76	106	115	38
(in billions of dollars)	(172)	(220)	(234)	(52)
	$N=52$	$N=30$	$N=26$	$N=26$
Panel B: Comtrade data.				
Robot imports per thousand workers	$37K	$112K	$70K	$4K
between 1996 and 2015 (thousand dollars)	($89K)	($118K)	($118K)	($11K)
Robot imports per million dollars of total	$272	$268	$279	$219
intermediate imports between 1996 and 2015	($145)	($138)	($143)	(%158)
Value added in manufacturing 1990	36	101	64	7.5
(in billions of dollars)	(116)	(207)	(159)	(18)
	N=130	N=34	N=65	N=65
Robot exports per thousand workers	$42K	$110K	$69K	$16K
between 1996 and 2015 (thousand dollars)	($115K)	($168K)	($127K)	($95K)
Robot exports per million dollars of total	$292	$375	$314	$89
intermediate exports between 1996 and 2015	($590)	($314)	($307)	($1,613)
Value added in manufacturing 1990	52	121	93	11
(in billions of dollars)	(148)	(237)	(202)	(20)
	N=103	N=35	N=52	N=51
Panel C. USPTO patents sample.				
Robot-related patents granted between	718	1,578	1,406	49
1990 and 2016 by the USPTO	(3,365)	(4,928)	(4,728)	(148)
Robot-related patents granted by USPTO	13.4	13.5	13.5	12.8
for every other thousand patents	(3.3)	(3.0)	(3.0)	(8.1)
Value added in manufacturing 1990	77	135	118	36
(in billions of dollars)	(179)	(248)	(241)	(61)
	N=68	N=31	N=34	N=34

Notes: The table presents summary statistics for the main variables used in our cross-country analysis. The data are presented separately for the full sample, the OECD sample, and countries above and below the median aging between 1990 and 2025 in each sample. Section 3 in the main text describes the sources and data in detail.

Table A3: Summary statistics for industries

	Robot installations per thousand workers							
	Normalized using average employment	Normalized using KLEMS employment	Normalized using UNIDO employment	Percent increase in value added	Change in labor share (p.p.)	Reliance on middle-aged workers	Share of replaceable tasks	Share of KLEMS employment
Prone to the use of robots								
Automotive	2.94	7.69	5.52	46.0%	-5.93	7.78	0.35	1.2%
Chemicals, plastics, and pharmaceuticals	1.27	1.32	1.25	38.4%	-3.86	8.15	0.30	2.1%
Electronics	1.07	0.76	0.74	54.0%	-6.84	8.10	0.33	2.4%
Metal machinery	0.43	0.44	0.46	48.3%	-4.19	6.79	0.34	1.9%
Other industries								
Metal products	0.84	1.14	0.92	44.1%	-7.25	6.44	0.37	1.8%
Basic metals	0.15	0.49	0.32	51.6%	-9.77	6.13	0.37	0.7%
Food and beverages	0.54	0.46	0.33	33.0%	-1.24	7.80	0.30	2.2%
Wood and furniture	0.11	0.39	0.10	37.6%	-0.82	7.78	0.35	0.6%
Other vehicles	0.06	0.31	0.17	58.8%	-13.64	6.48	0.35	0.6%
Glass and non-metals	0.09	0.26	0.14	49.1%	-5.48	6.94	0.34	0.8%
Textiles	0.03	0.08	0.03	32.9%	0.39	5.88	0.31	2.2%
Paper and printing	0.04	0.06	0.03	33.1%	-0.96	7.10	0.21	1.7%
Miscellaneous manufacturing	0.15	0.37		34.5%	-0.71	6.34	0.39	1.1%
Research and education	0.09	0.04		30.3%	0.82	5.94	0.01	6.1%
Mining	0.01	0.09		56.3%	-10.58	8.52	0.14	0.6%
Agriculture	0.02	0.02		19.9%	11.80	3.85	0.01	5.7%
Construction	0.03	0.01		38.7%	-4.46	8.08	0.08	7.1%
Utilities	0.00	0.01		53.3%	-5.14	8.04	0.07	0.8%
Services	0.01	0.00		36.7%	-0.16	6.91	0.03	60.5%
Summary statistics								
Average	0.42	0.20	0.81	36.7%	-0.55	6.82	0.09	
Unweighted Average	0.42	0.73	0.83	41.9%	-3.40	7.00	0.24	
Countries covered	50	21	44	21	21	US	US	

Notes: The table presents summary statistics for each of the 19 industries covered in the IFR data. The bottom rows present summary statistics for each variable. We follow the Boston Consulting Group in labeling the automotive, chemicals, plastics, pharmaceuticals, electronics, and metal machinery industries as being prone for the use of industrial robots (Boston Consulting Group, 2015). We compute the reliance on middle-aged workers using the 1990 US Census. The measure is defined as the share of middle-aged (21 to 55 years) to older (56 years or more) workers employed in each industry. The share of replaceable tasks comes from Graetz and Michaels (2018). Section 3 in the main text describes the sources of the data.

Table A4: Estimates of the impact of aging on the adoption of industrial robots using different definitions of middle-aged and older workers.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)			
	OLS estimates		IV estimates	
	All countries	OECD	All countries	OECD
	(1)	(2)	(3)	(4)
	Panel A. Middle-aged from 21-50; Older from 51 onwards			
Aging between 1990 and 2025	0.497	0.777	0.567	0.944
	(0.193)	(0.269)	(0.194)	(0.277)
Observations	52	30	52	30
First-stage F stat.			18.1	11.3
Overid $p-$ value			0.79	0.50
	Panel B. Middle-aged from 21-60; Older from 61 onwards			
Aging between 1990 and 2025	0.911	1.237	1.023	1.245
	(0.323)	(0.414)	(0.333)	(0.425)
Observations	52	30	52	30
First-stage F stat.			19.8	8.1
Overid $p-$ value			0.62	0.36
	Panel C. Middle-aged from 21-55; Older from 56-65			
Aging between 1990 and 2025	1.975	2.860	1.854	2.812
	(0.721)	(0.823)	(0.748)	(0.968)
Observations	52	30	52	30
First-stage F stat.			29.1	21.7
Overid $p-$ value			0.24	0.26
	Panel D. Middle-aged from 21-55; Older from 56-75			
Aging between 1990 and 2025	1.024	1.527	1.130	1.680
	(0.349)	(0.445)	(0.349)	(0.482)
Observations	52	30	52	30
First-stage F stat.			21.3	12.5
Overid $p-$ value			0.41	0.39
	Panel E. Middle-aged from 35-55; Older from 56 onwards			
Aging between 1990 and 2025	1.975	2.860	1.854	2.812
	(0.721)	(0.823)	(0.748)	(0.968)
Observations	52	30	52	30
First-stage F stat.			29.1	21.7
Overid $p-$ value			0.24	0.26
Covariates included:				
Baseline country covariates	✓	✓	✓	✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots using different measures of aging. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). The aging variable varies by panel. In Panel A, it is is the expected change in the ratio of workers above 51 to workers aged 21-50 between 1990 and 2025 (from the UN Population Statistics). In Panel B, it is is the expected change in the ratio of workers above 61 to workers aged 21-60 between 1990 and 2025 (from the UN Population Statistics). In Panel C, it is is the expected change in the ratio of workers aged 56-65 to workers aged 21-55 between 1990 and 2025 (from the UN Population Statistics). In Panel D, it is is the expected change in the ratio of workers aged 56-75 to workers aged 21-55 between 1990 and 2025 (from the UN Population Statistics). In Panel E, it is is the expected change in the ratio of workers aged 56-65 to workers aged 35-55 between 1990 and 2025 (from the UN Population Statistics). Columns 1-2 present OLS estimates. Columns 3-4 present IV estimates where aging is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. We present results for two samples: columns 1 and 3 use the full sample; columns 2 and 4 use the OECD sample. All models control for region dummies and the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. All regressions are unweighted, and the standard errors are robust against heteroscedasticity.

Table A5: Estimates of the impact of aging on the adoption of industrial robots controlling for the influence of outliers.

	All Countries		OECD sample	
	(1)	(2)	(3)	(4)
	Panel A. Removing Korea			
Aging between 1990 and 2025	0.457	0.271	0.590	0.301
	(0.172)	(0.109)	(0.210)	(0.164)
Observations	51	51	29	29
	Panel B. Removing Korea, weighted by manufacturing value added			
Aging between 1990 and 2025	1.021	0.556	1.183	0.673
	(0.253)	(0.165)	(0.238)	(0.246)
Observations	51	51	29	29
	Panel C. Reweighting by employment in industry			
Aging between 1990 and 2025	0.931	0.721	1.508	1.216
	(0.231)	(0.212)	(0.176)	(0.314)
Observations	52	52	30	30
	Panel D. Removing outliers based on residuals			
Aging between 1990 and 2025	0.502	0.318	0.679	0.305
	(0.166)	(0.106)	(0.194)	(0.164)
Observations	50	49	28	28
	Panel E. Quantile (median) regression			
Aging between 1990 and 2025	0.544	0.277	0.684	0.360
	(0.252)	(0.138)	(0.195)	(0.182)
Observations	52	52	30	30
	Panel F. Huber M-regression			
Aging between 1990 and 2025	0.498	0.345	0.796	0.368
	(0.170)	(0.135)	(0.267)	(0.234)
Observations	52	52	30	30
Baseline country covariates	✓	✓	✓	✓
Initial robot density and manufacturing value added		✓		✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots controlling for the influence of outliers. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). The aging variable is the expected change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025 (from the UN Population Statistics). Panel A presents OLS estimates excluding South Korea from the sample. Panel B presents OLS estimates excluding South Korea from the sample but weighting the data by value added in manufacturing. Panel C presents estimates weighted by employment in manufacturing (instead of value added). Panel D presents quantile (median) regressions. Panel E presents a Huber-M estimator. We present results for two samples: columns 1-2 use the full sample; columns 2-3 use the OECD sample. Columns 1 and 3 include region dummies, the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 2 and 4 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. The standard errors are robust against heteroscedasticity.

Table A6: OLS estimates of the impact of population change in different age groups on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Population in two age groups between 1990-2025					
Change in the log of population	-0.451	-0.510	-0.538	-0.756	-1.202	-0.971
aged 20-55 years	(0.148)	(0.286)	(0.292)	(0.213)	(0.447)	(0.477)
Change in the log of population	0.366	0.368	0.307	0.605	0.478	0.312
$\geq$ 56 years	(0.190)	(0.203)	(0.202)	(0.237)	(0.328)	(0.368)
Robots per thousand workers in 1993			0.080			0.058
			(0.014)			(0.030)
Observations	52	52	52	30	30	30
R-squared	0.47	0.59	0.71	0.42	0.63	0.72
	Panel B. Population in two age groups between 1990-2025					
Change in the log of population	-0.489	-0.572	-0.543	-0.821	-1.187	-0.909
aged 20-55 years	(0.164)	(0.289)	(0.304)	(0.230)	(0.408)	(0.470)
Change in the log of population	0.377	0.399	0.351	0.643	0.630	0.476
aged 55-75 years	(0.195)	(0.231)	(0.232)	(0.243)	(0.402)	(0.489)
Robots per thousand workers in 1993			0.073			0.053
			(0.012)			(0.031)
Observations	52	52	52	30	30	30
R-squared	0.47	0.59	0.69	0.44	0.62	0.70
	Panel C. Population in two age groups between 1990-2025, weighted by manufacturing value added					
Change in the log of population	-0.781	-1.184	-0.762	-1.026	-1.303	-0.761
aged 20-55 years	(0.236)	(0.260)	(0.263)	(0.216)	(0.299)	(0.351)
Change in the log of population	0.623	0.451	0.426	0.872	0.896	0.750
$\geq$ 56 years	(0.174)	(0.380)	(0.392)	(0.113)	(0.515)	(0.558)
Robots per thousand workers in 1993			0.072			0.057
			(0.024)			(0.038)
Observations	52	52	52	30	30	30
R-squared	0.68	0.82	0.86	0.65	0.82	0.85
	Panel D. Population in two age groups between 1990-2025, weighted by manufacturing value added					
Change in the log of population	-0.866	-1.198	-0.819	-1.130	-1.348	-0.921
aged 20-55 years	(0.207)	(0.254)	(0.288)	(0.140)	(0.220)	(0.309)
Change in the log of population	0.713	0.702	0.692	0.980	1.381	1.388
aged 55-75 years	(0.179)	(0.486)	(0.533)	(0.111)	(0.515)	(0.703)
Robots per thousand workers in 1993			0.069			0.064
			(0.022)			(0.039)
Observations	52	52	52	30	30	30
R-squared	0.74	0.82	0.85	0.77	0.84	0.87
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added			✓			✓

Notes: The table presents OLS estimates of the relationship between changes in population and the adoption of robots. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). The explanatory variables include the expected change in the log of population in different age groups between 1990 and 2025 (from the UN population statistics). The exact age groups used in the analysis vary across the panels. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. The regressions in Panels A, B and C are unweighted, while the regressions in Panels D and E are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity.

Table A7: Estimates of the impact of aging on the adoption of industrial robots controlling for the change in overall population.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging between 1990 and 2025	0.814	0.748	0.463	1.183	0.807	0.425
	(0.271)	(0.235)	(0.227)	(0.426)	(0.259)	(0.308)
Change population 1990-2015	0.131	0.060	-0.154	0.131	-0.290	-0.411
	(0.148)	(0.239)	(0.205)	(0.205)	(0.350)	(0.377)
Observations	52	52	52	30	30	30
R-squared	0.48	0.59	0.70	0.38	0.55	0.66
	Panel B. IV estimates					
Aging between 1990 and 2025	0.897	0.844	0.727	1.570	0.794	0.668
	(0.295)	(0.312)	(0.339)	(0.515)	(0.393)	(0.494)
Change population 1990-2015	0.152	0.130	0.036	0.239	-0.299	-0.245
	(0.145)	(0.275)	(0.237)	(0.239)	(0.387)	(0.422)
Observations	52	52	52	30	30	30
First-stage F stat.	19.5	8.2	6.3	4.0	7.1	3.4
Overid $p-$ value	0.28	0.59	0.09	0.55	0.32	0.11
Anderson-Rubin Wald test $p-$ value	0.01	0.05	0.00	0.04	0.04	0.00
	Panel C. Single-IV estimates					
Aging between 1990 and 2025	1.007	0.912	0.613	1.541	1.312	1.078
	(0.347)	(0.412)	(0.468)	(0.472)	(0.582)	(0.816)
Change between 1990-2015	0.181	0.180	-0.046	0.231	0.077	0.037
	(0.148)	(0.283)	(0.279)	(0.223)	(0.444)	(0.549)
Observations	52	52	52	30	30	30
First-stage F stat.	39.0	28.3	19.1	26.2	14.4	8.4
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). The aging variable is the expected change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025 (from the UN Population Statistics). In addition, all specifications control for the change in the log of population between 1990 and 2015. Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Panel C presents IV estimates where the aging variable is instrumented using the decline in birth rates between 1960 and 1980. For our IV estimates, we report the first-stage $F-$statistic. When using multiple instruments, we also report the $p-$value of Hansen's overidentification test, and the $p-$value of Anderson and Rubin's test for the coefficient on aging being zero. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. All regressions are unweighted, and the standard errors are robust against heteroscedasticity.

Table A8: OLS estimates of the impact of past and expected aging on the adoption of industrial robots, weighted regressions using manufacturing value added as weights.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Estimates of past vs. expected aging					
Aging between 1990 and 2025	1.153	1.179	0.707	1.313	1.333	0.863
	(0.248)	(0.203)	(0.209)	(0.206)	(0.177)	(0.288)
Aging between 1950 and 1990	-1.044	0.317	0.812	-1.326	0.188	0.565
	(0.474)	(0.434)	(0.433)	(0.499)	(0.449)	(0.457)
Observations	52	52	52	30	30	30
R-squared	0.73	0.82	0.87	0.67	0.79	0.83
	Panel B. Estimates of past aging					
Aging between 1950 and 1990	-0.592	0.560	1.282	-0.793	0.473	0.983
	(0.402)	(0.579)	(0.492)	(0.466)	(0.655)	(0.507)
Observations	52	52	52	30	30	30
R-squared	0.38	0.46	0.82	0.06	0.17	0.76
	Panel C. Estimates of current vs. future aging					
Aging between 1990 and 2015	1.626	0.896	0.385	1.780	0.974	0.462
	(0.500)	(0.447)	(0.430)	(0.508)	(0.429)	(0.468)
Aging between 2015 and 2025	0.576	1.448	1.311	0.700	1.665	1.596
	(0.591)	(0.397)	(0.535)	(0.625)	(0.333)	(0.637)
Test for equality	0.24	0.46	0.29	0.25	0.32	0.24
Observations	52	52	52	30	30	30
R-squared	0.68	0.82	0.86	0.55	0.80	0.84
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added			✓			✓

Notes: The table presents OLS estimates of the relationship between past and expected aging and the adoption of robots from weighted regressions using manufacturing value added as weights. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). The aging variable varies across panels: Panels A and B present estimates using the change in the ratio of workers above 56 to workers between 21 and 55 between 1950 and 1990 (from the UN Population Statistics) as an explanatory variable. Panel C separately estimates coefficients for aging between 1990 and 2015 (current aging) and between 2015 and 2025 (expected aging). We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. The standard errors are robust against heteroscedasticity.

Table A9: Estimates of the impact of aging between 1990 and 2015 on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging between 1990 and 2015	1.162	1.005	0.775	1.463	1.295	0.889
	(0.393)	(0.351)	(0.338)	(0.616)	(0.478)	(0.435)
Observations	52	52	52	30	30	30
R-squared	0.43	0.54	0.67	0.24	0.44	0.60
	Panel B. IV estimates					
Aging between 1990 and 2015	1.409	1.192	1.097	2.574	1.305	0.983
	(0.393)	(0.363)	(0.354)	(0.941)	(0.450)	(0.380)
Observations	52	52	52	30	30	30
First-stage F stat.	16.8	10.4	8.8	3.2	3.9	5.5
Overid $p-$ value	0.45	0.73	0.09	0.68	0.45	0.17
Anderson-Rubin Wald test $p-$ value	0.02	0.03	0.00	0.03	0.03	0.00
	Panel C. Single-IV estimates					
Aging between 1990 and 2015	2.435	2.067	1.662	5.110	3.101	2.458
	(0.943)	(0.895)	(0.991)	(2.391)	(1.156)	(1.273)
Observations	52	52	52	30	30	30
First-stage F stat.	13.4	12.4	8.2	3.6	12.8	7.6
	Panel D. OLS estimates weighted by manufacturing value added					
Aging between 1990 and 2015	2.029	1.996	0.964	2.256	2.185	0.983
	(0.578)	(0.538)	(0.382)	(0.601)	(0.539)	(0.491)
Observations	52	52	52	30	30	30
R-squared	0.66	0.73	0.82	0.50	0.63	0.78
	Panel E. IV estimates weighted by manufacturing value added					
Aging between 1990 and 2015	2.702	2.240	1.598	2.531	2.090	1.000
	(0.612)	(0.464)	(0.401)	(0.676)	(0.479)	(0.455)
Observations	52	52	52	30	30	30
First-stage F stat.	5.4	6.6	11.7	6.3	9.0	17.1
Overid $p-$ value	0.11	0.23	0.23	0.10	0.24	0.23
Anderson-Rubin Wald test $p-$ value	0.00	0.01	0.00	0.00	0.00	0.00
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015 (from the UN Population Statistics). Panels A and D presents OLS estimates. Panels B and E presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Panel C presents IV estimates where the aging variable is instrumented using the decline in birth rates between 1960 and 1980. For our IV estimates, we report the first-stage $F-$statistic. When using multiple instruments, we also report the $p-$value of Hansen's overidentification test, and the $p-$value of Anderson and Rubin's test for the coefficient on aging being zero. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. The regressions in Panels A, B and C are unweighted, while the regressions in Panels D and E are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity.

Table A10: Cross-sectional estimates of relationship between the ratio of older to middle-aged workers and the stock of industrial robots.

	Dependent variable: Stock of industrial robots per thousand worker					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Older to middle-age ratio in 2025	14.225	11.272	8.607	18.278	14.473	12.166
	(3.689)	(3.224)	(3.330)	(4.114)	(3.326)	(6.180)
log of GDP per capita in 2014		0.971	-0.420		2.329	0.910
		(0.781)	(1.231)		(1.771)	(3.731)
Observations	53	53	53	31	31	31
R-squared	0.45	0.59	0.61	0.28	0.52	0.52
	Panel B. IV estimates					
Older to middle-age ratio in 2025	13.909	8.189	5.250	18.683	11.875	9.588
	(3.677)	(3.699)	(3.284)	(4.751)	(4.302)	(5.055)
Observations	53	53	53	31	31	31
First-stage F stat.	34.2	26.3	16.7	12.8	30.0	7.5
Overid $p-$ value	0.93	0.93	0.64	0.62	0.67	0.73
Anderson-Rubin Wald test $p-$ value	0.02	0.02	0.05	0.01	0.01	0.06
	Panel C. OLS estimates weighted by manufacturing value added					
Older to middle-age ratio in 2025	18.304	19.318	17.818	19.228	21.302	33.543
	(5.117)	(3.991)	(7.360)	(5.376)	(5.027)	(16.825)
Observations	53	53	53	31	31	31
R-squared	0.67	0.76	0.76	0.45	0.64	0.66
	Panel D. IV estimates weighted by manufacturing value added					
Older to middle-age ratio in 2025	12.689	14.767	12.868	16.368	18.857	34.023
	(4.120)	(3.291)	(5.654)	(4.859)	(4.359)	(17.490)
Observations	53	53	53	31	31	31
First-stage F stat.	15.2	13.8	36.5	76.2	75.8	5.9
Overid $p-$ value	0.22	0.33	0.48	0.15	0.60	0.45
Anderson-Rubin Wald test $p-$ value	0.00	0.02	0.04	0.00	0.00	0.00
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Manufacturing value added			✓			✓

Notes: The table presents OLS and IV cross-sectional estimates of the relationship between aging and the adoption of robots. In all panels, the dependent variable is the stock of industrial robots in 2014 (from the IFR) normalized by thousand industrial workers. The main explanatory variable is the expected ratio of workers above 56 to workers between 21 and 55 between in 2025 (from the UN Population Statistics). Panels A and C present OLS estimates. Panels B and D present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic. When using multiple instruments, we also report the $p-$value of Hansen's overidentification test, and the $p-$value of Anderson and Rubin's test for the coefficient on aging being zero. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 2014 values of log GDP per capita, log of population, and average years of schooling. Columns 3 and 6 add the log of the 1990 value added in manufacturing. The regressions in Panels A and B are unweighted, while the regressions in Panels C and D are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity.

Table A11: Estimates of the impact of aging, unions, and the wage level on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging between 1990 and 2025	0.955	0.980	0.783	1.167	1.067	0.839
	(0.275)	(0.275)	(0.277)	(0.304)	(0.338)	(0.377)
Baseline union density	0.243	0.260	0.179	0.435	0.431	0.336
	(0.094)	(0.101)	(0.112)	(0.125)	(0.126)	(0.145)
log of hourly wages in 1993		0.129	0.072		0.186	0.149
		(0.104)	(0.101)		(0.182)	(0.199)
Observations	46	46	46	30	30	30
R-squared	0.63	0.65	0.71	0.67	0.68	0.71
	Panel B. IV estimates					
Aging between 1990 and 2025	0.922	0.980	0.920	1.232	1.231	1.154
	(0.279)	(0.263)	(0.242)	(0.296)	(0.329)	(0.361)
Baseline union density	0.237	0.260	0.209	0.446	0.455	0.400
	(0.073)	(0.081)	(0.090)	(0.109)	(0.112)	(0.124)
log of hourly wages in 1993		0.129	0.087		0.142	0.098
		(0.087)	(0.088)		(0.153)	(0.166)
Observations	46	46	46	30	30	30
First-stage F stat.	11.6	11.0	10.8	5.0	5.7	5.7
Overid $p-$ value	0.13	0.15	0.05	0.59	0.55	0.37
	Panel C. Single-IV estimates					
Aging between 1990 and 2025	1.146	1.187	1.018	1.645	1.635	1.637
	(0.447)	(0.439)	(0.485)	(0.425)	(0.453)	(0.602)
Baseline union density	0.278	0.299	0.231	0.514	0.515	0.499
	(0.103)	(0.109)	(0.123)	(0.145)	(0.144)	(0.163)
log of hourly wages in 1993		0.141	0.098		0.034	0.021
		(0.097)	(0.101)		(0.209)	(0.210)
Observations	46	46	46	30	30	30
First-stage F stat.	15.0	15.0	12.9	16.1	13.4	9.0
Covariates included:						
Baseline country covariates	✓	✓	✓	✓	✓	✓
Initial robot density and manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots. In all panels, the dependent variable is the change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). In addition, we also estimate the impact of the baseline unionization rate (from Rama and Artecona, 2002) and wage level (from the Penn World Tables) in a country. Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Panel C presents IV estimates where the aging variable is instrumented using the decline in birth rates between 1960 and 1980. For our IV estimates, we report the first-stage $F-$statistic. When using multiple instruments, we also report the $p-$value of Hansen's overidentification test. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. All regressions are unweighted, and the standard errors are robust against heteroscedasticity.

Table A12: Estimates of the impact of aging on the percent increase in robots by country.

	Increase in the log of Robots			Increase in the log of 1+ Robots		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging between 1990 and 2025	2.170	1.929	0.879	3.231	3.512	2.343
	(0.910)	(0.782)	(1.126)	(1.442)	(1.505)	(1.666)
Observations	23	23	23	52	52	52
R-squared	0.70	0.75	0.78	0.83	0.87	0.88
	Panel B. IV estimates					
Aging between 1990 and 2025	2.422	2.554	1.138	3.949	4.648	3.217
	(1.296)	(1.050)	(0.855)	(2.216)	(2.225)	(2.276)
Observations	23	23	23	52	52	52
First-stage F stat.	6.4	3.6	1.8	23.9	15.6	15.0
Overid $p-$ value	0.03	0.09	0.08	0.10	0.01	0.02
	Panel C. Single-IV estimates					
Aging between 1990 and 2025	2.280	4.451	4.053	6.868	5.687	4.763
	(1.563)	(2.025)	(4.149)	(2.669)	(2.613)	(2.524)
Observations	23	23	23	53	52	52
First-stage F stat.	16.8	9.7	2.4	29.0	40.6	39.1
	Panel D. OLS estimates weighted by manufacturing value added					
Aging between 1990 and 2025	2.145	2.347	2.169	3.229	3.678	2.759
	(1.161)	(0.977)	(1.467)	(1.034)	(0.738)	(1.271)
Observations	23	23	23	52	52	52
R-squared	0.48	0.73	0.73	0.95	0.96	0.96
	Panel E. IV estimates weighted by manufacturing value added					
Aging between 1990 and 2025	2.115	2.496	2.428	2.715	3.578	3.592
	(1.229)	(0.817)	(1.077)	(1.107)	(0.871)	(1.187)
Observations	23	23	23	52	52	52
First-stage F stat.	9.7	19.2	3.9	8.5	8.5	14.4
Overid $p-$ value	0.04	0.14	0.15	0.55	0.29	0.20
Baseline country covariates		✓	✓		✓	✓
Manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots. The dependent variable varies by column. In columns 1-3, it is the change in the log of the stock of industrial robots between 1993 and 2014 (from the IFR). In columns 4-6, it is the change in the log of one plus the stock of industrial robots between 1993 and 2014 (from the IFR). The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panels A and D present OLS estimates. Panels B and E present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Panel C presents IV estimates where the aging variable is instrumented using the decline in birth rates between 1960 and 1980. For our IV estimates, we report the first-stage $F-$statistic. When using multiple instruments, we also report the $p-$value of Hansen's overidentification test. All columns control for the initial density of robots (in logs). Columns 2 and 5 include region dummies, the 1993 values of log GDP per capita, log of population, average years of schooling, and the ratio of workers above 56 to workers aged 21-55 in 1990. Finally, columns 3 and 6 add the log of the 1990 value added in manufacturing as a covariate. The regressions in Panels A, B and C are unweighted, while the regressions in Panels D and E are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity.

Table A13: Robustness analysis of the impact of aging on imports and exports of robots.

	Baseline		log of one plus share		Share		Exclude outliers	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Imports of robots for the full sample								
Aging between 1995 and 2025	1.818	1.969	1.832	1.849	4.899	4.314	1.847	1.761
	(0.768)	(0.962)	(0.765)	(0.968)	(1.598)	(1.971)	(0.761)	(0.987)
Observations	130	130	135	135	135	135	116	116
R-squared	0.58	0.58	0.58	0.58	0.63	0.63	0.61	0.61
Instruments F-stat		10.7		10.8		10.8		10.3
Overid p-value		0.68		0.78		0.92		0.75
Panel B. Imports of robots for the OECD sample								
Aging between 1995 and 2025	2.160	1.691	2.149	1.683	1.618	1.248	2.007	1.724
	(0.724)	(0.806)	(0.721)	(0.802)	(0.599)	(0.621)	(0.714)	(0.762)
Observations	34	34	34	34	34	34	33	33
R-squared	0.79	0.79	0.79	0.79	0.76	0.76	0.81	0.81
Instruments F-stat		9.6		9.6		9.6		12.6
Overid p-value		0.04		0.04		0.06		0.06
Panel C. Exports of robots for the full sample								
Aging between 1995 and 2025	4.657	5.199	4.231	5.279	14.389	15.683	4.511	5.372
	(0.985)	(1.167)	(0.953)	(1.131)	(5.228)	(6.899)	(0.973)	(1.136)
Observations	103	103	136	136	136	136	93	94
R-squared	0.83	0.83	0.85	0.85	0.64	0.64	0.87	0.87
Instruments F-stat		15.0		15.6		15.6		14.7
Overid p-value		0.14		0.17		0.34		0.09
Panel D. Exports of robots for the OECD sample								
Aging between 1995 and 2025	4.144	4.803	4.107	4.758	4.687	5.484	4.554	4.973
	(1.165)	(1.177)	(1.153)	(1.167)	(1.839)	(2.005)	(1.025)	(1.124)
Observations	35	35	35	35	35	35	33	33
R-squared	0.77	0.77	0.77	0.77	0.62	0.62	0.81	0.81
Instruments F-stat		12.2		12.2		12.2		13.1
Overid p-value		0.14		0.14		0.19		0.23
Baseline country covariates and manufacturing value added	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents OLS and IV estimates of the relationship between aging and imports and exports of industrial robots. Columns 1 and 2 present our baseline estimates. Columns 3 and 4 present results using the log of one plus robot imports (or exports) per million dollars imported (exported). Columns 5 and 6 present results using the share of robot imports (or exports) per million dollars imported (exported), and normalizes the estimates relative to the mean of this variable. Finally, columns 7 and 8 return to our baseline estimates, but exclude outliers—countries with a standardized residual above 1.96 or below -1.96. The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1995 and 2025 (from the UN Population Statistics). The sample used varies by panel: Panels A and C present estimates for the full set of countries. Panels B and D present estimates for the OECD. In even columns, the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. All columns include region dummies, the 1995 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55, the log of the 1990 value added in manufacturing, and the log of intermediate imports (Panels A and B) or exports (Panels C and D). All regressions are weighted by value added in manufacturing in 1990, and the standard errors are robust against heteroscedasticity.

Table A14: Robustness analysis of the impact of aging on robotics-related patents.

	Baseline		log of one plus share		Share		Exclude outliers	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Robotics-related patents for the full sample							
Aging between 1990 and 2025	1.411	0.755	0.546	0.669	1.327	0.631	1.345	0.814
	(0.444)	(0.572)	(0.612)	(0.937)	(0.441)	(0.613)	(0.444)	(0.559)
Observations	68	68	125	125	125	125	62	63
R-squared	0.64	0.63	0.50	0.50	0.39	0.38	0.67	0.66
Instruments F-stat		5.0		6.1		6.1		4.9
Overid p-value		0.21		0.07		0.13		0.19
	Panel B. Robotics related patents for the OECD sample							
Aging between 1990 and 2025	1.593	1.342	0.800	0.630	1.616	1.349	1.670	1.448
	(0.547)	(0.464)	(0.797)	(0.647)	(0.666)	(0.581)	(0.535)	(0.444)
Observations	31	31	35	35	35	35	29	29
R-squared	0.66	0.66	0.46	0.46	0.63	0.62	0.72	0.72
Instruments F-stat		18.6		20.4		20.4		17.3
Overid p-value		0.33		0.13		0.37		0.27
	Panel C. Robotics related patents for the OECD sample excluding the US							
Aging between 1990 and 2025	1.481	1.240	0.306	0.348	1.424	1.206	1.731	1.447
	(0.626)	(0.522)	(0.819)	(0.644)	(0.723)	(0.605)	(0.554)	(0.479)
Observations	30	30	34	34	34	34	28	28
R-squared	0.63	0.63	0.50	0.50	0.58	0.58	0.69	0.69
Instruments F-stat		21.9		27.2		27.2		17.7
Overid p-value		0.40		0.20		0.41		0.25
Baseline country covariates and manufacturing value added	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents OLS and IV estimates of the relationship between aging and robotics-related patents. Columns 1 and 2 present our baseline estimates. Columns 3 and 4 present results using the log of one plus robotics-related patents per thousand utility patents. Columns 5 and 6 present results using the share of robotics-related patents per thousand utility patents, and normalizes the estimates relative to the mean of this variable. Finally, columns 7 and 8 return to our baseline estimates, but exclude outliers—countries with a standardized residual above 1.96 or below -1.96. The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). The sample used varies by panel: Panel A presents estimates for the full set of countries. Panel B presents estimates for the OECD. In even columns, the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. All columns include region dummies, the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55, the log of the 1990 value added in manufacturing, and the log of total utility patents. All regressions are weighted by value added in manufacturing in 1990, and the standard errors are robust against heteroscedasticity.

Table A15: Robustness for IV estimates of aging on the location of robot integrators in the US.

	Dependent variable: Location, number and employment of robot integrator				
	(1)	(2)	(3)	(4)	(5)
	Panel A. Baseline specification removing outliers				
Aging between 1990 and 2015	1.386	0.587	0.527	0.491	0.496
	(0.358)	(0.188)	(0.193)	(0.223)	(0.206)
Exposure to robots			0.083	0.080	0.122
			(0.020)	(0.020)	(0.020)
Observations	671	683	678	680	670
First-stage F stat.	11.4	19.5	19.9	22.1	21.9
Overid $p-$ value	0.00	0.72	0.71	0.71	0.97
	Panel B. Baseline specification weighting by employment in manufacturing				
Aging between 1990 and 2015	0.163	3.031	2.229	2.319	2.760
	(1.279)	(1.411)	(1.325)	(1.348)	(1.398)
Exposure to robots			0.020	0.014	0.117
			(0.027)	(0.027)	(0.031)
Observations	722	722	722	722	712
First-stage F stat.	8.1	8.7	9.4	9.1	7.8
Overid $p-$ value	0.00	0.58	0.39	0.40	0.34
	Panel C. Log of one plus number of integrators				
Aging between 1990 and 2015	1.834	0.745	0.517	0.505	0.575
	(0.594)	(0.351)	(0.335)	(0.334)	(0.326)
Exposure to robots			0.130	0.128	0.168
			(0.023)	(0.023)	(0.043)
Observations	722	722	722	722	712
First-stage F stat.	11.4	20.6	23.1	23.9	23.3
Overid $p-$ value	0.00	0.84	0.60	0.58	0.61
	Panel D. Log of one plus employment in integrators				
Aging between 1990 and 2015	5.593	2.510	1.711	1.667	1.772
	(1.676)	(1.047)	(0.990)	(0.985)	(0.984)
Exposure to robots			0.354	0.347	0.524
			(0.078)	(0.081)	(0.123)
Observations	722	722	722	722	712
First-stage F stat.	11.4	20.6	23.1	23.9	23.3
Overid $p-$ value	0.00	0.92	0.76	0.73	0.65
Covariates included:					
Regional dummies	✓	✓	✓	✓	✓
Demographic covariates		✓	✓	✓	✓
Industry composition			✓	✓	✓
Other shocks				✓	✓
Excluding highly exposed commuting zone					✓

Notes: The table presents IV estimates of the relationship between aging and the location of robot integrators across US commuting zones. The dependent variable varies by panel. In Panels A and B, the dependent variable is a dummy for the presence of robot integrators in each US commuting zone (from Leigh and Kraft, 2018). In Panels C and D, the dependent variable is the log of one plus the number of integrators and employees in integrators, respectively (both from Leigh and Kraft, 2018). Aging is the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015 (from the NBER-SEER). All panels present IV estimates, where aging is instrumented using the size of five-year birth cohorts between 1950 and 1985. For all estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. Column 1 includes Census region dummies. Column 2 includes the 1990 values for the log of average income, the log of the population, the initial ratio of older to middle-aged workers, and the share of workers with different levels of education in each commuting zone. Column 3 includes the exposure to robots measure from Acemoglu and Restrepo (2018a) and also controls for the shares of employment in manufacturing, agriculture, mining, construction, and finance and real estate in 1990. Column 4 includes additional demographic characteristics measured in 1990, including the racial composition of commuting zones and the share of male and female employment, and controls for other shocks affecting US markets, including offshoring, trade with China and the decline of routine jobs. Finally, column 5 excludes the top 1% commuting zones with the highest exposure to robots. The regressions in Panel B are weighted by manufacturing employment in 1990, and all other regressions are unweighted. In parenthesis we report standard errors that are robust against heteroscedasticity and correlation in the error terms within states.

Table A16: Estimates of the impact of aging on robot installations per year.

	Dependent variable: Installations of industrial robots per thousand workers per year					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging between 1990 and 2025	1.275	1.067	0.646	1.785	1.519	0.862
	(0.405)	(0.385)	(0.276)	(0.482)	(0.427)	(0.351)
Observations	1144	1144	1144	660	660	660
Countries	52	52	52	30	30	30
R-squared	0.40	0.53	0.74	0.20	0.55	0.72
	Panel B. IV estimates					
Aging between 1990 and 2025	1.540	1.050	0.816	2.619	1.472	1.093
	(0.435)	(0.375)	(0.287)	(0.533)	(0.459)	(0.370)
Observations	1144	1144	1144	660	660	660
Countries	52	52	52	30	30	30
First-stage F stat.	29.0	20.8	17.9	10.0	9.4	11.9
Overid $p-$ value	0.60	0.86	0.11	0.89	0.75	0.09
Anderson-Rubin Wald test $p-$ value	0.01	0.02	0.00	0.01	0.08	0.00
	Panel C. Single-IV estimates					
Aging between 1990 and 2025	1.775	1.294	0.689	2.840	1.865	1.256
	(0.541)	(0.531)	(0.425)	(0.721)	(0.509)	(0.564)
Observations	1144	1144	1144	660	660	660
Countries	52	52	52	30	30	30
First-stage F stat.	32.5	28.0	19.7	15.1	30.1	17.9
	Panel D. OLS estimates weighted by manufacturing value added					
Aging between 1990 and 2025	2.056	2.128	0.977	2.327	2.405	1.149
	(0.540)	(0.383)	(0.267)	(0.521)	(0.318)	(0.347)
Observations	1144	1144	1144	660	660	660
Countries	52	52	52	30	30	30
R-squared	0.70	0.80	0.89	0.36	0.79	0.89
	Panel E. IV estimates weighted by manufacturing value added					
Aging between 1990 and 2025	1.924	1.921	1.217	2.239	2.247	1.333
	(0.492)	(0.390)	(0.298)	(0.556)	(0.355)	(0.336)
Observations	1144	1144	1144	660	660	660
Countries	52	52	52	30	30	30
First-stage F stat.	8.0	8.7	22.6	12.0	19.4	31.2
Overid $p-$ value	0.05	0.22	0.20	0.33	0.34	0.21
Anderson-Rubin Wald test $p-$ value	0.00	0.03	0.00	0.00	0.00	0.00
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and yearly installations of industrial robots. The dependent variable is installations of industrial robots per thousand workers for each country-year pair between 1993 and 2014 (from the IFR). The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panels A and D present OLS estimates. Panels B and E present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Panel C presents IV estimates where aging is instrumented using the decline in birth rates between 1960 and 1980. For our IV estimates, we report the first-stage $F-$statistic. When using multiple instruments, we also report the $p-$value of Hansen's overidentification test, and the $p-$value of Anderson and Rubin's test for the coefficient on aging being zero. We present results for two samples: columns 1-3 use the full sample; columns 4-6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. The regressions in Panels A, B and C are unweighted, while the regressions in Panels D and E are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity and correlation within countries.

Table A17: Estimates of the impact of aging on robot installations by country-industry pairs per year for manufacturing industries.

		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Installation of robots in country-industry pairs normalizing by industrial employment from UNIDO						
	Panel A. OLS estimates						
Aging between 1990 and 2025	3.765	10.994	8.111		10.232	7.739	
	(1.425)	(3.555)	(2.666)		(3.703)	(3.052)	
Aging × reliance on middle-aged		3.507	2.692	2.797	0.984	0.848	1.028
		(1.299)	(1.105)	(1.090)	(0.383)	(0.457)	(0.511)
Aging × opportunities for automation		20.108	14.451	13.183	7.871	5.895	5.649
		(5.464)	(4.636)	(4.682)	(2.965)	(2.335)	(2.194)
Observations	5866	5866	5866	5866	5866	5866	5866
Countries in sample	44	44	44	44	44	44	44
	Panel B. IV estimates						
Aging between 1990 and 2025	4.032	12.545	9.472		11.924	9.250	
	(1.524)	(4.094)	(3.352)		(4.102)	(3.550)	
Aging × reliance on middle-aged		4.151	3.099	3.220	1.065	0.755	1.019
		(1.426)	(1.209)	(1.220)	(0.421)	(0.421)	(0.501)
Aging × opportunities for automation		23.211	18.234	14.830	9.731	7.728	7.239
		(8.259)	(7.350)	(7.115)	(3.492)	(2.962)	(2.750)
Observations	5866	5866	5866	5866	5866	5866	5866
Countries in sample	44	44	44	44	44	44	44
Instruments F-stat	17.9	11.7	15.2	11.5	8.7	10.7	7.7
Overid p-value	0.57	0.25	0.27	0.17	0.25	0.10	0.35
Covariates included:							
Baseline country covariates	✓	✓	✓	✓	✓	✓	✓
Initial robot density			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots for industry-country cells. In all panels, the dependent variable is robot installations per thousand workers in each industry-country cell for all available years between 1993 and 2014 (from the IFR). The explanatory variables include aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025); the interaction between aging and industry reliance on middle-aged workers (proxied using 1990 US Census data on the age distribution of workers in each industry); and the interaction between aging and two measures of opportunities for automation: the replaceability index from Graetz and Michaels (2018) in columns 2-4; and a measure of opportunities for the use of robots from the BCG in columns 5-7. Panel A presents OLS estimates. Panel B presents IV estimates where aging is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test All columns include region dummies, the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the initial robot density in 1993 for each industry-country cell as a control. All these covariates are allowed to affect industries differently. Columns 4 and 7 add a full set of country dummies. All regressions weigh industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries.

Table A18: Estimates of the impact of aging and past aging on robot installations by country-industry pairs per year.

		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Installation of robots in country-industry pairs normalizing by average employment in an industry from ILO						
	Panel A. Estimates of past vs. expected aging						
Aging between 1990 and 2025	1.598	4.179	2.752		6.794	4.712	
	(0.421)	(1.084)	(0.831)		(1.776)	(1.448)	
Aging × reliance on middle-aged		0.882	0.610	0.611	0.262	0.181	0.182
		(0.242)	(0.206)	(0.203)	(0.085)	(0.084)	(0.083)
Aging × opportunities for automation		6.807	4.379	4.388	6.078	4.285	4.303
		(2.187)	(1.448)	(1.426)	(1.617)	(1.273)	(1.257)
Past aging between 1950 and 1990	-0.573	-1.462	0.694		-0.923	1.833	
	(0.739)	(1.921)	(1.396)		(2.915)	(2.260)	
Past aging × reliance on middle-aged		0.068	0.267	0.266	0.035	0.002	0.002
		(0.399)	(0.300)	(0.303)	(0.155)	(0.114)	(0.114)
Past aging × opportunities for automation		-5.422	0.762	0.740	-0.510	2.171	2.144
		(4.160)	(2.903)	(2.986)	(2.573)	(2.115)	(2.149)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
R-squared	0.36	0.37	0.45	0.47	0.39	0.47	0.48
	Panel B. Estimates of past aging						
Past aging between 1950 and 1990	-0.053	-0.075	1.699		1.342	3.648	
	(0.743)	(1.960)	(1.444)		(3.115)	(2.432)	
Past aging × reliance on middle-aged		0.364	0.478	0.475	0.123	0.055	0.057
		(0.449)	(0.332)	(0.335)	(0.171)	(0.121)	(0.121)
Past aging × opportunities for automation		-3.135	2.523	2.369	1.532	3.857	3.797
		(4.073)	(2.934)	(2.986)	(2.808)	(2.308)	(2.328)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
Covariates included:							
Baseline country covariates	✓	✓	✓	✓	✓	✓	✓
Initial robot density			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents OLS estimates of the relationship between aging and the adoption of robots for industry-country cells. In all panels, the dependent variable is robot installations per thousand workers in each industry-country cell for all available years between 1993 and 2014 (from the IFR). The explanatory variables include past aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1950 and 1990); current aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015); the interaction between aging and industry reliance on middle-aged workers (proxied using 1990 US Census data on the age distribution of workers in each industry); and the interaction between aging and two measures of opportunities for automation: the replaceability index from Graetz and Michaels (2018) in columns 2-4; and a measure of opportunities for the use of robots from the BCG in columns 5-7. All columns include region dummies, the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the initial robot density in 1993 for each industry-country cell as a control. All these covariates are allowed to affect industries differently. Columns 4 and 7 add a full set of country dummies. All regressions weigh industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries.

Table A19: Estimates of the impact of aging on the log of one plus robot installations per worker in each country-industry cell.

	Dependent variable: log of one plus installation of robots in country-industry pairs						
		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. OLS estimates						
Aging between 1990 and 2025	0.426	0.997	0.582		1.589	1.038	
	(0.111)	(0.254)	(0.200)		(0.356)	(0.273)	
Aging × reliance on middle-aged		0.170	0.112	0.113	0.028	0.013	0.014
		(0.042)	(0.034)	(0.033)	(0.018)	(0.020)	(0.019)
Aging × opportunities for automation		1.713	0.912	0.926	1.419	0.968	0.982
		(0.611)	(0.517)	(0.510)	(0.325)	(0.232)	(0.229)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
	Panel B. IV estimates						
Aging between 1990 and 2025	0.329	0.810	0.575		1.372	1.017	
	(0.111)	(0.267)	(0.221)		(0.396)	(0.313)	
Aging × reliance on middle-aged		0.170	0.112	0.112	0.040	0.014	0.015
		(0.050)	(0.039)	(0.038)	(0.020)	(0.021)	(0.020)
Aging × opportunities for automation		1.223	0.916	0.898	1.244	0.956	0.954
		(0.635)	(0.535)	(0.526)	(0.366)	(0.277)	(0.273)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
Instruments F-stat	19.1	.	6.6	7.8	.	6.4	8.9
Overid p-value	0.63	0.13	0.35	0.28	0.11	0.15	0.06
Covariates included:							
Baseline country covariates	✓	✓	✓	✓	✓	✓	✓
Initial robot density			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots for industry-country cells. In all panels, the dependent variable is robot installations per thousand workers in each industry-country cell for all available years between 1993 and 2014 (from the IFR). The explanatory variables include aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025); the interaction between aging and industry reliance on middle-aged workers (proxied using 1990 US Census data on the age distribution of workers in each industry); and the interaction between aging and two measures of opportunities for automation: the replaceability index from Graetz and Michaels (2018) in columns 2-4; and a measure of opportunities for the use of robots from the BCG in columns 5-7. Panel A presents OLS estimates. Panel B presents IV estimates where aging is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. All columns include region dummies, the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the initial robot density in 1993 for each industry-country cell as a control. All these covariates are allowed to affect industries differently. Columns 4 and 7 add a full set of country dummies. The standard errors are robust against heteroscedasticity and correlation within countries.

Table A20: Estimates of the impact of aging on robot installations by country-industry pairs per year removing outliers.

	Dependent variable: Installation of robots in country-industry pairs						
		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A. OLS estimates			
Aging between 1990 and 2025	0.561	1.534	0.886		3.615	1.948	
	(0.162)	(0.372)	(0.293)		(0.501)	(0.371)	
Aging × reliance on middle-aged		0.242	0.146	0.145	0.082	0.032	0.036
		(0.058)	(0.044)	(0.049)	(0.032)	(0.032)	(0.035)
Aging × opportunities for automation		2.776	1.688	1.642	3.283	1.827	1.973
		(0.892)	(0.879)	(0.887)	(0.469)	(0.322)	(0.429)
Observations	10290	10281	10334	10351	10260	10330	10345
Countries in sample	50	50	50	50	50	50	50
				Panel B. IV estimates			
Aging between 1990 and 2025	0.410	1.386	0.857		3.487	1.953	
	(0.151)	(0.367)	(0.280)		(0.529)	(0.390)	
Aging × reliance on middle-aged		0.247	0.149	0.146	0.100	0.039	0.044
		(0.058)	(0.043)	(0.047)	(0.038)	(0.037)	(0.039)
Aging × opportunities for automation		2.004	1.511	1.605	3.094	1.810	1.968
		(0.944)	(0.843)	(0.853)	(0.534)	(0.380)	(0.522)
Observations	10287	10281	10334	10351	10260	10331	10345
Countries in sample	50	50	50	50	50	50	50
Instruments F-stat	28.6	12.5	8.0	10.4	16.9	13.0	13.5
Overid p-value	0.14	0.20	0.51	0.34	0.17	0.52	0.19
Covariates included:							
Baseline country covariates	✓	✓	✓	✓	✓	✓	✓
Initial robot density			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots for industry-country cells removing observations with standardized residuals above 1.96 or below -1.96. In all panels, the dependent variable is robot installations per thousand workers in each industry-country cell for all available years between 1993 and 2014 (from the IFR). The explanatory variables include aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025); the interaction between aging and industry reliance on middle-aged workers (proxied using 1990 US Census data on the age distribution of workers in each industry); and the interaction between aging and two measures of opportunities for automation: the replaceability index from Graetz and Michaels (2018) in columns 2-4; and a measure of opportunities for the use of robots from the BCG in columns 5-7. Panel A presents OLS estimates. Panel B presents IV estimates where aging is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. All columns include region dummies, the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1990. Columns 3 and 6 add the initial robot density in 1993 for each industry-country cell as a control. All these covariates are allowed to affect industries differently. Columns 4 and 7 add a full set of country dummies. The standard errors are robust against heteroscedasticity and correlation within countries.

Table A21: Estimates of the impact of aging using EUKLEMS and Penn World tables data on output and the share of labor.

	OLS estimates				IV estimates			
	EUKLEMS data	Penn World tables data			EUKLEMS data	Penn World tables data		
	EUKLEMS sample		OECD	Baseline sample	EUKLEMS sample		OECD	Baseline sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Change in GDP (or value added) between 1995 and 2007							
Aging between 1995 and 2025	-0.225	-0.311	0.031	0.344	-0.455	-0.718	-0.049	0.321
	(0.232)	(0.275)	(0.232)	(0.204)	(0.337)	(0.367)	(0.379)	(0.296)
Observations	21	21	30	52	21	21	30	52
First-stage F stat.					5.5	5.5	9.4	17.9
Overid $p-$ value					0.19	0.26	0.11	0.00
	Panel B. Change in labor share between 1995 and 2007							
Aging between 1995 and 2025	-0.413	-0.173	-0.090	-0.110	-0.445	-0.013	0.070	-0.061
	(0.148)	(0.075)	(0.072)	(0.062)	(0.232)	(0.080)	(0.069)	(0.057)
Observations	21	21	30	50	21	21	30	50
First-stage F stat.					5.5	5.5	9.4	17.2
Overid $p-$ value					0.34	0.48	0.63	0.32

Notes: The table presents OLS and IV estimates of the relationship between aging and the change in GDP (Panel A) and the labor share (Panel B) across countries. Aging is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Columns 1-4 present OLS estimates. Columns 5-8 present IV estimates where aging is instrumented using the size of five-year birth cohorts between 1950 and 1985. For our IV estimates, we report the first-stage $F-$statistic and the $p-$value of Hansen's overidentification test. We present results for several samples: columns 1-2 and 5-6 use the EUKLEMS sample; columns 3 and 7 use the OECD sample, and columns 4 and 8 use the sample of all countries with IFR data. In columns 1 and 5 we use data from EUKLEMS aggregated to the country level. In the remaining tables, we use data from the Penn World Tables, version 9.0 (Feenstra, Inklaar and Timmer, 2015). All models control for regional dummies, the 1995 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21-55 in 1995. All regressions are unweighted, and the standard errors are robust against heteroscedasticity.