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 36 and 55). We then show that demographic change—corresponding to an increasing 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 further 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 labor share to decline relatively in industries that are most 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

Advances in automation and robotics technology are poised to transform many aspects of the production process (e.g., Brynjolfsson and McAfee, 2012, Autor, 2015, Ford, 2016), and have already made important inroads in modern manufacturing (e.g., Graetz and Michaels, 2015, Acemoglu and Restrepo, 2017a). But there are major differences in how rapidly these technologies are spreading across countries. The number of industrial robots per thousand workers in US manufacturing stands at 9.14 in 2014, while the same number is considerably higher in Japan (14.20), Germany (16.95) and South Korea (20.14). 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, 2017). These differences in automation are not only notable given the central role that this and other automation technologies are likely to play in the next several decades, but they may also be related to a puzzling fact noted in Acemoglu and Restrepo (2017b): despite the potential negative effects of aging on productivity and output, there is no negative relationship between aging and GDP growth across countries.

In this paper, we advance the hypothesis that cross-country differences in automation are at least in part explained by differential demographic trends, and emphasize the productivity implications of automation induced by demographics. Focusing on robotics where we have access to comparable data, the United States, and to some degree the United Kingdom, are lagging behind in robotics because they are not aging as rapidly as Germany, Japan and South Korea. This is not because of differential demand for robots and automation in the service sector in countries undergoing rapid aging—our focus is on the manufacturing sector. Rather, we document that this pattern reflects the response of firms to the relative scarcity of middle-aged workers, who appear to be most substitutable for robots.

We start with a simple model of technology adoption. 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, while older workers specialize in nonproduction services. The importance of production tasks relative to nonproduction services varies across industries. Firms can also automate and substitute machines for labor in production tasks.

In our model technology is endogenous: firms can invest to automate additional tasks in their industry. Using this framework, we show that demographic changes that reduce the ratio of middle-aged to older workers induce the adoption of additional automation technologies. This effect is particularly pronounced in industries that rely more on middle-aged workers and those that have greater opportunities for automation. The productivity implications of demographic change are however ambiguous: on the one hand, demographic change affects output per worker given technology—and this effect is negative when middle-aged wage is greater than the wage of older workers. On the other hand, the induced automation response enables the substitution of cheaper machines for labor, increasing productivity.

The bulk of the paper investigates these issues empirically, focusing on industrial robots as well as a few other automation technologies. Our results point to a sizable impact of aging on the adoption of robots and other automation technologies. We start with suggestive evidence on the substitutability between robots and workers of different ages. We document that workers between the ages of 31 and 55 are more likely to be employed in blue-collar occupations than in white-collar or service occupations and in highly-robotized industries than in other industries. We also show that the introduction of robots is associated with a relative decline of blue-collar occupations. Finally, we find that exposure to robots has a negative impact on employment and earnings of middle-aged workers across US commuting zones, with no corresponding negative impact on older workers. These three pieces of evidence support our working hypothesis for the rest of the paper—that robots are more substitutable for middle-aged workers than older workers.

We then 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 of the workforce. Our main specifications focus on long differences, where our left-hand side variable is the change in the number of robots per thousand (industry) workers 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 26 and 55—invest significantly more in robotics. The effects we estimate are quantitatively large. Aging alone explains close to 40% of the cross-country variation in the adoption of industrial robots. Moreover, 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 estimated 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.

These results are robust to a range of controls allowing for differential trends across countries in investment in robotics. For example, they are virtually unchanged when we control for differential trends by initial GDP per capita, population level, robot density, capital output ratio, various human capital variables, wage levels, and unionization rates. Because age composition is potentially endogenous due to migration patterns 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. We also confirm these results using an alternative estimate of investment in robotics: imports of industrial robots computed from bilateral trade data.

The effects of demographic change on technology are not confined to robotics. Using bilateral trade data, we also 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), and also verify that there is no such relationship for technologies that appear more broadly labor-augmenting (such as manual machine tools and non-automatic machines as well as computers).

These effects are not confined to the adoption of automation technologies either. Using data on exports of automation technologies and patents, we provide additional evidence that countries undergoing more rapid demographic change are developing more automation technologies.

We also estimate the effects of aging on the adoption of robots at the commuting zone level in the United States. Though we do not have measures of investments in robots for commuting zones, we use Leigh and Kraft's (2016) measure of the number of integrators in an area as a proxy for robotics-related activity. Since these integrators specialize in installation, reprogramming and maintenance of industrial robots, their presence is indicative of significant installation of robots in the area. Using this measure, we confirm the relationship between demographic change and the adoption of robots.

As noted above, a sharper prediction of the directed technological change approach to automation is 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 of aging on labor productivity and industry-level labor share. Consistent with our theoretical expectations, we find a positive impact of demographic change on labor productivity in industries that are most amenable to automation as well as a pronounced impact on labor share in the same industries. These results suggest that the lack of a negative relationship between aging and GDP mentioned above might be partly due to the more rapid adoption of automation technologies in countries undergoing significant demographic change.

Our paper is related to a few recent literatures. The first is a literature estimating the implications of automation technologies 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 greater wage inequality and decline of middle-skill occupations. More recently, Graetz and Michaels (2015) and Acemoglu and Restrepo (2017a) estimate the effects of the adoption of robotics technology on employment and wages (and in the former case, also on productivity). Our work is complementary to but quite different from these papers since we focus not on the implications of automation technologies, but on the determinants of their adoption.

Second, a growing literature focuses on 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).[1] 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.[2] A few works focusing on the effects of demographic change on

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[1] A related literature explores the fiscal costs of demographic change for social security (e.g., Kotlikoff et al., 2002, and Attanasio et al., 2007).

[2] As mentioned above, our short paper, Acemoglu and Restrepo (2017b), 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.

factor prices (e.g., Poterba, 2001, Krueger and Ludwig, 2007) and human capital (e.g., Ludwig, Schelkle and Vogel, 2012) are more related, but we are not aware of any papers studying the impact of aging on technology, except the independent and simultaneous work by Abelianisky and Prettner (2017). There are several important 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 further 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 related 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 investigate 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. (2017) 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. None of these papers investigate the implications of demographic change on technology adoption or robotics technologies.

Finally, our conceptual approach builds on 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 (2016, 2018), Acemoglu and Autor (2011) and Zeira (1998). One contribution of the theory part of our paper is to 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 and descriptive statistics. Section 4 provides evidence that robotics technology is more highly substitutable to middle-aged workers than older workers. Section 5 presents our cross-country evidence on the effect of demographic change on the adoption of robots and other automation technologies. Section 6 provides evidence on the impact of demographic change on innovation and development of automation technologies. Section 7 investigates the relationship between demographics and robots across US commuting zones. Section 8 presents evidence that the effects of demographic change on the adoption of robotics technology are most pronounced in industries that rely more on middle-aged workers and those with greater opportunities for automation. Section 9 considers the relationship between demographic change and productivity and the labor share at the industry level. Section 10 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 simple model of directed technology adoption, 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 the tasks necessary for production, and *technology monopolists* invest in the development of new technologies that automate tasks performed by middle-aged workers.[3]

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:

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

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, $S(i)$.[4] 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.[5]

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[3] 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.

[4] 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.

[5] The assumption that $\sigma > 1$ is for simplicity. The model can be extended to cover the case with $\sigma < 1$ if we

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. We can, but do not need to, impose that $\zeta \leq 1$.

Following Acemoglu and Restrepo (2016, 2018), 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 production tasks in industry i. Labor and machines are perfect substitutes in (technologically) automated tasks (those with $z \leq \theta(i)$ 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 embedding automation technology $\theta(i)$, $q(\theta(i))$, are supplied by a technology monopolist that owns the intellectual property rights over these technologies and that serves industry i. This technology monopolist produces each unit of $q(\theta(i))$ using $1-\eta$ units of industry i's output.[6] The net output in industry i is then obtained by subtracting the total cost of 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 starkly captures the comparative advantage of middle-aged workers for production tasks.[7] As we document in Section 4, it is reasonable in the context of robotics technologies;

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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.

[6] 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.

[7] This assumption simplifies the analysis relative to a more general setup where both types of workers can produce both types of inputs but middle-aged workers have a comparative advantage in production tasks.

these technologies are used mostly in industrial applications to automate tasks that used to be performed by blue-collar workers. As such, this type of automation directly competes against middle-aged workers who have the physical dexterity to perform such tasks.

We denote the total 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 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,

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

where the last equality in each expression defines the demand for that factor. Finally, we assume that machines are supplied at a 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. These decisions depend 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*, $\theta^A(i)$, which satisfies

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

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:[8]

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

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

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[8] Let $L(i) = \int_0^1 l(i,s)dsdi$ and $M(i) = \int_0^1 m(i,s)dsdi$ 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 also suggested by (7), an increase in $\theta(i)$ (and hence $\theta^A(i)$) makes the production of $X(i)$ less labor intensive (Acemoglu and Restrepo, 2016, 2018).

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 values for W^E and V^E are then given by the tangency 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 of Figure 1.

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, declining thereafter, 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 for which $\pi(i) > 0$ 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 other 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 relatively abundant and thus cheap. When $\phi > \widetilde{\phi}$, the middle-aged wage is sufficiently high that automation becomes cost-saving and profitable.

What is the effect of automation on factor prices? As in Acemoglu and Restrepo (2016, 2018), 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. 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.[9]

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. Thus, we can 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 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 will ensure that (15) has a unique solution. The exponent $\rho(i) > 0$ captures heterogeneity

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[9] 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 the industries adopting the automation technologies. For example, if $\theta(i)$ increases in a single industry with $\pi(i) > 0$, we have that $L(i)/S(i)$ declines in that industry.

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

The next proposition establishes the existence of an equilibrium with endogenous technology.

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[10] 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 $\theta(i)$.

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

To illustrate this proposition, suppose first that the mapping $W^E(\phi, \Theta^R(W))$ is decreasing in W.[11] In this case, automation decisions across industries are strategic substitutes and the equilibrium with endogenous technology is unique as shown 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 thus provides one of our most important 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, in the next proposition, we derive how the responsiveness of technologies 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 investigate both implications.

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[11] 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

As noted in the Introduction, the endogenous response of automation technologies might fundamentally alter the implications of demographic change for productivity. With exogenous technology, Proposition 1 showed that the effects of aging for aggregate productivity are ambiguous. 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 between 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 8 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 $\alpha(i)$): on the one hand, industries that rely more heavily on middle-aged workers are more exposed to the increase in wages; 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 together highlight too 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 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, we consider an extension to a global economy with multiple countries, where some of them are ahead of others in the development of automation technologies. In this setup, not only will we see imports and exports of automation technologies (as in our empirical work), but we also find that 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.[12] In our cross-country analysis we use the change in the stock of robots divided by industry 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 industry workers.[13] The resulting measure of the stock of robots per thousand (industry) workers

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[12] 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.

[13] ILO's industry employment data includes employment in manufacturing, mining, construction and utility, which cover the sectors currently using robots.

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 1 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 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, 2016). 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, 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.[14] We also use the Comtrade data to compute imports and exports of other intermediates related to industrial automation. Panel B of Table 1 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 1 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).

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

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[14] 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.

Several reasons explain why there is a 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, that 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.

robot integrators, obtained from Leigh and Kraft (2016).[15] 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 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 (2017b) to measure the local effects of robots.

3.3 Industry-level 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 A2 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 data the ILO data described above, while the second uses from the EUKLEMS dataset, 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).[16] 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 A2 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 (2015), 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

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[15] 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 except for Alaska and Hawaii.

[16] 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.

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 1 confirm that these are among the industries experiencing the fastest growth in the adoption of robots.

4 The Substitution between Robots and Workers

The key assumption in our model is that, relative to older workers, middle-aged workers specialize in production tasks that can be automated using industrial robots. In this section, we provide four different pieces of evidence consistent with this assumption. First, we review the engineering literature relevant to this question, which emphasizes that one of our key automation technologies, industrial robots, has been since the 1980s aimed at automating labor-intensive tasks in manufacturing, including machining, welding, painting, palletizing, assembly, material handling, and quality control (Ayres et al., 1987, Groover et al. 1986). A survey by the Japanese Robotics Association cited in Ayres et al. (1987) shows that industrial robots reduce costs when they substitute for blue-collar workers in plastic forming processes, machining, die casting, inspection, arc welding, and loading and packaging. These tasks are typically performed by middle-aged workers with the requisite strength and physical dexterity.

Our second strategy confirms the same notion by presenting descriptive statistics on the age distribution of workers across different industries and occupations using data from the the 1990 US Census, the 2000 US Census, and the 2007 American Community Survey. Specifically, Panel A of Figure 4 plots the ratio of workers employed in blue-collar jobs relative to workers employed in white-collar and service jobs. 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 and large decline in this ratio starting around age 50 (in the 2007 ACS) and age 55 (in the 1990 Census). This supports our presumption that middle-aged workers are overrepresented in blue-collar jobs. Panel B of the figure, on the other hand, shows that middle-aged workers are also overrepresented in industries that later became more robotized, and consistent with robots replacing these middle-aged workers, their over-representation is declining in later decades.

Our third strategy is complementary to the second and shows that as an industry adopts more robots, the employment and wage bill shares of production workers in that industry decline. Namely, 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 (2017a), we measure the exposure to robots using the adoption of robots in the same (three-digit) industries among comparable European countries between 1993 and 2007, which captures the common technological developments driving the adoption of robots throughout the world.

Figure 5 shows that US industries undergoing greater penetration of robots between 1993 and 2007 experienced significant declines in the employment and wage bill shares of production workers during the same period. This evidence thus suggests that, consistent with our theoretical framework, robots are substituting for production workers, which from Figure 4 tend to be the middle-aged ones.

Our final strategy is the most direct one for measuring substitution patterns as it explicitly looks at the impact of automation on the wages and employment of workers of different ages. In this strategy, we follow Acemoglu and Restrepo's (2017a) approach of estimating the impact of exposure to robots across US commuting zones. To conserve space, we refer the reader to that paper, and here we simply use the measure of exposure to robots computed there.[17] We then estimate the following models for employment and wages by 10-year age group across commuting zones:

$$\Delta L_{z,a} = \beta_a^L \begin{array}{c}\textit{Exposure to robots}\\ \textit{from 1993 to 2007}_z\end{array} + \epsilon_{z,a}^L \text{and} \Delta \ln W_{z,a} = \beta_{z,a}^W \begin{array}{c}\textit{Exposure to robots}\\ \textit{from 1993 to 2007}_z\end{array} + \epsilon_{z,a}^W,$$

where $\Delta L_{z,a}$ is the change in the employment rate of age group a in commuting zone z between 1990 and 2007, and $\Delta \ln W_{z,a}$ is the change in the average wage of workers in age group a in commuting zone z between 1990 and 2007. Figure 6 presents the estimates of the coefficients β_a^L and β_a^W (together with 95% confidence intervals based on heteroscedasticity-robust standard errors). We report three specifications similar to those in Acemoglu and Restrepo (2017a), except that in line with the focus here all regressions are unweighted (while given the focus there on aggregate changes, the main specifications in Acemoglu and Restrepo, 2017a, were weighted by population). The first one we report is the baseline specification in Acemoglu and Restrepo (2017a) and controls for Census region fixed effects, demographic differences across commuting zones, broad industry shares, and the impact of trade with China and Mexico, routinization, and offshoring.[18] The second specification, in addition, removes the seven 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 the impact of exposure to robots, to have the same impact on all workers.

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[17] Briefly, this measure is

$$\begin{array}{l}\textit{Exposure to robots}\\ \textit{from 1993 to 2007}_z\end{array} = \sum_{i \in \mathcal{I}} \ell_{zi}^{1970} \left(p_{30}\left(\frac{R_{i,2007}}{L_{i,1990}}\right) - p_{30}\left(\frac{R_{i,1993}}{L_{i,1990}}\right)\right),$$

where $R_{i,t}/L_{i,t}$ is the number of robots per thousand workers in industry i at time t, the sum runs over all the industries in the IFR data, ℓ_{zi}^{1970} stands for the 1970 share of commuting zone z employment in industry i, which we compute from the 1970 Census, and $p_{30}\left(\frac{R_{i,t}}{L_{i,1990}}\right)$ denotes the 30th percentile of robot usage among European countries in industry i and year t.

In that paper, we establish robustness to variations in the construction of this variable, and also report two-stage least squares estimates combining this measure of exposure to robots with changes in robots in US industries.

[18] Specifically, we control for log population, the share of working-age population (between 16 and 65 years); the shares of population with college degree and with high school, the share of Blacks, Hispanics and Asians, and the baseline shares of employment in manufacturing, durable manufacturing and construction, as well as the share of female employment in manufacturing. The variables for exposure to China trade, Mexico trade, routine jobs and offshoring are described in detail in Acemoglu and Restrepo (2017a).

For both employment and wages we obtain negative effects concentrated on workers between the ages of 35 and 54, and no negative effects on those older than 55.[19] In Figure A1 in the Appendix, we report similar results by five-year age bins, confirming these age thresholds.

Overall, the results in this section support the assumption that, relative to older workers, middle-aged workers tend to specialize in blue-collar jobs where they perform the tasks that can be performed by industrial robots. As a result, it appears to be the middle-aged workers who experience lower wages and employment when industrial robots are adopted.

5 Demographic Change and Automation

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

5.1 Main results

Table 2 starts with a flexible specification for the relationship between demographics and the adoption of robots. Our focus throughout will be on long-differences specifications, where we look at the relationship between various demographic change variables and the adoption of robots between 1993 and 2014. Our first regression equation is

$$\Delta \frac{R_c}{L_c} = \beta_M \Delta \ln \text{Middle-aged}_c + \beta_O \Delta \ln \text{Older}_c + \Gamma X_{c,1990} + \varepsilon_c, \tag{18}$$

where $\Delta \frac{R_c}{L_c}$ is the (annualized) change in the stock of robots per thousand workers between 1993 and 2014 in country c (where we keep the denominator fixed as employment in 1990 from the ILO, which avoids potentially endogenous changes in employment impacting our left-hand side variable). The right-hand side variables are the (expected) changes between 1990 and 2025 in the log population of two age groups: middle-aged workers aged 21-55 and older workers above the age of 56 (where the change between 2017 and 2025 is based on UN population forecasts described in Section 3). The vector $X_{c,1990}$ includes additional baseline covariates, and ε_c is the error term. Unless otherwise indicated, all of our regressions are unweighted and all standard errors are robust against heteroskedasticity.

Panel A of Table 2 presents our OLS estimates of equation (18). Columns 1-3 are for the full sample of 52 countries. Column 1 controls only 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, which control for trends among countries with different initial levels of

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[19] In weighted regressions, the estimates for employment are very 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 in some large commuting zones.

development and demographic characteristics. Column 3 also includes the stock of industrial robots per thousand workers in 1993, which allows for the possibility that countries with more robots at the beginning of the sample may adopt robots at differential rates. Columns 4-6 present the same specifications for the OECD sample.

In all six columns of Panel A, we find that a *decline* in middle-aged population and an *increase* in the older population are associated with faster robot adoption, although some of the estimates are not precise for the OECD sample. These findings support the key prediction of our model, where incentives to automate do not depend on the total population but on the relative scarcity of middle-aged workers.

The quantitative magnitudes are large but plausible. For example, in column 1, the coefficient estimate on population of the middle-aged group is -0.45 (s.e.=0.15). This estimate implies that a 10 percent decline in the population of the middle-aged group (which is roughly the decline expected for Germany) is associated with 0.045 additional robots per thousand workers per year, or 0.9 additional robots per thousand workers over the whole sample period. Moreover, these demographic shifts alone explain 30% of the variation in robot adoption across all countries and 42% of the variation in the OECD sample.

Panel B shows that we obtain very similar results when we define older workers as those between 56 and 75 years of age. The estimates in this panel show that the positive coefficient on the change in the older population is not driven by workers above 75, who tend to have a low labor market attachment and should not affect the incentives for automation. Finally, in Panel C we split middle-aged workers in two groups: between 21 and 35, and between 36 and 55. We again find a negative estimate for the change in the population of those between 36 and 55, and a positive estimate for the change in the population of those above 56.

In line with the logic of our model, the results in Table 2 suggest that the adoption of robotics technologies is associated with demographic changes that increase the share of older workers and reduce the share of middle-aged workers—the aging of the population. This observation motivates a more parsimonious specification, linking the adoption of robots to the ratio of older to middle-aged workers, which we explore in Table 3 and focus on in the rest of the paper:

$$\Delta \frac{R_c}{L_c} = \beta \text{Aging}_c + \Gamma X_{c,1990} + \varepsilon_c, \tag{19}$$

where Aging_c is defined as the change between 1990 and 2025 in the ratio of older workers (above 56 years of age) to middle-aged workers (those between 21 and 55), and we refer to this change simply as "aging". Table A3 in the Appendix shows that alternative measures of aging (with different cutoffs for older workers) produce similar results.

Table 3 reports estimates of equation (19) for the same specifications as in Table 2. Panel A focuses on OLS models. The estimates in Panel A confirm the positive effect of aging on the adoption of robots. The results are now more precisely estimated and are significant at 5% in all specifications. The quantitative effects are again substantial. The specification in column 1 has a R^2

of 0.43 (and the partial R^2 of the aging variable alone is close to 0.40 as noted in the Introduction). In our preferred specification in column 3, the coefficient estimate on the aging variable is 0.5 (s.e.=0.19). This implies that a 20 percentage point increase in our aging variable, which is roughly the difference between Germany and the United States (0.5 vs. 0.28, respectively), leads to an increase of 0.1 robots per thousand workers per year or two additional robots per thousand workers over our sample period, which is about 25% of the Germany-US difference in the adoption of robots.

In line with our findings in Table 2, The results in Table A4 in the Appendix confirm that once we control for our measure of aging there is no relationship between the change in population and the adoption of robots—the patterns we are reporting are all about the relative size of middle-aged and older cohorts.[20]

Figure 7 depicts the relationship between demographic change and the number of robots per thousand workers in the full sample of countries and in the OECD (from the models estimated in columns 3 and 6 in Table 3). Even though South Korea is an outlier, we can also see that this relationship is not driven by outliers (a point formally established in Table A5 in the Appendix, where we present several strategies to remove outliers or their influence).

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 patterns, which would bias our OLS estimates. To address this concern, we instrument the (expected) aging between 1990 and 2025 using the average birth rates over each five-year intervals 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). Panel B shows that the IV estimates of the effect of demographic change on the adoption of robots are slightly larger than their OLS counterparts.[21]

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, we report 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 very similar effect of aging on the adoption of robots, but now the first-stage F-statistic is above 20 in all columns except in column 4 (for the OECD sample without any covariates).

5.2 Placebo exercises, robustness and additional results

In this subsection we first show that past demographic changes have no predictive power for the adoption of robotics technology, and then document the robustness of the results in Table 3 to a

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[20] These results and the similar ones in Table 2 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 Abelianisky and Prettner, 2017).

[21] In this and all subsequent tables, when we have more than one instrument, we perform and report the p-value from Hanson's overidentification test. This test does not reject the joint validity of our instruments.

range of variations.

In Panel A of Table 4, we include the same aging variable on the right-hand side, but now measured between 1950 and 1990. 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 for other reasons even before the 1990s. The results in Table 4 are reassuring in this respect, and show no correlation between our aging variable between 1950 and 1990 and the change in the number of robots since 1990. Panel B of Table 4 presents a complementary exercise where we simultaneously include past aging and expected aging (between 1990 and 2025) as explanatory variables. The results show that only expected aging is a significant determinant of the adoption of robots.

Panel C of Table 4 further 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 contemporaneous aging and expected aging are positively associated with the adoption of robots. Indeed, in no specification can we reject the null hypothesis that contemporaneous and expected aging have the same impact on robot adoption, as shown by the test for the equality of the two coefficients reported in the panel. Expected aging plays a particularly important role in the OECD sample, where it is significant at the 10% level in all models. These results support our choice of focusing on (expected) aging between 1990 and 2025 in our baseline models. (Table A6 in the Appendix shows that our main results are very similar if we use the contemporaneous variable in our main specifications.)

We have so far reported on long-differences specifications, focusing on the change in the stock of robots between 1993 and 2014. This is the most 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-difference specifications fail to exploit higher frequency covariation between aging and the adoption of robots within subperiods. To exploit this additional source of variation, Table 5 turns to stacked-differences models, where for each 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 the aging variable 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 comparable to the estimates in Table 3. 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 (1993 values of log GDP per capita, local population, average schooling and ratio of older to middle-aged workers). Panel B presents the corresponding IV estimates. The estimates confirm our main results in Table 3. In columns 3 and 6, we go one step further relative to our earlier specifications and also include linear country trends. These specifications thus only exploit the differential rate at which demographic change proceeds and additional robots are adopted in the two subperiods for each country. The estimates in these demanding specifications are significant and in fact very similar to our baseline estimates, bolstering our confidence in the interpretation and robustness of our results.

Besides aging, our model suggests that other factors affecting wages, such as unionization, and the (middle-age) wage level itself are important determinants of the adoption of robots. We explore these issues in Table A7 in the Appendix, where in addition to estimating the impact of aging on robot adoption, we control for the baseline union membership and the log of the average hourly wage in 1993.[22] 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. The results provide some support for the idea that countries with greater unionization rates adopted 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 does not seem to have a robust impact on the adoption of robots.[23]

Finally, we explored models in logs rather than in the number of robots per thousand workers as in our baseline specification. In Table A9, 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 very similar to our baseline estimates.

5.3 Other automation technologies

We next show that there is a similar relationship between demographic change and other automation technologies using imports data from Comtrade. We first confirm the results presented so far using imports of industrial robots. Specifically, we estimate a variant of equation (19) with the log of robot imports relative to other intermediate imports between 1996 and 2015 as the dependent variable.[24] Because these measures are imprecise for countries with small total imports, throughout

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[22] 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.

[23] 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.

[24] There are several points to note here. First, since imports (and later exports and patents) are flow variables, our dependent variable corresponds to the growth in the stock of these intermediates, which is similar to our baseline specification with the growth of the stock of robots on the left-hand side in equation (19). 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 also focuses on the sample of countries importing

we focus on regressions weighted by total imports between 1996 and 2015.

Panels A and B of Table 6 presents our OLS and IV estimates. The table has the same structure as previous ones, with the exception that in columns 3 and 6 we control for the log of intermediate imports. Moreover, because Comtrade covers more countries, our sample now includes 131 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. The IV coefficient estimate in column 3, 2.234 (s.e.=0.675), implies that a 20 percentage point increase in aging, once again corresponding to the difference between Germany and the US, leads to a 46% 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). Figure 8 provides regression plots for the full sample (Panel A) and the OECD sample (Panel B), where the size of the markers indicate total imports for each country.

Figure 10 turns to imports of other type of equipment—again from the Comtrade data—and reports estimates of the IV models in columns 3 and 6 of Table 6. We chose three sets of intermediates. The first set includes intermediates related to the automation of blue-collar industrial jobs: dedicated machinery (including robots), numerically controlled machines, automatic machine tools, automatic welding machines, weaving and knitting machines, dedicated textile machinery, automatic conveyors, and automatic regulating instruments. The second set comprises technologies used for similar industrial tasks but that do not involve automation. This set includes manual machine tools, manual welding machines, machines that are not numerically controlled, other regulating instruments, other conveyors, and other industrial machinery. Finally, we consider intermediates that are not used in the automation of blue-collar tasks and thus should not become more profitable when the population ages. This set includes vending machines, laundry machines, agricultural machinery (including tractors) and computers.[25] The evidence in Figure 10 is consistent with the idea that aging is associated with the adoption of a range of technologies for industrial automation. In particular, for the full sample of countries, aging leads to a statistically significant and sizable increase in the relative imports of all of our (industrial) automation technologies, except automatic conveyors. For the OECD, the pattern is more mixed. 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.[26]

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or exporting the relevant intermediates (and later patenting), which is thus more similar to our regressions focusing on countries installing robots. In Table A10 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.

[25] 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, 2017a).

[26] 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.

6 DEMOGRAPHIC CHANGE AND INNOVATION

While our theory links demographic change to both the adoption and development of new automation technologies, the evidence so far has focused on adoption. We next turn to two measures of innovation and development of new automation technologies. The first is the export of the same measures of intermediates related to automation technologies, starting with industrial robots. The exporting of these technologies is a sign of innovation related to this area (e.g., the introduction of new varieties of machinery or quality improvements leading to greater exports). Motivated by this reasoning, we investigate whether countries undergoing more rapid demographic change increase their exports of automation technologies.[27] We start with a variant of equation (19) focusing on the log of robot exports relative to other intermediate exports between 1996 and 2015 as the dependent variable. Similar to our strategy with imports, we weight our regressions by total exports between 1996 and 2015.

Panels C and D of Table 6 present OLS and IV estimates and have an identical structure to 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 105 countries, 35 of which are in the OECD.[28] Consistent with our theoretical expectations, the results indicate that demographic change is associated with greater exports of industrial robots relative to other intermediate goods. The IV estimate in column 3 of 4.354 (s.e.=1.309) implies that a 20 percentage point increase in expected aging, once again corresponding to the difference between Germany and the US, leads to an 88% increase in robotics exports, which more than closes the gap between the two countries (which is about 63%). The two panels of Figure 9 depict these relationships for the full sample and the OECD sample (marker size now indicates total exports).

Panel B of Figure 10 then turns to other types of machinery and focuses on the same IV models for the full sample and the OECD as in Panel A. We now find a strong effect of aging on the (relative) export of intermediates embodying industrial automation technologies. This relationship is statistically significant for all of our measures (except for automatic conveyors) both in the full sample and in the OECD sample. Reassuringly, we again do not see a similar relationship for other technologies.[29]

Our second strategy is to look at patents related to robotics as described in Section 3. We estimate a variant of equation (19) with the log of robotics-related patents relative to other utility patents granted between 1990 and 2015 as the dependent variable. (This normalization ensures that our findings are not driven by an overall increase in patenting activity among countries undergoing more rapid demographic change). As we did with imports and exports, we weight our regressions by total patenting activity between 1990 and 2015. The weighting accounts for the sizable differences

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

[28] Because we are looking at exporting activity, these models include Japan as well.

[29] 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.

across countries in their propensity to file for a patent in the United States. Panels A and B of Table 7 present our OLS and IV estimates. Our sample now includes 69 countries active in robotics-related patent classes, 31 of which are in the OECD. The results show a strong association between demographic change and robotics-related patents (relative to other utility patents). The IV estimate in column 3, for example, is 1.354 (s.e.=0.172) and implies that a 20 percentage point increase in expected aging, once again 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 48% of the gap between the two countries. Figure 11 presents this relationship visually.

We investigated the robustness of these results in number of dimensions. Some of those are shown in Figure 12. Specifically, we use alternative definitions of automation patents and also verify that 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 with abstract containing words related to robots or to industrial robots; patents with abstract containing words related to industrial machinery; and finally patents with abstract containing words related to numerical control. In all these cases we find a positive association between demographic change and the number of patents in these classes (relative to all utility patents). 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.[30]

7 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. As explained above, we proxy for robotics-related activity relying on Leigh and Kraft's (2016) data on the location of robot integrators. Panel A of Table 8 reports estimates of the model

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

across 722 US commuting zones. Here z indexes a commuting zone, Integrators_z is a dummy variable for whether a commuting zone has any robot integrators. Aging_z now designates the change in the ratio of workers above 56 to those between 21 and 55 between 1990 and 2015 in commuting zone z, 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 the

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[30] 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.

standard errors are robust against heteroskedasticity and spatial correlation at the state level.

Because people can migrate across commuting zones more easily than across countries, the endogeneity of local age composition is a more important issue in this case than in our cross-country analysis. 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 (similar to our single instrument models in the cross-country analysis).

Column 1 controls only for regional dummies (Midwest, Northeast, South, and West). Column 2 includes baseline characteristics of commuting zones measured in 1990—a point in time in which the US had few industrial robots and integrators (see Ayres and Miller, 1981). These characteristics include the log of the 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. Column 3 includes the exposure to robots measure already used above to capture the opportunities for the use of robots in each commuting zone based on its industrial composition. This column also controls for the shares of employment in manufacturing, agriculture, mining, construction, and finance and real estate in 1990. Finally, column 4 includes additional covariates to which we did not have access to in our cross-country analysis, including the racial composition of commuting zones, the share of male and female employment (all measured in 1990) and controls for exposure to Chinese imports, Mexican imports, offshoring and routine jobs (see Acemoglu and Restrepo, 2017a).

For all specifications, the qualitative pattern of the estimates are similar across the three panels, though the OLS estimates are considerably smaller than their IV counterparts, presumably reflecting the endogeneity of current age composition in the local labor market. For both of our IV specifications, we find that robot integrators tend to 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, 2017a). A 10 percentage point increase in our aging variable—which is approximately 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%).

These relationships are shown visually in Figures 13 and 14. The first presents a map of commuting zones that house robot integrators next to the predicted aging patterns across commuting zones. The strong association between these two variables is clearly visible from these maps. The second figure presents binned scatter plots of the relationship between aging or predicted aging and the location of integrators.

Columns 6 and 7 explore whether the impact of aging concentrates in commuting zones with a high share of manufacturing employment. Our theoretical mechanism should only operate when there is significant manufacturing activity in an area. Consistent with this expectation, we find that integrators locate in commuting zones undergoing rapid aging but only when these are above the median in the distribution of manufacturing employment (column 6); aging does not appear to be related to the locational choices of integrators in commuting zones with little manufacturing employment (column 7).[31]

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.

8 DEMOGRAPHICS AND ROBOTS: INDUSTRY-LEVEL RESULTS

Our theoretical analysis in Section 2 highlighted that the response of robotics technology to demographic change—an increase in the ratio of older to middle-aged workers—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. We now investigate these predictions using the industry-level data from IFR.

Table 9 estimates regression models similar to those reported so far, except that we now use annual data varying by country and industry and also include interactions with industry characteristics:

$$\begin{aligned}\frac{IR_{i,c,t}}{L_{i,c,1990}} =& \beta \text{Aging}_c + \beta_R \text{Aging}_c \times \text{Reliance on Middle-Aged Workers}_i \\ &+ \beta_P \text{Aging}_c \times \text{Opportunities for Automation}_i + \Gamma_{i,t} X_{c,1990} + \alpha_i + \delta_t + \varepsilon_{i,c,t},\end{aligned} \tag{20}$$

where the left-hand side variable, in contrast to equation (19), denotes the (annual) installation of new robots per thousand workers (with the denominator still corresponding to employment in 1990). 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 also allow the covariates in $X_{c,1990}$ to have time-varying coefficients and include industry and year effects, α_i and δ_t, in this case. 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 50 countries and runs between 1993 and 2014, but is unbalanced since, as indicated in Table A1, data are missing for several country×industry×year combinations.[32] Standard errors are now robust against heteroscedasticity, and cross-industry and temporal correlation at the country level.

To construct the denominator of 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 $L_{i,c,1990} = L_{c,1990}/19$ (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

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[31] Table A12 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 population, or use the log of the employment of integrators as the dependent variable.

[32] 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 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, 2015 and Michaels, Natraj, and Van Reenen, 2014).

EUKLEMS data, which cover all the industries in our sample, but only for 22 countries. Finally, Table A13 in the Appendix uses the UNIDO data on employment by country-industry pair, which covers manufacturing industries for 44 countries.[33]

Column 1 in all panels presents estimates of equation (20) without the interaction terms. Though not reported, our covariates, $X_{c,1990}$, include region dummies, the log of GDP per capita, log population, average years of schooling and the ratio of older to middle-aged workers in 1990.

The remaining columns include the interaction of aging with reliance on middle-aged workers and opportunities for automation. In columns 2-4, the 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. The estimates in column 2 of Panel A, for example, indicate that a 10 percentage point increase in aging leads to an increase of 0.15 ($= 1.66 \times 0.9 \times 0.1$) annual robot installations per thousand workers in an industry at the 75th percentile of reliance on middle-aged workers compared to an industry at the 25th percentile. For instance, in electronics, which is at the 75th percentile of reliance on middle-aged workers, a 10 percentage point increase in aging is predicted to increase robot installations by 0.25 per thousand workers per year, while in basic metals, which is at the 25th percentile, the same change is predicted to lead to only 0.1 more robots per thousand workers. Similarly, a 10 percentage point increase in aging is associated with an increase of 0.155 ($= 0.27 \times 5.738 \times 0.1$) annual robot installations per thousand workers in an industry at the 75th percentile of the replaceability index compared to an industry in the 25th percentile. For example, automobile manufacturing is approximately at the 75th percentile of the replaceability index, and a 10 percentage point increase in aging increases robot installations by 0.21 per thousand workers per year in this industry, while the same change is predicted to increase installation of robots only by about 0.05 per thousand workers in construction or utilities, which are at the 25th percentile.

In 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.[34] In columns 4 and 7 we control for a full set of country fixed effects (and we no longer estimate the main effect of aging). 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.

We turn to the IV specifications in Panels B and D. As in our cross-country analysis, we

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[33] Table A8 in the Appendix shows that if we estimate an analogue of equation (20) using yearly data on robot installation for countries, the results are very similar to our baseline cross-country estimates in Table 3. 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).

[34] Because we do not observe the stock of robots for all country-industry pairs in 1993, we follow Graetz and Michales (2015) and impute these stocks when they are missing in 1993. To do so, we deflate 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.

instrument demographic change 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 corresponding first-stages for the interaction terms. The IV estimates are quantitatively similar to the OLS ones.[35]

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

9 Productivity and the Labor Share

We finally turn to the relationship between aging and changes in productivity (real value added per worker) 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 induces. Nevertheless, our model also makes some unambiguous predictions: because of the induced increase in automation, 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 on the labor share in industries with the greatest opportunities for automation.

Panels A and B of Table 10 estimate a version of equation (20) with the change in log (real) added per worker in industry i in country c between 1995 and 2007 as the left-hand side variable (instead of annual robot installations) and the same interactions on the right-hand side. Because this productivity measure from EUKLEMS data is only available from 1995 onwards, we adjust our aging variable to be between 1995 and 2025. We allow the baseline covariates in $X_{c,1995}$ to affect industries differently, and we continue to include industry effects, α_i, and to use the same weighting scheme as in the previous section. The standard errors are again robust against heteroscedasticity and correlation at the country level.[36]

The structure of Table 10 is similar to that of Table 9. Panel A presents OLS estimates for productivity and Panel B reports IV estimates. Column 1 in Panel A shows that aging reduces the average growth of value added per worker. A 10 percentage point increase in aging is associated with a 14.5% decline in value added per worker (s.e.=5.6%) in Panel A. These results differ from the findings in Acemoglu and Restrepo (2017b), where we showed that there was no negative effect of aging on growth in GDP per capita. The negative estimates in column 1 here are driven by the smaller samples in the EUKLEMS, and are not robust to using other measures of economic activity. For instance, as reported in Table A18 in the Appendix, if we estimate the analogue of

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[35] We also confirmed that past demographic changes have neither main effects nor interaction effects (with reliance on middle-aged workers or opportunities for automation) and also verified that these results are robust under different specifications and to excluding outliers. These results are presented in Tables A14, A15, and A16 in the Appendix.

[36] In the Appendix we also present analogous results from the OECD STAN database.

this equation at the country level for a larger sample, there is no significant negative relationship.

Of greater interest given the theoretical predictions highlighted in Section 2 is the interaction between aging and opportunities for automation. Here, we find a positive interaction, indicating that in the presence of aging, industries with greater potential for automation are experiencing relative productivity gains. The magnitudes are sizable. For example, the IV estimate in column 2 of Panel B shows that a 10 percentage points increase in aging causes an increase of 18% ($= 0.4 \times 4.6 \times 0.1$) in the growth of value added per worker in an industry at the 95th percentile of the replaceability index compared to an industry at the 5th percentile. In fact, our estimates imply that aging increases productivity in the former industry while it reduces it in the latter.[37]

Panels C and D of Table 10 present regressions for the labor share. Column 1 shows that, on average, industries located in countries undergoing more rapid demographic change experienced a decline in their labor share.[38] More importantly for our focus here, we find that these effects are more pronounced in industries that have greater opportunities for automation. 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 extent of heterogeneous effects on the labor share across industries is again quantitatively significant.

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—and has ambiguous effects in the aggregate.

10 CONCLUSION

The populations of most developed and many developing countries are aging rapidly. Many economists see these demographic changes as major "headwinds" potentially slowing down or even depressing economic growth in the decades to come. However, a reasoning based on directed technological change models—which highlight the effects of changing scarcity of different types of labor on the adoption and development of technologies substituting for these factors—suggests that these demographic changes should be associated with major technological responses.

We have documented that this is indeed the case; countries and US labor markets undergoing more major demographic change have invested significantly more in new robotic and other automation technologies. We have argued that this is because ongoing demographic changes are increasing the scarcity of middle-aged workers and industrial automation is 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-

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

[38] As was the case with productivity, these results do not extend beyond the sample considered here. Table A18 in the Appendix shows that, if we estimate the analogue of equation (20) at the country level for the larger sample, there is no relationship between aging and the labor share.

country variation in investment in robotics. We have also shown using data on intermediate exports and patents that demographic change not only encourages the adoption of automation technologies but also their development.

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 significantly more adoption of new robots and as a result, lead to greater productivity—even if the direct effect of aging might be negative. Using industry-level productivity 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 study the effects of aging on technology adoption and productivity using more disaggregated industry-level or firm-level data, to which we do not have access in this paper. Second, it is necessary to further investigate whether the effects of demographic change on technology adoption are being mediated through wages and whether other factors affecting wages, such as differences in labor market institutions, also have similar effects on technology. Third, it would be interesting to investigate 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.

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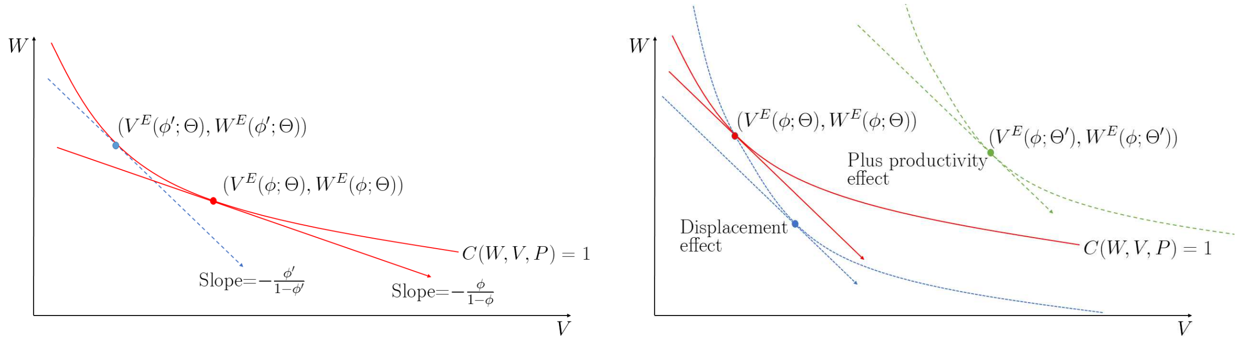
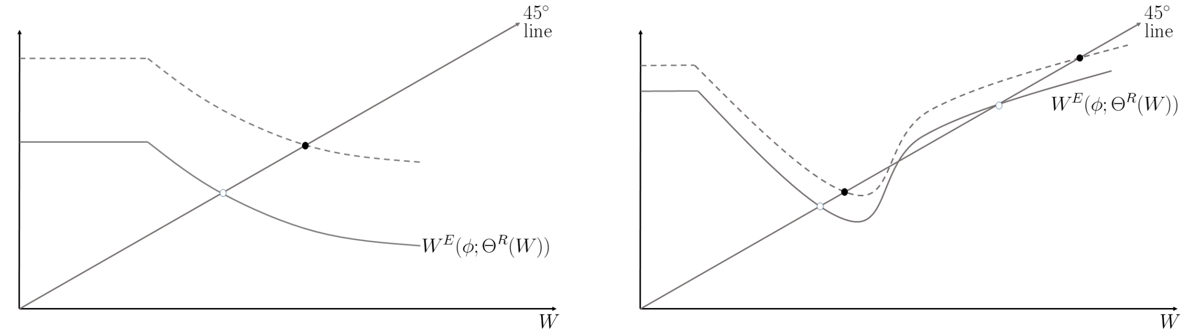
Main Figures and Tables:



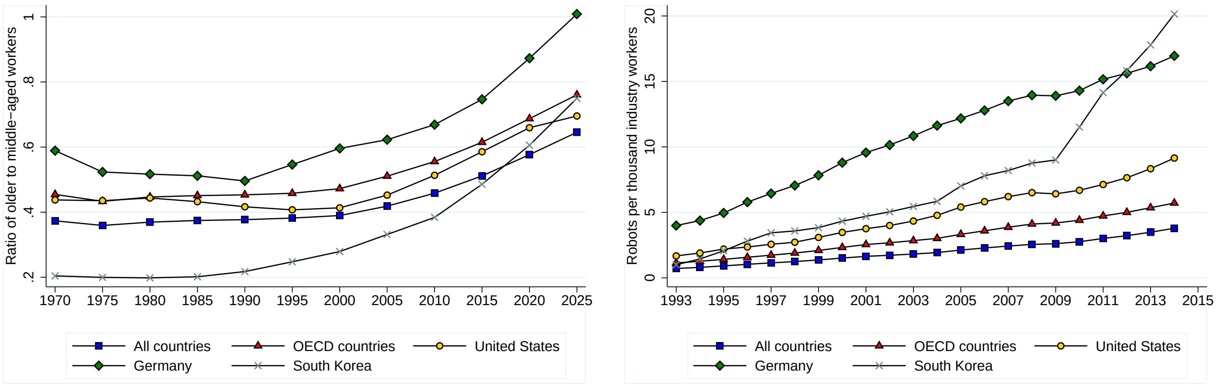
Panel A Panel B

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

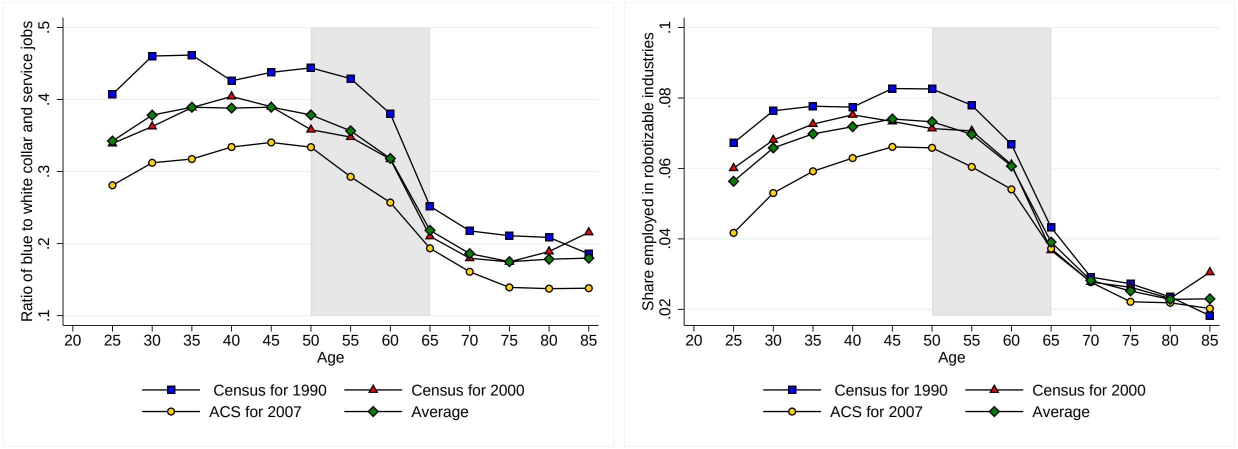
FIGURE 2: Equilibrium middle-aged wage with endogenous technology. Panel A: unique equilibrium. Panel B: multiple equilibria. Aging shifts the mapping W^E up, and this increases the equilibrium wage in the least and the greatest equilibrium.



Panel A

Panel B

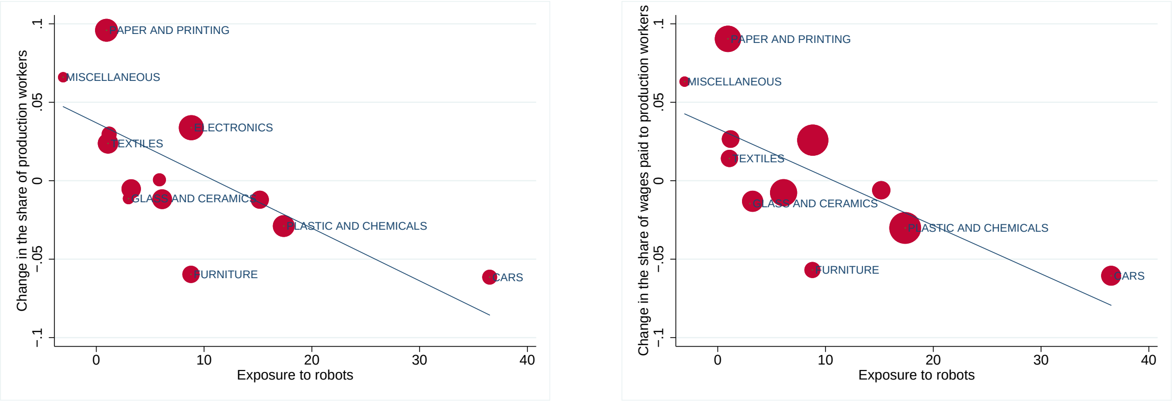
FIGURE 3: Panel A presents trends in aging—the ratio of older (56 years of age or older) to middle-aged (between 21 and 55 years of age) workers—using data and forecasts from the UN. Panel B presents trends in robot adoption. Robot adoption is measured by the number of robots per thousand industry workers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



Panel A

Panel B

FIGURE 4: 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 5: 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.

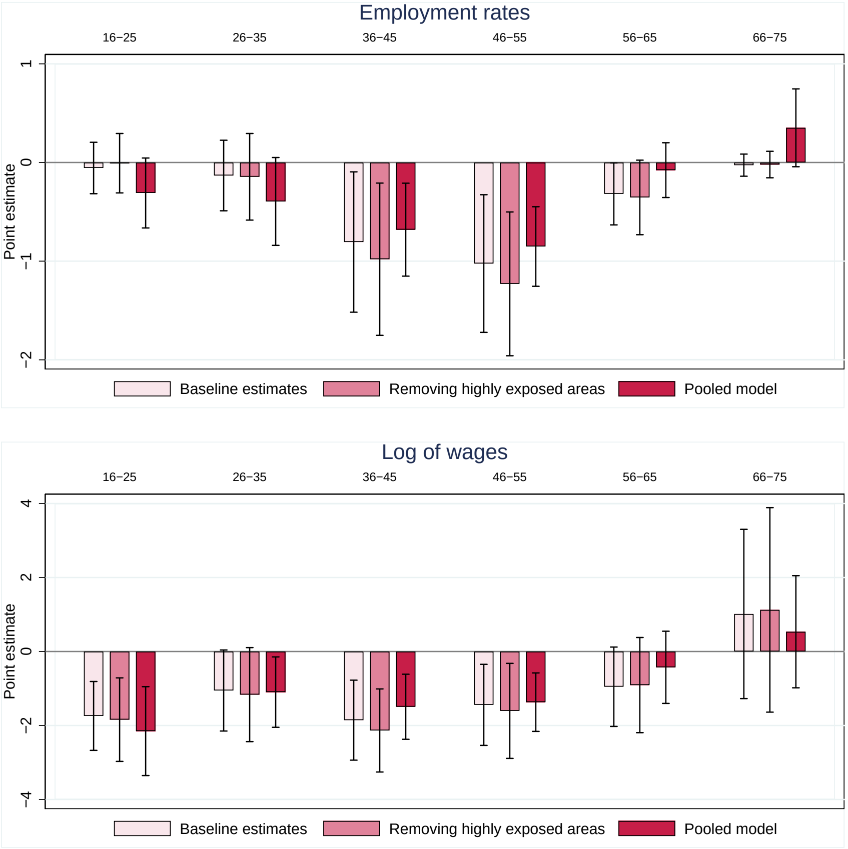
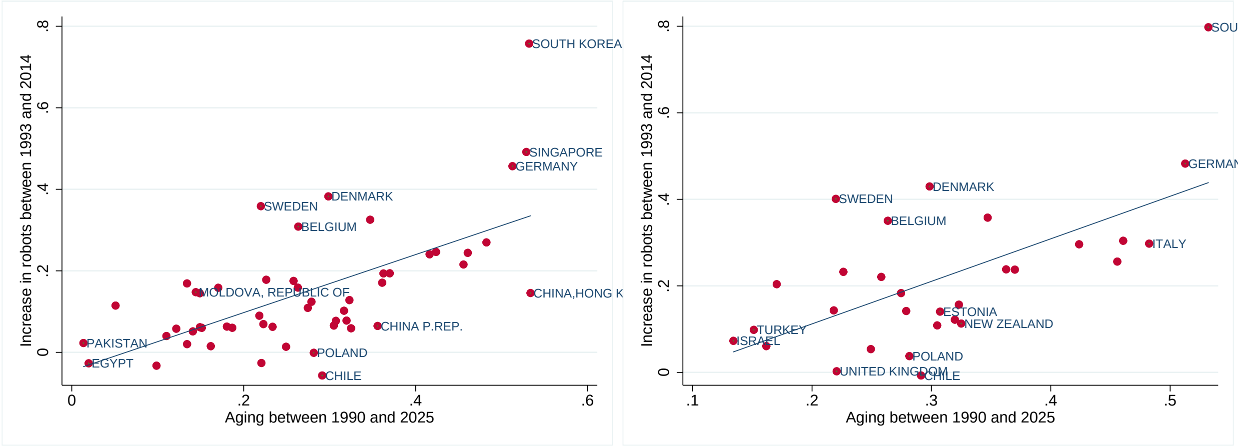


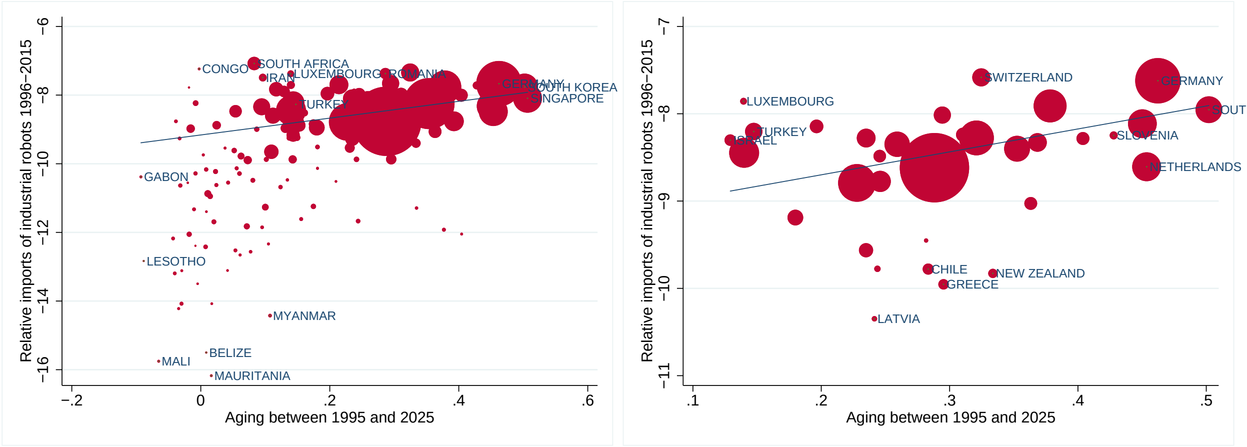
FIGURE 6: The figure presents estimates of the impact of one additional robot per thousand workers on the employment and wages of different age groups across US commuting zones. The three specifications and the data used are described in the main text and in Acemoglu and Restrepo (2017a).



Panel A

Panel B

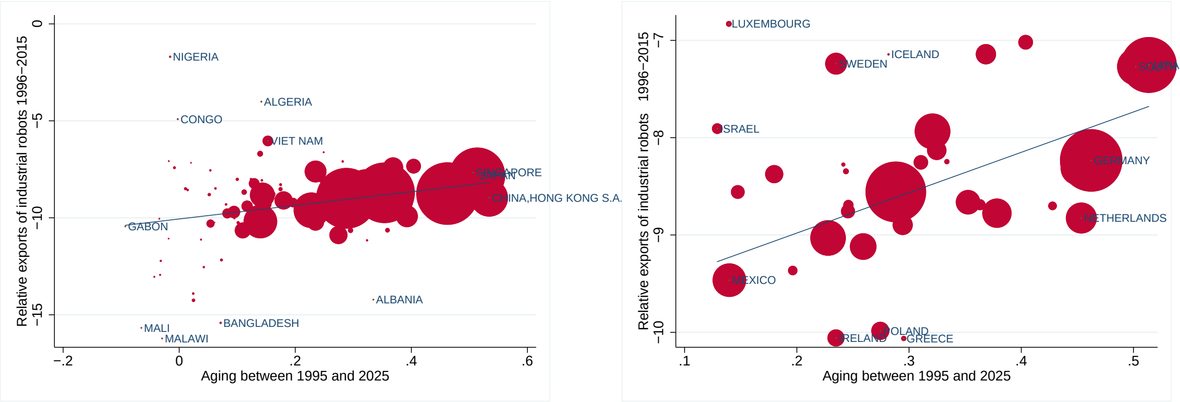
Figure 7: Relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the increase in the number of industrial robots per thousand workers between 1993 and 2014. The plots partial out the covariates included in the regression models in columns 2 and 5 of Table 3.



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 imports of industrial robots between 1996 and 2015 (relative to total 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 6. Marker size indicates total imports.



Panel A Panel B

FIGURE 9: 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 total 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 6. Marker size indicates total exports.

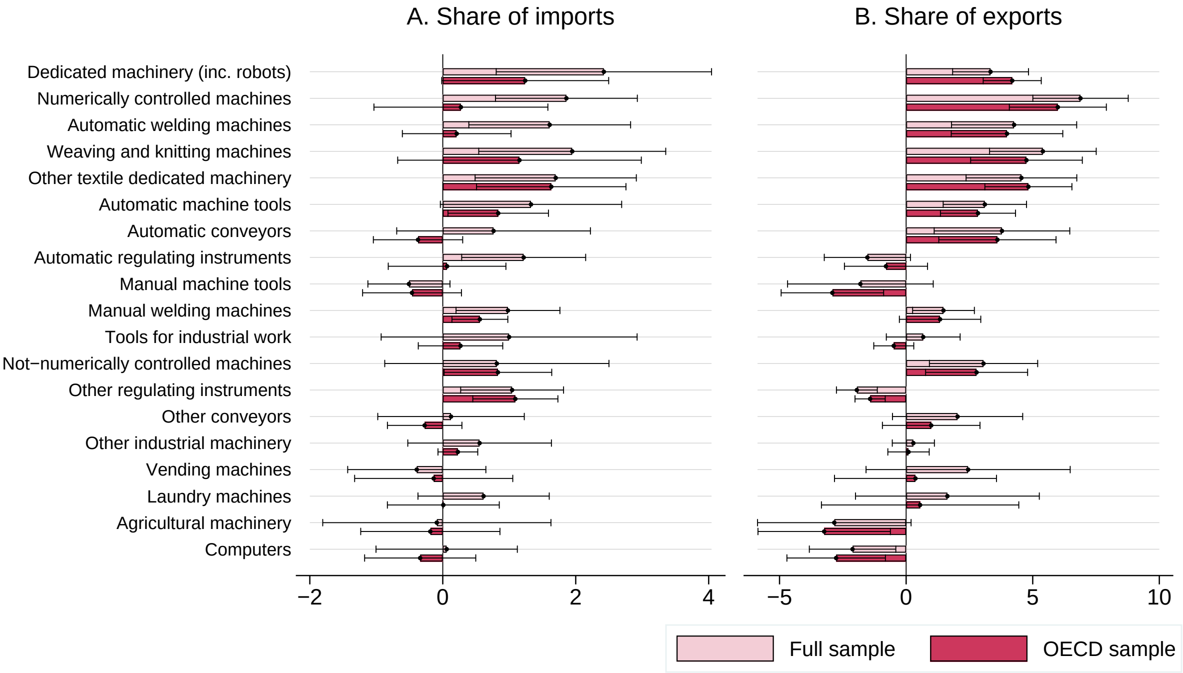
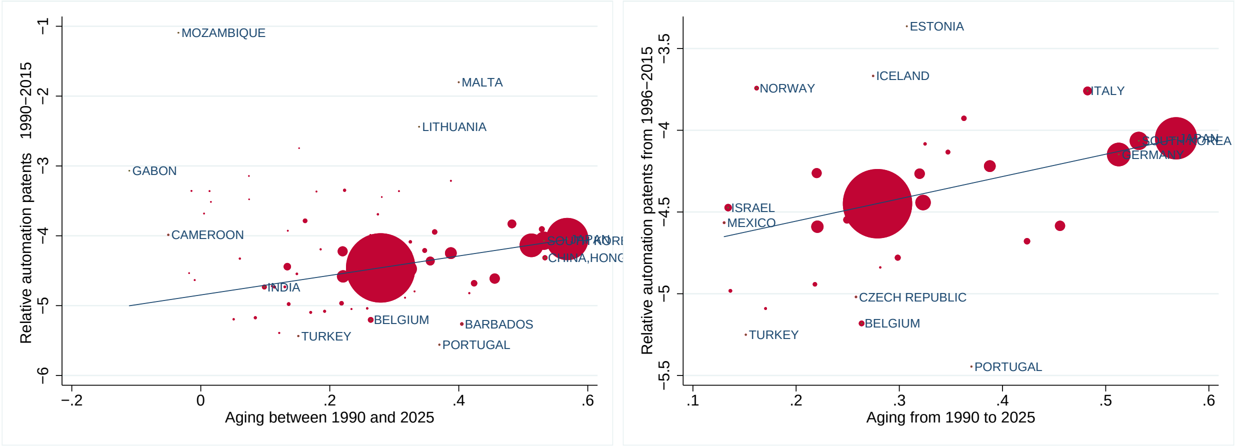


FIGURE 10: Estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of imports (Panel A) and exports (Panel B) of intermediate goods between 1990 and 2015. These outcomes are normalized by the total intermediate exports 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 11: 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 7. Marker size indicates total patents.

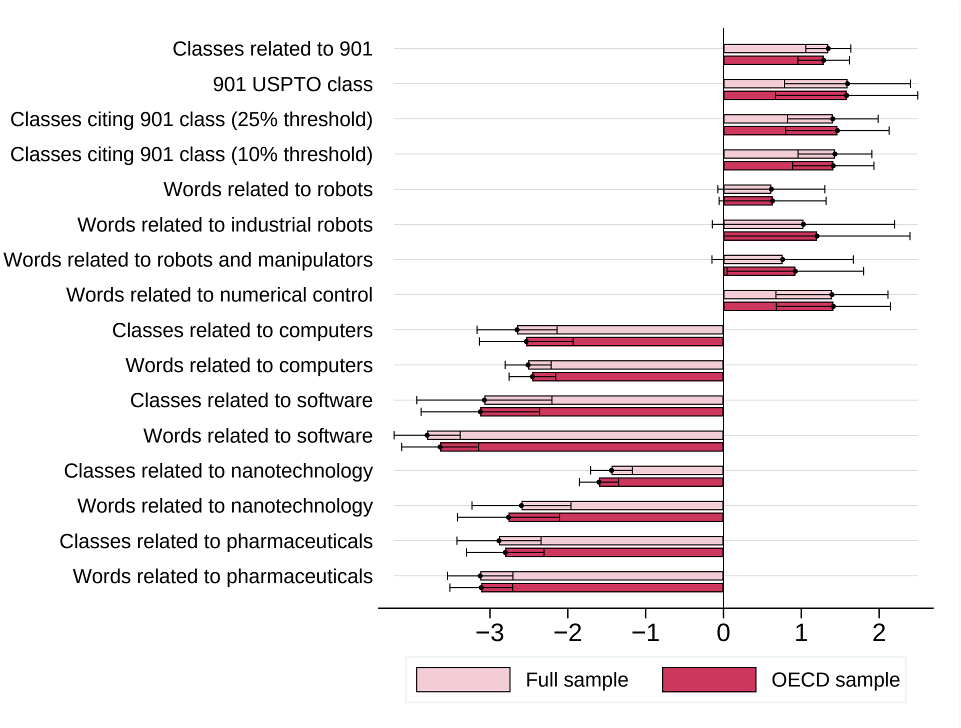
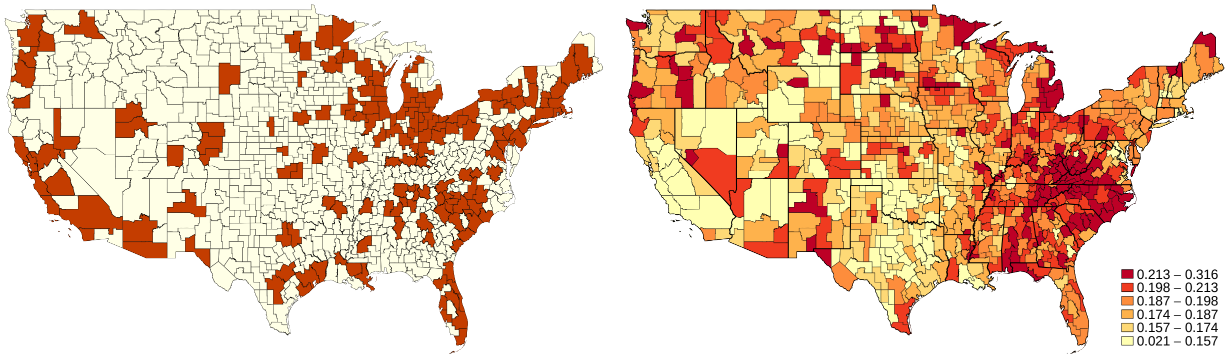
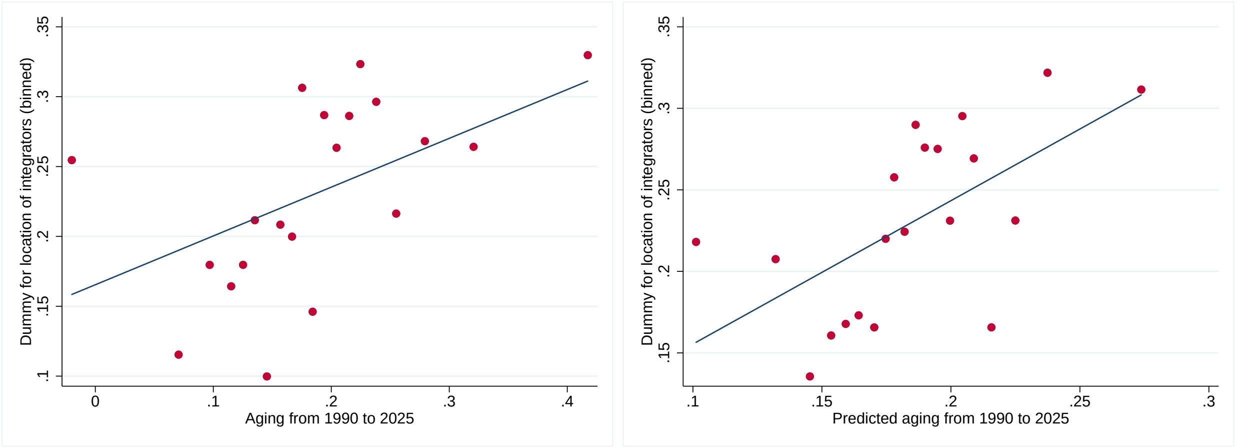


FIGURE 12: Estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of patents in the indicated category between 1990 and 2015. These outcomes are normalized by the total patents granted by the USPTO during this period. The figure presents separate estimates for the full sample of countries with patent data and for OECD countries.



Panel A Panel B

FIGURE 13: 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).



Panel A Panel B

FIGURE 14: Binned plot of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2015) and predicted aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2015 instrumented using birthrates from 1950 to 1985) and the location of robot integrators in the US (from Leigh and Kraft, 2016). The plots partial out the covariates included in the regression models in column 4 in Table 8.

Table 1: 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)
	$N = 52$	$N = 30$	$N = 26$	$N = 26$
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)
	N=131	N=34	N=65	N=66
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)
	N=105	N=35	N=52	N=53
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)
	N=69	N=31	N=34	N=35

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 2: 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*	-0.500**	-0.756***	-1.202**	-1.066**
aged 21-55 years	(0.148)	(0.286)	(0.234)	(0.213)	(0.447)	(0.446)
Change in the log of population	0.366*	0.368*	0.286	0.605**	0.478	0.423
$\geq$ 56 years	(0.190)	(0.203)	(0.173)	(0.237)	(0.328)	(0.345)
Robots per thousand workers in 1993			0.076***			0.066***
			(0.011)			(0.023)
Observations	52	52	52	30	30	30
R-squared	0.47	0.59	0.71	0.42	0.63	0.71
	Panel B. Population in two age groups between 1990-2025					
Change in the log of population	-0.489***	-0.469***	-0.357**	-0.821***	-0.839***	-0.652***
aged 21-55 years	(0.164)	(0.162)	(0.156)	(0.230)	(0.210)	(0.210)
Change in the log of population	0.377*	0.495***	0.230*	0.643**	0.904***	0.576*
aged 56-75 years	(0.195)	(0.164)	(0.131)	(0.243)	(0.264)	(0.282)
Robots per thousand workers in 1993			0.078***			0.068***
			(0.011)			(0.017)
Observations	52	52	52	30	30	30
R-squared	0.47	0.52	0.67	0.44	0.55	0.66
	Panel C. Population in three age groups between 1990-2025					
Change in the log of population	0.010	0.007	-0.150	-0.160	-0.243	-0.355
aged 21-35 years	(0.150)	(0.152)	(0.161)	(0.213)	(0.213)	(0.230)
Change in the log of population	-0.618***	-0.582***	-0.193	-0.753***	-0.632**	-0.265
aged 36-55 years	(0.195)	(0.210)	(0.223)	(0.247)	(0.243)	(0.294)
Change in the log of population	0.511**	0.646***	0.265**	0.773***	1.119***	0.767***
aged 56-75 years	(0.197)	(0.142)	(0.126)	(0.262)	(0.281)	(0.259)
Robots per thousand workers in 1993			0.076***			0.068***
			(0.014)			(0.021)
Observations	52	52	52	30	30	30
R-squared	0.52	0.57	0.67	0.47	0.60	0.69
Covariates included:						
Country covariates in 1993		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

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. All regressions are unweighted, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 3: 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***	0.559**	1.117***	0.983***	0.777***
	(0.252)	(0.237)	(0.211)	(0.366)	(0.298)	(0.275)
log of GDP per capita in 1993		0.032	-0.015		0.037	-0.024
		(0.030)	(0.023)		(0.052)	(0.055)
log of population in 1993		0.031***	0.015*		0.039***	0.021*
		(0.010)	(0.009)		(0.012)	(0.012)
Robots per thousand workers in 1993			0.076***			0.071***
			(0.011)			(0.022)
Observations	52	52	52	30	30	30
R-squared	0.47	0.59	0.70	0.38	0.54	0.63
	Panel B. IV estimates					
Aging between 1990 and 2025	0.874***	0.767***	0.692***	1.576***	1.018***	0.956***
	(0.263)	(0.241)	(0.217)	(0.473)	(0.316)	(0.298)
log of GDP per capita in 1993		0.028	-0.022		0.036	-0.021
		(0.028)	(0.022)		(0.047)	(0.051)
log of population in 1993		0.031***	0.015*		0.039***	0.021*
		(0.009)	(0.008)		(0.011)	(0.011)
Robots per thousand workers in 1993			0.072***			0.063***
			(0.013)			(0.024)
Observations	52	52	52	30	30	30
First-stage F stat.	25.2	17.8	17.0	7.7	7.1	8.6
Overid $p-$ value	0.67	0.66	0.10	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**	0.613**	1.622***	1.265***	1.088**
	(0.361)	(0.329)	(0.310)	(0.555)	(0.402)	(0.427)
log of GDP per capita in 1993		0.023	-0.018		0.031	-0.018
		(0.031)	(0.022)		(0.051)	(0.055)
log of population in 1993		0.030***	0.015**		0.035***	0.021*
		(0.009)	(0.008)		(0.012)	(0.012)
Robots per thousand workers in 1993			0.074***			0.058**
			(0.013)			(0.028)
Observations	52	52	52	30	30	30
First-stage F stat.	32.4	27.9	24.1	14.6	29.9	23.8
Covariates included:						
Country covariates in 1993		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

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). 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. All regressions are unweighted, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 4: 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. Placebo test					
Aging between 1950 and 1990	-0.098	0.226	0.537	-0.357	0.095	0.325
	(0.378)	(0.411)	(0.351)	(0.587)	(0.456)	(0.355)
Observations	52	52	52	30	30	30
R-squared	0.25	0.42	0.62	0.02	0.26	0.48
	Panel B. Past vs. expected aging					
Aging between 1990 and 2025	0.801^{***}	0.717^{***}	0.524^{**}	1.105^{***}	0.988^{***}	0.777^{**}
	(0.263)	(0.229)	(0.199)	(0.348)	(0.306)	(0.277)
Aging between 1950 and 1990	-0.304	-0.052	0.271	-0.243	0.192	0.330
	(0.377)	(0.329)	(0.259)	(0.436)	(0.315)	(0.301)
Observations	52	52	52	30	30	30
R-squared	0.49	0.59	0.70	0.38	0.54	0.63
	Panel C. Current vs. expected aging					
Aging between 1990 and 2015	0.694^{**}	0.524^{*}	0.427	0.861^{**}	0.688^{*}	0.528
	(0.268)	(0.288)	(0.260)	(0.366)	(0.347)	(0.339)
Aging between 2015 and 2025	0.855^{*}	0.935^{*}	0.719	1.398^{**}	1.320^{**}	1.066^{*}
	(0.442)	(0.520)	(0.517)	(0.527)	(0.564)	(0.573)
Test for equality	0.75	0.54	0.67	0.31	0.38	0.48
Observations	52	52	52	30	30	30
R-squared	0.47	0.59	0.70	0.38	0.55	0.63
Covariates included:						
Country covariates in 1993		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

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: Panel A presents a placebo test 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). Panel B adds 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). Finally, 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. All regressions are unweighted, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 5: 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^{***}	0.611^{***}	0.448^{**}	0.983^{**}	0.776^{***}	0.583^{*}
	(0.291)	(0.218)	(0.206)	(0.440)	(0.273)	(0.323)
Observations	104	104	104	60	60	60
R-squared	0.28	0.48	0.13	0.15	0.39	0.13
	Panel B. IV estimates					
Contemporary aging	1.157^{***}	0.924^{***}	0.797^{*}	1.752^{**}	1.105^{***}	1.122^{*}
	(0.401)	(0.311)	(0.473)	(0.773)	(0.418)	(0.647)
Observations	104	104	104	60	60	60
First-stage F stat.	10.4	6.7	4.1	6.6	4.6	4.2
Overid $p-$ value	0.50	0.16	0.49	0.64	0.38	0.47
Anderson-Rubin Wald test $p-$ value	0.02	0.00	0.14	0.00	0.00	0.00
Covariates included:						
Country covariates in 1993		✓	✓		✓	✓
Initial robot density in 1993		✓	✓		✓	✓
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). 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, 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, and the 1993 value of robots per thousand workers. Columns 3 and 6 include country fixed effects. All regressions are unweighted, and the standard errors are robust against heteroscedasticity and correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 6: 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	2.055**	2.452***	2.181***	2.218*	2.627***	2.587***
	(0.994)	(0.754)	(0.754)	(1.262)	(0.887)	(0.898)
Log of the GDP per capita in 1995		-0.172	-0.422		-0.354	-0.461
		(0.151)	(0.272)		(0.295)	(0.344)
Log of intermediate imports			0.256			0.164
			(0.216)			(0.317)
Observations	131	131	131	34	34	34
R-squared	0.29	0.50	0.52	0.13	0.62	0.62
Panel B. IV estimates						
Aging between 1995 and 2025	1.646	2.693***	2.346***	1.590	2.176**	2.035**
	(1.015)	(0.792)	(0.774)	(1.295)	(0.865)	(0.863)
Log of the GDP per capita in 1995		-0.185	-0.418		-0.334	-0.449
		(0.139)	(0.262)		(0.276)	(0.322)
Log of intermediate imports			0.243			0.181
			(0.216)			(0.269)
Observations	131	131	131	34	34	34
Instruments F-stat	19.77	19.49	12.99	20.82	13.64	12.75
Overid p-value	0.19	0.56	0.35	0.59	0.17	0.10
Dependent variable: log of exports of industrial robots relative to intermediates						
Panel C. OLS estimates						
Aging between 1995 and 2025	5.213***	3.511***	3.916***	5.891***	4.148***	4.609***
	(1.391)	(1.029)	(1.229)	(1.639)	(1.154)	(1.276)
Log of the GDP per capita in 1995		0.462*	0.565**		0.980*	1.002*
		(0.252)	(0.261)		(0.484)	(0.492)
Log of intermediate exports			-0.152			-0.222
			(0.215)			(0.262)
Observations	105	105	105	35	35	35
R-squared	0.66	0.77	0.78	0.45	0.72	0.73
Panel D. IV estimates						
Aging between 1995 and 2025	5.712***	3.827***	4.389***	7.267***	4.934***	5.607***
	(1.518)	(1.122)	(1.428)	(1.668)	(1.100)	(1.200)
Log of the GDP per capita in 1995		0.438*	0.576**		0.975**	1.010**
		(0.229)	(0.248)		(0.455)	(0.457)
Log of intermediate exports			-0.205			-0.347
			(0.215)			(0.249)
Observations	105	105	105	35	35	35
Instruments F-stat	20.88	19.72	12.89	15.71	15.59	9.98
Overid p-value	0.11	0.08	0.06	0.29	0.33	0.33
Covariates included:						
Country covariates in 1995		✓	✓		✓	✓

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 intermediate imports (Panels A and B) or exports (Panels C and D) as an additional covariate. All regressions are weighted by total intermediate imports (Panels A and B) or exports (Panels C and D), and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 7: 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	1.151***	1.173***	1.396***	1.165***	1.208***	1.364***
	(0.239)	(0.118)	(0.188)	(0.232)	(0.122)	(0.200)
Log of the GDP per capita in 1990		-0.075	0.133		-0.099	0.040
		(0.099)	(0.174)		(0.200)	(0.259)
Log of patents at USPTO			-0.121**			-0.103*
			(0.052)			(0.056)
Observations	69	69	69	31	31	31
R-squared	0.53	0.76	0.80	0.50	0.79	0.82
Panel B. IV estimates						
Aging between 1990 and 2025	1.145***	1.137***	1.347***	1.166***	1.161***	1.288***
	(0.215)	(0.102)	(0.175)	(0.219)	(0.132)	(0.201)
Log of the GDP per capita in 1990		-0.081	0.117		-0.120	0.001
		(0.094)	(0.158)		(0.193)	(0.240)
Log of patents at USPTO			-0.115**			-0.095*
			(0.047)			(0.049)
Observations	69	69	69	31	31	31
Instruments F-stat	106.30	41.12	24.06	180.45	53.85	62.78
Overid p-value	0.64	0.23	0.11	0.44	0.26	0.15
Covariates included:						
Country covariates in 1990		✓	✓		✓	✓

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 as an additional covariate. All regressions are weighted by total utility patents granted to each country, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 8: Estimates of the impact of aging on the location of robot integrators in the US.

	Dependent variable: Dummy for presence of robot integrator					
	All commuting zones				Manuf. areas	Other areas
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. OLS estimates			
Aging between 1990 and 2015	0.058	0.335***	0.259**	0.350***	0.702***	0.169*
	(0.168)	(0.103)	(0.101)	(0.099)	(0.221)	(0.091)
Exposure to robots			0.048**	0.049**	0.045	0.016
			(0.020)	(0.020)	(0.028)	(0.021)
Observations	722	722	722	722	361	361
R-squared	0.00	0.44	0.47	0.48	0.51	0.49
			Panel B. IV estimates			
Aging between 1990 and 2015	1.338**	0.642***	0.530**	0.879***	1.636***	0.229
	(0.581)	(0.224)	(0.218)	(0.240)	(0.547)	(0.235)
Exposure to robots			0.042**	0.042**	0.030	0.015
			(0.021)	(0.020)	(0.029)	(0.019)
Observations	722	722	722	722	361	361
First-stage F stat.	4.2	21.5	20.0	22.9	9.8	8.4
Overid $p-$ value	0.00	0.52	0.19	0.65	0.54	0.33
			Panel C. Single-IV estimates			
Aging between 1990 and 2015	2.574***	0.916***	0.784**	1.302***	2.279***	0.359
	(0.823)	(0.286)	(0.309)	(0.372)	(0.759)	(0.440)
Exposure to robots			0.037*	0.037*	0.019	0.013
			(0.021)	(0.020)	(0.029)	(0.021)
Observations	722	722	722	722	361	361
First-stage F stat.	16.4	58.8	61.9	50.9	29.1	22.6
Covariates included:						
Regional dummies	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓	✓
Industry composition			✓	✓	✓	✓
Additional covariates				✓	✓	✓

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, 2016). 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. We present results for three samples: columns 1-4 use the full sample; column 5 focuses on commuting zones with share of employment in manufacturing above the median; and column 6 focuses on commuting zones with share of employment in manufacturing below the median. 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 (2017a) and also controls for the shares of employment in manufacturing, agriculture, mining, construction, and finance and real estate in 1990. Finally, 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. All regressions are unweighted, and in parenthesis we report standard errors that are robust against heteroscedasticity and correlation in the error terms within states. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 9: 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***	3.743***	2.577***		6.734***	4.850***	
	(0.439)	(1.033)	(0.843)		(1.851)	(1.537)	
Aging × reliance on middle-aged		0.900***	0.634***	0.635***	0.264***	0.182**	0.183**
		(0.252)	(0.215)	(0.211)	(0.090)	(0.086)	(0.085)
Aging × opportunities for automation		5.740***	4.052***	4.056***	6.046***	4.440***	4.458***
		(1.752)	(1.465)	(1.451)	(1.681)	(1.356)	(1.340)
Observations	10,602	10,602	10,602	10,602	10,602	10,602	10,602
Countries in sample	50	50	50	50	50	50	50
Panel B. IV estimates.							
Aging between 1990 and 2025	1.430***	3.635***	2.842***		6.585***	5.246***	
	(0.477)	(1.192)	(0.959)		(2.175)	(1.768)	
Aging × reliance on middle-aged		0.952***	0.676***	0.674***	0.327***	0.193**	0.194**
		(0.312)	(0.244)	(0.240)	(0.112)	(0.094)	(0.093)
Aging × opportunities for automation		5.347***	4.927***	4.891***	5.902***	4.835***	4.823***
		(1.935)	(1.617)	(1.599)	(1.986)	(1.594)	(1.575)
Observations	10,602	10,602	10,602	10,602	10602	10,602	10,602
Countries in sample	50	50	50	50	50	50	50
Instruments F-stat	19.1	.	6.1	7.7	.	7.4	8.4
Overid p-value	0.86	0.22	0.46	0.49	0.17	0.15	0.07
Dependent variable: Installation of robots in country-industry pairs normalizing by industry employment from KLEMS							
Panel C. OLS estimates.							
Aging between 1990 and 2025	0.786***	3.789***	2.013**		5.179***	3.455***	
	(0.184)	(1.002)	(0.762)		(1.257)	(1.003)	
Aging × reliance on middle-aged		0.398***	0.442***	0.403***	0.116*	0.171**	0.139*
		(0.129)	(0.123)	(0.126)	(0.065)	(0.071)	(0.073)
Aging × opportunities for automation		8.320***	3.027	3.354*	4.665***	3.018***	3.070***
		(2.415)	(1.793)	(1.759)	(1.159)	(0.900)	(0.885)
Observations	5,833	5,833	5,833	5,833	5,833	5,833	5,833
Countries in sample	21	21	21	21	21	21	21
Panel D. IV estimates.							
Aging between 1990 and 2025	0.849***	4.051***	2.446***		5.817***	4.148***	
	(0.195)	(1.077)	(0.847)		(1.413)	(1.230)	
Aging × reliance on middle-aged		0.466***	0.380**	0.337*	0.182***	0.108	0.072
		(0.134)	(0.179)	(0.181)	(0.063)	(0.107)	(0.109)
Aging × opportunities for automation		8.661***	4.458**	4.810***	5.180***	3.752***	3.814***
		(2.659)	(1.787)	(1.748)	(1.346)	(1.088)	(1.065)
Observations	5,833	5,833	5,833	5,833	5,833	5,833	5,833
Countries in sample	21	21	21	21	21	21	21
Instruments F-stat	32.5	60.6	116.7	23.4	57.1	89.2	19.1
Overid p-value	0.06	0.29	0.38	0.17	0.36	0.30	0.18
Covariates included:							
Country covariates in 1993	✓	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓	✓		✓	✓
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 (2015) 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 industry 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. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 10: 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	-1.447**	0.121	0.387		0.264	0.564	
	(0.552)	(1.182)	(1.038)		(1.122)	(1.019)	
Aging × reliance on middle-aged		-0.246	-0.304	-0.263	-0.238	-0.297	-0.263
		(0.236)	(0.218)	(0.221)	(0.231)	(0.215)	(0.226)
Aging × opportunities for automation		2.932**	3.166**	3.094***	1.119**	1.229**	1.232**
		(1.232)	(1.180)	(0.937)	(0.502)	(0.488)	(0.464)
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	-1.707***	1.318	1.634*		1.138	1.534	
	(0.595)	(1.156)	(0.982)		(1.224)	(1.059)	
Aging × reliance on middle-aged		-0.589**	-0.669***	-0.596**	-0.538**	-0.622**	-0.568*
		(0.261)	(0.241)	(0.300)	(0.263)	(0.246)	(0.318)
Aging × opportunities for automation		4.609***	4.916***	4.330***	1.450***	1.617***	1.523***
		(1.193)	(1.295)	(0.916)	(0.430)	(0.419)	(0.378)
Observations	399	399	399	399	399	399	399
Countries in sample	21	21	21	21	21	21	21
Instruments F-stat	9.49	42.97	10.69	5.58	61.30	20.47	5.65
Overid p-value	0.14	0.47	0.56	0.37	0.32	0.38	0.38
	Dependent variable: Change in the labor share between 1995 and 2007						
	Panel A. OLS estimates						
Aging between 1995 and 2025	-0.335***	-2.528***	-2.586***		-2.928***	-2.997**	
	(0.104)	(0.855)	(0.893)		(1.025)	(1.065)	
Aging × reliance on middle-aged		0.651**	0.664**	0.630**	0.671**	0.685**	0.659**
		(0.245)	(0.251)	(0.260)	(0.254)	(0.260)	(0.273)
Aging × opportunities for automation		-1.057*	-1.109*	-0.923	-0.713**	-0.739**	-0.681**
		(0.576)	(0.599)	(0.563)	(0.293)	(0.304)	(0.305)
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	-0.323***	-3.293***	-3.207***		-4.026***	-3.982***	
	(0.121)	(0.864)	(0.868)		(1.144)	(1.151)	
Aging × reliance on middle-aged		0.998***	0.993***	1.038***	1.035***	1.034***	1.103***
		(0.289)	(0.292)	(0.344)	(0.308)	(0.311)	(0.365)
Aging × opportunities for automation		-0.540	-0.449	-0.395	-0.857***	-0.859***	-0.922***
		(0.534)	(0.631)	(0.547)	(0.253)	(0.276)	(0.345)
Observations	399	399	399	399	399	399	399
Countries in sample	21	21	21	21	21	21	21
Instruments F-stat	9.49	42.97	10.69	5.58	61.30	20.47	5.65
Overid p-value	0.31	0.74	0.74	0.64	0.44	0.51	0.35
Covariates included:							
Country covariates in 1995	✓	✓	✓	✓	✓	✓	✓
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 (2015) 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. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

APPENDIX: OMITTED PROOFS

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

$$1 = C(W^E(\phi,\Theta),V^E(\phi,\Theta),P), \tag{A1}$$

$$\frac{1-\phi}{\phi} = \frac{C_W(W^E(\phi,\Theta),V^E(\phi,\Theta),P)}{C_V(W^E(\phi,\Theta),V^E(\phi,\Theta),P)}, \tag{A2}$$

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

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

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

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

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.[39]

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:

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

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[39] 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

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

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 $\alpha(i)\rho(i)$.[40] ■

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

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[40] 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:

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

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.

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 the previous 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 much easier for the technology monopolists in country U. We capture this by positing:

$$\begin{aligned}\rho^U(i) =& \rho(i;\theta^J(i))\\ \rho^J(i) =& \rho(i),\end{aligned}$$

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* $\phi^J > \widetilde{\phi}^J$ *and* $\overline{\phi}^U(\Theta = \{0\}_{i\in\mathcal{I}}) > \phi^U > \widetilde{\phi}^U$. *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 $\overline{\phi}^U(\Theta = \{0\}_{i\in\mathcal{I}}) > \phi^U > \widetilde{\phi}^U$, 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. ■

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 10, 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 846899, 845700 to 845799, and 851500 to 851599), 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 instruments*: For regulating instruments (six-digit HS codes 902500-903299), the HS classification distinguishes those that are "automatic" from the rest. Based on this distinction we create two separate categories: *automatic regulating instruments* and *other regulating instruments*. Both 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."

Appendix Figures and Tables

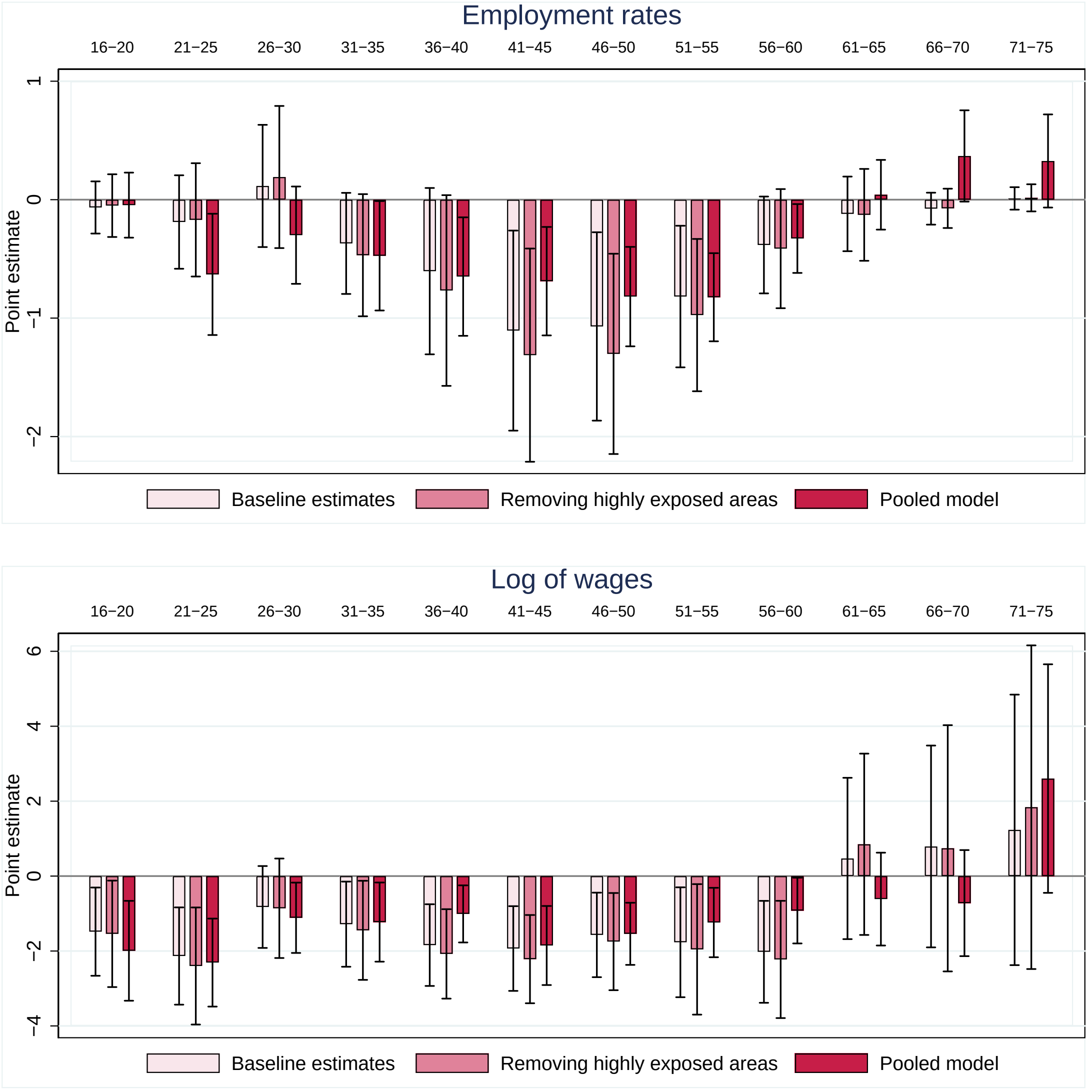

Figure A1: The figure presents estimates of the impact of one additional robot per thousand workers on the employment and wages of people in different age groups. These estimates are computed by exploiting differences in the exposure to robots across US commuting zones. The three specifications and the data used are described in the main text and in Acemolgu and Restrepo (2017a).

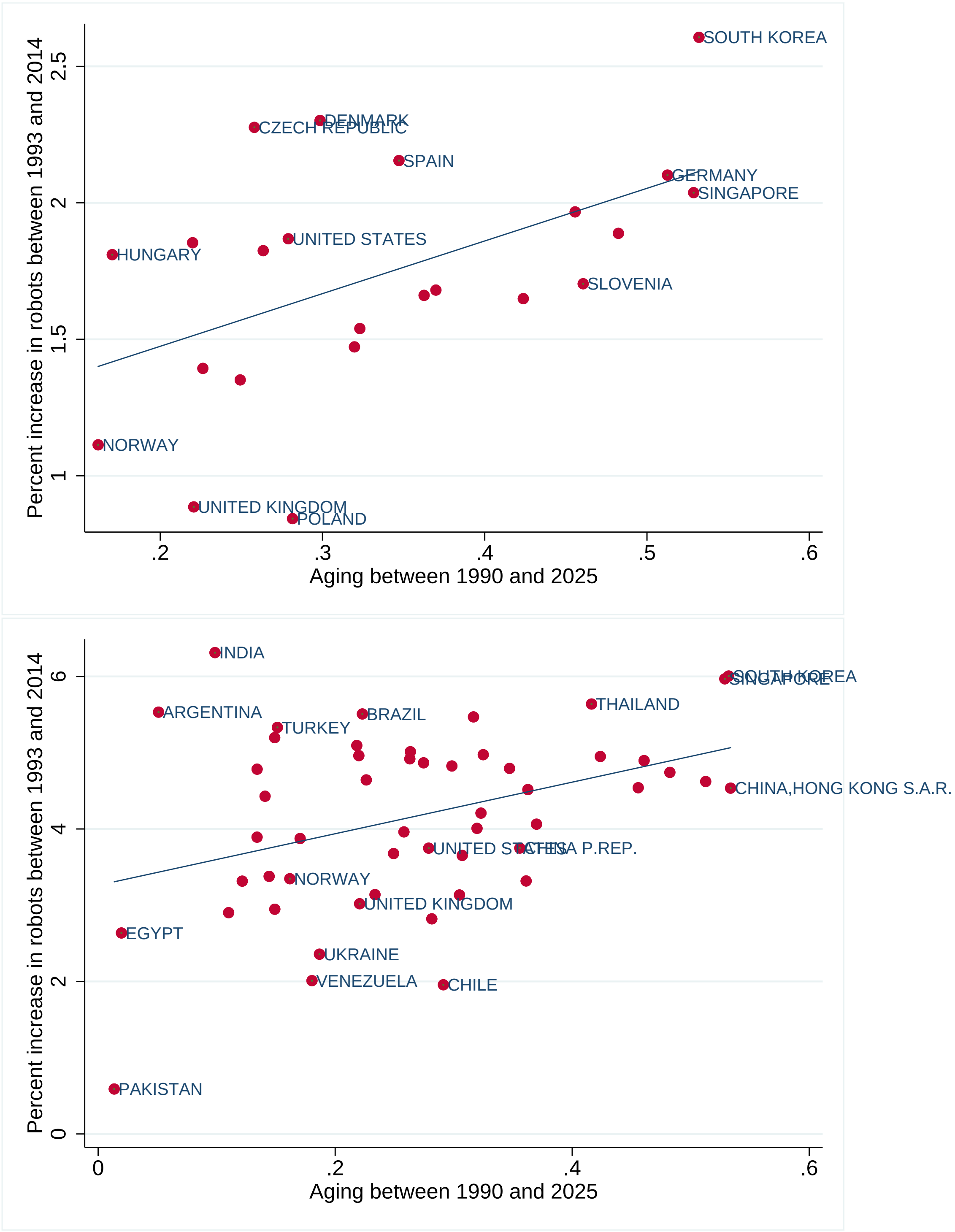

Figure A2: Residual plots of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the increase in the number of industrial robots per thousand workers between 1993 and 2014. The plots partial out the covariates included in the regression models in columns 2 and 5 of Table A9.

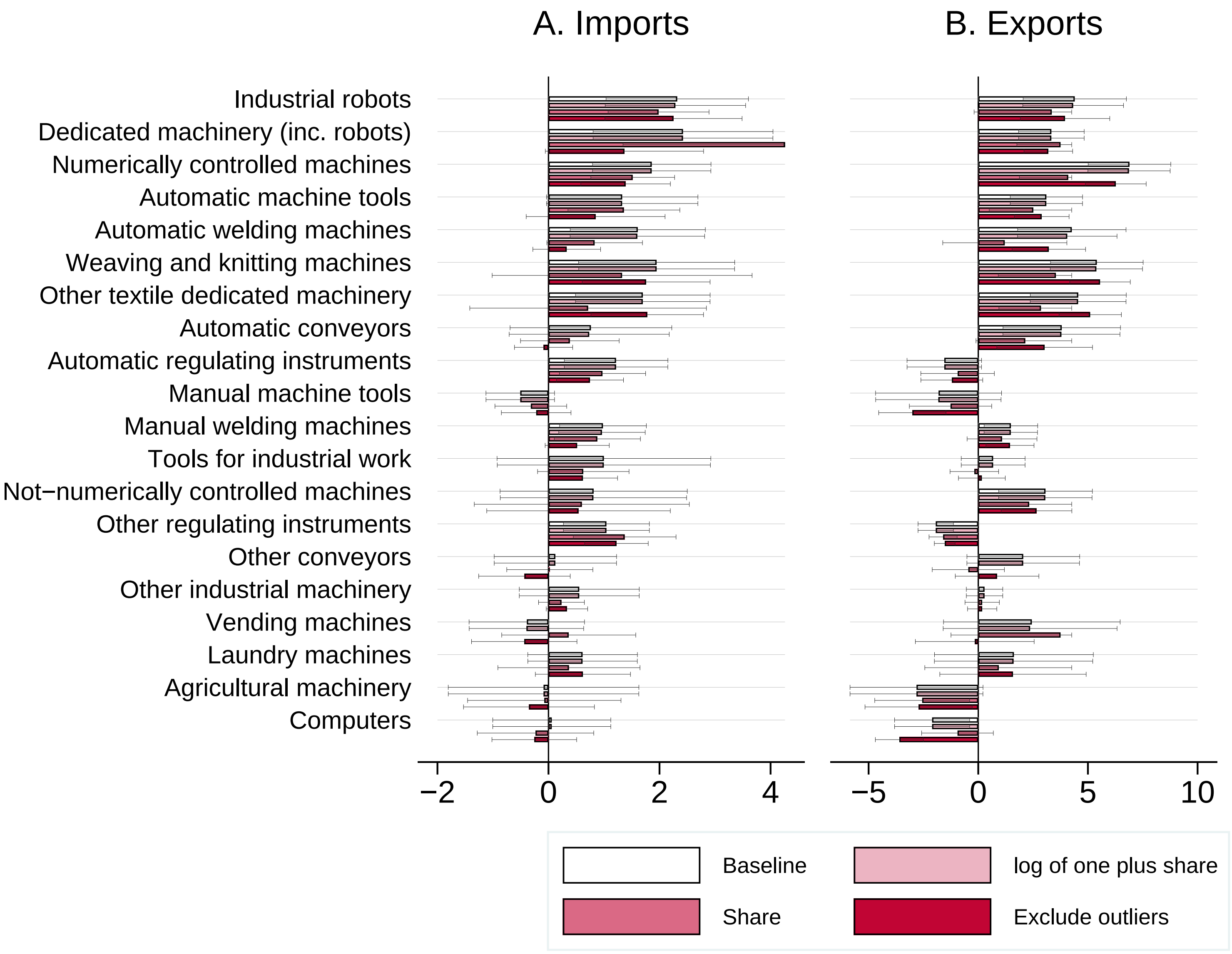

Figure A3: Estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and exports (left panel) and imports (right panel) of different intermediate goods between 1990 and 2015. These outcomes are normalized by the total intermediate 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).

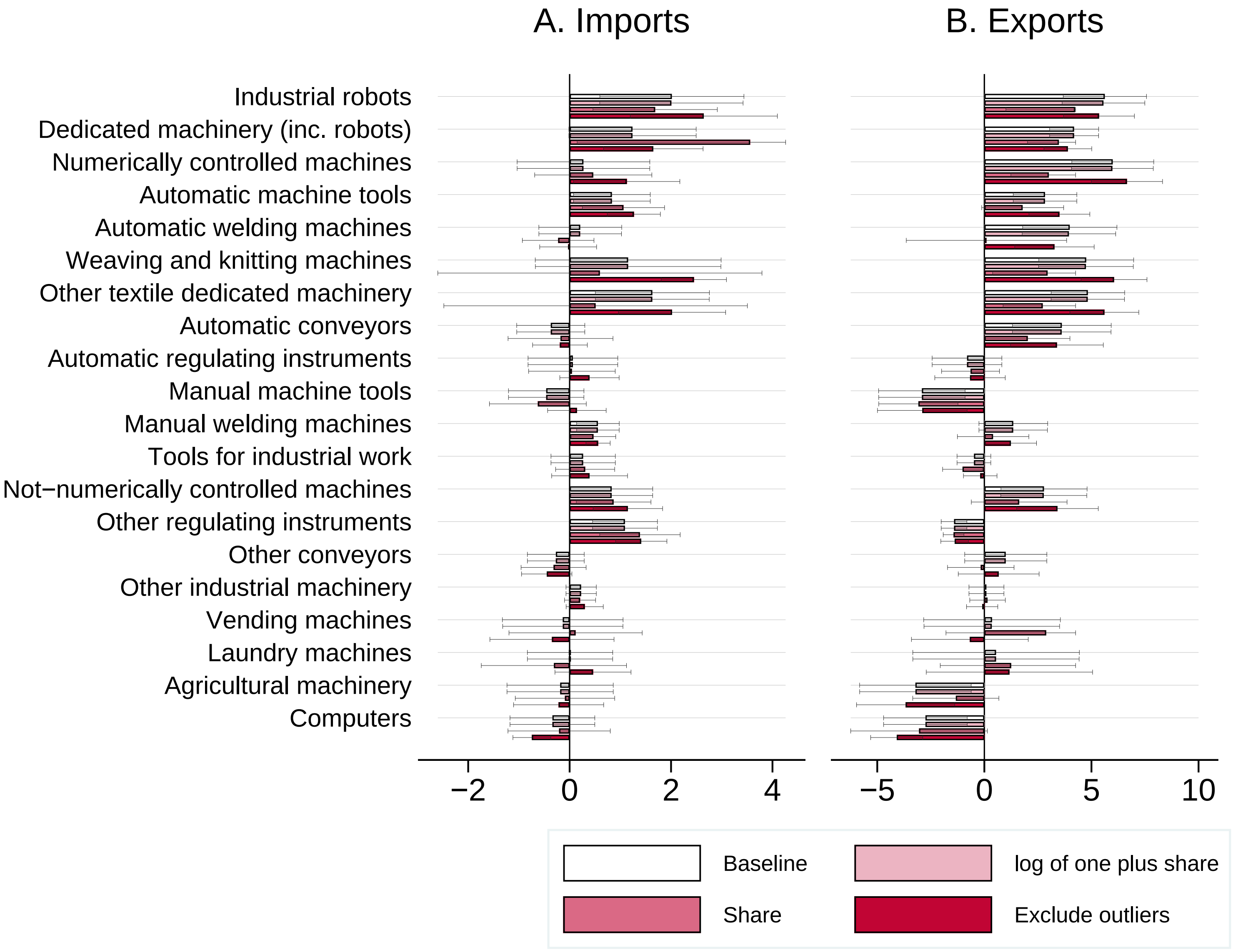

FIGURE A4: OECD estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and exports (left panel) and imports (right panel) of different intermediate goods between 1990 and 2015. These outcomes are normalized by the total intermediate 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).

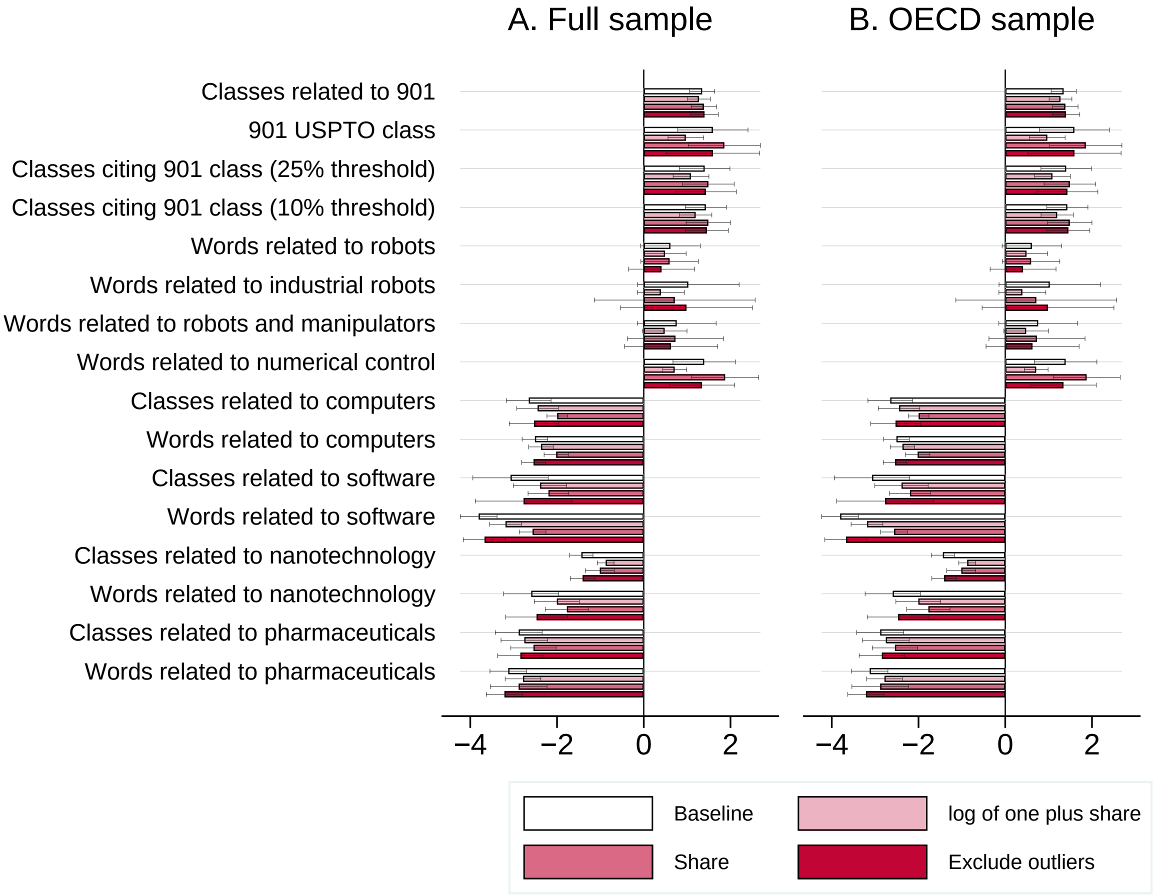

Figure A5: Estimates of the relationship between aging (change in the ratio of workers above 56 to workers aged 21-55 between 1990 and 2025) and the log of patents with different characteristics between 1990 and 2015. These outcomes are normalized by the total patents granted by the USPTO during this 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).

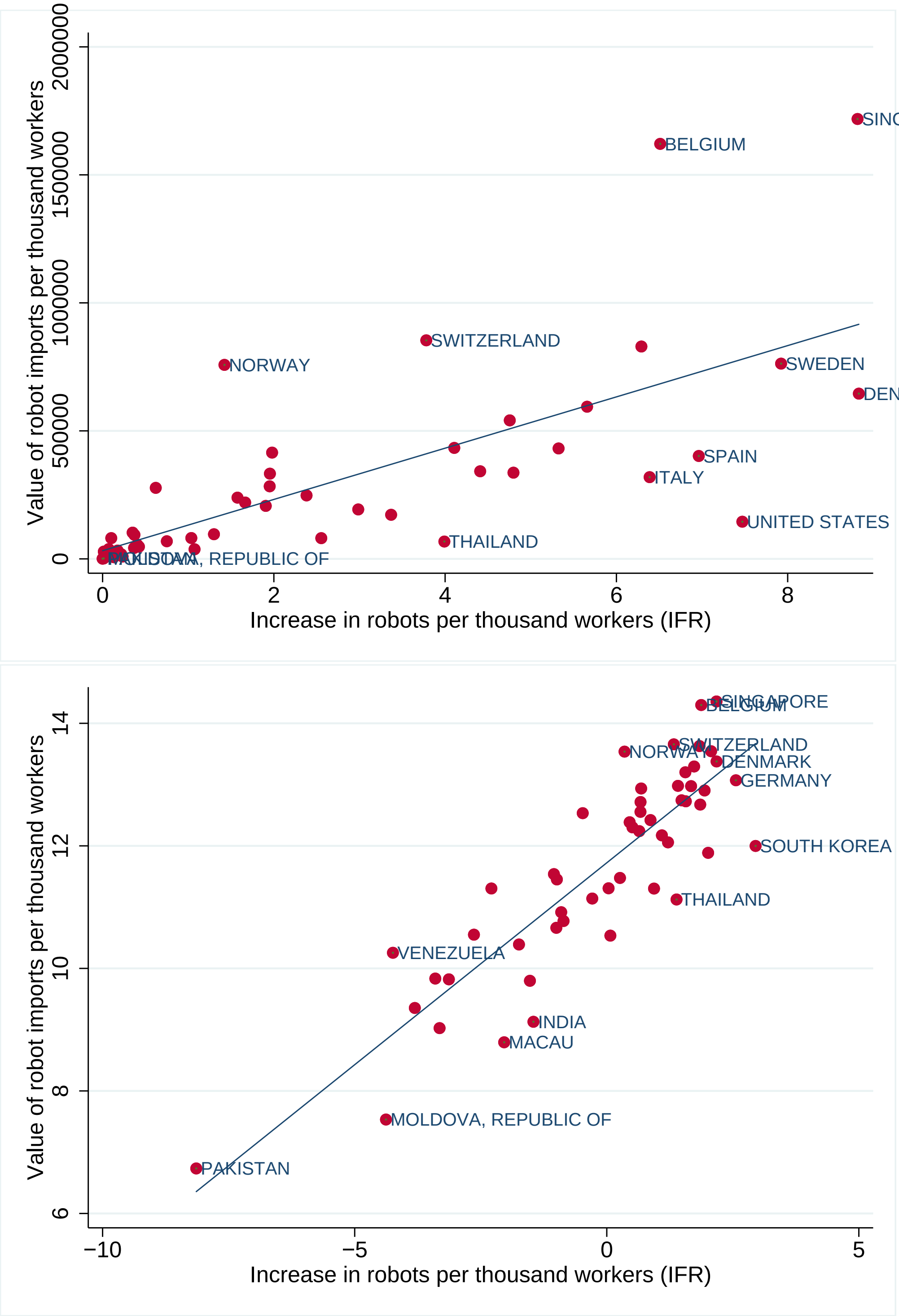

FIGURE A6: Scatter plots of the relationship between imports of robots per thousand workers (in 2007 dollars, from Comtrade) and the increase in the number of industrial robots per thousand workers between 1993 and 2014, both in levels and in logs.

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 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 (2015). Section 3 in the main text describes the sources of the data.

Table A3: 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 (1)	OECD (2)	All countries (3)	OECD (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:				
Country covariates in 1993	✓	✓	✓	✓

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 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 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. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A4: 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	0.810***	0.745***	0.452**	1.181**	0.775***	0.587**
	(0.271)	(0.239)	(0.201)	(0.431)	(0.265)	(0.279)
Change in population	0.141	0.063	-0.190	0.143	-0.392	-0.361
between 1990 and 2015	(0.172)	(0.291)	(0.261)	(0.245)	(0.442)	(0.449)
Observations	52	52	52	30	30	30
R-squared	0.48	0.59	0.70	0.38	0.55	0.64
	Panel B. IV estimates					
Aging between 1990 and 2025	0.899***	0.851**	0.705**	1.573***	0.771*	0.890**
	(0.297)	(0.331)	(0.290)	(0.522)	(0.424)	(0.420)
Change in population	0.168	0.158	0.036	0.278	-0.395	-0.104
between 1990 and 2015	(0.170)	(0.346)	(0.288)	(0.289)	(0.502)	(0.471)
Observations	52	52	52	30	30	30
First-stage F stat.	19.1	7.1	6.7	4.1	5.1	6.0
Overid $p-$ value	0.28	0.60	0.10	0.56	0.31	0.12
Anderson-Rubin Wald test $p-$ value	0.01	0.06	0.00	0.04	0.05	0.00
	Panel C. Single-IV estimates					
Aging between 1990 and 2025	1.009***	0.921**	0.579	1.549***	1.327**	1.156*
	(0.349)	(0.427)	(0.412)	(0.477)	(0.644)	(0.646)
Change in population	0.201	0.220	-0.077	0.269	0.111	0.123
between 1990 and 2015	(0.173)	(0.358)	(0.334)	(0.270)	(0.607)	(0.548)
Observations	52	52	52	30	30	30
First-stage F stat.	38.0	26.4	24.3	26.6	11.2	10.0
Covariates included:						
Country covariates in 1993		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

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. All regressions are unweighted, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

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**	0.311***	0.590**	0.419***
	(0.172)	(0.104)	(0.210)	(0.135)
Observations	51	51	29	29
	Panel B. Removing outliers based on residuals			
Aging between 1990 and 2025	0.502***	0.336***	0.679***	0.432***
	(0.166)	(0.098)	(0.194)	(0.118)
Observations	50	49	28	27
	Panel C. Quantile (median) regression			
Aging between 1990 and 2025	0.544**	0.295**	0.684***	0.427
	(0.214)	(0.127)	(0.240)	(0.268)
Observations	52	52	30	30
	Panel D. Huber M-regression			
Aging between 1990 and 2025	0.498***	0.369***	0.796***	0.511**
	(0.170)	(0.129)	(0.267)	(0.238)
Observations	52	52	30	30
	Panel E. Robust regression			
Aging between 1990 and 2025	0.312**	0.297**	0.578**	0.402*
	(0.139)	(0.113)	(0.237)	(0.208)
Observations	52	52	29	29
	Panel F. Reweighting by employment in industry			
Aging between 1990 and 2025	0.931***	0.683***	1.508***	1.301***
	(0.231)	(0.202)	(0.176)	(0.315)
Observations	52	52	30	30
Country covariates in 1993	✓	✓	✓	✓
Initial robot density in 1993		✓		✓

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 estimates weighted by employment in industry. Panel C presents quantile (median) regressions. Panel D presents a Huber-M estimator. Panel E presents a robust regression. 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. The standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

TABLE A6: 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^{***}	0.780^{**}	1.463^{**}	1.295^{**}	0.964^{**}
	(0.393)	(0.351)	(0.298)	(0.616)	(0.478)	(0.417)
log of GDP per capita in 1993		0.053^{*}	-0.002		0.076	-0.006
		(0.030)	(0.024)		(0.057)	(0.054)
Robots per thousand workers in 1993			0.081^{***}			0.083^{***}
			(0.011)			(0.021)
Observations	52	52	52	30	30	30
R-squared	0.43	0.54	0.67	0.24	0.44	0.56
	Panel B. IV estimates					
Aging between 1990 and 2015	1.409^{***}	1.192^{***}	1.087^{***}	2.574^{***}	1.305^{***}	1.086^{***}
	(0.393)	(0.363)	(0.304)	(0.941)	(0.450)	(0.387)
log of GDP per capita in 1993		0.046^{*}	-0.010		0.076	-0.001
		(0.027)	(0.023)		(0.050)	(0.048)
Robots per thousand workers in 1993			0.077^{***}			0.081^{***}
			(0.013)			(0.021)
Observations	52	52	52	30	30	30
First-stage F stat.	16.8	10.4	10.3	3.2	3.9	4.3
Overid $p-$ value	0.45	0.73	0.12	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^{**}	1.561^{*}	5.110^{**}	3.101^{***}	2.756^{**}
	(0.943)	(0.895)	(0.842)	(2.391)	(1.156)	(1.277)
log of GDP per capita in 1993		0.015	-0.021		0.103	0.056
		(0.042)	(0.032)		(0.079)	(0.092)
Robots per thousand workers in 1993			0.069^{***}			0.046
			(0.019)			(0.047)
Observations	52	52	52	30	30	30
First-stage F stat.	13.4	12.4	10.2	3.6	12.8	7.8
Covariates included:						
Country covariates in 1993		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

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). 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. All regressions are unweighted, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A7: 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***	0.891**
	(0.275)	(0.275)	(0.259)	(0.304)	(0.338)	(0.336)
Baseline union density	0.243**	0.260**	0.179	0.435***	0.431***	0.348**
	(0.094)	(0.101)	(0.111)	(0.125)	(0.126)	(0.138)
log of hourly wages in 1993		0.129	0.071		0.186	0.152
		(0.104)	(0.102)		(0.182)	(0.194)
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***	0.913***	1.232***	1.231***	1.188***
	(0.279)	(0.263)	(0.227)	(0.296)	(0.329)	(0.333)
Baseline union density	0.237***	0.260***	0.207**	0.446***	0.455***	0.407***
	(0.073)	(0.081)	(0.091)	(0.109)	(0.112)	(0.119)
log of hourly wages in 1993		0.129	0.083		0.142	0.094
		(0.087)	(0.087)		(0.153)	(0.166)
Observations	46	46	46	30	30	30
First-stage F stat.	11.6	11.0	10.9	5.0	5.7	6.5
Overid $p-$ value	0.13	0.15	0.05	0.59	0.55	0.40
	Panel C. Single-IV estimates					
Aging between 1990 and 2025	1.146**	1.187***	1.003**	1.645***	1.635***	1.543***
	(0.447)	(0.439)	(0.459)	(0.425)	(0.453)	(0.501)
Baseline union density	0.278***	0.299***	0.227*	0.514***	0.515***	0.479***
	(0.103)	(0.109)	(0.121)	(0.145)	(0.144)	(0.144)
log of hourly wages in 1993		0.141	0.091		0.034	0.026
		(0.097)	(0.097)		(0.209)	(0.206)
Observations	46	46	46	30	30	30
First-stage F stat.	15.0	15.0	13.6	16.1	13.4	13.1
Covariates included:						
Country covariates in 1993	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓			✓

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. All regressions are unweighted, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A8: 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***	0.640**	1.785***	1.519***	0.949***
	(0.405)	(0.385)	(0.244)	(0.482)	(0.427)	(0.312)
Robots per thousand workers in 1993			0.317***			0.253***
			(0.072)			(0.091)
Observations	1,144	1,144	1,144	660	660	660
Countries	52	52	52	30	30	30
R-squared	0.40	0.53	0.73	0.20	0.55	0.71
	Panel B. IV estimates					
Aging between 1990 and 2025	1.540***	1.050***	0.795***	2.619***	1.472***	1.169***
	(0.435)	(0.375)	(0.251)	(0.533)	(0.459)	(0.345)
Robots per thousand workers in 1993			0.312***			0.244***
			(0.064)			(0.082)
Observations	1,144	1,144	1,144	660	660	660
Countries	52	52	52	30	30	30
First-stage F stat.	29.0	20.8	19.9	10.0	9.4	11.6
Overid $p-$ value	0.60	0.86	0.12	0.89	0.75	0.10
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**	0.671*	2.840***	1.865***	1.314***
	(0.541)	(0.531)	(0.366)	(0.721)	(0.509)	(0.489)
Robots per thousand workers in 1993			0.316***			0.238***
			(0.064)			(0.083)
Observations	1,144	1,144	1,144	660	660	660
Countries	52	52	52	30	30	30
First-stage F stat.	32.5	28.0	24.3	15.1	30.1	24.0
Covariates included:						
Country covariates in 1993		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

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). 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. All regressions are unweighted and the standard errors are robust against heteroscedasticity and correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A9: 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)
	Panel A. OLS estimates			
Aging between 1990 and 2025	2.170**	1.929**	3.268**	3.382**
	(0.910)	(0.782)	(1.428)	(1.466)
Robots per thousand workers in 1993	-0.619***	-0.527***	-1.103***	-1.091***
	(0.119)	(0.148)	(0.135)	(0.136)
log of GDP per capita in 1993		-0.337		0.322
		(0.229)		(0.335)
Observations	23	23	52	52
R-squared	0.70	0.75	0.85	0.87
	Panel B. IV estimates			
Aging between 1990 and 2025	2.422*	2.554**	3.728*	4.479**
	(1.296)	(1.050)	(2.125)	(2.214)
Robots per thousand workers in 1993	-0.628***	-0.557***	-1.110***	-1.099***
	(0.112)	(0.117)	(0.131)	(0.122)
log of GDP per capita in 1993		-0.318		0.261
		(0.196)		(0.319)
Observations	23	23	52	52
First-stage F stat.	6.4	3.6	23.4	14.7
Overid $p-$ value	0.03	0.09	0.14	0.03
	Panel C. Single-IV estimates			
Aging between 1990 and 2025	2.280	4.451**	6.806***	5.676**
	(1.563)	(2.025)	(2.565)	(2.585)
Robots per thousand workers in 1993	-0.623***	-0.648***	-0.993***	-1.190***
	(0.114)	(0.148)	(0.122)	(0.151)
log of GDP per capita in 1993		-0.261		0.682
		(0.248)		(0.474)
Observations	23	23	53	52
First-stage F stat.	16.8	9.7	28.2	44.9
Country covariates in 1993		✓		✓

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 1-2, it is the change in the log of the stock of industrial robots between 1993 and 2014 (from the IFR). In columns 1-2, 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). 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. Columns 2 and 4 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, and the 1993 value of robots per thousand workers. All regressions are unweighted, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

TABLE A10: Robustness analysis of the impact of aging on imports and exports of robots.

	BASELINE		LOG OF ONE PLUS SHARE		SHARE OF ROBOTS		EXCLUDE OUTLIERS	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
Panel A. Imports of robots for the full sample								
Aging between 1995 and 2025	2.181^{***}	2.346^{***}	2.172^{***}	2.312^{***}	5.172^{***}	5.225^{***}	2.212^{***}	2.259^{***}
	(0.754)	(0.774)	(0.747)	(0.764)	(1.680)	(1.439)	(0.748)	(0.762)
Observations	131	131	136	136	136	136	119	119
R-squared	0.52	0.52	0.53	0.53	0.52	0.52	0.54	0.54
Instruments F-stat		13.0		13.1		13.1		12.7
Overid p-value		0.35		0.35		0.46		0.49
Panel B. Imports of robots for the OECD sample								
Aging between 1995 and 2025	2.587^{***}	2.035^{**}	2.574^{***}	2.024^{**}	1.969^{**}	1.470^{**}	2.603^{***}	2.132^{**}
	(0.898)	(0.863)	(0.894)	(0.859)	(0.762)	(0.663)	(0.877)	(0.831)
Observations	34	34	34	34	34	34	31	31
R-squared	0.62	0.62	0.62	0.62	0.56	0.55	0.68	0.67
Instruments F-stat		12.8		12.8		12.8		12.6
Overid p-value		0.10		0.10		0.12		0.12
Panel C. Exports of robots for the full sample								
Aging between 1995 and 2025	3.916^{***}	4.389^{***}	3.833^{***}	4.317^{***}	2.266^{*}	1.811	3.939^{***}	4.419^{***}
	(1.229)	(1.428)	(1.194)	(1.392)	(1.188)	(1.163)	(1.239)	(1.432)
Observations	105	105	138	138	138	138	96	96
R-squared	0.78	0.78	0.78	0.78	0.15	0.15	0.78	0.78
Instruments F-stat		12.9		13.9		13.9		12.5
Overid p-value		0.06		0.07		0.23		0.06
Panel D. Exports of robots for the OECD sample								
Aging between 1995 and 2025	4.609^{***}	5.607^{***}	4.563^{***}	5.544^{***}	4.563^{*}	5.285^{**}	4.697^{***}	5.673^{***}
	(1.276)	(1.200)	(1.268)	(1.192)	(2.476)	(2.486)	(1.278)	(1.181)
Observations	35	35	35	35	35	35	33	33
R-squared	0.73	0.72	0.73	0.72	0.47	0.47	0.74	0.73
Instruments F-stat		10.0		10.0		10.0		9.5
Overid p-value		0.33		0.32		0.39		0.33
Country covariates in 1995	✓	✓	✓	✓	✓	✓	✓	✓

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, and the log of intermediate imports (Panels A and B) or exports (Panels C and D). All regressions are weighted by total intermediate imports (Panels A and B) or exports (Panels C and D), and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A11: Robustness analysis of the impact of aging on robotics-related patents.

	Baseline		log of one plus share		Share of robots		Exclude outliers	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
	Panel A. Robotics-related patents for the full sample							
Aging between 1990 and 2025	1.396***	1.347***	1.300***	1.274***	1.422***	1.381***	1.402***	1.353***
	(0.188)	(0.175)	(0.160)	(0.159)	(0.158)	(0.177)	(0.192)	(0.178)
Observations	69	69	126	126	126	126	64	64
R-squared	0.80	0.80	0.75	0.75	0.68	0.68	0.81	0.81
Instruments F-stat		24.1		29.7		29.7		23.3
Overid p-value		0.11		0.11		0.12		0.10
	Panel B. Robotics related patents for the OECD sample							
Aging between 1990 and 2025	1.364***	1.288***	1.269***	1.204***	1.662***	1.577***	1.365***	1.289***
	(0.200)	(0.201)	(0.178)	(0.183)	(0.222)	(0.235)	(0.204)	(0.202)
Observations	31	31	35	35	35	35	29	29
R-squared	0.82	0.82	0.79	0.79	0.82	0.82	0.82	0.82
Instruments F-stat		62.8		66.3		66.3		59.8
Overid p-value		0.15		0.10		0.29		0.13
Country covariates in 1990	✓	✓	✓	✓	✓	✓	✓	✓

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, and the log of total utility patents. All regressions are weighted by total utility patents, and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A12: Robustness analysis for the IV estimates of aging on the location of robot integrators in the US.

	Dependent variable: Location of robot integrator					
	All commuting zones				Manuf. areas	Other areas
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Log of one plus size of integrators					
Aging between 1990 and 2015	4.334*	1.271	0.534	2.380**	3.891*	1.436
	(2.454)	(1.020)	(1.047)	(1.060)	(2.158)	(1.174)
Observations	722	722	722	722	361	361
First-stage F stat.	4.2	21.5	20.0	22.9	9.8	8.4
Overid $p-$ value	0.00	0.40	0.13	0.65	0.71	0.36
	Panel B. Baseline specification removing outliers					
Aging between 1990 and 2015	1.765***	0.657***	0.468*	0.993***	1.541***	0.256
	(0.568)	(0.211)	(0.246)	(0.231)	(0.424)	(0.173)
Observations	703	688	682	686	342	339
First-stage F stat.	5.4	21.4	18.6	25.3	9.2	8.1
Overid $p-$ value	0.00	0.17	0.14	0.89	0.10	0.74
	Panel C. Baseline specification weighting by population					
Aging between 1990 and 2015	-2.683*	2.404***	2.449**	1.435	2.380***	-0.618
	(1.621)	(0.843)	(1.028)	(1.046)	(0.678)	(1.520)
Observations	722	722	722	722	361	361
First-stage F stat.	4.6	8.2	4.8	10.7	9.9	9.2
Overid $p-$ value	0.00	0.20	0.25	0.10	0.30	0.07
Covariates included:						
Regional dummies	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓	✓
Industry composition			✓	✓	✓	✓
Additional covariates				✓	✓	✓

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 panel A, the dependent variable is the log of one plus the number of employees in robot integrators (from Leigh and Kraft, 2016). In panels B and C, the dependent variable is a dummy for the presence of robot integrators in each US commuting zone (from Leigh and Kraft, 2016). 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). All panels present IV estimates, where the aging variable 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. We present results for three samples: columns 1-4 use the full sample; column 5 focuses on commuting zones with share of employment in manufacturing above the median; and column 6 focuses on commuting zones with share of employment in manufacturing below the median. 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 (2017a) and also controls for the shares of employment in manufacturing, agriculture, mining, construction, and finance and real estate in 1990. Finally, 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. The regressions in panel B are weighted by population, 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. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A13: 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 industry employment from UNIDO							
Panel A. OLS estimates							
Aging between 1990 and 2025	3.765^{**}	11.395^{**}	8.624^{**}		10.232^{***}	7.739^{**}	
	(1.425)	(4.427)	(3.434)		(3.703)	(3.052)	
Aging × reliance on middle-aged		3.814^{**}	2.934^{**}	3.023^{**}	0.984^{**}	0.848^{*}	1.028^{*}
		(1.421)	(1.187)	(1.169)	(0.383)	(0.457)	(0.511)
Aging × opportunities for automation		35.509^{**}	28.337^{**}	26.000^{**}	7.871^{**}	5.895^{**}	5.649^{**}
		(16.850)	(13.007)	(11.962)	(2.965)	(2.335)	(2.194)
Observations	5,866	5,866	5,866	5,866	5866	5,866	5,866
Countries in sample	44	44	44	44	44	44	44
Panel B. IV estimates							
Aging between 1990 and 2025	4.032^{***}	13.055^{***}	10.438^{***}		11.924^{***}	9.250^{***}	
	(1.524)	(4.823)	(3.949)		(4.102)	(3.550)	
Aging × reliance on middle-aged		4.538^{***}	3.465^{***}	3.538^{***}	1.065^{**}	0.755^{*}	1.019^{**}
		(1.556)	(1.316)	(1.318)	(0.421)	(0.421)	(0.501)
Aging × opportunities for automation		40.220^{**}	38.568^{**}	33.033^{**}	9.731^{***}	7.728^{***}	7.239^{***}
		(18.711)	(15.356)	(13.906)	(3.492)	(2.962)	(2.750)
Observations	5,866	5,866	5,866	5,866	5866	5,866	5,866
Countries in sample	44	44	44	44	44	44	44
Instruments F-stat	17.9	11.5	8.8	13.4	8.7	10.7	7.7
Overid p-value	0.57	0.22	0.04	0.68	0.25	0.10	0.35
Covariates included:							
Country covariates in 1993	✓	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓	✓		✓	✓
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 (2015) 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 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. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A14: 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. Placebo test						
Past aging between 1950 and 1990	-0.053	0.368	1.643		1.342	3.648	
	(0.743)	(1.788)	(1.305)		(3.115)	(2.432)	
Past aging × reliance on middle-aged		0.316	0.472	0.467	0.123	0.055	0.057
		(0.445)	(0.334)	(0.336)	(0.171)	(0.121)	(0.121)
Past aging × opportunities for automation		-0.404	2.912	2.822	1.532	3.857	3.797
		(3.209)	(2.362)	(2.384)	(2.808)	(2.308)	(2.328)
Observations	10,602	10,602	10,602	10,602	10,602	10,602	10,602
Countries in sample	50	50	50	50	50	50	50
	Panel B. Past vs. expected aging						
Aging between 1990 and 2025	1.598***	3.801***	2.527***		6.794***	4.712***	
	(0.421)	(0.989)	(0.796)		(1.776)	(1.448)	
Aging × reliance on middle-aged		0.899***	0.617***	0.618***	0.262***	0.181**	0.182**
		(0.240)	(0.203)	(0.200)	(0.085)	(0.084)	(0.083)
Aging × opportunities for automation		5.889***	3.957***	3.964***	6.078***	4.285***	4.303***
		(1.681)	(1.400)	(1.387)	(1.617)	(1.273)	(1.257)
Past aging between 1950 and 1990	-0.573	-0.892	0.743		-0.923	1.833	
	(0.739)	(1.712)	(1.242)		(2.915)	(2.260)	
Past aging × reliance on middle-aged		0.014	0.257	0.256	0.035	0.002	0.002
		(0.400)	(0.303)	(0.307)	(0.155)	(0.114)	(0.114)
Past aging × opportunities for automation		-2.382	1.422	1.410	-0.510	2.171	2.144
		(3.104)	(2.256)	(2.304)	(2.573)	(2.115)	(2.149)
Observations	10,602	10,602	10,602	10,602	10,602	10,602	10,602
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
Covariates included:							
Country covariates in 1993	✓	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓	✓		✓	✓
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 (2015) 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. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A15: 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***	0.909***	0.534***		1.589***	1.038***	
	(0.111)	(0.219)	(0.174)		(0.356)	(0.273)	
Aging × reliance on middle-aged		0.174***	0.113***	0.114***	0.028	0.013	0.014
		(0.042)	(0.035)	(0.034)	(0.018)	(0.020)	(0.019)
Aging × opportunities for automation		1.545***	0.816*	0.828*	1.419***	0.968***	0.982***
		(0.488)	(0.464)	(0.456)	(0.325)	(0.232)	(0.229)
Observations	10,602	10,602	10,602	10,602	10,602	10,602	10,602
Countries in sample	50	50	50	50	50	50	50
				Panel B. IV estimates			
Aging between 1990 and 2025	0.329***	0.761***	0.544***		1.372***	1.017***	
	(0.111)	(0.235)	(0.191)		(0.396)	(0.313)	
Aging × reliance on middle-aged		0.170***	0.111***	0.111***	0.040**	0.014	0.015
		(0.050)	(0.040)	(0.039)	(0.020)	(0.021)	(0.020)
Aging × opportunities for automation		1.222**	0.975**	0.957**	1.244***	0.956***	0.954***
		(0.504)	(0.444)	(0.434)	(0.366)	(0.277)	(0.273)
Observations	10,602	10,602	10,602	10,602	10,602	10,602	10,602
Countries in sample	50	50	50	50	50	50	50
Instruments F-stat	19.1	.	6.7	7.9	.	6.4	8.9
Overid p-value	0.63	0.08	0.34	0.38	0.11	0.15	0.06
Covariates included:							
Country covariates in 1993	✓	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓	✓		✓	✓
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 (2015) 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 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. The standard errors are robust against heteroscedasticity and correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A16: 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^{***}	1.342^{***}	0.757^{***}		3.615^{***}	1.948^{***}	
	(0.162)	(0.315)	(0.236)		(0.501)	(0.371)	
Aging × reliance on middle-aged		0.243^{***}	0.153^{***}	0.151^{***}	0.082^{**}	0.032	0.036
		(0.060)	(0.045)	(0.050)	(0.032)	(0.032)	(0.035)
Aging × opportunities for automation		2.304^{***}	1.280^{*}	1.257^{*}	3.283^{***}	1.827^{***}	1.973^{***}
		(0.691)	(0.697)	(0.727)	(0.469)	(0.322)	(0.429)
Observations	10290	10282	10336	10348	10260	10330	10345
Countries in sample	50	50	50	50	50	50	50
	Panel B. IV estimates						
Aging between 1990 and 2025	0.410^{***}	1.294^{***}	0.782^{***}		3.487^{***}	1.953^{***}	
	(0.151)	(0.304)	(0.222)		(0.529)	(0.390)	
Aging × reliance on middle-aged		0.249^{***}	0.150^{***}	0.145^{***}	0.100^{***}	0.039	0.044
		(0.059)	(0.044)	(0.048)	(0.038)	(0.037)	(0.039)
Aging × opportunities for automation		1.916^{***}	1.490^{**}	1.587^{**}	3.094^{***}	1.810^{***}	1.968^{***}
		(0.707)	(0.631)	(0.672)	(0.534)	(0.380)	(0.522)
Observations	10287	10282	10336	10351	10260	10331	10345
Countries in sample	50	50	50	50	50	50	50
Instruments F-stat	28.6	26.0	10.5	12.8	16.9	13.0	13.5
Overid p-value	0.14	0.24	0.43	0.28	0.17	0.52	0.19
Covariates included:							
Country covariates in 1993	✓	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓	✓		✓	✓
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 (2015) 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 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. The standard errors are robust against heteroscedasticity and correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A17: IV estimates of the impact of aging on value added and the labor share for country-industry pairs using STAN data.

		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Change in value added between 1995 and 2007						
Aging between 1995 and 2025	-2.072***	0.572	0.982		0.619	0.873	
	(0.480)	(0.970)	(0.828)		(1.043)	(0.913)	
Aging × reliance on middle-aged		-0.499**	-0.462**	-0.383*	-0.457**	-0.417*	-0.347
		(0.228)	(0.230)	(0.227)	(0.230)	(0.235)	(0.234)
Aging × opportunities for automation		3.970***	3.877***	3.080***	1.481***	1.297***	1.062***
		(1.310)	(1.159)	(0.758)	(0.502)	(0.432)	(0.407)
Observations	462	462	462	462	462	462	462
Countries in sample	27	27	27	27	27	27	27
Instruments F-stat	16.66	17.34	12.37	11.11	10.68	9.32	11.53
Overid p-value	0.99	0.43	0.48	0.30	0.41	0.40	0.27
	Dependent variable: Change in labor share between 1995 and 2007						
Aging between 1995 and 2025	0.037	-0.245	-0.254		-0.368	-0.379	
	(0.131)	(0.290)	(0.287)		(0.339)	(0.338)	
Aging × reliance on middle-aged		0.067	0.070	0.043	0.071	0.074	0.049
		(0.067)	(0.070)	(0.075)	(0.067)	(0.070)	(0.077)
Aging × opportunities for automation		-0.292	-0.307	-0.056	-0.212	-0.219	-0.116
		(0.573)	(0.589)	(0.408)	(0.242)	(0.254)	(0.206)
Observations	448	448	448	448	448	448	448
Countries in sample	26	26	26	26	26	26	26
Instruments F-stat	16.15	14.08	9.63	9.54	12.97	10.90	13.74
Overid p-value	0.44	0.20	0.21	0.15	0.18	0.18	0.06
Covariates included:							
Country covariates in 1995	✓	✓	✓	✓	✓	✓	✓
Initial value added in 1995			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents IV estimates of the relationship between aging and value added and the labor share for industry-country cells. In Panel A, the dependent variable is the change in value added per worker between 1995 and 2007 for each industry-country cell (from the STAN data). In Panel B, the dependent variable is the change in the labor share between 1995 and 2007 for each industry-country cell (from the STAN 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 (2015) in columns 2-4; and a measure of opportunities for the use of robots from the BCG in columns 5-7. In all panels, we 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. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A18: 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	-1.407**	-0.311	0.031	0.344*	-1.668**	-0.718*	-0.049	0.321
	(0.569)	(0.275)	(0.232)	(0.204)	(0.655)	(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					0.13	0.26	0.11	0.00
Panel B. Change in labor share between 1995 and 2007								
Aging between 1995 and 2025	-0.360**	-0.173**	-0.090	-0.110*	-0.343	-0.013	0.070	-0.061
	(0.156)	(0.075)	(0.072)	(0.062)	(0.222)	(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					0.29	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. 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). Columns 1-4 present OLS estimates. Columns 5-8 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 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. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.