Review of Economic Studies (2021) **0**, 1–44 doi:10.1093/restud/rdab031

Advance access publication 10 June 2021

Demographics and Automation

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First version received March 2019*; Editorial decision February* 2021*; Accepted May* 2021 (*Eds.*)

We argue theoretically and document empirically that aging leads to greater (industrial) automation, because it creates a shortage of middle-aged workers specializing in manual production tasks. We show that demographic change is associated with greater adoption of robots and other automation technologies across countries and with more robotics-related activities across U.S. commuting zones. We also document more automation innovation in countries undergoing faster aging. Our directed technological change model predicts that the response of automation technologies to aging should be more pronounced in industries that rely more on middle-aged workers and those that present greater opportunities for automation and that productivity should improve and the labor share should decline relatively in industries that are more amenable to automation. The evidence supports all four of these predictions.

Key words: Aging, Automation, Demographic change, Economic growth, Directed technological change, Productivity, Robots, Tasks, Technology.

JEL Codes: J11, J23, J24, O33, O47, O57

1. INTRODUCTION

Automation and robotics technologies are poised to transform the nature of production and work, and have already changed many aspects of modern manufacturing (*e.g.* Brynjolfsson and McAfee, 2012; Ford, 2016; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). The most common narrative sees automation as the natural next step in the technological developments based on the silicon chip (Brynjolfsson and McAfee, 2012). Though there is undoubtedly some truth to this narrative, we argue that it ignores another powerful driver of automation: demographic change. Indeed, automation technologies have made much greater inroads in countries with more rapidly-aging populations. For example, the number of industrial robots per thousand industrial workers in the U.S. stands at 8.4 in 2014, while the same number is considerably higher in countries undergoing rapid demographic change, such as Japan (13.8), Germany (17.1), and South Korea (19.7).[1] Similarly, the U.S. lags behind Germany and Japan in the production of robots—a single

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

The editor in charge of this paper was Dirk Krueger.

major producer of industrial robots is headquartered in the U.S., compared to six in each of Germany and Japan (Leigh and Kraft, 2018).

In this article, we advance the hypothesis that the development and adoption of robots and other industrial automation technologies have received a big boost from demographic changes in several countries, most notably Germany, Japan, and South Korea. In fact, aging alone accounts for close to a half of the cross-country variation in the adoption of robots and other automation technologies. This is not because of automation in services in aging societies—our focus is on the manufacturing sector and industrial automation, and we do not find similar effects of aging on other technologies. Rather, we document that this pattern reflects the response of firms to the relative scarcity of middle-aged workers, who typically perform manual production tasks and are being replaced by robots and industrial automation technologies.

We start with a simple model of technology adoption and innovation to clarify how demographic change affects incentives to develop and use automation technologies. We assume (and later empirically document) that middle-aged workers have a comparative advantage relative to older workers in manual production tasks, which require physical activity and dexterity, and document that demographic changes that reduce the ratio of middle-aged to older workers increase labour costs in production, and encourage the adoption and development of automation technologies.[2] This effect is predicted to be particularly pronounced in industries that rely more on middle-aged workers and those that have greater technological opportunities for automation. Aging-induced automation can also undo some of the adverse economic consequences of demographic change. The bulk of the article investigates these predictions empirically. Our results point to a sizable impact of aging on the adoption of robots and other automation technologies. We first use country-level data on the stock of robots per thousand workers between 1993 and 2014 from the International Federation of Robotics (IFR) and document a strong and robust association between aging—measured as an increase in the ratio of workers above 56 to those between 21 and 55—and robot adoption. We also confirm that, consistent with theoretical expectations, it is not past but current and future demographic changes that predict robot adoption.

These correlations are not driven by reverse causality or omitted characteristics (such as human capital or labour market institutions). We estimate a very similar pattern when we instrument demographic changes by past birthrates, thus purging aging from the response of immigration and emigration to technological changes and show that the relationship between demographic change and robot adoption is not mediated by and is robust to controlling for changes in educational attainment and female labour force participation.

The effects we estimate are sizable. Aging alone explains about 35% of the cross-country variation in robot adoption. A 10 percentage point increase in our aging variable is associated with 1.6 more robots per thousand workers—compared to the average increase of 3 robots per thousand workers observed during this period. This magnitude suggests, for instance, that if the U.S. had the same demographic trends as Germany, the gap in robot adoption between the two countries would be 50% smaller.

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

2. Throughout, by "middle-aged" we refer to middle-aged and younger workers.

broadly labour-augmenting (such as manual machine tools and non-automatic machines as well as computers).

Our theory predicts an equally strong relationship between demographics and *innovation* in automation technologies. Using data on exports and patents, we provide evidence that countries undergoing more rapid demographic change are developing and exporting more automation technologies. Once again, there is no similar relationship between demographic change and exports or patents for other types of technologies. Our export results further show that automation technologies developed in rapidly-aging countries are spreading to the rest of the world.

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

Other predictions of our theoretical framework receive support from the data as well. First, consistent with our theoretical approach, we document that automation is directly substituting for production/blue-colour workers, which are disproportionately middle-aged. Second, we show that, as in our theory, the response of robot adoption to demographic change is more pronounced in industries that rely more on middle-aged workers and that present greater opportunities for automation. Finally, again consistent with our theory, we estimate a positive impact of demographic change on labour productivity and a negative impact on the labour share in industries that are most amenable to automation.

Our article is related to several lines of work. The first is the literature estimating the implications of automation on labour markets. Early work (*e.g.* Autor et al., 2003; Goos and Manning, 2007; Autor and Dorn, 2013; Michaels et al., 2014; Gregory et al., 2016) provides evidence that automation of routine jobs has been associated rising wage inequality and shrinking middle-skill occupations. More recently, Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) estimate the effects of robot adoption on employment, wages, and productivity. Our work differs from these papers since, rather than the implications of automation, we focus on its determinants.

Second, a growing literature emphasizes the potential costs of aging, arguing that it leads to slower economic growth (*e.g.* Gordon, 2016) and can cause aggregate demand shortages and secular stagnation (see the essays in Baldwin and Teulings, 2014). We differ from this literature by focusing on the effects of demographic changes on automation—an issue that does not seem to have received much attention in this literature.[3] A few works focusing on the effects of demographic change on factor prices (*e.g.* Poterba, 2001; Krueger and Ludwig, 2007), human capital (*e.g.* Ludwig et al., 2012) and R&D working via lower interest rates (*e.g.* Hashimoto and Tabata, 2016) are related as well, but we are not aware of any papers studying the impact of aging on technology, except the independent and simultaneous work by Abeliansky and Prettner (2017). There are several differences between our work and this article. These authors focus on the effect of the slowdown of population growth, rather than age composition. They do not study innovation in automation technologies or the industry-level variation. We show that the effects we estimate are not driven by the level of population or its slower growth, thus distinguishing our results from theirs.

3. Our short paper, Acemoglu and Restrepo (2017), 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.

Third, our work is related to the technology adoption and directed technical change literatures. Our modelling of automation as the substitution of capital for labour at an expanding range of tasks builds on the work of Zeira (1998) as well as more recent task-based frameworks such as Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018a,b, 2020). In contrast to the main works in the directed technical change literature, which focus on factor-augmenting technologies and the market size and product price effects (*e.g.* Acemoglu, 2002), our task-based framework emphasizes the central role of the cost of labour (especially the wage in the production sector driven by the scarcity of middle-aged workers) and shows that a higher cost of labour always leads to greater adoption and development of automation technologies. Our model, which incorporates multiple sectors and heterogeneous labour, additionally generates new predictions which we investigate empirically. Most of the existing empirical works on directed technological change also focus on the effects of market size on new products that serve a specific market or factor-augmenting technologies that complement a particular factor of production. For example, Finkelstein (2004) shows that public policies increasing vaccination have triggered more clinical trials for new vaccines, while Acemoglu and Linn (2004) and Costinot et al. (2018) document that demographic changes increase innovation for pharmaceuticals whose market size has expanded. Hanlon (2015) exploits the Civil War-induced decline in U.S. cotton exports to the U.K. and the corresponding increase in Indian cotton exports, which required different types of weaving machines. He shows that there was a rapid increase in weaving patents and that, consistent with the strong relative bias result in Acemoglu (2002), these new technologies more than reversed the initial increase in the relative U.S.–Indian cotton price. Instead, our empirical work, consistently with our theory, focuses on how the scarcity and high cost of a type of worker generates incentives for innovation targeted at replacing these workers. This focus is shared by a few recent papers on technology adoption. Manuelli and Seshadri (2014) use a calibrated model to show that stagnant wages slowed down the adoption of tractors before 1940. Clemens et al. (2018) find that the exclusion of Mexican *braceros*—temporary agricultural workers—induced farms to adopt mechanic harvesters and switch to crops with greater potential for mechanization, while Lewis (2011) shows that in U.S. metropolitan areas receiving fewer low-skill immigrants between 1980 and 1990 equipment and fabricated metal plants adopted more automation technologies. We are not aware of other works that investigate such forces in the context of the development of new technologies (rather than their adoption).

The rest of the article is organized as follows. We introduce our model of directed technology adoption in the next section. Section 3 discusses our data sources. Section 4 presents our cross-country evidence on the effects of demographic change on the adoption of robots and other automation technologies. Section 5 provides evidence on the impact of demographic change on innovation and development of automation technologies. Section 6 explores the relationship between demographics and robots across U.S. commuting zones. Section 7 investigates the mechanisms at the root of the effect of aging on automation technologies. We demonstrate that (industrial) automation technologies are indeed used predominantly to automate tasks performed by middle-aged workers and confirm the predictions of our framework concerning the differential effects of demographic change across industries. Section 8 concludes, while the Supplementary Appendix contains proofs omitted from the text and additional data details and empirical results.

2. THEORY

In this section, we present a simple model of directed technology adoption and innovation, and derive a number of results on the relationship between demographic change and automation, which will guide our empirical work in the rest of the article.

2.1. *The environment*

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

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

where $Y(i)$ 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, $X(i)$, service, or support (non-production) tasks, $S(i)$ and intermediates that embody the state of technology for this industry, $q(\theta(i))$:

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

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.

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.

As in Acemoglu and Restrepo (2018a), we model automation as the substitution of machines for labour in production tasks. Each task $X(i,z)$ is performed either by labour 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 labour employed in task z in industry i, and $m(i,z)$ denotes machines used in industry i to produce task z. In addition, $A(i)$ designates the productivity of labour relative to machines in industry i. Labour 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 labour and hence corresponds to an advance in automation technology for industry i.

Intermediates for industry i, $q(\theta(i))$, are supplied by a technology monopolist that owns the intellectual property rights over these technologies. This technology monopolist produces each unit of $q(\theta(i))$ using $1-\eta$ units of industry i's output.[4] 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 and older workers. We simplify the analysis throughout the article by imposing:

4. The assumptions that the elasticity of substitution between industries, σ, is greater than one, the elasticity between production tasks, service tasks, and intermediates is equal to one, and the cost of intermediates to industry i is in terms of that industry's output are all adopted for simplicity and can be relaxed without changing our conclusions.

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

The comparative advantage of middle-aged workers in production tasks is driven by their ability to perform manual tasks that require physical activity and dexterity (rather than differences in education or general skills, which we will control for in our empirical work). This structure of comparative advantage is consistent with the fact that industrial automation technologies are designed to automate tasks that are typically performed by blue-collar workers (Groover et al., 1986; Ayres et al., 1987) and is further supported by the empirical evidence we present in Section 7.1. In reality, of course, worker productivity in manual tasks declines slowly with age, but we simplify the analysis by limiting ourselves to a world with two types of workers for simplicity (and extending the model to a setup with a smooth comparative advantage schedule is conceptually straightforward but notationally cumbersome).

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

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

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

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 employment levels for middle-aged workers, 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:

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

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. Our normalization of the marginal cost of intermediate production to $1-\eta$ units of the industry's product implies that the profit-maximizing price is $p(\theta(i)) = P_Y(i)$, and industry i's output price can be derived from equation (2) as $P_Y(i) = \lambda(i) P_X(i)^{\alpha(i)} V^{1-\alpha(i)}$, where $P_X(i)$ denotes the price of $X(i)$ and $\lambda(i) = (1-\eta)\alpha(i)^{-\alpha(i)}(1-\alpha(i))^{\alpha(i)-1}$.

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

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

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

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

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

where we are imposing without loss of any generality that when indifferent, firms do not switch to machines. Equation (6) highlights a key aspect of task-based models (*e.g.* Zeira, 1998): firms adopt available automation technologies when the effective wage of middle-aged workers is high.

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

$$P_Y(i) = \lambda(i)\left(\theta^A(i)P_M^{1-\zeta} + (1-\theta^A(i))\left(\frac{W}{A(i)}\right)^{1-\zeta}\right)^{\frac{\alpha(i)}{1-\zeta}} V^{1-\alpha(i)}, \tag{7}$$

which highlights that greater automation reduces the cost share of middle-aged workers, thus making the technology for production tasks less labour-intensive.

The next proposition establishes the existence and uniqueness of the equilibrium and characterizes its structure. In what follows, we denote the share of older workers in the population by $\phi = \frac{S}{L+S}$, 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,

$$1 = \left(\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma} di\right)^{\frac{1}{1-\sigma}}, \tag{8}$$

and the relative demand for workers,

$$\frac{1-\phi}{\phi} = \frac{V}{W}\frac{\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma}\alpha(i)s_L(i)di}{\int_{i\in\mathcal{I}} P_Y(i)^{1-\sigma}(1-\alpha(i))di.} \tag{9}$$

2. $W^E(\phi,\Theta)$ is increasing in ϕ, and $V^E(\phi,\Theta)$ is decreasing in ϕ.

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

Panel A of Figure 1 depicts the characterization of the equilibrium with exogenous technology. Let $C(W,V,P_M)$ denote the cost of producing one unit of the final good, which is represented by the right-hand side of equation (8). The equilibrium wages, W^E and V^E, are then given by the tangency of the isocost curve $C(W,V,P_M) = 1$ (condition (8)) with a line of slope $-\frac{1-\phi}{\phi}$

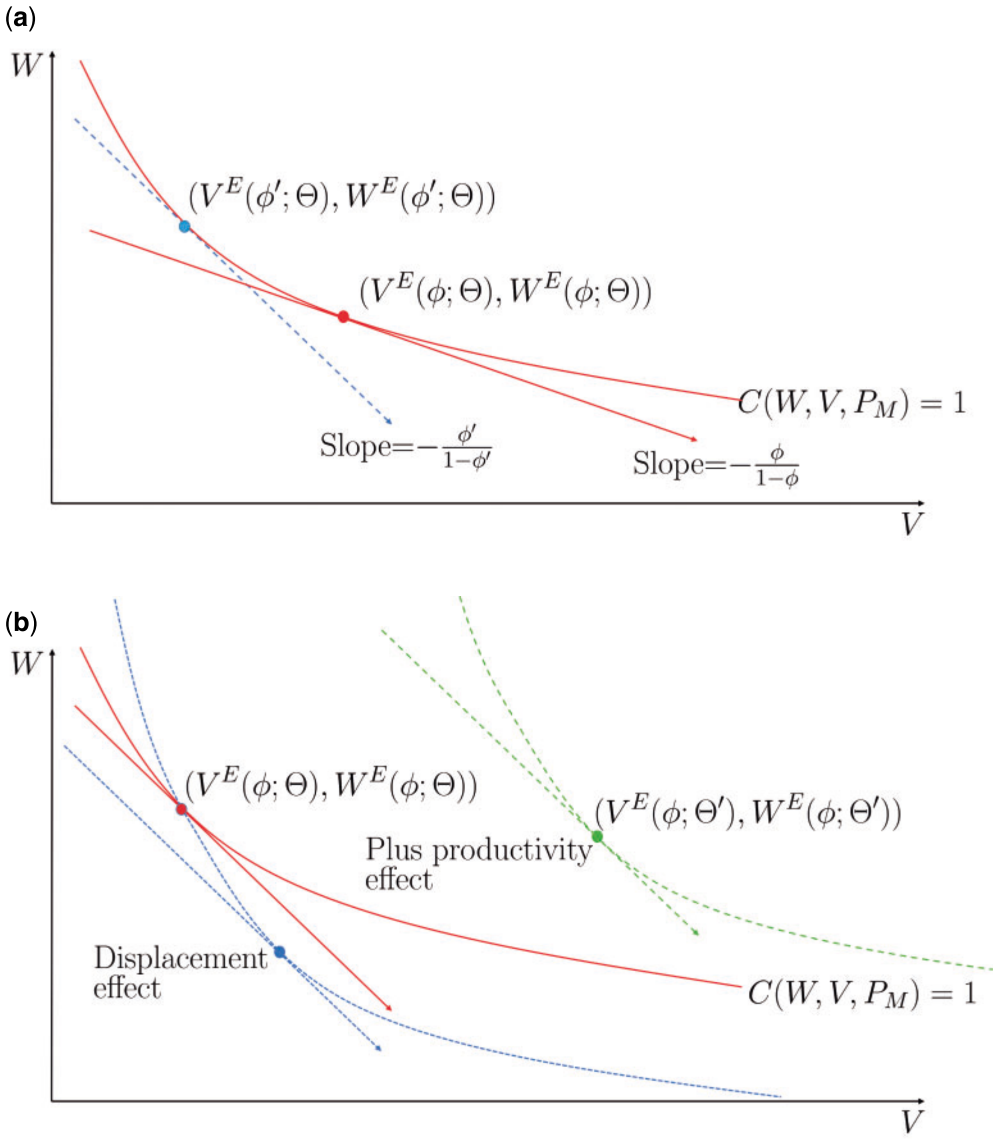

FIGURE 1

Determination of equilibrium wages W^E and V^E. The downward-slopping red curve is the isocost $C(W,V,1)=1$ (condition (8)). In Panel (a), 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 (9)). In Panel (b), automation rotates the isocost curve clockwise (displacement effect) and shifts it outwards (productivity effect).

(at which point we have $\frac{\partial C(W,V,P_M)/\partial W}{\partial C(W,V,P_M)/\partial V}=\frac{1-\phi}{\phi}$, which is condition (9)). Aging—an increase in ϕ—raises W^E and lowers V^E along the convex isocost curve $C(W,V,P_M)=1$, as shown in Panel A.

On the other hand, aging has an ambiguous effect on aggregate output per worker. In particular, in the Supplementary Appendix, we show that

$$\frac{1}{2-\eta}\frac{\partial y^E(\phi,\Theta)}{\partial\phi}=V^E(\phi,\Theta)-W^E(\phi,\Theta)+P_M\frac{\partial m^E(\phi,\Theta)}{\partial\phi}. \tag{10}$$

This expression clarifies that the impact 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 $\partial m^E/\partial\phi$ can be positive, offsetting this effect). Existing evidence (*e.g.* Murphy and Finis Welch, 1990) suggests that earnings peak when workers are in their 40s, which in our model implies $V<W$ and thus creates a tendency for aging to reduce productivity. This negative effect echoes the concerns raised by Gordon (2016) on the potential for slower growth in the next several decades because of demographic change.

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

Proposition 2 *For $\phi\le\phi'$, we have $\mathcal{I}^+(\phi,\Theta)\subseteq\mathcal{I}^+(\phi',\Theta)$.*

This proposition leads to our *first empirical implication:* aging leads to greater adoption of automation technologies, because the greater (relative) scarcity of middle-aged workers increases their wage in production and encourages the adoption of machines to substitute for them.[5]

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 monopolist $\frac{1-\eta}{2-\eta}P_Y(i)Y(i)\cdot C_i(\theta(i))$ 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 helps simplify the algebra.

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

$$\max_{\theta(i)\in[0,1]}\ln\pi^M(i)=(1-\sigma)\ln P_Y(i)+\ln(1-C_i(\theta(i))), \tag{11}$$

5. While aging increases automation and W, automation itself has an ambiguous effect on W as in Acemoglu and Restrepo (2018a). This is because, on the one hand, automation displaces middle-aged workers from the tasks they were previously performing and squeezes them into fewer tasks, and on the other hand, it increases productivity and raises the demand for all workers. It is straightforward to show 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. Panel B of Figure 1 illustrates these competing effects and also highlights that automation always increases older workers' wage, V.

where $P_Y(i)$ is given by equation (7). This expression clarifies that monopolists have an incentive to develop automation technologies that reduce $P_Y(i)$, 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 ensures that (11) has a unique solution. The exponent $\rho(i)>0$ represents heterogeneity across industries in the technological possibilities for automation; a higher $\rho(i)$ characterizes industries in which, due to the nature of tasks, monopolists can more easily develop new automation technologies.

Given the convexity assumptions on H, the maximization problem in equation (11) yields a unique technology choice for each industry depending only on parameters and the middle-aged wage, W. We represent the relationship between the middle-aged wage and the equilibrium technology choices with the mapping $\Theta^R(W)$.

We define an *equilibrium with endogenous technology* as an allocation where technology choices $\Theta^R(W)$ maximize (11), and given technology choices $\Theta^R(W)$, Proposition 1 applies. In particular, given $\Theta^R(W)$, this proposition implies that the middle-age wage is $W^E(\phi, \Theta^R(W))$. Thus, an equilibrium with endogenous technology can be determined from a middle-aged wage, W^*, that is a solution to the following fixed point problem,

$$W^* = W^E(\phi, \Theta^R(W^*)). \tag{12}$$

Lemma 1 *The maximization problem in equation* (11) *exhibits increasing differences in W and $\theta(i)$. Thus, $\Theta^R(W)$ is nondecreasing in W.*

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. Economically, automation allows firms to substitute machines for middle-aged labour, and when this labour is more expensive, automation is more profitable. We next establish:

Proposition 3 *For any $\phi \in (0,1)$, there exists an equilibrium with endogenous technology, where the middle-aged wage, W^*, satisfies the fixed point condition in equation* (12). *Each fixed point W^* defines a unique set of technology choices $\Theta^* = \{\theta^*(i)\}_{i\in\mathcal{I}}$ given by $\Theta^* = \Theta^R(W^*)$.*

To illustrate this proposition, suppose that the mapping $W^E(\phi, \Theta^R(W))$ is decreasing in W.[6] In this case, automation decisions across industries are strategic substitutes—because more automation in one industry reduces the middle-aged wage and discourages automation in other industries. Consequently, the equilibrium with endogenous technology is unique as in Panel A of Figure 2.

In general, $W^E(\phi, \Theta^R(W))$ need not be decreasing in W, because strong productivity gains from automation could make the middle-aged wage increasing in automation. In this case, we

6. Supplementary 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 $\widetilde{W} < \widetilde{A}(i)P_M$ for almost all $i \in \mathcal{I}$). When $\phi \leq \widetilde{\phi}$, the unique equilibrium involves $\Theta^* = 0$.

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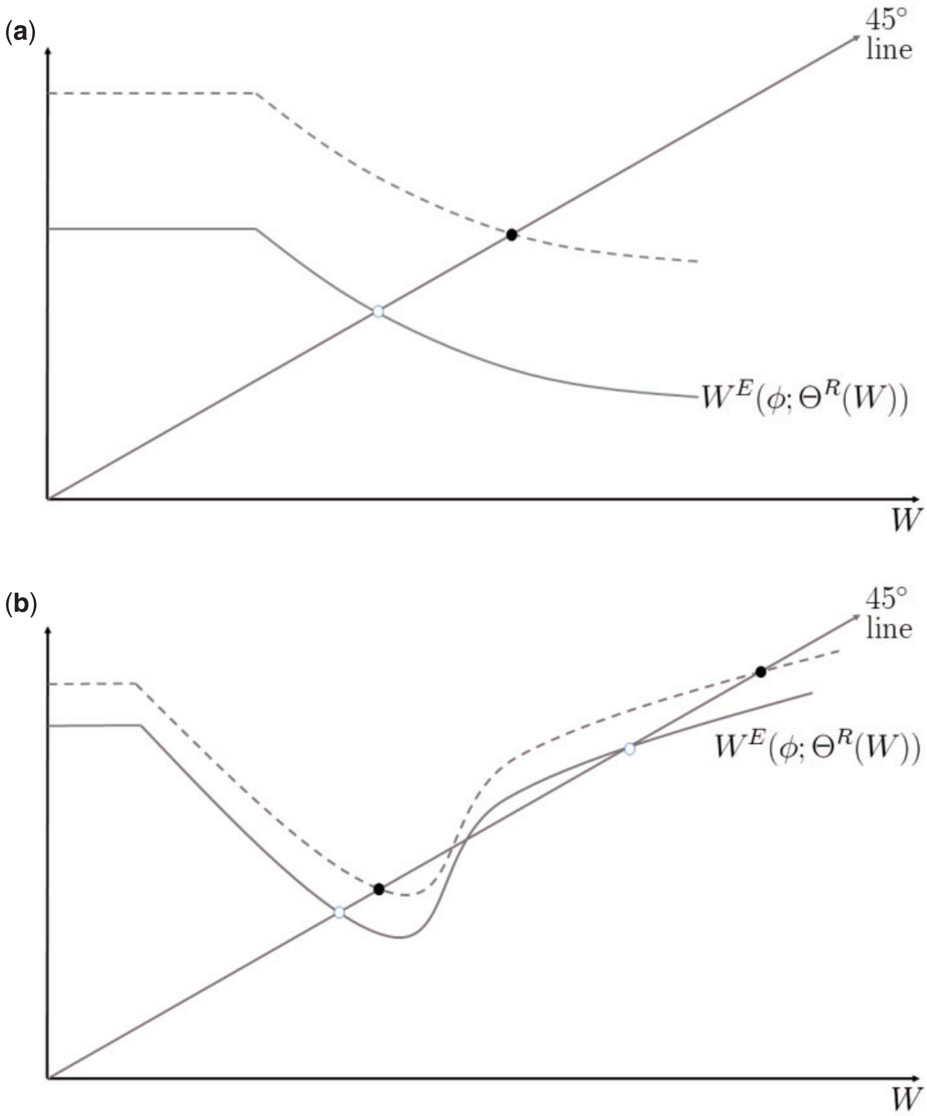

FIGURE 2

Equilibrium middle-aged wage with endogenous technology. Panel (a) shows the case of a unique equilibrium. Panel (b) shows a case with multiple equilibria. Aging shifts the mapping W^E up, and this increases the equilibrium wage in the least and the greatest equilibrium.

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 (12). Supplementary 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).

The next proposition contains our most important theoretical results:

Proposition 4 *In the least and the greatest equilibrium:*

1. an increase in ϕ—aging—increases the equilibrium wage W^* and expands the set of automation technologies, Θ^*, and the set of industries that adopt them, $\mathcal{I}^+(\phi,\Theta^*)$;
2. $\theta^*(i)$ (and thus $\theta^A(i)$) exhibits increasing differences in ϕ and $\alpha(i)$, and ϕ and $\rho(i)$.

The first part of this proposition provides our *second empirical implication:* aging leads to greater development of automation technologies (and also confirms that in this endogenous technology environment aging continues to induce greater adoption of automation technologies). This empirical implication is intuitive. Machines compete against middle-aged workers, and a greater scarcity of these workers always increases their wage and thus the relative profitability of automation, which in turn triggers automation innovations. This is true regardless of whether the equilibrium is unique.

The second part of the proposition leads to our *third empirical implication:* aging increases innovation in automation technologies relatively more 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 $\rho(i)$).

2.4. *Implications for productivity*

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

Proposition 5 *In the least and the greatest equilibrium, equilibrium output in industry i, $Y^*(i)$, exhibits increasing differences in ϕ and $\rho(i)$.*

This proposition leads to our *fourth empirical implication:* industries that have greater opportunities for automation (larger $\rho(i)$) increase their relative productivity in more rapidly-aging economies. Moreover, for the same reason, these industries will also experience a greater decline in their labour share (recall from equation (7) that automation makes industry production less labour-intensive). These results are driven by the fact that, as Proposition 4 highlights, the endogenous response of technology is stronger in industries with greater $\rho(i)$. The same is true for industries with $\alpha(i)$, but there are no unambiguous results for these industries, because they are also more adversely affected by the increase in the middle-aged wage.

Proposition 5 additionally highlights that the aggregate productivity implications of aging are ambiguous when automation technologies are endogenous, and as a result, demographic change may not impact GDP negatively once technology adjusts.

2.5. *Extensions*

In Supplementary Appendix, we consider two extensions of this framework. First, we endogenize the industry-level labour-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 labour in production tasks. 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 labour-augmenting technologies. But it also fosters automation and thus reduces the set of tasks performed by middle-aged workers, making labour-augmenting technologies less profitable. This implication is consistent with our finding that aging has no effect on non-automation technologies.

Second and more importantly, we establish a link between demographic change in some countries and the adoption of automation technologies throughout the world. We do this by considering an extension of our model to a global economy, where some countries are experiencing more rapid aging and thus are ahead of others in the development of automation technologies. In this setup, we establish three important results: (1) there will be imports and exports of automation technologies (as in our empirical work); (2) advances in automation technologies in one country will be later adopted in other countries; and (3) the effects of automation technologies are potentially different in countries developing these technologies in response to demographic change versus those adopting them as a result global technological advances. In particular, Proposition 4 applies to the former set of countries and implies that demography-induced development and adoption of robots will never reduce wages. In contrast, as highlighted in Acemoglu and Restrepo (2020), in the latter set of countries robot adoption driven by advances in world technology can lead to lower wages and employment.

3. DATA AND TRENDS

In this section, we present our data sources and describe 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 our main measure is 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 UN World Population Prospects for 2015, which provides data on population by age and a forecast of these variables up to 2050. As Figure 3 shows, demographic change has been ongoing since 1990, both globally and in the OECD—a trend that is expected to continue into the future. Aging is much faster in Germany and South Korea and is slower in the U.S. 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 (see Acemoglu and Linn, 2004, for evidence for this type of forward-looking behaviour in pharmaceutical innovations). 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 some of our specifications, we instrument aging using crude birth rates between 1950 and 1985 (defined as births per thousand people), which we also obtained from the UN World Population Prospects.

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 United States Patent and Trademark Office (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. Supplementary Table A1

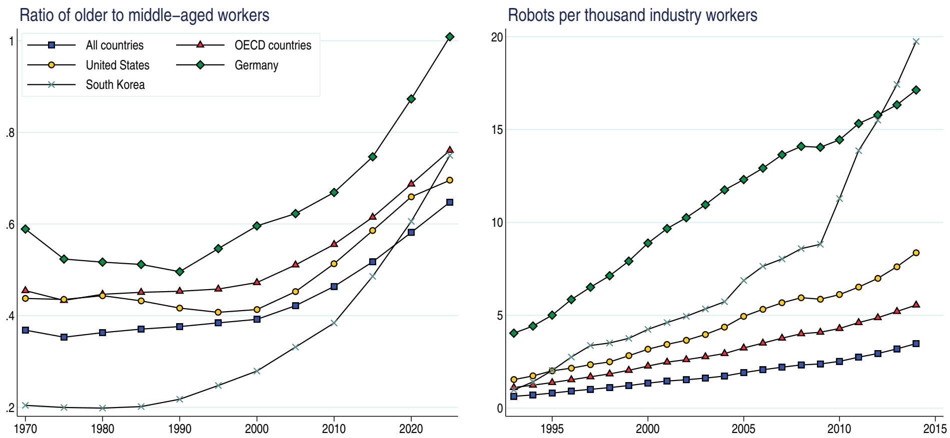

FIGURE 3

The left panel 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. The right panel presents trends in robot adoption. Robot adoption is measured by the number of robots (using robot data from the IFR) per thousand industrial workers (from the ILO).

in the Supplementary Appendix provides the list of countries covered by the IFR.[7] In our cross-country analysis, we use the change in the stock of robots divided by industrial employment as our dependent variable. The denominator is constructed using industry employment data for 1990 from the International Labour Organization (ILO) (as described in footnote 1). To account for differences in hours worked, we adjust the employment figures using hours per worker from the Penn World Tables. The resulting measure of the stock of robots per thousand industrial workers covers 60 countries between 1993 and 2014, and is illustrated in Figure 3. The figure underscores the pattern we noted in Section 1—that Germany and South Korea are considerably ahead of the U.S. in terms of the adoption of robotics technology.

Panel A of Table 1 provides summary statistics for all 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 0.63 in 1993 to 3.47 in 2014, but this increase was much more pronounced among rapidly-aging countries (from 0.87 to 5.05) than among the slowly-aging countries (from 0.40 to 1.90).

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, has significant robot imports). In addition, to account for entrepôt trade, we remove re-exports

7. Although the IFR 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. The IFR also reports data for Belarus, Bosnia and Herzegovina, North Korea, Puerto Rico, and Uzbekistan, which are excluded from our sample because they do not have data on key covariates, and for the oil-rich economies of Iran, Kuwait, Oman, Saudi Arabia, and United Arab Emirates, which are excluded both because they have few robots and also because their demographics are heavily influenced by immigration.

TABLE 1
Summary statistics for countries

	All countries	OECD	Rapidly aging countries	Slowly aging countries
Panel A: Demographics data				
Ratio of older to middle-aged workers	0.27	0.45	0.34	0.21
in 1990	(0.12)	(0.09)	(0.13)	(0.06)
Change in older to middle-aged workers	0.16	0.31	0.30	0.03
between 1990 and 2025	(0.17)	(0.12)	(0.13)	(0.06)
Change in older to middle-aged workers	0.07	0.16	0.16	−0.01
between 1990 and 2015	(0.11)	(0.08)	(0.09)	(0.04)
	$N=196$	$N=35$	$N=98$	$N=98$
Panel B: IFR data				
Robots per thousand workers in 2014	3.47	5.55	5.05	1.90
	(4.52)	(4.86)	(5.27)	(2.94)
Robots per thousand workers in 1993	0.63	1.11	0.87	0.40
	(1.09)	(1.24)	(1.15)	(1.00)
Annualized increase between 1993 and 2014	0.14	0.21	0.20	0.07
	(0.18)	(0.19)	(0.21)	(0.10)
	$N=60$	$N=31$	$N=30$	$N=30$
Panel C: Comtrade data				
Robot imports per thousand workers	$132K	$397K	$242K	$19K
between 1996 and 2015 (thousand dollars)	($273K)	($327K)	($349K)	($55K)
Robot imports per million dollars of total	$271	$271	$273	$250
intermediate imports between 1996 and 2015	($155)	($148)	($154)	($168)
	$N=129$	$N=33$	$N=64$	$N=65$
Robot exports per thousand workers	$187K	$495K	$279K	$96K
between 1996 and 2015 (thousand dollars)	($559K)	($859K)	($523K)	($585K)
Robot exports per million dollars of total	$332	$414	$366	$66
intermediate exports between 1996 and 2015	($335)	($327)	($366)	($260)
	$N=103$	$N=35$	$N=51$	$N=52$
Panel D. USPTO patents sample				
Robot-related patents granted between	724	1,576	1,399	49
1990 and 2016 by the USPTO	(3,335)	(4,918)	(4,649)	(148)
Robot-related patents granted by USPTO	14.4	14.8	14.9	12.6
for every other thousand patents	(6.8)	(4.7)	(5.1)	(10.8)
	$N=69$	$N=31$	$N=34$	$N=34$

Notes: The table presents summary statistics for the main variables used in our cross-country analysis. For each variable, we present mean and standard deviation (in parentheses). 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.

of robots and keep only countries whose imports of robots net of re-exports are positive. We also excluded Luxembourg, which appears to be a significant port of entry for imported robots into the European Union. Likewise, when analyzing the export data, we keep only countries whose exports of robots (without including re-exports) are positive. The resulting data cover 129 countries importing robots between 1996 and 2015, and 103 countries exporting robots between 1996 and 2015.[8] We use the Comtrade data to compute imports and exports of other intermediates related to industrial automation. Panel B of Table 1 summarizes the Comtrade data. The average

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

There are several reasons why there is a relatively large number of countries exporting robots. First, some exporting firms may use ports located in different countries to send their robots (*e.g.* German and Belgium robot producers can export from Luxembourg). Second, there are likely some classification errors by custom authorities. Finally, some countries may imports of robots per thousand industrial workers in our sample is $132,000 (roughly the cost of two industrial robots), while the same number is about twice as large for rapidly-aging countries.

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. Supplementary 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 patent cross references. 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 724, while the same number is about twice as large for the OECD and for rapidly-aging countries.

For our covariates, we use data on GDP per capita, population, and average years of schooling obtained from version 9.0 of the Penn World Tables (Feenstra et al., 2015), and data on manufacturing value added in 1990 from the United Nations Industrial Development Organization (UNIDO). In some specifications, we control for changes in educational attainment from the Barro-Lee dataset (for 1990–2010) and changes in relative female labour force participation from the ILO (for 1990–2015).

3.2. *Data on robot integrators*

We do not have data on the adoption or use of robots within the U.S. Instead, we proxy robotics-related activities in a commuting zone using a dichotomous measure of whether it houses robot integrators, obtained from Leigh and Kraft (2018).[9] 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 (2020) to measure the local effects of robots.

3.3. *Industry data*

In addition to the country-level data, the IFR reports data on robot installations by year separately for 19 industries in 58 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 Supplementary Table A1 shows, these data are not available in every year for every country-industry pair, so in our industry analysis, we focus on an unbalanced panel of annual data rather than long differences. Supplementary 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 is the average industrial employment from the ILO

sell used inventory. All of these add measurement error to this variable, but should not bias our results. In the exports data, Nigeria is a massive outlier, with a share of robotic exports two orders of magnitudes greater than other countries, which is almost certainly a classification mistake in the data. We thus exclude Nigeria from regressions for industrial robots, though because we focus on weighted regressions the results are very similar even if it is included.

9. Commuting zones, defined in Tolbert and Sizer (1996), are groupings of counties approximating local labour markets. We use 722 commuting zones covering the entire U.S. continental territory (excluding Alaska and Hawaii).

data described above, while the second uses data from EUKLEMS, which provides the 1995 employment levels for all 19 industries in our analysis, but only covers 24 of the countries in our sample (Jägger, 2016).[10] From the EUKLEMS data, we also use information on value added per worker (in real dollars) and the change in the share of labour in value added, which are available between 1995 and 2007 and cover all 19 industries included in the IFR data. The third and fourth columns of Supplementary 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 U.S. Census data. Heavy manufacturing industries, construction and utilities have significantly greater reliance on middle-aged workers. We use two proxies for the opportunities for automation (focusing in particular on robots). The first is the *replaceability index* constructed by Graetz and Michaels (2018), which is derived from data on the share of hours spent by U.S. workers on tasks that can be performed by industrial robots. The replaceability index is strongly correlated with robot adoption and explains 20% of the total variation in robot installations across industries. The second measure is a dummy variable for the automobiles, electronics, machinery, and chemicals, plastics, and pharmaceutical industries, which are identified in a recent Boston Consulting Group's report (BCG, 2015) as having the greatest technological opportunities for robots, based on the types of tasks that workers perform. Table 1 confirms that these are among the industries experiencing the fastest growth in robot adoption. Supplementary Figure A1 summarizes the cross-industry variation in reliance on middle-aged workers and the replaceability index.

4. DEMOGRAPHIC CHANGE AND AUTOMATION

In this section, we investigate our first empirical implication using cross-country data and establish a robust positive association between aging and the adoption of automation technologies.

4.1. *Main results: robot adoption*

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

$$\frac{\Delta R_c}{L_c} = \beta \text{Aging}_c + \Gamma X_{c,1990} + \varepsilon_c. \tag{13}$$

Here, $\frac{\Delta R_c}{L_c}$ is the (annualized) *change* in the stock of robots between 1993 and 2014 in country c normalized by industrial employment (in thousands of full time workers) in 1990 from the ILO. We keep the denominator fixed in 1990 to avoid endogenous changes in employment impacting our left-hand side variable. Aging_c is the expected *change* between 1990 and 2025 in the ratio of older workers (who are above the age of 56) to middle-aged workers (between the ages of 21 and 55).[11] Finally, the vector $X_{c,1990}$ includes covariates and ε_c is an heteroscedastic error term.

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

11. The relative employment rates of workers of different age groups in blue-collar and white-collar occupations documented in Section 7.1 motivate the use of 55 years of age as our baseline cutoff to define older and middle-aged workers. Supplementary Table A3 shows that our results are robust to different ways of classifying middle-aged and older workers.

We present both unweighted specifications and regressions weighted by manufacturing value added in 1990, which are useful because robots and the industrial automation technologies that motivate our model are used much more intensively in manufacturing than in other sectors.

Panel A of Table 2 presents our unweighted OLS estimates of equation (13). Columns 1–4 are for our full sample of 60 countries. Column 1 controls for dummies for East Asia and the Pacific, South Asia, Middle East and North Africa, Africa, Eastern Europe and Central Asia, Latin America and the Caribbean, and OECD countries to account for regional trends. Column 2, which is our baseline specification, adds the 1993 values of log GDP per capita, log population, average schooling and the ratio of middle-aged and older workers as covariates; these variables control for differential trends depending on initial levels of economic development and demographic characteristics. Column 3 additionally includes the stock of industrial robots per thousand workers in 1993 and the log of manufacturing value added in 1990 as controls and thus allows for the possibility that countries with more robots or a larger manufacturing sector at the beginning of the sample may have subsequently adopted robots at different rates. These variables may capture some of the effects of demographic change that had started in the 1980s, motivating our preference for column 2 as our baseline specification. Column 4 adds changes in educational attainment and female labour force participation, though we note that these variables are themselves affected by demographic change and may thus be "bad controls." Columns 5–8 present the same specifications for the 31 countries in the OECD sample.

In all eight columns of Panel A, we find that aging is associated with the adoption of robots. All estimates are statistically significant and sizable. The specification in column 1 has a R^2 of 48% (and the R^2 of aging by itself is 35% and its partial R^2 is 30%). In our baseline specification in column 2, the coefficient estimate on aging is 0.73 (s.e. = 0.22). This implies that a 20 percentage point increase in our aging variable, which is roughly the difference between Germany and the U.S. (0.51 versus 0.28, respectively), leads to an increase of 0.15 robots per thousand workers per year. This adds up to three additional robots per thousand industrial workers over our sample period, which accounts for 50% of the difference between Germany and the U.S. in robot adoption.

Figure 4 depicts the relationship between demographic change and the number of robots per thousand workers in the full sample of countries and in the OECD (using our baseline models in columns 2 and 6 in Table 2). Supplementary Table A4 presents several strategies to show that the relationship between aging and robot adoption is not driven by outliers and is not unduly affected by South Korea, which is both aging most rapidly and adopting the most robots in our sample. Though the point estimates are smaller in some specifications in Supplementary Table A4, they are always statistically and economically significant.

The OLS relationships shown in Panel A do not necessarily correspond to the causal effect of demographic change on robot adoption for at least three reasons. First, aging of the workforce may proxy for other concurrent factors, such as increases in educational attainment, changes in female labour force participation or labour market institutions. Our main specifications already include average baseline education, and columns 4 and 8 additionally control for changes in schooling and in female labor force participation over our sample period, which do not appreciably alter the relationship between aging and robot adoption. We also show in Supplementary Table A6 that our results do not change when we control for various labour market institutions, including prevalence of union bargaining, employment protection, and labour taxes.[12] These institutions

12. Changes in educational attainment and female labour force participation and labour market institutions do not change the effects of aging partly because, as Supplementary Table A5 shows, aging is only weakly correlated or uncorrelated with these variables (with the exception of unionization rates, which shows some negative correlation). We return to a discussion of the effects of education and gender in Section 7.4.

TABLE 2

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)	(7)	(8)
	Panel A. OLS estimates							
Aging between 1990 and 2025	0.778	0.726	0.589	0.528	1.110	0.974	0.736	0.653
	(0.231)	(0.221)	(0.229)	(0.179)	(0.364)	(0.302)	(0.293)	(0.211)
Increase in schooling 1990–2010				0.457				1.104
				(0.433)				(0.511)
Change in relative FLFP 1990–2015				−0.062				−0.384
				(0.162)				(0.251)
Observations	60	60	60	60	31	31	31	31
R^2	0.48	0.61	0.70	0.72	0.36	0.54	0.63	0.73
	Panel B. IV estimates							
Aging between 1990 and 2025	0.961	0.784	0.734	0.631	1.661	1.012	0.961	0.872
	(0.251)	(0.223)	(0.239)	(0.188)	(0.474)	(0.322)	(0.321)	(0.244)
Observations	60	60	60	60	31	31	31	31
First-stage F-stat.	28.2	19.2	18.5	15.9	8.4	7.8	8.0	6.6
Overid p-value	0.55	0.48	0.08	0.06	0.73	0.25	0.07	0.04
Anderson–Rubin Wald test p-value	0.00	0.01	0.00	0.00	0.01	0.03	0.00	0.00
	Panel C. Single-IV estimates							
Aging between 1990 and 2025	1.113	0.873	0.676	0.642	1.819	1.276	1.111	1.196
	(0.354)	(0.317)	(0.340)	(0.327)	(0.586)	(0.398)	(0.467)	(0.356)
Observations	60	60	60	60	31	31	31	31
First-stage F stat.	33.3	30.7	20.7	16.9	13.1	29.9	20.3	28.1
	Panel D. OLS estimates weighted by manufacturing value added							
Aging between 1990 and 2025	1.134	1.248	0.875	0.689	1.248	1.385	0.922	0.718
	(0.331)	(0.202)	(0.232)	(0.206)	(0.357)	(0.182)	(0.272)	(0.275)
Observations	60	60	60	60	31	31	31	31
R^2	0.67	0.81	0.85	0.87	0.56	0.78	0.83	0.87
	Panel E. IV estimates weighted by manufacturing value added							
Aging between 1990 and 2025	1.118	1.212	1.086	0.867	1.220	1.331	1.069	0.852
	(0.288)	(0.192)	(0.242)	(0.208)	(0.369)	(0.189)	(0.263)	(0.264)
Observations	60	60	60	60	31	31	31	31
First-stage F-stat.	7.4	8.0	18.8	19.0	9.1	14.9	22.4	14.6
Overid p-value	0.14	0.11	0.14	0.02	0.48	0.18	0.22	0.03
Anderson–Rubin Wald test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Covariates included:								
Baseline country covariates		✓	✓	✓		✓	✓	✓
Initial robot density and manufacturing value added			✓	✓			✓	✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots. In all panels, the dependent variable is the annualized change in the stock of industrial robots per thousand workers between 1993 and 2014 (from the IFR). Aging is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panels A and D present OLS estimates. Panels B and E present IV estimates where aging is instrumented using the average birth rates over each five-year interval from 1950–4 to 1980–4. Panel C presents IV estimates where aging is instrumented using the decline in birth rates between 1960 and 1980. For our IV estimates, we report the first-stage F-statistic. When using multiple instruments, we also report the p-value of Hansen's overidentification test, and the p-value of Anderson and Rubin's test for the coefficient on aging being zero. We present results for two samples: columns 1–4 use the full sample; columns 5–8 use the OECD sample. Columns 1 and 5 include region dummies. Columns 2 and 6 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 7 add the 1993 value of robots per thousand workers and the log of the 1990 value added in manufacturing. Finally, columns 4 and 8 add the change in the share of the population with college and the change in the female labor force participation (FLFP) relative to men. The regressions in Panels A, B, and C are unweighted, while the regressions in Panels D and E are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity.

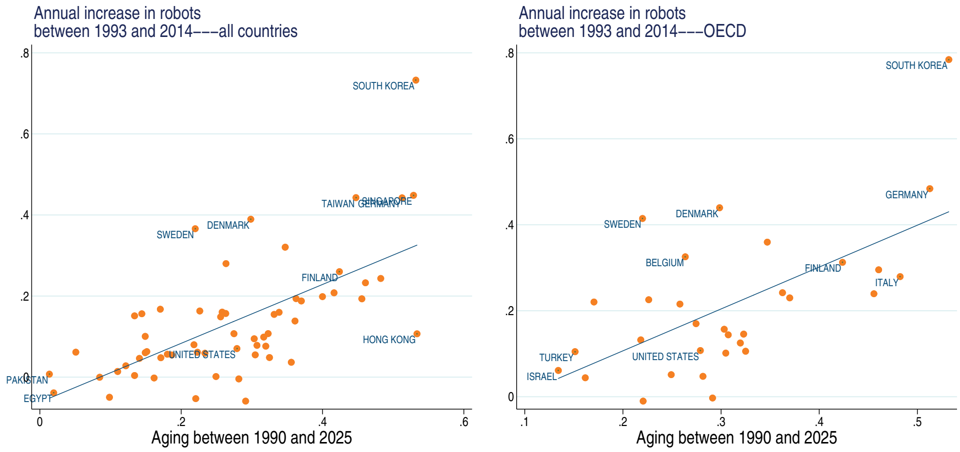

FIGURE 4

Relationship between aging (change in the ratio of workers above 56 to workers aged 21–55 between 1990 and 2025) and the increase in the number of industrial robots per thousand workers between 1993 and 2014. The left panel is for the full sample and the right panel is for the OECD sample. The plots correspond to the specifications in Panel A, columns 2 and 6, of Table 2.

themselves are associated with more robot adoption, presumably because they raise labour costs and thus encourage automation.

A second concern is that our results may be driven by changes in industry composition that differ by demographic structure. In Section 7, we confirm that the same results hold when we focus on within industry variation (thus purging variation in industry composition).

Third, and more importantly, aging may be endogenous to technology adoption because immigration and emigration, and even mortality patterns, could respond to wages and employment opportunities. We deal with this concern by developing an instrumental-variables (IV) strategy based on past birth rates. Namely, we instrument expected aging between 1990 and 2025 using the average birth rates over each five-year interval from 1950–4 to 1980–4. Past birth rates are unlikely to have varied across countries in anticipation of future technology adoption decisions, and the exclusion restriction that they do not impact technology adoption, except through demographic factors, is plausible (especially given our aforementioned controls for educational attainment and female labour force participation).[13] The first-stage estimates for this IV strategy are presented in Supplementary Table A7 (in Panel B we report the first-stage F-statistics; for example, in column 1, this is 28.2).[14]

13. In fact, the fertility boom and the subsequent bust following World War II provide an ideal source of variation for our purposes, since they are generally explained by a number of exogenous social factors resulting from the Great Depression (Easterlin, 1961), the social changes brought by the war (Doepke et al., 2015) and improvements in maternal health (Albanesi and Olivetti, 2014).

14. Two other potential concerns with our IV strategy do not appear to be important either. First, past birth rates may capture the effects of previous generations' age composition. This is unlikely to drive our results, however, since we control for baseline demographic composition. Moreover, we find very similar results in Supplementary Table A8 when we exploit age-adjusted fertility rates as instruments. Second, past birth rates and aging may proxy for some latent institutional or technological characteristics of the country. We deal with this concern explicitly in Table 3, which looks at differential changes across subperiods with more or less aging for the same country.

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

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Contemporaneous aging	1.323	1.067	0.916	1.722	1.065	1.056
	(0.384)	(0.364)	(0.481)	(0.767)	(0.427)	(0.632)
Observations	120	120	120	62	62	62
First-stage F stat.	14.0	8.3	4.1	7.1	4.9	4.1
Overid p-value	0.15	0.22	0.55	0.56	0.32	0.48
Anderson–Rubin Wald test p-value	0.00	0.00	0.10	0.00	0.00	0.00
	Panel B. IV estimates					
Contemporaneous aging	1.323	1.067	0.916	1.722	1.065	1.056
	(0.384)	(0.364)	(0.481)	(0.767)	(0.427)	(0.632)
Observations	120	120	120	62	62	62
First-stage F stat.	14.0	8.3	4.1	7.1	4.9	4.1
Overid p-value	0.15	0.22	0.55	0.56	0.32	0.48
Anderson–Rubin Wald test p-value	0.00	0.00	0.10	0.00	0.00	0.00
	Panel C. OLS estimates weighted by manufacturing value added					
Contemporaneous aging	1.349	0.761	0.525	1.461	0.711	0.544
	(0.420)	(0.261)	(0.328)	(0.468)	(0.302)	(0.412)
Observations	120	120	120	62	62	62
R^2	0.43	0.62	0.05	0.26	0.56	0.06
	Panel D. IV estimates weighted by manufacturing value added					
Contemporaneous aging	1.349	0.761	0.525	1.461	0.711	0.544
	(0.420)	(0.261)	(0.328)	(0.468)	(0.302)	(0.412)
Observations	120	120	120	62	62	62
R^2	0.43	0.62	0.05	0.26	0.56	0.06
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Initial robot density and manufacturing value added		✓	✓		✓	✓
Country trends			✓			✓

Notes: The table presents OLS and IV stacked-differences estimates of the relationship between aging and the adoption of robots for the two periods 1993–2005 and 2005–14. In all panels, the dependent variable is the annualized 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 contemporaneous change in the ratio of workers above 56 to workers between 21 and 55 for both periods as well (from the UN Population Statistics) between 1990–2005 and 2005–2015. Panels A and C present OLS estimates. Panels B and D present IV estimates where the aging variable is instrumented using the average birth rates over each five-year interval from 1950–4 to 1980–4. For our IV estimates, we report the first-stage F-statistic, the p-value of Hansen's overidentification test, and the p-value of Anderson and Rubin's test for the coefficient on aging being zero. We present results for two samples: columns 1–3 use the full sample; columns 4–6 use the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5 include the 1993 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21–55 in 1990, the 1993 value of robots per thousand workers, and the log of the 1990 value added in manufacturing. Columns 3 and 6 include country fixed effects. The regressions in Panels A and B are unweighted, while the regressions in Panels C and D are weighted by value added in manufacturing in 1990. Standard errors are robust against heteroscedasticity and correlation within countries.

The IV estimates of the effect of demographic change on robot adoption reported in Panel B are slightly larger than their OLS counterparts.[15] For instance, the estimate in column 2 is now

15. In all tables, when we have more than one instrument, we report the $p-$value from Hansen's overidentification test. Except for columns 4 and 8 where we are including the bad controls (changes in education and female labor force participation), this test does not reject the joint validity of our instruments at the 5% level.

0.78, which implies that the same 20 percentage point increase in aging is now associated with 0.16 more robots per thousand workers per year.

One potential concern with our IV estimates is that our first-stage is borderline weak in the OECD sample. We address this concern in two ways. First, Panel B reports the p-value of the Anderson–Rubin test for the coefficient β being equal to zero (which is valid even when instruments are weak so long as they satisfy the exclusion restriction). Second, Panel C reports estimates where we use a single instrument computed as the percent decline in birth rates from 1960 to 1980. With this single instrument, the first-stage F-statistic is above 13 in all columns and the IV estimates are similar.

Panels D and E present OLS and IV estimates from regressions weighted by manufacturing value added in 1990. The estimates are larger than their counterparts in Panels A and B. Correspondingly, with the IV estimate in column 2, the differential demographic trends of Germany and the U.S. explain about 80% of the difference in the adoption of robots between the two countries.[16]

We have so far reported estimates from long-differences specifications, focusing on the change in the stock of robots between 1993 and 2014. These models do not exploit the covariation between the timing of aging and robot adoption within subperiods, and, as noted in footnote 14, may be capturing permanent institutional or technological differences correlated with aging or past birth rates across countries. Table 3 presents stacked-differences specifications that deal with these concerns. Now 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 aging between 1990 and 2005 and between 2005 and 2015, respectively. To ease the comparison with our previous estimates, we re-scale the coefficients so that they are directly comparable to the estimates in Table 2. Panel A presents our OLS estimates. Columns 1 and 4 show estimates from our most parsimonious model where we only control for region and period dummies. Columns 2 and 5 include all the country level covariates as controls (baseline values of log GDP per capita, log population, average schooling, ratio of older to middle-aged workers, stock of industrial robots per thousand workers, and the log of manufacturing value added). Panel B presents the corresponding IV estimates, while Panels C and D report results from weighted regressions.[17] The estimates confirm the results in Table 2. In columns 3 and 6, we go one step further and include linear country trends. These specifications take out any fixed country characteristics (including permanent differences in institutions and technological capabilities) and only exploit within-country, between-period differences in aging and robot adoption. The estimates in these demanding specifications are similar to our baseline findings, and statistically significant at 10% or less except in column 6 in Panel C.

Supplementary Table A11 shows that *past* demographic changes do not predict robot adoption. Namely, aging between 1950 and 1990, with or without expected demographic change after 1990

16. Table 2 uses the ratio of older to middle-aged population as our main explanatory variable. In Supplementary Table A9, we justify this specification by showing that, when included separately, the change in the log population of middle-aged workers has a negative impact on robot adoption, while the change in the log population of older workers has a positive impact of a similar magnitude. In line with these findings, Supplementary Table A10 further shows that, once we control for our measure of aging, there is no relationship between the change in population and robot adoption. Thus our main results are driven by the size of the middle-aged cohorts relative to older cohorts, motivating our claim in Section 1 that there is no robust relationship between the level or change in population and automation (which contrasts with the results in Abeliansky and Prettner, 2017). Finally, Panel D of this table shows that the dependency ratio—the ratio of the population above 65 to those below 65—is insignificant when included together with our aging variable, also confirming that robot adoption is shaped by the age composition of the workforce, not its size.

17. The first-stage F statistics are lower in this case, reflecting the difficulty of separately predicting aging in these two shorter periods.

and in both weighted and unweighted specifications, has no predictive power for robot adoption after 1993. This is reassuring since robot adoption, which took off after 1990, should respond to current and future rather than to pre-1990 developments.

Supplementary Table A12 investigates whether it is current or future aging, or both, that matter for robot adoption. In particular, we simultaneously include aging between 1990 and 2015 and expected aging between 2015 and 2025. As hypothesized in our baseline specification, both contemporaneous aging and expected aging between 2015 and 2025 have the same impact on robot adoption, justifying our baseline specification that focuses on expected aging between 1990 and 2025. In line with this, Supplementary Table A13 demonstrates that our results are similar if we exploit only contemporary aging between 1990 and 2015, as we did in our stacked-differences specification in Table 3.

In addition, Supplementary Table A14 presents the cross-sectional (level) relationship between demographic structure (the ratio of older to middle-aged workers) and the stock of robots, and shows that countries with an older workforce use significantly more robots. Finally, Supplementary Table A15 demonstrates the robustness of our results to using percent changes in robots—either $\Delta\ln(1+R_c)$ or $\Delta\ln R_c$—as the dependent variable rather than changes in the number of robots per thousand industry workers.

4.2. *Other automation technologies*

We now show a similar relationship between aging and other automation technologies from Comtrade imports data. We first confirm the results presented so far using imports of industrial robots.[18] To do so, we estimate a variant of equation (13) with the log of robot imports relative to other intermediate imports between 1996 and 2015 as the dependent variable.[19] Because these measures are imprecise for countries with little trade and small manufacturing sectors, which tend to trade few intermediates, we focus on regressions weighted by manufacturing value added in 1990.[20]

Panels A and B of Table 4 present OLS and IV estimates, respectively. The table has the same structure as the previous ones, with the exception that in columns 3 and 6 we now control for the log of intermediate imports instead of initial robot density. Because Comtrade data cover more countries, our sample now includes 129 countries, 33 of which are in the OECD. We find that aging countries tend to import more industrial robots relative to other intermediate goods. Figure 5 provides regression plots for the full sample and the OECD sample. The implied

18. Supplementary Figure A6 shows that, for the countries in our sample, imports of robots (measured from Comtrade) and robot installations (from the IFR) are positively correlated. A bivariate regression between imports and installations yields a coefficient of \$52,940 or \$99,670 excluding Germany and Korea (both of which produce many of the robots they use). These point estimates align with the cost of one industrial robot, which ranges from \$50,000 to \$120,000 dollars.

19. Several points are worth noting. First, since imports (and later exports and patents) are flow variables, our dependent variable corresponds to the growth in the stock of these intermediates, in line with our baseline specification with the change in robots on the left-hand side in equation (13). Second, our normalization ensures that our findings are not driven by an overall increase in imports in aging countries. Third, because data on robot imports and exports are only available between 1996 and 2015, in these models we focus on aging between 1995 and 2025, and measure all of our controls in 1995 rather than in 1993. Finally, we choose the specification with logs as the baseline because it turns out to be less sensitive to outliers, and we are already limiting our sample to countries with positive imports or exports of the relevant intermediates (and later patenting)—the IFR sample is defined in a similar way, as it only includes countries with positive robot installations. In Supplementary Table A16 and Supplementary Figures A13 and A14, we show the OLS version of our estimates and the robustness of our results to different specifications and to samples that include countries with zero imports, exports or patents.

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

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

	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: log of imports of industrial robots relative to intermediates					
	Panel A. OLS estimates					
Aging between 1995 and 2025	3.527	3.182	1.847	3.527	3.311	2.181
	(1.285)	(0.866)	(0.768)	(1.518)	(0.863)	(0.728)
Observations	129	129	129	33	33	33
R^2	0.29	0.50	0.58	0.28	0.71	0.79
	Panel B. IV estimates					
Aging between 1995 and 2025	3.262	3.188	1.962	3.270	2.889	1.674
	(1.471)	(0.903)	(0.961)	(1.731)	(0.820)	(0.808)
Observations	129	129	129	33	33	33
First-stage F stat.	13.7	12.0	10.8	23.7	10.9	9.5
Overid p-value	0.16	0.69	0.67	0.32	0.11	0.04
Anderson–Rubin Wald test p-value	0.01	0.22	0.15	0.01	0.07	0.02
	Dependent variable: log of exports of industrial robots relative to intermediates					
	Panel C. OLS estimates					
Aging between 1995 and 2025	6.141	4.395	4.657	6.309	4.516	4.144
	(1.048)	(0.952)	(0.985)	(1.131)	(1.147)	(1.165)
Observations	103	103	103	35	35	35
R^2	0.78	0.83	0.83	0.61	0.76	0.77
	Panel D. IV estimates					
Aging between 1995 and 2025	7.014	4.713	5.199	6.903	4.645	4.803
	(0.935)	(1.039)	(1.167)	(1.064)	(1.230)	(1.177)
Observations	103	103	103	35	35	35
First-stage F stat.	11.6	13.1	15.0	36.4	19.0	12.2
Overid p-value	0.10	0.16	0.14	0.11	0.22	0.14
Anderson–Rubin Wald test p-value	0.00	0.00	0.00	0.00	0.00	0.00
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Manufacturing value added and baseline imports/exports of intermediates			✓			✓

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 average birth rates over each five-year interval from 1950–4 to 1980–4. For our IV estimates, we report the first-stage F-statistic and 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 1995 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21–55. Columns 3 and 6 add the log of the 1990 value added in manufacturing and the log of intermediate imports (Panels A and B) or exports (Panels C and D) as additional covariates. All regressions are weighted by value added in manufacturing in 1990, and the standard errors are robust against heteroscedasticity.

quantitative magnitudes are similar to those reported so far. The IV coefficient estimate in column 2 of Table 4, 3.2 (s.e. = 0.9), implies that a 20 percentage point increase in aging, corresponding to the difference between Germany and the U.S., leads to a 64% increase in (industrial) robot imports relative to total intermediate imports and closes half of the gap between the two countries (which is comparable to the quantitative magnitudes for robot installations in our baseline estimates).

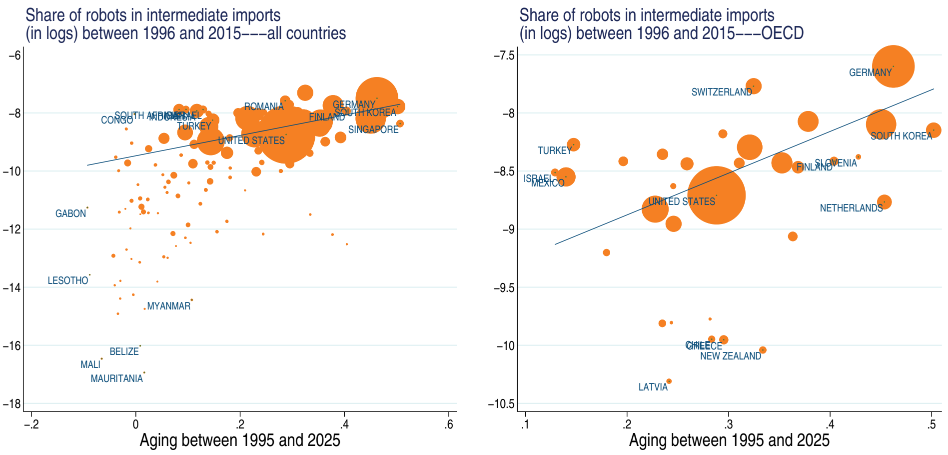

FIGURE 5

Relationship between aging (change in the ratio of workers above 56 to workers aged 21–55 between 1990 and 2025) and the log of imports of industrial robots between 1996 and 2015 (relative to imports of intermediates). The left panel is for the full sample and the right panel is for the OECD sample. The plots correspond to the specifications in Panel A, columns 2 and 5, of Table 4. Marker size indicates manufacturing value added.

Moreover, aging accounts for over 20% of the cross-country variation in robot imports, and 28% of the variation within the OECD.

Figure 7 turns to imports of other equipment from the Comtrade data and reports estimates from our baseline IV specification in columns 2 and 5 of Table 4. We provide results for three sets of imported intermediates. The first set includes intermediates related to industrial automation: dedicated machinery (including robots), numerically controlled machines, automatic machine tools, automatic welding machines, weaving and knitting machines, other dedicated textile machinery, automatic conveyors, and regulating and control instruments. The second set comprises non-automated capital goods used for similar industrial tasks: heavy capital goods (including furnaces, ovens, and electrical motors) and capital goods used in food manufacturing (machines used for brewing and baking in industrial contexts), tools for industrial work, machines that are not numerically controlled, manual machine tools, manual welding machines, and tools for transferring materials. Finally, we consider intermediates related to non-industrial technologies, which should not become more profitable when the population ages—at least not through the channels we have been emphasizing. This set includes laundry machines, vending machines, agricultural machinery (including tractors), and computers.[21] The evidence in Figure 7 is consistent with the idea that aging is associated with the adoption of a range of technologies for industrial automation. For the full sample of countries, aging leads to a sizable increase in the relative imports of all of our industrial automation technologies, except automatic conveyors. For the OECD, the estimates are less precise but paint a similar picture. Reassuringly from the viewpoint of our theory, in neither sample do we find a relationship between aging and imports of technologies unrelated to industrial automation, including computers. The finding that aging has

21. Computers are of interest in and of themselves. As emphasized in Acemoglu and Restrepo (2020), they are quite distinct from automation technologies and are often used to complement labour in existing tasks as well as automating a smaller subset of tasks.

no impact on non-industrial automation technologies, such as laundry and vending machines, also weighs against demand-side explanations for our results (such as older individuals demanding more automated goods and services).

The results presented in this subsection are robust to a range of checks. For example, Supplementary Figures A13 and A14 show that they are very similar when we use OLS, when we instead use $\log(1+x)$ or shares on the left-hand side, and when we exclude outliers.

Overall, the evidence in this section supports our first empirical implication on the relationship between aging and adoption of (industrial) automation technologies.

5. DEMOGRAPHIC CHANGE, EXPORTS, AND INNOVATION

In this section, we investigate our second empirical implication, linking demographic change to the development of automation technologies. We first look at export of intermediates that embody automation technologies, based on the reasoning that new or improved varieties of specialized machinery are often exported to other countries.[22] We then investigate the relationship between demographic change and patents related to automation technologies.

We start with a variant of equation (13) focusing on log robot exports relative to other intermediate exports between 1996 and 2015 as dependent variable. Similar to our strategy with imports, we weight our regressions by manufacturing value added in 1990.

Panels C and D of Table 4 present OLS and IV estimates for exports of industrial robots. These panels follow the structure of Panels A and B, except that in columns 3 and 6 we control for the log of intermediate exports instead of imports. Our sample now includes 103 countries, 35 of which are in the OECD. Since we are looking at exports, these models include Japan as well. The results show that demographic change is associated with greater exports of industrial robots relative to other intermediate goods. Figure 6 depicts these relationships for the full sample and the OECD sample. The IV estimate in column 2, 4.7 (s.e. = 1.0), implies that a 20 percentage point increase in expected aging—the difference between Germany and the U.S.—doubles robotics exports, fully closing the gap between the two countries (which is about 63%). In this case, aging by itself accounts for about 50% of the cross-country variation in robot exports (and 60% within the OECD).

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

The export results, too, are robust to a range of different specifications. Supplementary Figures A3 and A4 show that the results are similar when we focus on OLS estimates, when we use $\log(1+x)$ or shares on the left-hand side, and when we exclude outliers (see Supplementary Table A16). They additionally provide support for our claim in Section 1 that automation technologies developed in rapidly-aging countries are adopted throughout the world.[23]

Our second measure of innovation and development of new automation technologies involves robotics-related patents, described in Section 3. We estimate a variant of equation (13) with the

22. Costinot et al. (2018) also look at exports as a measure of the development of new technologies but focus on pharmaceuticals.

23. Data from the IFR support this claim as well. An estimated 381,000 robots were installed globally in 2017, and over 80% of these robots were produced in and exported from Germany and Japan to over 50 countries. As a result of these exports, there are now 33 countries with more than one robot per thousand industrial workers and 17 countries with more than five robots per thousand industrial workers.

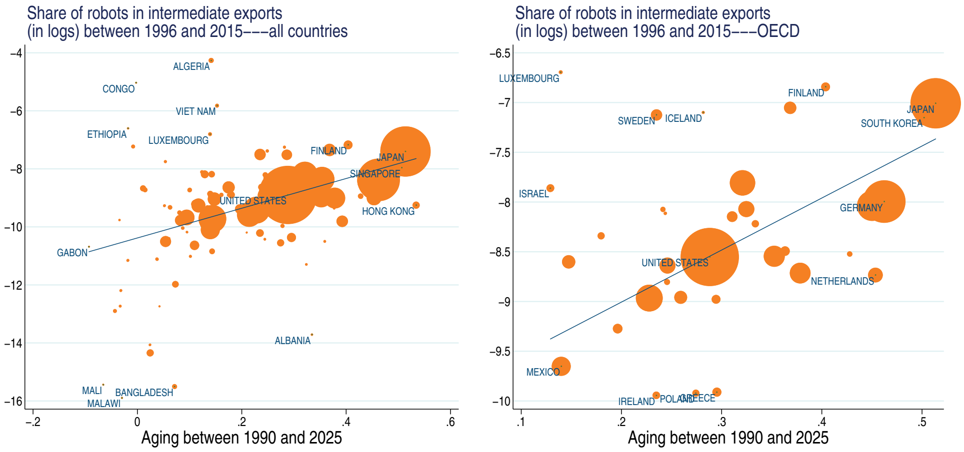

FIGURE 6

Relationship between aging (change in the ratio of workers above 56 to workers aged 21–55 between 1990 and 2025) and the log of exports of industrial robots between 1996 and 2015 (relative to exports of intermediates). The left panel is for the full sample and the right panel is for the OECD sample. The plots correspond to the specifications in Panel A, columns 2 and 5, of Table 4. Marker size indicates manufacturing value added.

log of robotics-related patents relative to other utility patents granted between 1990 and 2015 as the dependent variable. The normalization ensures that our findings are not driven by an overall increase in patenting activity at the USPTO among rapidly-aging countries. As before, we focus on regressions weighted by manufacturing value added in 1990, which ensures that countries with larger manufacturing sectors, and thus more patents, get greater weights. Panels A and B of Table 5 present our OLS and IV estimates. Our sample now includes 69 countries, 31 of which are in the OECD. The results show a strong positive association between demographic change and robotics-related patents (relative to other utility patents). Figure 8 presents these relationships visually. The IV estimate in column 2, for example, is 1.21 (s.e. = 0.31) and implies that a 20 percentage point increase in expected aging, corresponding to the difference between Germany and the U.S., leads to a 24% increase in robotics-related patents relative to all utility patents, which is about half of the gap between the two countries. Aging explains 35% of the cross-country variation in robotics-related patents (and 43% within the OECD).

We investigated the robustness of these results in a number of dimensions. Some of those are shown in Figure 9. To start with, the results are very similar with alternative definitions of automation patents, and reassuringly from the viewpoint of our explanation, there is no similar positive association when we look at patents related to computers, nanotechnology or pharmaceuticals—advanced technologies that are not directly related to industrial automation. Our alternative measures of robotics-related and other automation patents are: just the 901 USPTO class (as opposed to our baseline measure which in addition includes all patents referring to the 901 class); patents in classes that reference the 901 class frequently (using two thresholds: patents referencing the 901 class at least 10% of the time; and patents referencing the 901 class at least 20% of the time); patents whose abstract contains words related to robots or to industrial robots; patents whose abstract contains words related to robots or manipulators; and finally patents whose abstract contains words related to numerical control. In all these cases, we find a positive association between aging and the share of patents in these classes. The remaining entries in the

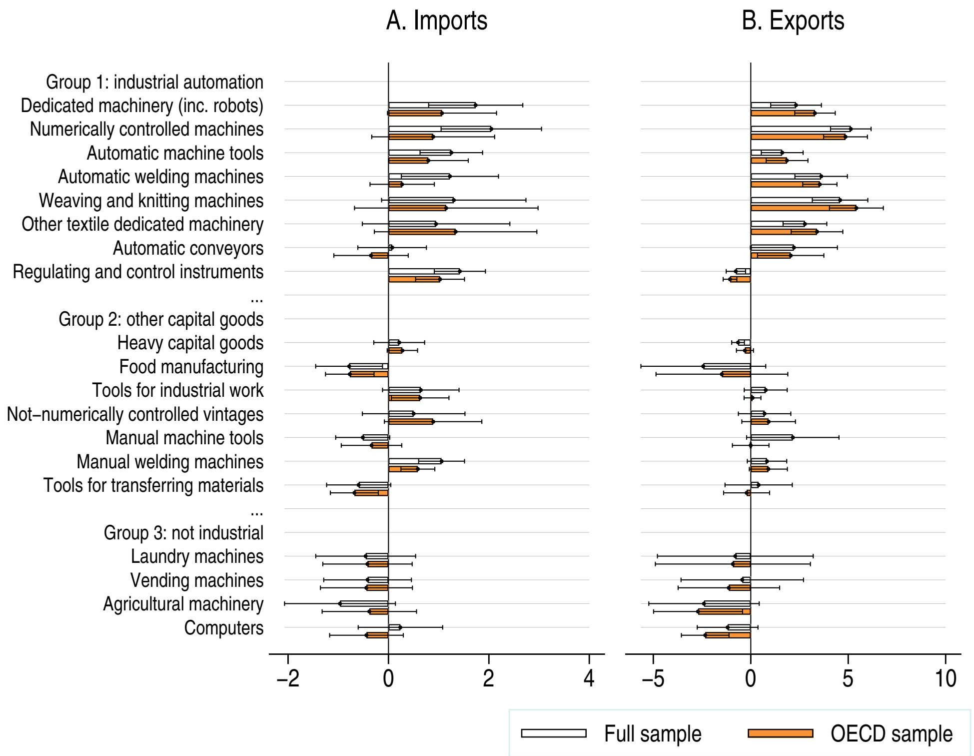

FIGURE 7

IV 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.

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.[24]

In summary, we find robust support for our second empirical application, linking demographic change to innovation in automation technologies.

6. DEMOGRAPHICS AND ROBOTS ACROSS U.S. COMMUTING ZONES

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

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

24. The construction of the various patent classes is further described in Supplementary Appendix, where we also show that our main results for patents are robust when we look at OLS estimates, when we use other functional forms or when we take into account the presence of outliers (see Supplementary Table A17).

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

	Dependent variable: log of robotics-related patents relative to utility patents					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging between 1990 and 2025	1.658	1.393	1.392	1.649	1.316	1.612
	(0.332)	(0.291)	(0.442)	(0.346)	(0.274)	(0.546)
Observations	69	69	69	31	31	31
R^2	0.58	0.63	0.64	0.43	0.59	0.66
	Panel B. IV estimates					
Aging between 1990 and 2025	1.620	1.211	0.759	1.838	1.385	1.357
	(0.401)	(0.307)	(0.554)	(0.434)	(0.325)	(0.466)
Observations	69	69	69	31	31	31
First-stage F-stat.	7.9	6.4	5.3	27.4	26.1	18.7
Overid p-value	0.19	0.11	0.33	0.41	0.12	0.33
Anderson–Rubin Wald test p-value	0.00	0.13	0.60	0.00	0.00	0.09
Covariates included:						
Baseline country covariates		✓	✓		✓	✓
Manufacturing value added			✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and robotics-related patents assigned to companies and inventors from different countries by the USPTO. In both panels, the dependent variable is the log of robotics-related patents relative to all utility patents granted between 1990 and 2015 (from Patents View). The aging variable is the expected change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the average birth rates over each five-year interval from 1950–4 to 1980–4. For our IV estimates, we report the first-stage F-statistic and 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 1995 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers aged 21–55. Columns 3 and 6 add the log of utility patents received by each country and the log of the 1990 value added in manufacturing as additional covariates. All regressions are weighted by value added in manufacturing in 1990, and the standard errors are robust against heteroscedasticity.

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

Because people migrate across commuting zones more frequently than across countries, the endogeneity of local age composition is a more significant issue in this case than in our cross-country analysis. To address it, in Panel B we instrument aging using the average birth rates of the commuting zone over five-year intervals from 1950–4 to 1980–4, while in Panel C, we present an alternative IV strategy using the decline in birth rates from 1950 to 1985 as a single instrument.

All panels in this table share the same structure. Column 1 controls for regional dummies (Midwest, Northeast, South, and West). Column 2 includes demographic characteristics of commuting zones measured in 1990—a period when the U.S. had few industrial robots and integrators. These characteristics include log average income, log population, the urbanization rate, the initial ratio of older to middle-aged workers, and the shares of people by education, race, and gender. Column 3 includes the measure of *exposure to robots* between 1990 and 2015 from Acemoglu and Restrepo (2020), which captures the extent to which a commuting zone specializes

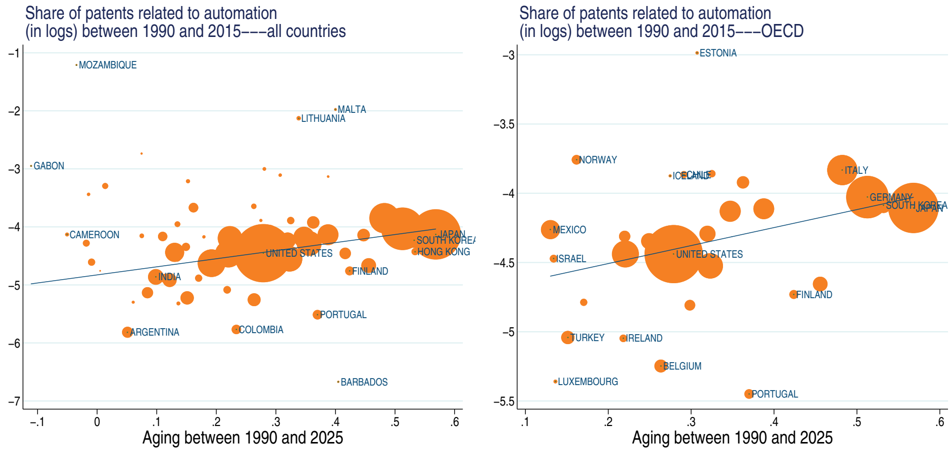

FIGURE 8

Relationship between aging (change in the ratio of workers above 56 to workers aged 21–55 between 1990 and 2025) and the log of automation patents granted to a country between 1990 and 2016 (relative to total patents at the USPTO). The left panel is for the full sample and the right panel is for the OECD sample. The plots correspond to the specifications in Panel A, columns 2 and 5, of Table 5. Marker size indicates manufacturing value added.

in industries that are prone to robot adoption.[25] This column also adds controls for the shares of employment in manufacturing, agriculture, mining, construction, and finance and real estate in 1990. Column 4 additionally controls for other major trends affecting U.S. labour markets—exposure to Chinese imports, offshoring, and the share of routine jobs. Finally, in column 5, we follow Acemoglu and Restrepo (2020) and exclude the top 1% commuting zone with the highest exposure to robots to ensure that the results are not being unduly affected by the most exposed commuting zones.

Overall, the results in this table, especially the IV estimates, suggest that integrators locate in commuting zones that are aging more rapidly as well as those with the greatest exposure to robots (as shown by Acemoglu and Restrepo, 2020). The estimates in column 4 of Panel B imply that a 10 percentage point increase in aging—the standard deviation among US commuting zones in

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

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

which is based on robot adoption trends among European countries. In particular, in this equation j indexes Denmark, Finland, France, Italy, or Sweden, and $m^j_{i,t}$ denotes the number of robots in country j's industry i at time t (from the IFR data), normalized by thousand of workers in industry in 1990. The term $g^j(i,t_0,t_1)$ gives the growth rate of output of industry i during this period, so that subtracting $g^j(i,t_0,t_1)m^j_{i,t_0}$ adjusts for the fact that some industries are expanding more than others (see Acemoglu and Restrepo, 2020). The exposure to robots of a commuting zone is then

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

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

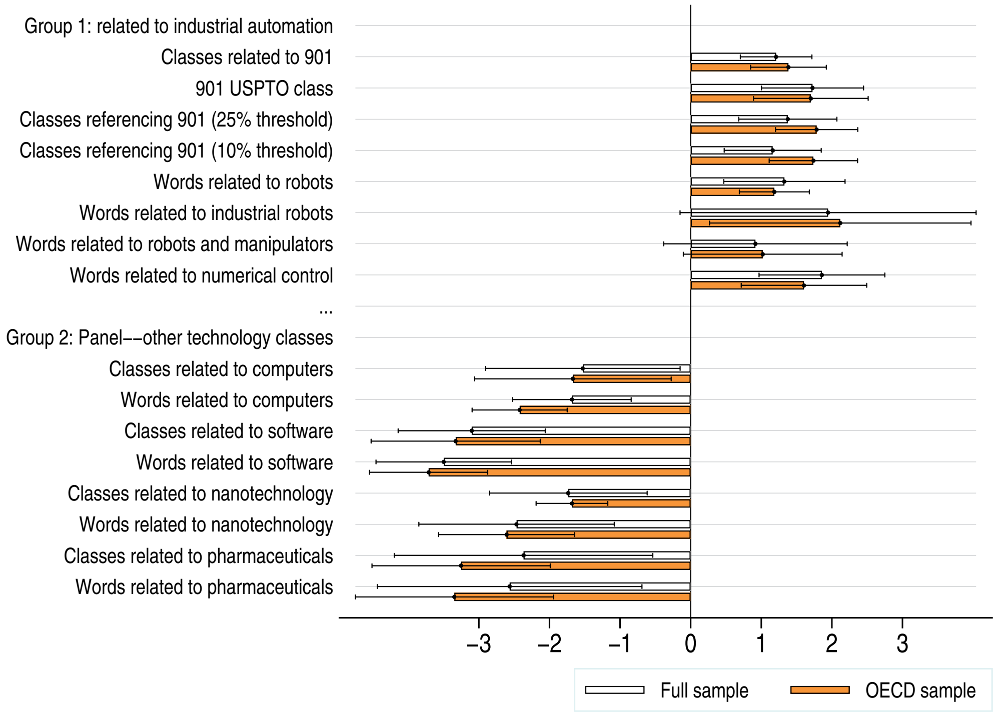

FIGURE 9

IV 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.

this period—is associated with a 6.45 percentage points increase in the probability of having an integrator (compared to an average probability of 20%).[26]

Supplementary Table A18 shows that our commuting zone-level results are robust across a range of specifications, for example, when we exclude outliers, estimate IV-probit models, weight observations by baseline population in the commuting zone, or use the log of the number and the employment of integrators as the dependent variable.

Figure 10 presents binned scatter plots of the relationship between predicted aging (from the IV and single-IV first stages) and the location of integrators corresponding to the IV estimates from the specification in column 4 in Panels B and C of Table 6.

Overall, even though the presence of integrators in an area does not fully capture the extent of industrial automation there, the evidence supports the link between aging and automation.

7. MECHANISMS

Our theory suggests that aging encourages automation because, relative to their older colleagues, middle-aged workers have a comparative advantage in manual production tasks, which are the

26. The effects of past birth rates on the current demographic structure of commuting zones are consistent with previous findings in the literature indicating that local shocks have persistent local effects. See, for example, Acemoglu and Restrepo (2020), Autor et al. (2013), Dustmann and Glitz (2015), and Lewis (2011).

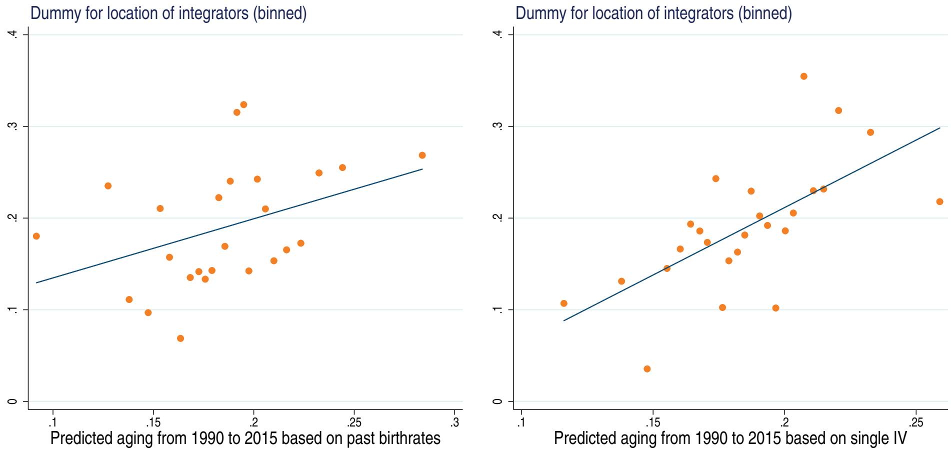

FIGURE 10

Binned plot of the relationship between predicted aging (change in the ratio of workers above 56 to workers aged 21–55 between 1990 and 2015) and the location of robot integrators in the U.S. (from Leigh and Kraft, 2018). The left panel predicts aging based on birthrates from 1950 to 1985, and thus corresponds to the IV estimates in Panel B, column 4 of Table 6. The right panel predicts aging based on the decline in birth rates between 1950 and 1985, and thus corresponds to the single-IV estimates in Panel C, column 4, of Table 6.

ones being automated using industrial automation technologies such as robots. When this is the case, aging also creates differential effects across industries as summarized by our third and fourth empirical implications. In this section, we provide evidence supporting these hypotheses and predictions.

7.1. *The substitution between robots and workers*

We first provide several pieces of evidence bolstering our hypothesis that middle-aged workers specialize in production tasks that can be automated using industrial robots and related technologies.

Using data from the 1990 and 2000 U.S. Censuses and the 2006–8 American Community Survey, we first document how the allocation of *employed* workers across industries and occupations varies with their age. The left panel of Figure 11 plots the ratio of workers employed in blue-collar jobs relative to workers employed in white-collar and service jobs for five-year age brackets. Blue-collar jobs include production workers and machinists, and represent about 10% of U.S. employment. White-collar jobs include clerks, accountants, secretaries, and salespersons and represent about 25% of U.S. employment, while service jobs account for another 15% of U.S. employment. The figure shows a sharp decline in this ratio starting around age 50 (in the 2006–8 ACS) and age 55 (in the 1990 Census). The right panel reveals a similar picture when we look at the share of workers by age employed in industries that later became more robotized. Both figures support the presumption that, relative to their older counterparts, middle-aged workers specialize in blue-collar jobs and in industries that are more prone to the use of industrial robots. Consistent with automation technologies replacing middle-aged workers in production tasks, both figures also show a decline over time in the share of middle-aged workers employed in blue-collar jobs and in industries prone to the use of industrial robots. Supplementary Figure A7 documents very similar results for other countries, bolstering the case that these specialization patterns reflect

TABLE 6

Estimates of the impact of aging on the location of robot integrators in the U.S.

	Dependent variable: Dummy for presence of robot integrator				
	(1)	(2)	(3)	(4)	(5)
	Panel A. OLS estimates				
Aging between 1990 and 2015	−0.085	0.143	0.142	0.148	0.177
	(0.145)	(0.090)	(0.077)	(0.080)	(0.076)
Exposure to robots			0.061	0.060	0.098
			(0.020)	(0.021)	(0.022)
Observations	722	722	722	722	712
R^2	0.03	0.41	0.45	0.45	0.46
	Panel B. IV estimates				
Aging between 1990 and 2015	1.372	0.769	0.633	0.645	0.649
	(0.385)	(0.241)	(0.230)	(0.231)	(0.229)
Exposure to robots			0.053	0.053	0.092
			(0.021)	(0.022)	(0.022)
Observations	722	722	722	722	712
First-stage F-stat.	11.2	19.9	21.8	21.6	21.5
Overid p-value	0.00	0.96	0.89	0.78	0.66
Anderson–Rubin Wald test p-value	0.00	0.03	0.04	0.02	0.02
	Panel C. Single-IV estimates				
Aging between 1990 and 2015	1.668	1.044	0.957	0.974	1.038
	(0.431)	(0.403)	(0.389)	(0.398)	(0.400)
Exposure to robots			0.048	0.047	0.087
			(0.022)	(0.023)	(0.022)
Observations	722	722	722	722	712
First-stage F-stat.	53.6	55.2	54.5	54.4	55.9
Covariates included:					
Regional dummies	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry composition			✓	✓	✓
Other shocks				✓	✓
Excluding highly exposed commuting zone					✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the location of robot integrators across U.S. commuting zones. In all panels, the dependent variable is a dummy for the presence of robot integrators in each U.S. commuting zone (from Leigh and Kraft, 2018). The aging variable is the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015 (from the NBER-SEER). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the average birth rates over each five-year interval from 1950–4 to 1980–4. 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, and the p-value of Anderson and Rubin's test for the coefficient on aging being zero. 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 (2020) and also controls for the shares of employment in manufacturing, agriculture, mining, construction, and finance and real estate in 1990. Column 4 includes additional demographic characteristics measured in 1990, including the racial composition of commuting zones and the share of male and female employment, and controls for other shocks affecting U.S. markets, including offshoring, trade with China and the decline of routine jobs. Finally, column 5 excludes the top 1% commuting zones with the highest exposure to robots. All regressions are unweighted, and in parenthesis we report standard errors that are robust against heteroscedasticity and correlation in the error terms within states.

the comparative advantage of middle-aged workers in manual production tasks rather than a U.S.-specific correlation between age and education.[27]

27. Acemoglu and Restrepo (2020) and Acemoglu et al. (2020) document that industries and firms adopting robots exhibit lower wage bill share of production workers. This supports our hypothesis that automation substitutes for workers employed in blue-collar jobs who, as we have just shown, tend to be middle-aged.

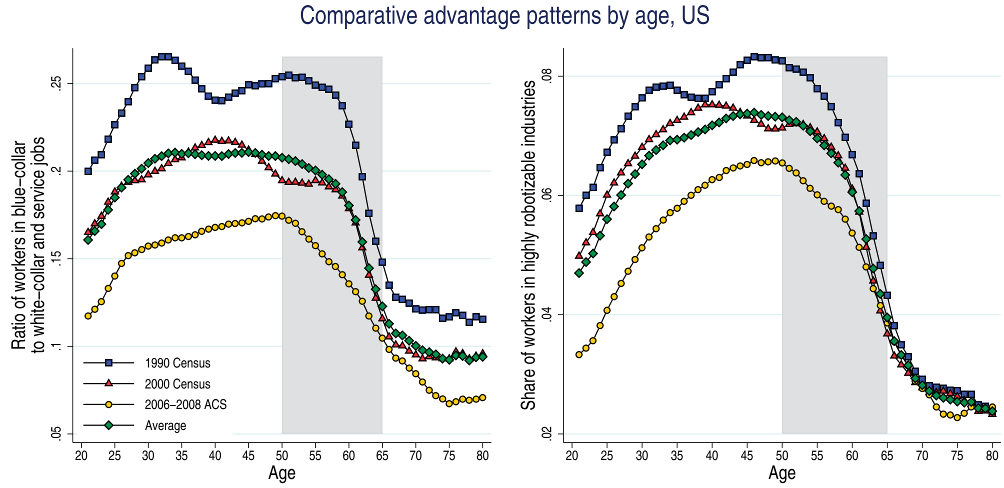

FIGURE 11

The figure plots specialization patterns by age for the U.S. The left panel plots the ratio of the number of employees in blue-collar production jobs to the number of employees in white-collar and service jobs by age in the U.S. The right panel plots the share of employees working in industries with the greatest opportunities for automation (car manufacturing, electronics, metal machinery, and chemicals, plastics, and pharmaceuticals) by age in the U.S. Both figures present data from the 1990 and 2000 Censuses, the 2006–8 American Community Survey, and an average of these series.

Finally, we look at the impact of automation on the wages and employment of workers by age. We follow Acemoglu and Restrepo (2020) and explore the impact of robots across U.S. commuting zones using the exposure to robots measure (see footnote 25). We then estimate the following model for employment and wages by 10-year age group across commuting zones:

$$\Delta Y_{z,a} = \beta_a \text{Exposure to robots}_{z,1993,2007} + \Gamma_a X_z + \epsilon_{z,a},$$

where $\Delta Y_{z,a}$ is the change in the employment rate (or the wage rate) of age group a in commuting zone z between 1990 and 2007, and X_z denotes the vector of covariates. Figure 12 presents the estimates of the coefficients for employment and wages for these groups (together with 95% confidence intervals). We report three specifications similar to those in Acemoglu and Restrepo (2020). The first one is the unweighted version of the baseline specification in Acemoglu and Restrepo (2020), which controls for Census region fixed effects, demographic differences across commuting zones, broad industry shares, the share of routine jobs and the impact of trade with China (as in Autor et al., 2013).[28] The second specification removes the top 1% of commuting zones with the highest exposure to robots, to ensure that our results are not being driven by the most exposed commuting zones. The last specification is identical to the first but uses commuting zone population in 1990 as weight as in the baseline specification of Acemoglu and Restrepo (2020).

For both employment and wages, the negative effects of industrial robot adoption concentrate on workers between the ages of 35 and 54, with mild effects on those older than 55 and no effects

28. Specifically, we control for the 1990 levels of log population, the share of population above 65; the shares of population with different education levels, the share of population by race and gender, and the shares of employment in manufacturing, light manufacturing, mining, and construction, as well as the share of female employment in manufacturing. The variables are described in detail in Acemoglu and Restrepo (2020).

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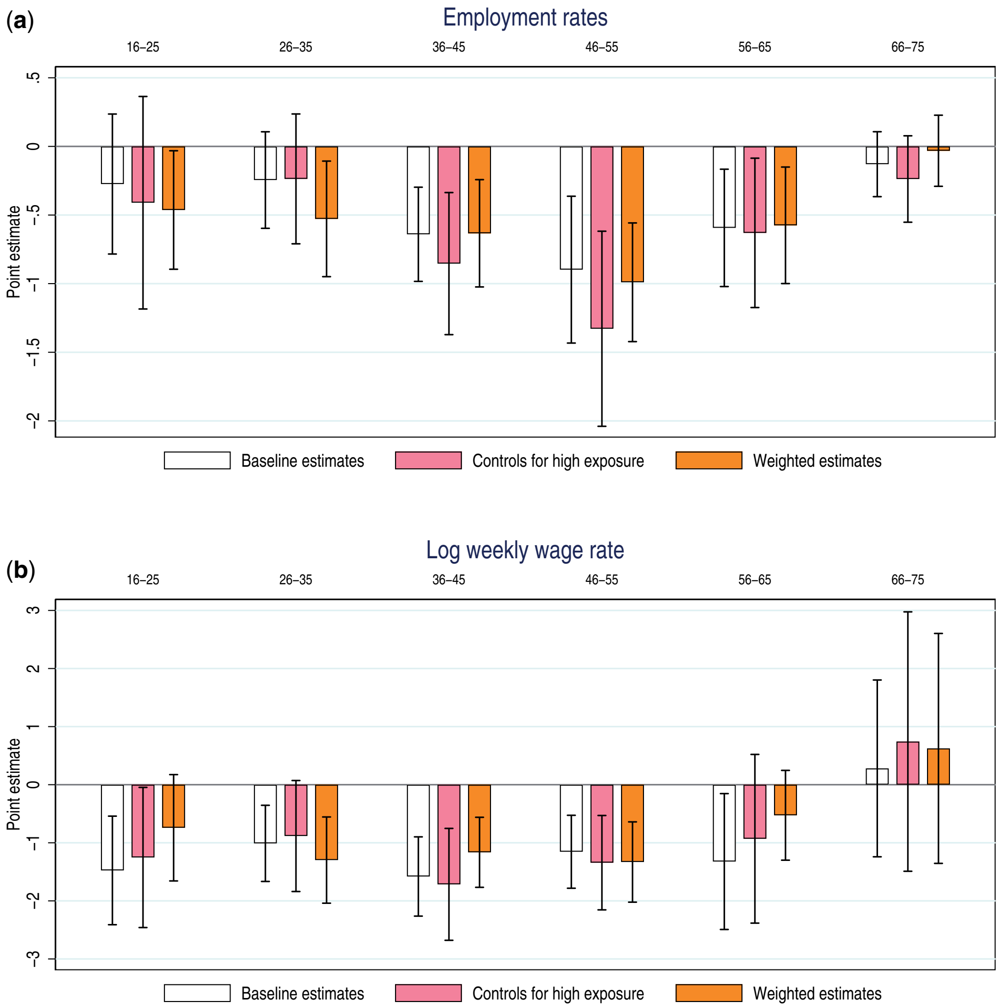

FIGURE 12

The figure presents estimates of the impact of one additional robot per thousand workers on the employment and wage rates of different age groups across U.S. commuting zones. The three specifications and the data used are described in the main text and in Acemoglu and Restrepo (2020). The spiked bars present 95% confidence intervals based on standard errors that are robust to heteroscedasticity and serial correlation within U.S. states.

on those above 65 (see Supplementary Figure A9 for similar results by five-year age bins). These results are our most direct evidence that, relative to older workers, the middle-aged specialize in tasks that can be performed by, and thus are more substitutable to, industrial robots.[29]

As a final check on our basic working hypotheses, in Supplementary Appendix, we investigate whether aging increases relative wages in manufacturing (because it creates a shortage of workers with the necessary skills). The estimates in Supplementary Table A19, which use data from the World Input–Output Tables, support this prediction, especially when we focus on the IV

29. The smaller negative effects we see in some specifications for workers aged 56–65 may reflect the spillovers on workers employed in non-manufacturing industries, documented in Acemoglu and Restrepo (2020).

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specifications. A similar pattern holds across U.S. commuting zones: Supplementary Table A20 shows that aging increases the relative wage of manufacturing workers and that this effect is more pronounced for blue-collar workers. Though less precisely estimated, we also find higher relative wages for middle-aged workers in commuting zones experiencing faster aging.

In summary, our key assumption that industrial automation substitutes for tasks performed by middle-aged workers receives support from the data. We find that aging creates a shortage of blue-collar manufacturing workers and raises their relative wage, generating incentives to adopt and develop automation technologies that substitute for these workers. We next turn to a detailed investigation of other empirical implications of our framework.

7.2. *Industry-level results*

Our third empirical implication is that the impact of aging should be more pronounced in industries that rely more on middle-aged workers and in industries in which these middle-aged workers engage in tasks that can be more productively automated. This subsection explores these predictions using robot adoption data by industry and country.

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

$$\frac{IR_{i,c,t}}{L_{i,c,1990}} = \beta \text{Aging}_c + \beta_R \text{Aging}_c \times \text{Reliance on Middle-Aged Workers}_i \\ + \beta_P \text{Aging}_c \times \text{Opportunities for Automation}_i + \Gamma_{i,t} X_{c,1990} + \alpha_i + \delta_t + \varepsilon_{i,c,t}. \tag{14}$$

In contrast to equation (13), the left-hand side variable now denotes the (annual) installation of new robots per thousand workers (where the denominator is always for 1990 to avoid endogenous changes in industry employment).[30] Aging_c is once again defined as the 1990–2025 change in the ratio of the population above 56 to those between 21 and 55. We include industry and year effects, and allow the covariates in $X_{c,1990}$ to have time-varying coefficients and affect industries differentially. As explained in Section 3, Reliance on Middle-Aged Workers_i and Opportunities for Automation_i capture the relevant dimensions of industry heterogeneity according to our theory. Our sample for this regression includes 58 countries for which industry data are available, and covers the 1993–2014 period but is unbalanced since, as indicated in Table A1, data are missing for several country $\times$ industry $\times$ year combinations.[31] Standard errors are now robust against heteroscedasticity, and cross-industry and temporal correlation at the country level.

To normalize our left-hand side variable, we use several approaches. First, in Panels A and B, we use the ILO country data to normalize robot installations by average industry employment, computed as $L_{c,1990}/19$ (recall that the IFR reports data for 19 industries). This normalization

30. Supplementary Table A21 shows that if we estimate an analogue of equation (14) using yearly data on robot installations, the results are similar to our baseline cross-country estimates in Table 2. 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).

31. 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 strategy used by Graetz and Michaels, 2018).

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

TABLE 7
Estimates of the impact of aging on robot installations by country–industry pairs

		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: installation of robots in country-industry pairs normalizing by average employment in an industry from ILO						
	Panel A. OLS estimates.						
Aging between 1990 and 2025	1.492	1.492	1.038		1.492	1.062	
	(0.400)	(0.400)	(0.307)		(0.400)	(0.317)	
Aging × reliance on middle-aged		0.873	0.628	0.628	0.268	0.186	0.186
		(0.222)	(0.190)	(0.188)	(0.079)	(0.077)	(0.076)
Aging × opportunities for automation		5.442	3.789	3.790	5.764	4.306	4.318
		(2.288)	(1.425)	(1.413)	(1.511)	(1.175)	(1.164)
Observations	11,837	11,837	11,837	11,837	11,837	11,837	11,837
Countries in sample	58	58	58	58	58	58	58
	Panel B. IV estimates.						
Aging between 1990 and 2025	1.364	1.364	1.103		1.364	1.120	
	(0.404)	(0.404)	(0.322)		(0.404)	(0.328)	
Aging × reliance on middle-aged		0.930	0.684	0.683	0.323	0.204	0.205
		(0.260)	(0.203)	(0.200)	(0.093)	(0.078)	(0.077)
Aging × opportunities for automation		3.628	3.562	3.526	5.520	4.586	4.575
		(2.088)	(1.650)	(1.640)	(1.652)	(1.295)	(1.280)
Observations	11,837	11,837	11,837	11,837	11,837	11,837	11,837
Countries in sample	58	58	58	58	58	58	58
First-stage F-stat.	23.8	23.8	9.9	10.8	23.8	12.0	11.2
Overid p-value	0.91	0.35	0.53	0.30	0.18	0.43	0.23
	Dependent variable: installation of robots in country-industry pairs normalizing by industrial employment from KLEMS						
	Panel C. OLS estimates.						
Aging between 1990 and 2025	0.743	0.740	0.414		0.678	0.382	
	(0.173)	(0.190)	(0.145)		(0.162)	(0.130)	
Aging × reliance on middle-aged		0.324	0.374	0.333	0.112	0.159	0.125
		(0.132)	(0.118)	(0.121)	(0.059)	(0.064)	(0.066)
Aging × opportunities for automation		9.914	4.038	4.376	4.405	2.810	2.854
		(2.669)	(2.035)	(2.010)	(1.142)	(0.868)	(0.855)
Observations	6,270	6,270	6,270	6,270	6,270	6,270	6,270
Countries in sample	24	24	24	24	24	24	24
	Panel D. IV estimates.						
Aging between 1990 and 2025	0.689	0.691	0.496		0.637	0.455	
	(0.204)	(0.217)	(0.150)		(0.194)	(0.140)	
Aging × reliance on middle-aged		0.295	0.219	0.173	0.136	0.039	0.002
		(0.143)	(0.195)	(0.192)	(0.067)	(0.112)	(0.111)
Aging × opportunities for automation		9.584	6.007	6.307	4.377	3.444	3.480
		(2.633)	(1.807)	(1.764)	(1.388)	(1.060)	(1.041)
Observations	6,270	6,270	6,270	6,270	6,270	6,270	6,270
Countries in sample	24	24	24	24	24	24	24
First-stage F stat.	12.8	45.1	24.9	8.9	28.0	25.2	9.7
Overid p-value	0.07	0.34	0.51	0.24	0.29	0.27	0.19
Covariates included:							
Baseline country covariates	✓	✓	✓	✓	✓	✓	✓
Initial robot density			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and the adoption of robots for industry-country cells. In all panels, the dependent variable is robot installations per thousand workers in each industry–country cell for all available years between 1993 and 2014 (from the IFR). The explanatory variables include aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025); the interaction between aging and industry reliance on middle-aged workers (proxied using 1990 US Census data on the age distribution of workers in each industry); and the interaction between aging and two measures of opportunities for automation: the replaceability index from Graetz and Michaels (2018) in columns 2–4; and a measure of opportunities for the use of robots from the BCG in columns 5–7. Panels A and B use data on average employment by industry from the ILO to normalize robot installations; whereas Panels C and D use data on industrial employment from KLEMS to normalize robot installations. Panels A and C present OLS estimates. Panels B and D present IV estimates where the aging variable is instrumented using the average birth rates over each five-year interval from 1950–4 to 1980–4. 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 weight industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries.

allows us to use all 58 countries for which there are industry-level robots data. Second, in Panels C and D, we use data from EUKLEMS, which cover all industries in our sample for 24 countries. Finally, Supplementary Table A22 uses data on employment by industry and country from UNIDO, which are just for manufacturing industries for 56 countries.

Column 1 presents estimates of equation (14) without the interaction terms. The positive estimates for aging across all panels show that, even within an industry, rapidly-aging countries adopted more robots than those aging slowly. This result confirms that the cross-country relationship between aging and robot adoption takes place within industries (as in our model) and dispels concerns related to composition effects accounting for our cross-country results.

The remaining columns include the interaction of aging with an industry's reliance on middle-aged workers and opportunities for automation (main effects are evaluated at the mean). In columns 2–4, Opportunity for Automation$_i$ is proxied using Graetz and Michaels's replaceability index, while in columns 5–7, it is proxied by a dummy for the industries identified by BCG (2015). The estimates in columns 2 and 5 show positive and statistically significant interactions with both variables in all panels. Those in column 2 of Panel A, for example, indicate that a 10 percentage point increase in aging leads to 0.2 ($=2.25\times 0.87\times 0.1$) more annual robot installations per thousand workers in an industry at the 90th percentile of reliance on middle-aged workers compared to an industry at the 10th percentile. In the chemicals, plastics and pharmaceuticals industry, which is at the 90th percentile of reliance on middle-aged workers, a 10 percentage point increase in aging raises robot installations by 0.25 per thousand workers per year, while in textiles, which is at the 10th percentile, the same change leads to 0.05 more installations per thousand workers. On the other hand, a 10 percentage point increase in aging is associated with 0.2 ($=0.36\times 5.44\times 0.1$) more robots per thousand workers in an industry at the 90th percentile of the replaceability index (such as metal products) compared to an industry below the 10th percentile (such as agriculture).

The remaining columns show that our results are robust to the inclusion of other controls. In columns 3 and 6, we include 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.[32] In columns 4 and 7, we control for a full set of country fixed effects (we no longer estimate the main effect of aging in this case). In these models, the interactions between aging and industry characteristics are identified solely from within-country variation, and reassuringly, are barely affected.

Finally, Panels B and D present IV specifications. As in our cross-country analysis, we instrument aging using past birth rates, and we also include interactions of these birth rates with our measures of reliance on middle-aged workers and opportunities for automation to generate instruments for the interaction terms. The IV estimates are similar to the OLS ones. We also confirmed that past demographic changes neither have significant main effects nor interaction effects, and further verified that these results are robust under different specifications and when outliers are excluded, as shown in Supplementary Tables A23, A24, and A25.

Overall, the cross-industry patterns support our third empirical implication: robot adoption responds to aging precisely in industries that rely more on middle-aged workers and that have greater opportunities for automation.

32. Because we do not observe the stock of robots for all country–industry pairs in 1993, we follow Graetz and Michaels (2018) and impute the missing values for the 1993 stocks by deflating the first observation in a country–industry pair using the growth rate of the stock of total robots in the country during the same period.

7.3. *Productivity and the labour share*

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

Panels A and B of Table 8 present OLS and IV estimates of a variant of equation (14) with the change in log value added per worker in industry i in country c between 1995 and 2007 as the left-hand side variable (instead of annual robot installations, so that now we have a single observation for each country–industry pair). Otherwise, the structure of Table 8 is identical to that of Table 7.[33]

Column 1 in Panel A shows a small and insignificant main effect of aging on value added per worker. A 10 percentage point increase in aging is associated with a 1.9% decline in value added per worker (s.e. = 3.8%).[34]

Of greater interest given our model's predictions is the interaction between aging and opportunities for automation. Columns 2–7 document a positive interaction, indicating that as countries age, industries with greater potential for automation experience relative labour productivity gains. The magnitudes are sizable. The IV estimate in column 2 of Panel B shows that 10 percentage points more aging causes an increase of 16% ($=0.36\times4.5\times0.1$) in value added per worker between 1995 and 2007 in an industry at the 90th percentile of the replaceability index compared to an industry at the 10th percentile.[35]

Finally, in Panels C and D of Table 8, we present regressions for the change in the labour share between 1995 and 2007. Column 1 shows that industries located in countries undergoing more rapid demographic change experienced declining labour shares. The remaining columns document 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 heterogeneous effects on the labour share across industries are again sizable.

Overall, consistent with our fourth empirical implication, aging increases relative labour productivity and reduces the labour share in industries that have the greatest opportunities for automation.

7.4. *The role of education and gender*

Aging is not the only aspect of demographic change affecting specialization patterns; education and gender do as well. Supplementary Table A26 shows that more educated workers and women

33. The only difference is that, because the value added data from EUKLEMS are available for most countries only after 1995, we compute our aging variable to be between 1995 and 2025.

34. The point estimate for aging is more negative than what we found in Acemoglu and Restrepo (2017), where we showed that there was no negative relationship between aging and growth in GDP per capita. The difference is driven by the smaller EUKLEMS sample, which only contains 24 countries.

35. The estimates of the interaction between aging and reliance on middle-aged workers are imprecise and statistically insignificant. As emphasized in Section 2, our model has no predictions for these interaction terms, because both the potentially negative direct effect of aging on productivity and the potentially positive technology response tend to be greater for industries that rely more on middle-aged workers.

TABLE 8

Estimates of the impact of aging on the value added of country-industry pairs per year

		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: change in log value-added per worker between 1995 and 2007						
	Panel A. OLS estimates						
Aging between 1995 and 2025	−0.193	−0.188	−0.216		−0.200	−0.226	
	(0.379)	(0.392)	(0.391)		(0.392)	(0.390)	
Aging × reliance on middle-aged		−0.184	−0.118	−0.202	−0.195	−0.127	−0.211
		(0.204)	(0.242)	(0.231)	(0.204)	(0.244)	(0.238)
Aging × opportunities for automation		2.742	2.552	2.900	1.116	0.993	1.117
		(1.161)	(1.174)	(0.977)	(0.445)	(0.466)	(0.455)
Observations	456	456	456	456	456	456	456
Countries in sample	24	24	24	24	24	24	24
	Panel B. IV estimates						
Aging between 1995 and 2025	−0.162	−0.164	−0.220		−0.192	−0.248	
	(0.437)	(0.444)	(0.456)		(0.446)	(0.458)	
Aging × reliance on middle-aged		−0.390	−0.417	−0.434	−0.367	−0.396	−0.424
		(0.266)	(0.299)	(0.315)	(0.284)	(0.319)	(0.340)
Aging × opportunities for automation		4.488	4.606	4.363	1.365	1.413	1.433
		(1.411)	(1.334)	(1.167)	(0.444)	(0.439)	(0.450)
Observations	456	456	456	456	456	456	456
Countries in sample	24	24	24	24	24	24	24
First-stage F-stat.	9.85	17.96	8.70	5.10	46.04	10.35	6.25
Overid p-value	0.06	0.48	0.47	0.55	0.32	0.34	0.41
	Dependent variable: change in the labor share between 1995 and 2007						
	Panel C. OLS estimates						
Aging between 1995 and 2025	−0.329	−0.356	−0.349		−0.349	−0.343	
	(0.117)	(0.123)	(0.126)		(0.121)	(0.124)	
Aging × reliance on middle-aged		0.631	0.613	0.593	0.656	0.641	0.622
		(0.262)	(0.278)	(0.294)	(0.271)	(0.289)	(0.309)
Aging × opportunities for automation		−0.875	−0.824	−0.645	−0.655	−0.627	−0.562
		(0.671)	(0.622)	(0.615)	(0.285)	(0.303)	(0.339)
Observations	456	456	456	456	456	456	456
Countries in sample	24	24	24	24	24	24	24
	Panel D. IV estimates						
Aging between 1995 and 2025	−0.296	−0.268	−0.263		−0.261	−0.260	
	(0.154)	(0.145)	(0.176)		(0.143)	(0.175)	
Aging × reliance on middle-aged		0.896	0.897	0.916	0.927	0.940	0.968
		(0.336)	(0.357)	(0.374)	(0.359)	(0.382)	(0.403)
Aging × opportunities for automation		−0.497	−0.504	−0.244	−0.704	−0.728	−0.676
		(0.709)	(0.653)	(0.622)	(0.277)	(0.316)	(0.370)
Observations	456	456	456	456	456	456	456
Countries in sample	24	24	24	24	24	24	24
First-stage F stat.	9.85	17.96	8.70	5.10	46.04	10.35	6.25
Overid p-value	0.15	0.52	0.55	0.43	0.44	0.52	0.71
Covariates included:							
Baseline country covariates	✓	✓	✓	✓	✓	✓	✓
Initial value added in 1995			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The table presents OLS and IV estimates of the relationship between aging and changes in log value added and the labor share for industry-country cells. In Panels A and B, the dependent variable is the change in value added per worker between 1995 and 2007 for each industry–country cell (from the KLEMS data). In Panels C and D, the dependent variable is the change in the labor share between 1995 and 2007 for each industry–country cell (from the KLEMS data). The explanatory variables include aging (defined as the change in the ratio of workers above 56 to workers between 21 and 55 between 1995 and 2025); the interaction between aging and industry reliance on middle-aged workers (proxied using 1990 US Census data on the age distribution of workers in each industry); and the interaction between aging and two measures of opportunities for automation: the replaceability index from Graetz and Michaels (2018) in columns 2–4; and a measure of opportunities for the use of robots from the BCG in columns 5–7. Panels A and C present OLS estimates. Panels B and D present IV estimates where the aging variable is instrumented using the average birth rates over each five-year interval from 1950-1954 to 1980-1984. 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 weight industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries.

are also less likely to be employed in blue-collar jobs and in industries with the greatest opportunities for automation, though age remains a powerful predictor of specialization patterns even when we control for education and gender. In particular, in the U.S., age is the main determinant of specialization in industries with the greatest opportunities for automation, and across countries, age and education are together the main factors influencing who is employed in blue-collar jobs.

Our theoretical mechanism then suggests that increases in education and female labour force participation should also be associated with greater scarcity of workers suitable for production tasks and thus trigger greater automation. Because we do not have exogenous sources of variation in education and female labour force participation, we can only explore these predictions in OLS regressions. The evidence presented in columns 4 and 8 of Table 2, which we probe further in Supplementary Table A27, is consistent with the predicted relationship for education, but not for gender. For example, the increase in schooling between 1990 and 2010 is positively and significantly correlated with robot adoption in the OECD sample and is positive but insignificant in the whole sample. The increase in (relative) female labour force participation shows a much less consistent pattern, especially once we control for aging.

We find it reassuring that changes in the educational attainment of the workforce have the predicted effect but also note that the explanatory power of this variable is much less than our aging variable (the partial R^2 of the aging variable is 39% within the OECD, while for education it is 17%). This reflects the greater cross-country variation in aging than educational upgrading in our sample period.

The lack of a significant association between female labour force participation and robot adoption is potentially puzzling and may have a number of causes, which should be investigated in future work. First, female labour force participation can respond to economic changes much faster than aging and, as already noted, we are not exploiting any exogenous source of variation. For example, female labour force participation increases as service jobs expand, but this may be negatively correlated with the size of the manufacturing sector and thus with industrial automation. Or growth in female employment may itself trigger such changes in industrial structure. Second, female labour force participation was already high in many countries in our sample and did not experience as sizable a change as the age composition of the workforce. A more in-depth exploration of the effects of the increase in female labour force participation on technology adoption and innovation is a promising and important area for future work.

8. CONCLUSION

Advances in robotics and other automation technologies are often viewed as the natural next phase of the march of technology. In this article, we argue that the adoption and development of these technologies are receiving a powerful boost from demographic changes throughout the world and especially from rapidly-aging countries such as Germany, Japan, and South Korea.

We show why aging should, theoretically, lead to industrial automation—because the relative scarcity of middle-aged workers with the skills to perform manual production tasks increases the value of technologies that can substitute for them. We then document that, consistent with this theoretical perspective, countries and local U.S. labour markets undergoing more rapid demographic change have invested more in new robotic and automation technologies. We also provide evidence that this is because of the implied scarcity of middle-aged workers and that industrial automation is indeed most substitutable with middle-aged workers. The effects of demographic change on investment in robots are robust and sizable. For example, differential aging alone accounts for about 35% of the cross-country variation in investment in robotics. We further document using data on intermediate exports and patents that demographic change encourages not just the adoption of automation technologies but also their development. Moreover, automation innovations in rapidly-aging countries are exported and used throughout the world.

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

The response of technology to aging means that the productivity implications of demographic changes are more complex than previously recognized. In industries most amenable to automation, aging can trigger significant increases in robot adoption and, as a result, lead to greater productivity. Using industry-level data, we find that the main effect of aging on productivity is ambiguous, but as in our theoretical predictions, industries with the greatest opportunities for automation are experiencing greater productivity growth and labour share declines relative to other industries in rapidly-aging countries.

Several questions raised in this article call for more research. First, it is important to extend the conceptual structure presented here in a more quantitative direction to investigate whether plausible directed technology adoption and innovation responses can generate both the magnitudes of automation technologies we have documented and a powerful effect throughout the world via exports of these technologies. Second, it would be fruitful to study the effects of aging on technology adoption and productivity using more disaggregated industry-level or firm-level data. Third, motivated by industrial automation, our focus has been on the substitution of machines for middle-aged workers in production tasks. With the advent of artificial intelligence, a broader set of tasks can be automated, and yet there is currently little research on the automation of nonproduction tasks. Finally, as already noted in Section 7.4, it is important to investigate the technological implications of the growth in female labour force participation and explore why this does not appear to be correlated with industrial automation.

Acknowledgments. We thank Dirk Krueger, Valerie Ramey, four anonymous referees and participants at the AEA Meetings, Brown University, the NBER Summer Institute and the Toulouse Network of Information Technology for comments and suggestions. We also thank Eric Donald, Giovanna Marcolongo, Mikel Petri, Joonas Tuhkuri, and Sean Wang for excellent research assistance, and Google, Microsoft, the NSF, the Sloan Foundation, the Smith Richardson Foundation, and the Toulouse Network on Information Technology for generous financial support.

Supplementary Data

Supplementary data are available at *Review of Economic Studies* online. The replication packages are available at http://doi.org/10.5281/zenodo.4619595.

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