Demographics and Automation*

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Abstract

We argue theoretically and document empirically that aging leads to greater (industrial) automation, and in particular, to more intensive use and development of robots. Using US data, we document that robots substitute for middle-aged workers (those between the ages of 36 and 55). We then show that demographic change—corresponding to an increasing ratio of senior to middle-aged workers—is associated with pronounced increases in the adoption of robots and other automation technologies across countries and with more robot-related activities in US commuting zones. We provide a directed technological change model that explains not only these main effects of aging, but also predicts that these responses should be more pronounced in industries that rely more on middle-aged workers and those that present greater opportunities for automation. Both of these predictions receive support from country-industry variation in the adoption of robots. Our model also implies that the productivity implications of aging are ambiguous when technology responds to demographic change, but we should expect productivity to increase relatively in industries that are most amenable to automation, and this is indeed the pattern we find in the data.

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

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

Work in Progress. Comments Welcome.

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1 Introduction

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

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

We start with a simple model of directed technology adoption. Two types of workers, "middle-aged" and "senior," are allocated across different tasks and industries. Middle-aged workers have a comparative advantage in production tasks, while senior workers specialize in nonproduction services. The importance of production tasks relative to nonproduction services varies across industries. Firms can also automate production and substitute machines for labor in production tasks.

Crucially, in our model technology is endogenous: firms can invest to automate additional tasks in their industry or to increase the productivity of middle-aged workers. Using this framework, we show that a demographic change that reduces the ratio of middle-aged to senior workers induces the adoption of additional automation technologies. This effect is particularly pronounced in industries that rely more on middle-aged workers and those that have greater opportunities for automation. The productivity implications of demographic change, on the other hand, are ambiguous: first, demographic change affects output per worker given technology—

and this effect tends to be negative when the wage of middle-aged workers is greater than that of older workers. Second, the induced adoption of robotics technology enables the substitution of cheaper machines for labor, increasing productivity. Third and counteracting this, greater investment in robotics may come at the cost of other technological investments, thus creating another drag on overall productivity.

The bulk of the paper investigates these issues empirically, focusing on industrial robots as well as a few other automation technologies. Our results point to a strong correlation between aging and the adoption of robotics and other automation technologies. We start with suggestive evidence on the substitutability between robots and workers of different ages.[1] First, we look at the age composition of employment in highly-robotized industries, which shows that workers between the ages of 31 and 55 are more likely to be employed in highly-robotized industries than in other industries. Second, we use the same strategy as in Acemoglu and Restrepo (2017a), exploiting differences in the exposure to robots across US commuting zones, but focusing on the effects of this exposure on workers of different age groups (rather than on overall employment and wages). We find that the negative effects of exposure to robots fall on the employment and earnings of workers (and men) between the ages of 36 and 55. These two pieces of evidence support our working hypothesis for the rest of the paper—that robots are more substitutable for middle-aged workers than older workers.

We then use country-level data on the stock of robots per thousand worker between 1993 and 2015 from that International Federation of Robotics (IFR) to investigate the effects of changing age composition of the workforce. Our main specifications focus on long-differences, where our left-hand side variable is the change in the number of robots per thousand workers between 1993 and 2014. Our results indicate that countries undergoing more rapid aging—measured as an increase in the ratio of workers above 56 to those between 26 and 55—are investing significantly more in robotics.[2] The effects we estimate are quantitatively large. Aging alone explains close to 40% of the cross-country variation in the adoption of industrial robots. Moreover, a 10 percentage points increase in our aging variable is associated with 0.9 more robots per thousand manufacturing workers—compared to the average increase of 3 robots per thousand manufacturing workers observed during this period. This estimated magnitude suggests, for instance, that if the United States had the same demographic trends as Germany, the gap in robotics between the two countries would be 25 percent smaller.

These results are robust to a range of controls allowing for differential trends across countries in investment in robotics. For example, they are virtually unchanged when we control for differential trends by initial GDP per capita, population level, robot density, capital output ratio,

[1] Though our focus is on automation more broadly, in most of our empirical work we use information on robots both because robotics is a particularly important type of automation technology, and also because the adoption of robots can be measured in a more consistent manner across countries and industries than other automation technologies.

[2] We verify that our results are not sensitive to the exact age cutoffs we use.

various human capital variables, wage levels, and unionization rates. Because age composition is potentially endogenous due to in- and out-migration from a country, which are likely to be correlated with economic trends, we verify our baseline results using an instrumental-variables (IV) strategy exploiting sizes of past birth cohorts. These estimates are very similar to the ordinary least squares (OLS) estimates. We also confirm these results using an alternative estimate of investment in robotics: imports of industrial robots computed from bilateral trade data. Though imports of robots are not a reliable measure of investments in robotics technology for countries that house major robots producers (in particular, Germany, Japan and Korea), this measure is highly correlated with our IFR measure, and confirms our results on the effects of demographics on the adoption of robotics technology.

The effect of demographic change on technology are not confined to robotics. Using bilateral trade data, we also show a similar relationship between aging and a number of other automation technologies (such as numerically controlled machines, weaving and knitting machines, vending machines and ATMs), and also verify that there is no such relationship for technologies that appear more broadly labor-augmenting (such as general equipment and various tools).

We also estimate the effects of aging on the adoption of robots at the commuting zone level in the United States. Though we do not have measures of investments in robots for commuting zones, we use Leigh and Kraft's (2016) measure of the number of integrators in an area as a proxy for robots-related activity (as we also did in Acemoglu and Restrepo, 2017a). Since these integrators are tasked with installation, reprogramming and maintenance of industrial robots, their presence is highly indicative of significant installation of robots in the area. Using this measure, we confirm the relationship between demographic change and the adoption of robots.[3]

As noted above, a sharper prediction of the directed technological change approach to automation is that the effects of demographic change should be particularly pronounced in industries that rely more on middle-aged workers (and also in industries that present greater opportunities for automation or robotics). Using the industry-level breakdown of investment in robots and robot per thousand workers in the IFR, we investigate these predictions as well, and find fairly robust support for them. Aging has little impact on robot adoption in industries that rely least in middle-aged workers, and a much stronger impact on industries that are most reliant on middle-aged workers.

Finally, we investigate the implications of demographic change on labor productivity. Our results here establish a positive impact of demographic change on labor productivity in industries that are most amenable to automation. This result is consistent with our theoretical predictions and also illustrates the critical role that automation technologies may be playing in an economy's adjustment to demographic change. Indeed, the lack of a negative relationship between aging

[3]Probably reflecting the endogeneity of the demographic structure of a commuting zone within the United States, these results are significant only with our IV estimates, which focus on demographic differences across commuting zones due to sizes of past birth cohorts.

and GDP mentioned above might be partly due to the more rapid adoption of automation technologies in countries undergoing significant demographic change—a pattern consistent with our theoretical and empirical results.

Overall, though the estimates presented in this paper do not necessarily correspond to causal effects—since demographic change could have other impacts on technology adoption, or despite our focus on changes coming from the relative sizes of past birth cohorts, it might be correlated with other trends—the correlations we document are very robust and highly suggestive. We find it reassuring too that differences in investments in robots are not explained by any of the secular trends we are controlling for, and as already noted above, they are unlikely to reflect changing demand for the types of products or services in an aging society (such as increased demand for health care), because we are focusing on the manufacturing sector. They also match the predictions of our directed technological change framework quite closely.

Our paper is related to a few recent literatures. The first is a literature estimating the implications of automation technologies on labor market outcomes. Early work in this literature (e.g., Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Michaels, Natraj and Van Reenen, 2014; Autor and Dorn, 2013; Gregory, Salomons and Zierahn, 2016) provides evidence suggesting that automation of routine jobs has been associated with greater wage inequality and decline of middle-skill occupations. More recently, Graetz and Michaels (2015) and Acemoglu and Restrepo (2017a) estimate the effects of the adoption of robotics technology on employment and wages (and in the former case, also on productivity). Our work is complementary to but quite different from these papers since we focus not on the implications of these technologies, but on the determinants of their adoption.

Second, a growing literature focuses on the potential costs of demographic change, in some cases seeing this as a major disruptive factor that will bring slow economic growth (e.g., Hansen, 1938; Gordon, 2016) and potentially other macroeconomic problems such as an aggregate demand-induced secular stagnation (see, e.g., Summers, 2013, and the essays in Baldwin and Teulings, 2014).[4] We differ from this literature by focusing on the effects of demographic changes on robots, and more broadly on technology adoption decisions—an issue that does not seem to have received much attention in this literature.[5] A few works focusing on the effects of demographic change on factor prices (e.g., Poterba, 2001; Krueger, 2004; Krueger and Ludwig, 2007) and human capital (e.g., Ludwig, Schelkle and Vogel, 2012; Geppert, Ludwig and Abiry, 2016) are more related, but we are not aware of any papers studying the impact of aging on technology, except the independent and simultaneous work by Abelianisky and Prettner (2017). There are

[4] A related literature explores the fiscal costs of demographic change for pensions and Social Security (see De Nardi et al., 1999; Storesletten 2000; Kotlikoff et al., 2002; Attanasio et al., 2007).

[5] As mentioned above, our short paper, Acemoglu and Restrepo (2017b), pointed out that despite these concerns, there is no negative relationship between aging and GDP growth, and suggested that this might be because of the effects of aging on technology adoption, but did not present any evidence on this linkage, nor did it develop the theoretical implications of demographic change on technology adoption and productivity.

several important differences between our work and this paper. These authors focus on the effect of the slowdown of population growth—rather than age composition—on different types of capital, one of which corresponds to automation (without any directed technological change). They also do not consider the industry-level variation (nor do they control for the various competing economic trends we include in our analysis). We show further that the effects we estimate are not driven by the level of population or its slower growth, thus distinguishing our results from theirs. Hence, overall, the two papers are not just independent but also complementary.

Third, our work is related to the literature on technology adoption. Within this literature, most closely related to our model and conceptual approach is Zeira's (1998) paper which develops a model of economic growth based on the substitution of capital for labor, but does not investigate the implications of demographic change on technology adoption. A few recent papers that study the implications of factor prices on technology adoption are more closely related to our work. In particular, Manuelli and Seshadri (2010) use a calibrated model to show that stagnant wages mitigated the adoption of tractors before 1940, while the rapid increase in wages after 1940 accounts for close to 30% of the increase in the adoption of tractors. Clemens et al. (2017) find that the exclusion of Mexican *Braceros*—temporary agricultural workers—induced farms to adopt mechanic harvesters and switch to crops with greater potential for mechanization, while Lewis (2011) shows that in US metropolitan areas receiving fewer low-skill immigrants between 1980 and 1990, metal plants adopted more automation technologies. Although the findings in these papers are consistent with the predictions of our model and our evidence, they do not investigate the implications of demographic change on technology adoption or robotics technologies.

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

The rest of the paper is organized as follows. We introduce our model of directed technology adoption in the next section. Section 3 presents our data sources and some descriptive statistics. Section 4 provides evidence bolstering the case that robotics technology is more highly substitutable to middle-aged workers than older workers. Section 5 presents our cross-country evidence on the effect of demographic change on the adoption of robots. Much of our analysis in this section exploits the IFR data, but we also bring other data sources to confirm the effect of the changing age composition of the workforce on robotics technology. Section 6 investigates the same relationship across US commuting zones. Section 7 presents evidence that the effects of demographic change on the adoption of robotics technology is most pronounced in industries that rely more on middle-aged workers and those with greater opportunities for robotization. Section 8 considers the relationship between demographic change and the capital-output ratio and productivity at the industry level. Section 9 concludes, while the Appendix contains proofs omitted from the text and additional empirical results.

2 Directed Technology Adoption

In this section, we introduce a model of directed technology adoption, which enables us to derive the main implications of demographic change on the adoption of different types of technologies. In our model, industries or sectors employ middle-aged workers, senior workers and machines to perform the tasks necessary for production. Also, technology firms with monopoly power invest in the development of new technologies that automate tasks or increase the productivity of middle-aged workers.[6]

2.1 The Environment

A unique final good Y is produced competitively by combining the output of a continuum of industries using the following constant elasticity of substitution (CES) aggregate:

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

Here $Y(i)$ is the net output of industry i and $\mathcal{I}$ denotes the set of industries.[7] Throughout, we choose the final good as the numeraire.

In each industry, (gross) output is produced by combining production tasks, service or support (nonproduction) tasks, and intermediates that embed technologies:

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

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

[7] The assumption that $\sigma > 1$ is for simplicity. Why we impose this assumption and how it can be relaxed is explained below when we discuss the incentives of technology monopolists.

where $X(i)$ designates the aggregate of production tasks used by industry i, $S(i)$ is the total amount of labor employed in service tasks, $q(\theta(i), A(i))$ is the quantity of intermediate goods used by this industry (with $\theta(i)$ and $A(i)$ corresponding to the technologies embedded in these intermediates as we describe below), $1 - \eta \in (0, 1)$ is the share of intermediates, and finally, $\alpha(i) \in (0, 1)$ designates the importance of production tasks relative to service tasks in the production function of industry i.[8]

The aggregate of production tasks, $X(i)$, is produced combining a unit measure of tasks through another CES aggregator:

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

where ζ is the elasticity of substitution across tasks.

Each task $X(i, z)$ is produced either by labor or machines:

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

where $l(i, z)$ denotes the amount of production labor employed in task z in industry i, and $m(i, z)$ denotes machines used in industry i to produce task z. Labor and machines are perfect substitutes in automated tasks (those with $z \leq \theta(i)$ in industry i). In addition, $A(i)$ corresponds to labor-augmenting technology, while $\theta(i)$ corresponds to the automation technology. In particular, $\theta(i)$ designates the automation threshold in industry i—tasks below this threshold are automated and can be produced with machines as well as labor. The technological know-how that enables the automation of additional tasks (as captured by $\theta(i)$) and labor-augmenting technology (as captured by $A(i)$) are both embedded in the intermediate goods, which explains the term $q(\theta(i), A(i))$ in the industry production function (2).

Firms in industry i purchase the intermediates $q(\theta(i), A(i))$ from a technology monopolist that owns the intellectual property rights over the technology in this industry. We assume that the technology monopolist supplying industry i can produce its intermediate good by using $1 - \eta$ units of the same industry's output.[9] The net output in industry i is obtained by subtracting the total cost of intermediates, $(1 - \eta)q(\theta(i), A(i))$, from the gross output of the industry:

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

There are two types of workers: L middle-aged workers, and S senior workers. The next assumption specifies the comparative advantage of the two types of workers and ensures that automation (robots) substitutes for middle-aged workers.

[8] We assume that $\sup_{i \in \mathcal{I}} \alpha(i) < 1$ and $\inf_{i \in \mathcal{I}} \alpha(i) > 0$, so that all (or more appropriately, "almost all") industries require both production and service tasks.

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

Assumption 1 *1. Each middle-aged worker is endowed with one unit of production labor, and each senior worker is endowed with one unit of service labor.*

2.

$$\zeta > \sigma.$$

The first part of this assumption imposes that middle-aged workers fully specialize in production tasks, while the second part provides a sufficient condition for machines to be more substitutable to the middle-aged workers they replace than senior workers.[10] Senior workers fully specialize in service or support tasks, which makes them complements to machines used in production.

We denote the wage of middle-aged workers by W, the wage of senior 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,

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

where the last equality on each line defines the demand for that factor. We assume that machines are supplied at a fixed rental price P.

2.2 Equilibrium with exogenous technology

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

Let $P_{Y(i)}$ denote the price of output in industry i, and $\chi(\theta(i), A(i))$ be the price of the intermediate for industry i when this embodies the automation and labor-augmenting technology pair $(\theta(i), A(i))$. The demand for intermediate goods from industry i is given by

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

[10] Allowing both types of workers to supply both production and service labor would lead to similar results as long as middle-aged workers have a comparative advantage in production tasks. Our formulation, which can be viewed as an extreme form of comparative advantage, simplifies the analysis and the exposition.

Facing this demand curve with elasticity $1/\eta$ and marginal cost of producing intermediates equal to $(1-\eta)P_{Y(i)}$, the technology monopolist for industry i will set the profit-maximizing price to $P_{Y(i)}$. Substituting this price into (4), and using (2) and (3), we derive the net output of industry i as

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

Also, the Cobb-Douglas production technology in equation (2) implies that

$$P_Y(i) = \lambda(i) P_X(i)^{\alpha(i)} V^{1-\alpha(i)}, \tag{5}$$

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

We next turn to automation decisions. These decisions will depend on the cost savings from automation, which in turn are determined by relative factor prices. In particular, let $\pi(i)$ denote the cost savings from automation in industry i (meaning the gap between costs when a task is produced by labor vs. machines). Then,

$$\pi(i) = \frac{1}{\zeta - 1}\left[\left(\frac{W}{A(i)P}\right)^{\zeta-1} - 1\right]. \tag{6}$$

When $\frac{W}{A(i)} > P$, the effective cost of producing with labor in industry i, $\frac{W}{A(i)}$, is greater than the cost of using a machine, P, and as a result, $\pi(i) > 0$ (recall that $\zeta > 1$). The specific functional form follows from the fact that the elasticity of substitution between tasks is ζ. Conversely, when $\frac{W}{A(i)} < P$, it is more expensive to produce with machines in industry i, and if firms in this industry did so, their costs would go up. Therefore, available automation technologies will be adopted if $\pi(i) > 0$. We can then summarize these automation decisions by defining an *automation threshold*, $\theta^A(i)$, which satisfies:

$$\theta^A(i) = \begin{cases} \theta(i) & \text{if } \pi(i) > 0 \\ 0 & \text{if } \pi(i) \leq 0. \end{cases} \tag{7}$$

Intuitively, available automation technologies will be adopted as soon as they enable positive cost savings (where we are assuming without loss of any generality that when indifferent, firms do not switch to machines). This discussion highlights a general point that plays an important role for the rest of our analysis— automation becomes more profitable precisely when the effective wage of middle-aged workers is high.

Using this automation threshold, $\theta^A(i)$, we can now compute the price of $X(i)$ as

$$P_{X(i)} = \left(\theta^A(i)P^{1-\zeta} + (1-\theta^A(i)(i))\left(\frac{W}{A(i)}\right)^{1-\zeta}\right)^{1-\zeta}, \tag{8}$$

and the share of middle-aged labor in the production of $X(i)$ as:[11]

$$s_L(i) = (1-\theta^A(i))\left(\frac{W}{A(i)P_X(i)}\right)^{1-\zeta} \in [0,1] \tag{9}$$

[11] Let $L(i) = \int_0^1 l(i,s)dsdi$ and $M(i) = \int_0^1 m(i,s)dsdi$ denote the amounts of middle-aged labor and machines

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

$$L^d = \frac{Y}{(2-\eta)W} \int_{i \in \mathcal{I}} \lambda(i)^{1-\sigma} P_X(i)^{\alpha(i)(1-\sigma)} V^{(1-\alpha(i))(1-\sigma)} \alpha(i) s_L(i) di \tag{10}$$

$$M^d = \frac{Y}{(2-\eta)P} \int_{i \in \mathcal{I}} \lambda(i)^{1-\sigma} P_X(i)^{\alpha(i)(1-\sigma)} V^{(1-\alpha(i))(1-\sigma)} \alpha(i)(1 - s_L(i)) di \tag{11}$$

$$S^d = \frac{Y}{(2-\eta)V} \int_{i \in \mathcal{I}} \lambda(i)^{1-\sigma} P_X(i)^{\alpha(i)(1-\sigma)} V^{(1-\alpha(i))(1-\sigma)} (1 - \alpha(i)) di. \tag{12}$$

The following proposition shows that an equilibrium with exogenous technology always exists and is unique, and provides a characterization of the equilibrium level of wages. In what follows, we let $\phi = \frac{S}{L+S}$ denote the share of senior workers in the population, and think of aging as an increase in ϕ.

Proposition 1

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

$$1 = \left(\int_{i \in \mathcal{I}} \lambda(i)^{1-\sigma} P_X(i)^{\alpha(i)(1-\sigma)} V^{(1-\alpha(i))(1-\sigma)} di \right)^{\frac{1}{1-\sigma}} ; \text{ and} \tag{13}$$

   the relative demand for workers,

$$\frac{1-\phi}{\phi} = \frac{V}{W} \frac{\int_{i \in \mathcal{I}} \lambda(i)^{1-\sigma} P_X(i)^{\alpha(i)(1-\sigma)} V^{(1-\alpha(i))(1-\sigma)} \alpha(i) s_L(i) di}{\int_{i \in \mathcal{I}} \lambda(i)^{1-\sigma} P_X(i)^{\alpha(i)(1-\sigma)} V^{(1-\alpha(i))(1-\sigma)} (1-\alpha(i)) di} \tag{14}$$

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

2. *Middle-aged wages $W^E(\phi,\Theta)$ are increasing in ϕ, and senior wages $W^E(\phi,\Theta)$ are decreasing in ϕ. On the other hand, ϕ has an ambiguous impact on output per capita $y^E(\phi,\Theta)$.*

Proof. See the Appendix. ■

Figure 1 depicts the characterization of the equilibrium with exogenous technology. Let $C(W,V,P)$ denote the cost of producing one unit of the final good, which is given by the right-hand side of equation (13). The equilibrium values for W^E and V^E are then given by the point on the iso-cost curve $C(W,V,P) = 1$—condition (13)—that satisfies $\frac{C_W(W,V,P)}{C_V(W,V,P)} = \frac{1-\phi}{\phi}$—condition (14).

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employed in industry i, respectively. Then total production in industry i can be written as

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

(see Acemoglu and Restrepo Amma 2016). Thus as also suggested by (8), an increase in $\theta(i)$ (and hence $\theta^A(i)$) makes the production of $X(i)$ less labor intensive.

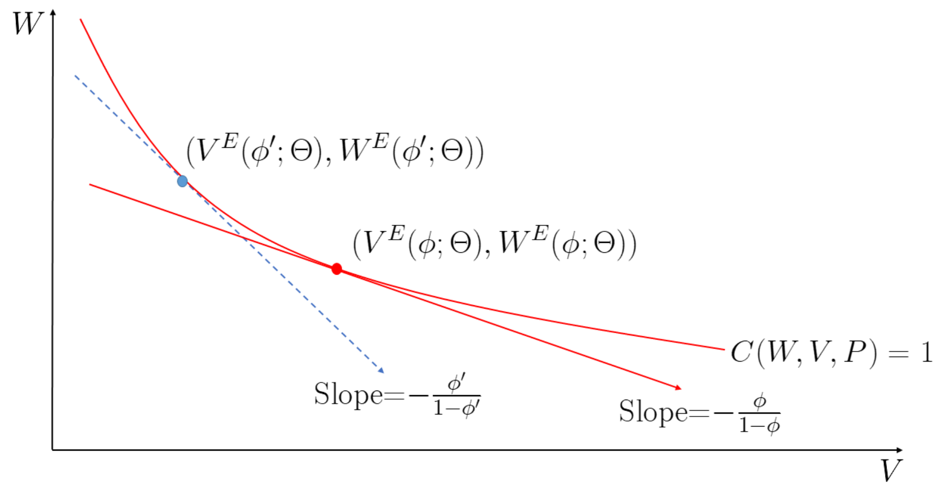

FIGURE 1: Equilibrium determination of wages, W^E, V^E. The downward-slopping curve is the iso-cost $C(W, V, 1) = 1$ (condition (13)). The equilibrium is given by the point in this curve at which $\frac{C_W}{C_V} = \frac{1-\phi}{\phi}$ (condition (14)).

Aging—an increase in ϕ—raises W^E and lowers V^E along the convex iso-cost curve $C(W, V, P) = 1$, as shown in Figure 1. Proposition 1 also shows that aging has an ambiguous effect on aggregate otutput per worker. In particular, in the Appendix we show that

$$\frac{1}{2-\eta} y^E_\phi(\phi, \Theta) = V^E(\phi, \Theta) - W^E(\phi, \Theta) + P \cdot m^E_\phi(\phi, \Theta). \tag{15}$$

This expression clarifies that the effect of aging on output depends on the wage of middle-aged workers relative to the wage of senior workers. In particular, if $V^E < W^E$, there will be a negative effect on productivity (though m^E_ϕ can be positive, offsetting this effect). Existing evidence (e.g., Murphy and Welch, 1990) suggests that earnings peak when workers are in their 40s, declining thereafter, which in our model implies $V < W$, and thus creates a tendency for aging to reduce productivity. This negative effect echoes the concerns raised by Gordon (2016) on the potential for slower growth in the next several decades because of demographic change.[12]

The next proposition shows how demographic change affects automation decisions. For this proposition and for what follows, it is convenient to denote by $\mathcal{I}^+(\phi, \Theta)$ the set of industries for which $\pi(i) > 0$ and new automation technologies are immediately adopted (i.e., $\theta^A(i) = \theta(i)$).

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

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

[12] An alternative justification for $V^E < W^E$ is to relax Assumption 1 and instead assume that middle-aged workers are endowed with skills to perform both production and service tasks. As workers age, they can no longer perform the physically more demanding production tasks and must work in service tasks. Then in equilibrium we would always have $V^E \leq W^E$.

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

Proof. See the Appendix. ■

The proposition shows that aging encourages the adoption of existing automation technologies. For $\phi < \widetilde{\phi}(A)$, there is no adoption of new automation technologies because, given the state of labor-augmenting technologies, the wage of middle-aged workers is sufficiently low that automation technologies do not save costs. This threshold, $\widetilde{\phi}(A)$, is independent of the distribution of $\theta(i)$'s across industries, because it demarcates the demographic composition of the economy such that automation is not profitable in any industry, i.e.,$\frac{W}{A(i)} \leq P$ for all i (and this is without reference to which tasks are available for automation). When $\phi > \widetilde{\phi}(A)$, the wage (and the effective wage) of middle-aged is sufficiently large that automation becomes cost-saving and profitable.

What is the effect of automation (when it does take place) on factor prices? As in Acemoglu and Restrepo (2016), this is determined by two competing forces: a *displacement effect*—when automation technologies are adopted, they squeeze middle-aged workers into fewer tasks, reducing the demand for middle-aged labor; a *productivity effect*—when automation technologies are adopted, they allow industries to reduce their costs and expand output, raising the demand for all types of workers. The productivity gains from automation in industry i depend on the cost-saving gains $\pi(i)$, introduced in (6). When $\pi(i)$ is small (but positive), available automation technologies will be adopted in industry i, generating the displacement effect, but only a minimal productivity effect. This reasoning implies that there exists a threshold $\overline{\pi} > 0$ such that, when new automation technologies are introduced in industry i with $\pi(i) \in (0, \overline{\pi})$, the displacement effect dominates the productivity effect, and automation reduces wages. This result is stated and some of its implications are developed in the next proposition. In this proposition we consider marginal changes in automation technologies in a set of industries, denoted by $\{d\theta(i)\}_{i \in \mathcal{I}}$ (with $d\theta(i) \geq 0$).

Proposition 3

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

    - *For $\phi < \widetilde{\phi}(A)$, these automation technologies are not adopted and there is no impact on factor prices.*
    - *For $\phi > \widetilde{\phi}(A)$, new automation technologies will be adopted in industries in $\mathcal{I}^+(\phi, \Theta)$. If $d\theta(i) > 0$ for a (positive measure) subset of $\mathcal{I}^+(\phi, \Theta)$, then these new technologies increase the wage of senior workers, V; reduce the relative wage of middle-aged workers, W/V; and have an ambiguous effect on the wage of middle-aged workers, W.*

- *Moreover, there exists a threshold* $\overline{\phi}(\Theta) > \widetilde{\phi}(A)$ *such that, if* $\widetilde{\phi}(A) < \phi < \overline{\phi}(\Theta)$*, then* $\pi(i) < \overline{\pi}$ *for* almost all *industries. In this region, if* $d\theta(i) > 0$ *for a (positive measure) subset of* $\mathcal{I}^+(\phi, \Theta)$*, the wage of middle-aged workers declines.*

2. *Consider an improvement in labor-augmenting technologies* $\{dA(i)\}_{i\in\mathcal{I}}$ *for a set of industries with positive measure. Then both the middle-aged and senior wages,* W *and* V*, and the relative wage of middle-aged workers,* W/V*, increase.*

Proof. See the Appendix. ■

Figure 2 illustrates the comparative statics from new automation technologies presented in part 1 of Proposition 3. The displacement effect corresponds to a clockwise rotation of the iso-cost curve $C(W, V, P) = 1$ around the equilibrium point, reducing W and increasing V. The productivity effect corresponds to an outward shift of the iso-cost curve, increasing both wages. The condition $\pi(i) < \overline{\pi}$ for all $i \in \mathcal{I}^+$ ensures that the shift of the iso-cost is sufficiently small that the displacement effect dominates the productivity effect. Intuitively, as also emphasized in Acemoglu and Restrepo (2016), new automation technologies reduce wages precisely when they generate limited cost savings and productivity effects.

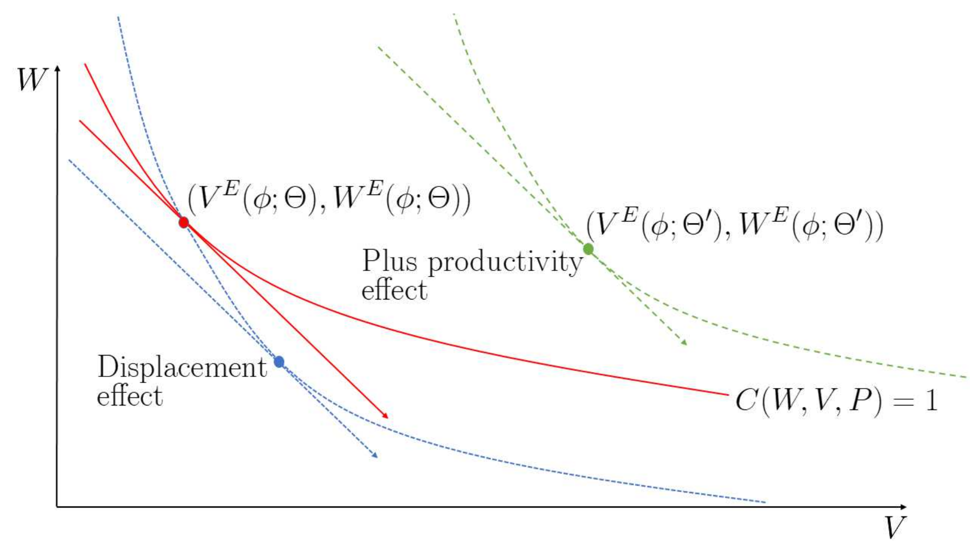

Figure 2: Impact of automation on wages. Automation rotates the iso-cost curve clockwise (displacement effect) and shifts it outwards (productivity effect).

2.3 Equilibrium with endogenous technology

Our analysis so far took the set of technologies, $\Theta = \{A(i), \theta(i)\}_{i\in\mathcal{I}}$, as given. We now endogenize these technologies using an approach similar to Acemoglu (2007, 2010). We assume that for industry i, there is a single technology monopolist who can develop new technologies and sell the intermediates embodying these technologies—the $q(A(i), \theta(i))$'s—to firms in that industry.

Developing a technology pair $\{\theta(i), A(i)\}$ costs the monopolists $\frac{1-\eta}{2-\eta}Y(i)P_Y(i)\cdot C(\theta(i),A(i);i)$ units of the final good, where $C(.;i)$ is an increasing and convex function that potentially varying across industries. The specification imposes that the cost of introducing innovations is proportional to $\frac{1-\eta}{2-\eta}Y(i)P_Y(i)$, which is adopted to simplify our notation and analysis.

Equation (4) shows that the monopolist in industry i earns profits $\frac{1-\eta}{2-\eta}Y(i)P_Y(i)$. Using the fact that $Y(i) = YP_Y(i)^{-\sigma}$, we can write the *net* profits from developing the technology pair $\{\theta(i), A(i)\}$ as $\frac{1-\eta}{2-\eta}YP_Y(i)^{1-\sigma}(1 - C(\theta(i), A(i); i))$. Moreover, because monopolists are infinitesimal, they take wages, the price of machinery, and Y as given. Thus, we can write the profit-maximizing problem of the technology monopolist for industry i in logs as:

$$\max_{\{\theta(i),A(i)\}} (1-\sigma)\alpha(i)\ln P_X(i) + \ln(1 - C(\theta(i), A(i); i)) \tag{16}$$

Monopolists have an incentive to invest in automation and labor-augmenting technologies because these inventions reduce the cost of production $P_X(i)$, which in turn reduces $P_Y(i)$ and increases their profits.[13]

To simplify the algebra, we assume that the cost function $C(.;i)$ can be written as

$$C(\theta(i), A(i); i) = 1 - (1 - G(A(i)))^{\frac{1}{\mu(i)}} (1 - H(\theta(i)))^{\frac{1}{\rho(i)}},$$

where G is an increasing and convex function that satisfies $G'(0) = 0$, $\lim_{A(i)\to\infty} G(A(i)) = 1$ and $\lim_{A(i)\to\infty} G'(A(i)) = \infty$. The exponent $\mu(i)$ captures the costs of developing new labor-augmenting technologies in industry i. Likewise H is increasing and convex, and satisfies $H'(0) = 0$, $\lim_{\theta(i)\to 1} H(\theta(i)) = 1$ and $\lim_{\theta(i)\to 1} H'(\theta(i)) = \infty$, and the exponent $\rho(i)$ captures heterogeneity across industries in the technological possibilities for automation. In particular, industries with a higher $\rho(i)$ face lower marginal costs from automation, and thus have greater potential for automation. In what follows, we let $h(\theta) = \frac{H'(\theta)}{1-H(\theta)}$ and $g(A) = \frac{G'(A)}{1-G(A)}$. Our assumptions on H, G imply that g, h are positive and increasing functions.

We can now define an *equilibrium with endogenous technology* as an equilibrium where technology choices maximize (16). The equilibrium level of endogenous technology is given by a fixed point $\Theta^* = \{\theta(i)^*, A(i)^*\}_{i\in\mathcal{I}}$ such that

$$\begin{aligned}\{\theta(i)^*, A(i)^*\} \in \arg\max_{\{\theta(i),A(i)\}} (1-\sigma)\alpha(i)\ln\left(\theta^A(i)P^{1-\zeta} + (1-\theta^A(i))\left(\frac{W^E(\phi,\Theta^*)}{A(i)}\right)^{1-\zeta}\right)\\ + \frac{1}{\mu(i)}\ln(1 - G(A(i))) + \frac{1}{\rho(i)}\ln(1 - H(\theta(i))) \text{ for all } i \in \mathcal{I}.\end{aligned} \tag{17}$$

Equation (17) shows that the equilibrium wage, $W = W^E(\phi, \Theta^*)$, is a sufficient statistic to determine the optimal choice of technology by monopolists. This observation simplifies the

[13] This is where our assumption that $\sigma > 1$ plays a critical role. When $\sigma \leq 1$, to prevent technology monopolists setting infinite markups, we can assume the existence of a fringe of firms that can inefficiently copy new technologies, forcing the monopolists to set limit prices. All of our results generalize to this case, highlighting that $\sigma > 1$ is adopted for simplicity.

characterization of the equilibrium with endogenous technology, as we only need to solve for the equilibrium wage. Let $\Theta^R(W) = \{A^R(W;i), \theta^R(W;i)\}_{i\in\mathcal{I}}$ denote the solution to the maximization problem in (17) when the equilibrium wage is given by W. An equilibrium wage is then given by a fixed point of the mapping:

$$W = W^E(\phi, \Theta^R(W)). \tag{18}$$

Before turning to the fixed-point problem in equation (18), we start by characterizing the behavior of $\theta^R(W,i)$ and $A^R(W,i)$ in the following lemma

Lemma 1

1. *The technology choices, $\theta^R(W;i)$ and $A^R(W;i)$, satisfy the first-order conditions:*

$$h(\theta^R(W;i)) \geq (\sigma-1)\alpha(i)\rho(i)\frac{s_L(i)}{1-\theta(i)}\pi(i), \tag{19}$$

$$g(A^R(W;i)) \geq (\sigma-1)\alpha(i)\mu(i)s_L(i)\frac{1}{A^R(W;i)}. \tag{20}$$

   (19) *holds with equality if $\theta^R(W;i) > 0$; (20) holds with equality if $A^R(W;i) > 0$.*

2. *Let $W = W^E(\phi, \Theta^*)$. The maximization problem in (17) exhibits increasing differences in W, $\theta(i)$ and $-A(i)$. Thus, $\theta^R(W;i)$ is increasing in W, and $A^R(W;i)$ is decreasing in W.*

3. *As $W \to 0$ we have that $\theta^R(W;i) = 0$ and $A^R(W;i) = \widetilde{A}(i)$, where*

$$\widetilde{A}(i)g(\widetilde{A}(i)) = (\sigma-1)\alpha(i)\mu(i).$$

Proof. See the Appendix. ■

The first part of the lemma provides (necessary) first-order conditions for $\theta^R(W;i)$ and $A^R(W;i)$. These conditions reveal that technology monopolists have stronger incentives to develop automation technologies when the middle-aged wage, W, is high. This is because cost-saving gains from automation, $\pi(i) \geq 0$, are large when W is high. Conversely, when W is low and/or middle-aged workers are producing a greater fraction of tasks, technology monopolists have greater incentives to develop labor-augmenting technologies.

The second part of the lemma establishes a critical supermodularity property, which will greatly simplify the rest of our analysis of endogenous technology. Namely, the additional automation induced by a high W further reduces the incentives to invest in labor-augmenting technologies. The reduction in labor-augmenting technologies in turn further increases the incentives to invest in automation. Consequently, higher middle-aged wages increase technology monopolists' efforts to automate additional tasks and reduce their investments in labor-augmenting technologies. This proposition also underscores that the middle-aged wage, W, is the key price mediating the equilibrium choice of technologies.

Finally, the third part of the lemma provides a technical result which we will use in the proof of the next proposition. More substantively, however, it also implies that as W becomes very low (and thus cost savings from automation disappear), technology monopolists will not invest in automation technologies. As a consequence, in an equilibrium with endogenous technology, we always have $\theta^A(i) = \theta(i)$ and all new technologies will be immediately adopted, and thus any comparative static result that applies to $\theta(i)$ also applies to $\theta^A(i)$.

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

PROPOSITION 4 *For any $\phi \in (0,1)$, there exists an equilibrium with endogenous technology. In any such equilibrium the wage, W^*, satisfies the fixed-point condition in equation (18). For each fixed point W^* there is a uniquely defined set of technology choices given by $\Theta^* = \Theta^R(W^*)$.*

PROOF. See the Appendix. ■

Suppose first that the mapping $W^E(\phi, \Theta^R(W))$ is decreasing in W.[14] In this case, automation decisions across industries are strategic substitutes and the equilibrium with endogenous technology is unique as shown in Figure 3.

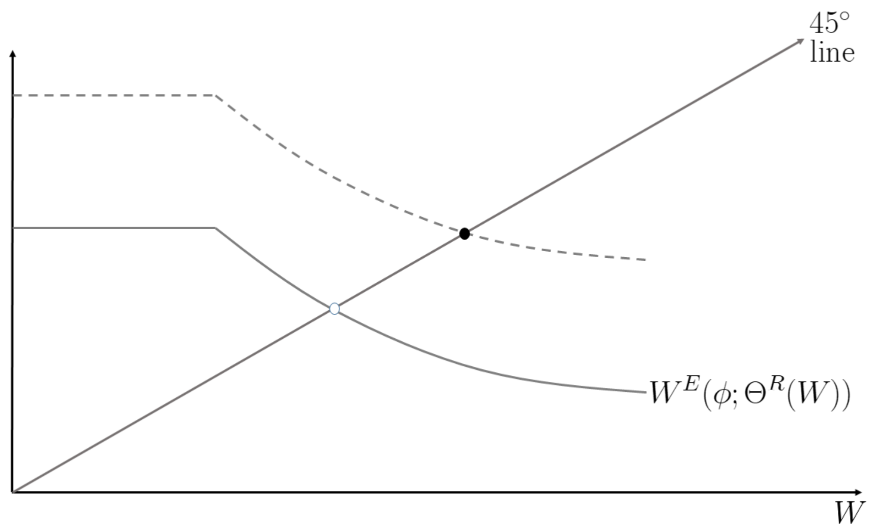

FIGURE 3: Wage determination in a scenario with a unique equilibrium. Aging shifts the mapping W^E up, and this increases the equilibrium wage in the unique equilibrium.

In general, $W^E(\phi, \Theta^R(W))$ need not be decreasing in W, and in particular, strong productivity gains from automation will make the middle-aged wage increasing in automation, creating

[14] A sufficient condition for this mapping to be decreasing is that the elasticity of the g function, ε_g, is sufficiently large in each industry (which guarantees that $A^R(W,i)$ is not very responsive to W), and that $\widetilde{\phi}(\widetilde{A}) < \phi < \overline{\phi}(\{\widetilde{A}(i), 0\}_{i\in\mathcal{I}})$ (so that the productivity gains from automation are positive for some industries but still smaller than $\overline{\pi}$). In this case, the mapping $W^E(\phi, \Theta^R(W))$ is constant for $W \leq \widetilde{W}$ and decreasing for $W > \widetilde{W}$ (here, $\widetilde{W}$ is the largest wage such that $\widetilde{W} < \widetilde{A}(i)P$ for almost all $i \in \mathcal{I}$). Note also that for $\phi \leq \widetilde{\phi}(\widetilde{A})$, the unique equilibrium involves $\theta(i)^* = 0$.

incentives for further automation in other sectors. Nevertheless, in this case an equilibrium with endogenous technology still exists, and there are also well-defined *least* and *greatest* equilibria as shown in Figure 4. This is because there is a unique value of the middle-aged wage, W, in each equilibrium, and technology choices are monotone in W (in view of the supermodularity in Lemma 1).

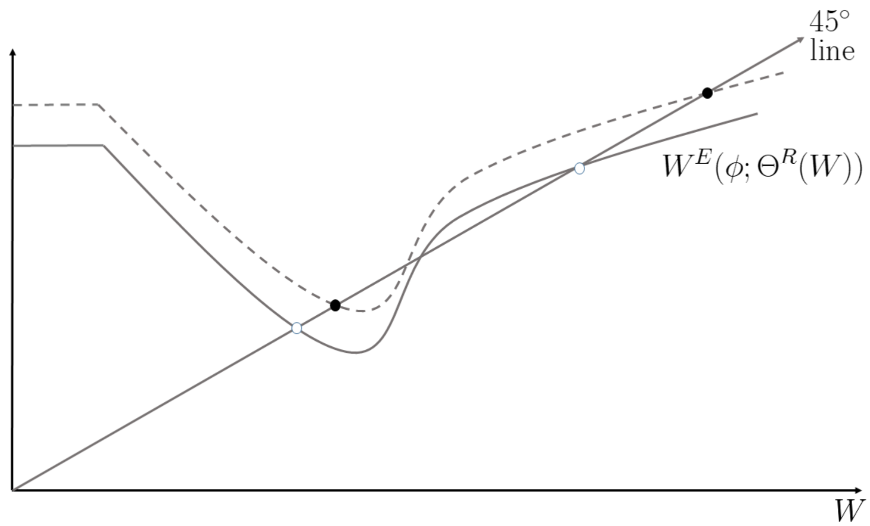

FIGURE 4: Wage determination in a scenario with multiple equilibria. Aging shifts the mapping W^E up, and this increases the equilibrium wage in the least and the greatest equilibrium.

The next proposition studies the implications of aging—an increase in ϕ—on equilibrium technology choices.

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

This proposition thus provides one of our most important results: aging always encourages automation, and this is regardless of whether automation has a positive or negative effect on the middle-aged wage and whether or not there are multiple equilibria (if there are multiple equilibria, it applies for the relevant equilibria, which are those with the least and greatest values of the middle-aged wage). Intuitively, machines compete against middle-aged workers, and a greater scarcity of these workers (relative to senior workers that are complementary to machines) always increases the relative profitability of using and developing automation technologies. The proposition also shows that the response of technology is not strong enough to overcome the initial increase in middle-aged wages brought by aging. This result is also intuitive: if the net effect of aging had been to reduce wages, then firms would not have had incentives to introduce the new automation technologies in the first place.[15]

Finally, in the next proposition, we derive how the responsiveness of technologies to aging varies by industry.

Proposition 6 *In the least or the greatest equilibrium, the effect of demographic change on automation technologies is greater in industries with larger* $\alpha(i)\rho(i)$*. In particular, if technology choices are locally differentiable, then*

$$\frac{d\theta(i)^*}{d\phi} = \Gamma_i \frac{d\ln W^*}{d\phi} > 0.$$

for all industries $i \in \mathcal{I}^+(\phi, A^*)$*, where* Γ_i *increases in* $\alpha(i)\rho(i)$*. Thus, among industries with the same levels of automation and labor-augmenting technologies, an increase in* ϕ*—aging—has a more pronounced impact on automation in industries that rely more heavily on middle-aged workers (i.e., those with high* $\alpha(i)$ *) and that present greater technological potential for automation (i.e., those with high* $\rho(i)$*).*

In our empirical work, we investigate both of the implications of this proposition. Though the latter—that investments in robotics technology will be more pronounced in industries that present greater opportunities for automation—is not surprising, the former implication, which links the responsiveness of technology to the baseline age composition of an industry, is novel and potentially interesting to study empirically.

2.4 Implications for productivity

As noted in the Introduction, the endogenous response of automation technologies might fundamentally alter the implications of demographic change for productivity. With exogenous technology, Proposition 1 showed that the effects of aging for aggregate productivity are ambiguous, but when the middle-aged wage is greater than the senior wage, aging tends to reduce aggregate output and productivity. We next show that with endogenous technology, aging creates a positive effect via the response of automation decisions, and when the workforce is aging, it tends to increase productivity in industries with greater opportunities for automation relative to others.

Proposition 7 *Let* ε_g *denote the elasticity of the* $g(A)$ *function with respect to* A*. There exists* $\bar{\varepsilon}_g$ *such that for* $\varepsilon_g > \bar{\varepsilon}_g$*, an increase in* ϕ*—aging—raises output in industries with greater* $\rho(i)$ *relative to industries with smaller* $\rho(i)$*.*

[15] This result does not imply that automation cannot reduce wages. First, when the productivity effect is small, the impact of automation is to reduce wages (relative to the benchmark with the same demographic changes but with technology held constant). Second, in a multi-country setting (as in Acemoglu and Restrepo, 2018), demographic changes in one country induce the development of automation technologies which then spread to other countries and may reduce wages there.

To illustrate this proposition, consider the extreme case where $A(i)^*$ is fixed exogenously at $\widetilde{A}(i)$,[16] and that technology choices are differentiable. Then the effect of aging on the output of industry i is

$$\frac{d\ln Y(i)^*}{d\phi} = \frac{d\ln Y^*}{d\phi} - \sigma\alpha(i)s_L(i)\frac{d\ln W^*}{d\phi} - \sigma(1-\alpha(i))\frac{d\ln V^*}{d\phi} + \sigma\alpha(i)\frac{s_L(i)}{1-\theta(i)^*}\pi(i)\Gamma_i\frac{d\ln W^*}{d\phi}.$$

The term $\sigma\alpha(i)\frac{s_L(i)}{1-\theta(i)^*}\pi(i)\Gamma_i\frac{d\ln W^*}{d\phi}$ captures the endogenous response of automation technology to demographic change. From Proposition 6, this endogenous response of technology is stronger in industries with greater $\alpha(i)$ and greater $\rho(i)$. The latter implies the result in Proposition 7—industries that have greater opportunities for automation invest more in automation technologies in response to aging and have better relative productivity performance. However, the effect of $\alpha(i)$ is ambiguous, because industries that rely more heavily on middle-aged labor also directly lose more due to aging. This discussion also highlights that the aggregate productivity implications of aging will be ambiguous in the presence of endogenous automation decisions, and as already anticipated in the Introduction, demographic change may not have major negative effects once technology adjusts.

3 Data

In this section, we present our various data sources. We also illustrate the differential trends across countries with different demographic changes and provide descriptive statistics that will be useful to assess the quantitative magnitudes of the results we present later.

3.1 Cross-country and commuting-zone data

Our main data source on robots is the International Federation of Robotics (IFR), which provides information on the stock of robots and new robot installations by industry, country and year. These data are compiled by surveying global robot suppliers. The data cover 52 countries from 1993 to 2014. Appendix Table A1 provides the list of countries in our sample.[17]

Table 1 summarizes our cross-country data on industrial robots. The denominator of the number of robots per thousand workers is constructed using employment data for 1990 from the International Labour Organization (ILO). We report summary statistics separately for the full IFR sample, for 30 OECD countries and also for countries that are above and below median in terms of demographic change (the measure of demographic change is explained below). In our

[16] The assumption that ε_g is sufficiently large ensures that we are close to this case and labor-augmenting technologies do not respond much to aging.

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

full sample, the number of robots per thousand workers increased from 0.72 in 1993 to 3.79 in 2014. We can further see that the increase in the stock of robots is more rapid for the OECD, and more importantly for our focus, it is also more rapid for countries that are undergoing more major demographic changes. The increase in the stock of robots per thousand workers for all countries and the OECD sample are also visible in Figure 5, which in addition shows the trends for the United States, Germany and Korea, underscoring the pattern we noted in the Introduction—that Germany and South Korea are considerably ahead of the United States in terms of the adoption of robotics technology.

Table 1 presents information on our demographic variables as well. Our main measure is the change in the ratio of senior (56 and older) workers to middle-aged workers (between 21 and 55). This measure is motivated by the patterns of substitution between robots and workers we document in the next section. We show in our empirical work that the exact age thresholds are not important for our results. Our main data source for demographic variables is the United Nations, which provides population by age and also population forecasts. Our baseline measure is for the change between 1990 and 2025, motivated by the fact that investments in robotics will have to take into account expected population trends. The table shows that our group of rapidly-aging countries has already undergone and are expected to further undergo significant demographic change (relative to the slowly-aging group). Figure 6 depicts these trends, and also shows that aging is much faster in Germany and South Korea and is slower in the United States than the OECD average.

Though not reported in the table, in our econometric models we also utilize country data on GDP per capita, population, average years of schooling, and the capital to output ratio obtained from version 9.0 of the Penn World Tables (Feenstra, Inklaar and Timmer, 2015).

We complement the IFR data with estimates of robots imports from the bilateral trade statistics in the Comtrade dataset, which covers 145 countries. We exclude from the sample the major robot producers (Germany, Japan and South Korea) for whom robot imports is not a reliable measure of investments in robotics technology, and countries that engage in significant entrepôt trade (Belgium, Hong Kong, Luxembourg and Singapore). The bottom rows of Table 1 provide summary statistics from this data set. We see a significant increase in the dollar value of robot imports between 1996 and 2015 for our full sample and a much larger increase for rapidly-aging countries.

For US labor markets, we use data compiled by Leigh and Kraft (2016) on the location of robot integrators in the United States to compute the number of integrators in each commuting zone.[18] As mentioned in the Introduction, integrators install, program and maintain robots, and given the nature of the services they provide, they tend to locate close to their customers. Thus, the location of these companies is proxy for the geographic distribution of robots-related activity

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

in the United States. We finally use data on "exposure to robots" and various economic outcomes across commuting zones. These data are constructed exactly as in Acemoglu and Restrepo (2017a), and to economize on space, we refer the reader to the descriptions in that paper. We only note here that data on demographic change across commuting zones are computed from the 1990 US Census and the American Community Survey (see Ruggles et al., 2010).

3.2 Industry-level data

In addition to the country-level data, the IFR reports data on robot installations by year separately for 19 industries in 50 of the countries in our sample, including 13 industries at the three-digit level within manufacturing and six non-manufacturing industries at the two-digit level. As Table A1 in the Appendix shows, these data are not available in every year for every country-industry pair, so in our analysis, we will focus on annual data rather than long differences. Table 2 summarizes the industry-level data. For each industry, we report the average number of robot installations per thousand workers, using two possible denominators, one from the UNIDO data set for employment at the three-digit manufacturing industries in 1995 (which covers 46 of the countries in our IFR data, but has no information on employment outside manufacturing), and another from the EUKLEMS dataset, which provides employment for all 19 of our industries, but only covers 22 of the countries in our sample (Jägger, 2016). We also use the EUKLEMS data to obtain information on the growth in value added per worker in real dollars from 1995 to 2007 for all the 19 industries included in the IFR data, and these data are reported in the third column of Table 2.[19] Finally, the last column of the table provides information on the age composition of workers in that industry in the United States in 1990 (computed from the 1990 Census).

In addition to the age composition of employment in an industry, our theoretical framework emphasizes the importance of the opportunities for automation. To proxy for this, we rely on two measures. The first is the "replaceability" index constructed by Graetz and Michaels (2015), which is derived from data on the share of hours spent by workers in the United States on tasks that can be performed by industrial robots. For this measure we only report the summary statistics at the bottom of the table; the full data by industry can be obtained from Graetz and Michaels (2015).[20] The second measure is a dummy variable for automobiles, electronics, metal products, metal machinery, and chemicals, plastics and pharmaceuticals, which are singled out by a recent report by the Boston Consulting Group (BCG, 2015) as industries with the

[19] We use employment levels in 1995 to normalize the number of robot installations because the data are missing for many countries before then. We also focus on the growth in value added per worker from 1995 to 2007 because post-2007 data are unavailable for many countries in our sample.

[20] A bivariate regression for the 19 industries in our sample shows that a 10 percentage point increase in the replaceability index is associated with 0.35 additional robot installations per thousand workers (standard error=0.16). Replaceability alone explains 22% of the total variation in the installation of robots across industries.

greatest technological opportunities for automation (and this is also the group of highly-robotized industry used in Acemoglu and Restrepo, 2017a). Table 1 confirms that these are the industries experiencing the most rapid growth in the adoption of robots in the IFR data.

4 The Substitution between Robots and Workers

In this section, we document the age pattern of substitution between robots and workers. Our main finding, which forms the basis of the analysis in the rest of the paper, is that robots are most highly substitutable for middle-aged workers (those between the ages of 35 and 54), and least substitutable with senior workers (those above 55).

We start by presenting the distribution of employment in highly-robotized industries (listed in the previous section). Table 2 shows that these industries correspond to the ones with the largest increase in the number of robots per thousand workers.

Figure 7 plots the age distribution of workers employed in highly-robotized industries as well as all employed workers and the overall population (above 20) in the United States. Since it is blue-collar workers that are at the greatest risk of displacement by industrial robots, we also show the age distribution of blue-color workers in highly-robotized industries. The three panels of the figure are for 1990, 2000 and 2007. All three panels show that all workers and blue-color workers in highly-robotized industries are more likely to be younger than 55 relative to both all employed workers and the full population. We interpret this evidence as supporting our presumption that industrial robots are more substitutable for the tasks performed by middle-aged workers than for the tasks performed by older (or younger) workers.[21]

Acemoglu and Restrepo (2017a) exploited differences in the historical industrial composition of US commuting zones to construct a measure of exposure to robots. Using this measure of exposure, we estimated the local employment and wage effects of robots. Here we use the same strategy to estimate the impact of robots on workers in different age groups located in highly exposed labor markets. To conserve space, we will not provide the full details of the approach in Acemoglu and Restrepo (2017a), instead, summarizing its main tenets. Acemoglu and Restrepo (2017a) focus for the most part on reduced-form models exploiting the potentially exogenous component of exposure to robots (coming from variation in industry-level adoption in other advanced economies).[22] We follow the same strategy here and construct the exposure to robots

[21] An alternative interpretation of this pattern is that robots are being introduced in industries where middle-aged workers are overrepresented because they are complementary to these workers. Though we do not find this a plausible hypothesis (since robots typically displace workers in certain tasks rather than directly complementing them), we provide an additional piece of evidence against it by showing that the introduction of industrial robots in a US local labor market has a strong negative impact on middle-aged workers.

[22] In that paper, we also report two-stage least squares estimates combining this measure of exposure to robots with changes in robots in US industries. IV estimates are very similar to the reduced-form results both in that paper and in the present context, and are omitted to save space.

measure as

$$\begin{array}{c}\textit{Exposure to robots} \\ \textit{from 1993 to 2007}_z\end{array} = \sum_{i \in \mathcal{I}} \ell_{zi}^{1970} \left(p_{30} \left(\frac{R_{i,2007}}{L_{i,1990}} \right) - p_{30} \left(\frac{R_{i,1993}}{L_{i,1990}} \right) \right), \tag{21}$$

where $R_{i,t}/L_{i,t}$ is the number of robots per thousand workers in industry i at time t, the sum runs over all the industries in the IFR data, ℓ_{zi}^{1970} stands for the 1970 share of commuting zone z employment in industry i, which we compute from the 1970 Census, and $p_{30}\left(\frac{R_{i,t}}{L_{i,1990}}\right)$ denotes the 30th percentile of robot usage among European countries in industry i and year t.[23]

Figure 8 reports estimates of the effects of robots on the employment rate and wages of workers in different 10-year age bins. More specifically, we estimate the following models for employment and wages by age group across commuting zones:

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

where $\Delta L_{z,a}$ is the change in the employment rate of age group a in commuting zone z between 1990 and 2007, and $\Delta \ln W_{z,a}$ is the change in the average wage of workers in age group a in commuting zone z between 1990 and 2007. We then plot the estimates of the coefficients β_a^L and β_a^W (together with 95% confidence intervals based on heteroscedasticity-robust standard errors). We focus on three specifications similar to those in Acemoglu and Restrepo (2017a), except that in line with the focus here all regressions are unweighted (while given the focus there on aggregate changes, the main specifications in Acemoglu and Restrepo, 2017a, were weighted by population). The first one we report is the baseline specification in Acemoglu and Restrepo (2017a) and controls for Census region fixed effects, demographic differences across commuting zones, broad industry shares, and the impact of trade with China and Mexico, routinization, and offshoring.[24] The second specification, in addition, removes the seven commuting zones with the highest exposure to robots, to ensure that the results are not being driven by the most exposed commuting zones. The last specification pools the data for all age groups and forces our covariates, except the impact of exposure to robots, to have the same impact on all workers. The top panel is for employment, while the bottom panel is for wages. In both cases, we see negative effects for workers between the ages of 35 and 54, and no negative effects on those younger than 35 and older than 55.[25] In Figure A1 in the Appendix, we report similar results

[23] Using baseline shares from 1970, 1980 or 1990 or using other moments of the distribution of robots across European nations leads to very similar results.

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

[25] In weighted regressions, the estimates for employment are very similar, but we do see some significant negative wage effects for older groups as well. This might reflect the downward wage pressure exerted by displaced middle-aged workers in some large commuting zones.

by five-year age bins, confirming these age thresholds.

Overall, the results in this section provide direct evidence that there is a high degree of substitution between robots and middle-aged workers (relative to older and in fact younger workers), and motivate the rest of our analysis.

5 Demographic Change and The Adoption of Robots

In this section, we present our main cross-country results, which show a robust negative association between the ratio of middle-aged to older workers and the adoption of robots.

5.1 Main Results

Table 3 starts with a flexible specification for the relationship between demographics and the adoption of robots. Since we have no strong priors on the time horizon at which firms should respond to demographic change, our focus throughout will be on long-differences specifications, where we look at the relationship between various demographic change variables and the change in robots-related activity between 1993 and 2014. More specifically, our regression equation is

$$\Delta \frac{R_c}{L_c} = \beta_y \Delta \ln \text{Young}_c + \beta_m \Delta \ln \text{Middle-aged}_c + \beta_o \Delta \ln \text{Old}_c + \Gamma X_{c,1990} + \varepsilon_c, \tag{22}$$

where $\Delta \frac{R_c}{L_c}$ is the (annualized) change in the stock of robots per thousand workers between 1993 and 2014 in country c (where we keep the denominator fixed as employment in 1990 from the ILO, which avoids potentially endogenous changes in employment impacting our left-hand side variable). The right-hand side variables are the changes between 1990 and 2025 in the log population of three age groups—those younger than 35, those between the ages of 36-55 and those above the age of 56 (where the change between 2017 and 2025 is based on the population forecasts of the United Nations described in Section 3). Our use of demographic change extending to 2025 is motivated by the fact that robot adoption decisions are typically forward-looking and what is relevant is not just the current population, but its composition in the near future. The IFR estimates that robots depreciate after 12 years, which implies that decisions to adopt robots in 2014 should take into account population trends at least until 2025. Indeed, we show below that demographic change in this extended time window has slightly greater explanatory power than just focusing on contemporaneous changes, though the qualitative results are similar either way (as we show in the Appendix). The vector $X_{c,1990}$ includes additional baseline covariates, and ε_c is the error term. Unless otherwise indicated, all of our regressions are unweighted and all standard errors are robust against heteroskedasticity.

Panel A of Table 3 presents our estimates of equation (22). Columns 1-3 are for the full sample. Column 1 is our most parsimonious specification, and regresses the change in robots per thousand workers on the population variables and regional dummies to account for differential cross-region trends.[26] Column 2 adds the 1990 values of log GDP per capita, log population, average schooling and the ratio of the population above 56 to those between 21 and 55 (a baseline control in our other tables) as covariates, thus allowing for differential trends in the adoption of robots by initial values of these variables. Column 3 also includes the stock of industrial robots per thousand workers in 1993, thus allowing countries with more robots at the beginning of the sample to diverge from those that were already behind in 1993.[27] Columns 4-6 parallel the first three columns, but present estimates for the OECD sample.

In all six columns of Panel A, a decline in the population of those between 36 and 55 (relative to the population of those above the age of 56) is associated with faster robot adoption. Though not always precise, these estimates confirm the expectations formed on the basis of the substitution patterns in the previous section, and indicate that the relative scarcity of workers most substitutable to robots—those in the middle-age category—do indeed increase the adoption of robots. The quantitative magnitudes are large but plausible. For example, in column 1, the coefficient estimate on population of the middle-aged group is -0.64 (standard error = 0.20). This estimate implies that a 10 percent decline in the population of the middle-aged group (which is roughly the decline expected for Germany) is associated with 0.064 additional robots per thousand workers per year, or 1.28 additional robots per thousand workers over the whole sample period (which is about a third of the average number of robots per thousand workers in 2014).

Panel B shows very similar patterns when we instead look at three age groups constructed as those between the ages of 21 and 35, between the ages of 36 and 55, and between the ages of 56 and 65, while at the same time controlling for change in total population. We again find a negative estimate for the change in the population of those between 36 and 55, and a positive estimate for the change in the population of those between the ages of 56 and 65. Interestingly, holding the age composition constant, changes in the overall population do not seem to correlate with the adoption of robots.[28]

Finally, Panel C shows that we obtain very similar results when we aggregate the workforce into two age groups: those between the ages of 26 and 55 and those above 56. The change in the population of the first group has a negative coefficient on the adoption of robots, while the change in the population of the second group has a positive coefficient.

[26] These regions are 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.

[27] This is particularly important, since there might be "mean reversion" patterns. Controlling for the initial stock of robots also enables us to be more flexible on the implied functional form (in particular, on the issue of logs vs. levels). In any case, as we show in Table A4 in the Appendix, the results are similar if we use $\ln(1 + R_c)$ or $\ln R_c$ as the dependent variable (where the latter specification leads to a smaller sample because the initial stock of robots is zero for several countries).

[28] This is the basis of our claim in the Introduction while discussing the work by Abelianisky and Prettner (2017) that we do not find evidence of direct effects from population to automation.

Overall, the results in Table 3 suggest that the adoption of robotics technologies is significantly correlated with changes in the age composition of the population—in particular, with demographic changes that increase the share of older workers and reduce the share of middle-aged workers. This motivates a more parsimonious specification, linking the adoption of robots to the ratio of older to middle-aged workers, which we explore in Table 4 and focus on in the rest of the paper. Namely, our main specification in the rest of the paper will be

$$\Delta \frac{R_c}{L_c} = \beta \text{Aging}_c + \Gamma X_{c,1990} + \varepsilon_c, \tag{23}$$

where the key difference from specification (22) is that we use the variable Aging_c, defined as the change between 1990 and 2025 in the ratio of "senior" workers (above 56 years of age) to middle-aged workers (those between 21 and 55). Table A3 in the Appendix shows that different choices for age cutoffs lead to similar results.

Table 4 reports estimates of equation (23) for the same specifications as in Table 3. Panel A focuses on OLS models, while Panel B estimates instrumental-variables (IV) models. Our IV models are motivated by the concern that changes in labor markets that influence the adoption of robots may also affect migration patterns and longevity, which would bias our OLS estimates. To address this concern, we instrument the (expected) aging from 1990 to 2025 using the average birth rates over five-year intervals from 1950-1954 to 1980-1984. These birth rates satisfy the requisite exogeneity assumption since past changes in birth rates are unlikely to be driven by contemporaneous wages or technologies, and explain a large portion of the variation in our demographic change variable (in column 3, the first stage F-statistic is 13.67).

The estimates in Panel A confirm the positive effect of an aging population on the adoption of robots. The results are now more precisely estimated and are significant at 5% or less in all specifications (partly because we have a single demographic change variable on the right-hand side rather than three or four correlated variables as in Table 3, where the qualitative patterns were similar but some estimates were less precise). The quantitative effects are again substantial. For example, our most parsimonious specification in column 1 has a R^2 of 0.43 (and the partial R^2 of the aging variable alone is close to 0.40 as noted in the Introduction). In our preferred specification in column 3, the coefficient estimate on the aging variable is 0.45 (standard error = 0.19). This implies that a 20 percentage point increase in our aging variable, which is approximately the difference between Germany and the United States (0.5 vs. 0.28, respectively), leads to an increase of 0.09 robots per thousand workers per year or 1.8 additional robots per thousand workers over our entire period of analysis and would account for 25 percent of the difference in the adoption of robots between Germany and the United States. Panel B shows that the IV estimates of the effect of demographic change on the adoption are similar, but slightly larger.

Figure 9 depicts the relationship between our measure of demographic change and the number of robots per thousand workers in the full sample of countries and in the OECD (from the models estimated in columns 3 and 6 in Table 4). The relationship between demographic change and the adoption of robots is clearly visible in both panels, and we can also see that this relationship is not driven by any outliers.

5.2 Placebo Exercises, Robustness and Additional Results

In this subsection we first show that past demographic changes have no predictive power for the adoption of robotics technology, then document the robustness of the results in Table 4 to a range of variations, and then finally present some additional results.

In Panel A of Table 5, we include the same aging variable on the right-hand side, but now it is measured between 1950 and 1990. Past demographic changes should have no impact on the adoption of robotics technology after 1990—unless countries that have adopted more robots since 1993 were on different demographic trends for other reasons even before the 1990s. The results in Table 5 are reassuring in this respect and show no correlation between our aging variable between 1950 and 1990 and the change in the number of robots per thousand workers since 1990. Figure 10 shows the partial regression relationship between the placebo demographic change measure (between 1950 and 1990) and the change in the number of robots per thousand workers between 1993 and 2014, both for all countries in our sample and for the OECD countries. Panel B of Table 5 presents a complementary exercise where we simultaneously include past aging and expected aging (from 1990 to 2025)as explanatory variables. The results show that only expected aging is an important determinant of the adoption of robots.

Panel C of Table 5 further investigates the question of whether it is contemporaneous demographic change or the expectation of future aging that is more strongly associated with the adoption of robots. We simultaneously include aging from 1990 to 2015—the contemporaneous demographic change—and expected aging from 2015 to 2025. The results are not as precise as before, because contemporaneous and expected aging are highly correlated. Nevertheless, our estimates show that both contemporaneous aging and expected aging are correlated with the adoption of robots. Indeed, in no specification can we reject the null hypothesis that contemporaneous and expected aging have the same impact on robot adoption. Expected aging plays a particularly important role in the OECD sample, where it is significant at the 10% level in all models. These results support our choice of focusing on (expected) aging between 1990 and 2025 in our baseline models. In any case, Table A2 in the Appendix shows that our main results are very similar if we use the contemporaneous variable in our main specifications.

We have so far focused on long-difference specifications, focusing on the change in the stock of robots between 1993 and 2014. This is the most transparent specification, especially in view of the evidence that it is not just contemporaneous but future demographic changes that are impacting the adoption of robots. Nevertheless, such long-difference specifications fail to exploit the potential covariation between demographic change and the adoption of robots in subperiods. To exploit this additional source of variation, Table 6 turns to stacked-differences models, where for each country we include two observations on the left-hand side—the change in the stock of robots from 1993 to 2005 and from 2005 to 2015. We then regress these changes on the aging variable from 1990 to 2005 and 2005 to 2015, respectively. Panel A presents our OLS estimates. Columns 1 and 4 give our most parsimonious model where we only control for region and period dummies. Columns 2 and 5 include all the country level covariates as controls (1990 values of log GDP per capita, local population, average schooling and ratio of older to middle-aged workers). Panel B presents the corresponding IV estimates. The estimates confirm our main results in Table 4. In columns 3 and 6, we go one step further relative to our earlier specifications and also include linear country trends (or country dummies in the change specification). These specifications only exploit the differential rate at which demographic change proceeds and additional robots are adopted in the two subperiods for each country. Remarkably, the estimates in these demanding specifications are not just highly significant, but they are also very similar to our baseline estimates, bolstering our confidence in the interpretation and robustness of our results.

Besides aging, our model suggests that other factors affecting wages, such as unionization, and potentially the wage level itself are important determinants of the adoption of robots. We explore these issues in Table 7, where in addition to estimating the impact of aging on robot adoption, we control for the baseline union membership and the log of average hourly wage in 1993.[29] Panel A presents OLS estimates and Panel B presents IV estimates, again instrumenting for aging with past birth rates. Because the data on union membership are only available for a subset of countries, our sample now consists of 38 countries, 30 of which are in the OECD. The results provide some support for the idea that countries with greater unionization rates adopted more robots, though this result is not as robust as the effects of demographic change documented so far. The positive effect of unionization on the adoption of robots is consistent with the view that unions raise labor costs and create additional incentives for firms to automate production. Quantitatively, our estimates in column 3 of Panel B imply that a 10 percentage point increase in union membership—roughly the difference between Germany and the United States—is associated with 0.021 additional robots per thousand workers per year (standard error=0.01), which amount to 0.42 robots over the whole 1993-2014 period. Though non-trivial, this quantitative effect is about a quarter of the impact of aging (when similarly scaled). The wage level, on the other hand, does not seem to have a robust impact on the adoption of robots. This might be because high wages reflect not just greater "wage push," but also higher productivity of workers, which is likely to discourage automation.

In preparation for our industry-level estimates, we next explore the annual data on robot

[29] We use the average share of workers belonging to a union between 1990 and 1995 as our measure of unionization (from the ILO and Visser, 2016). We obtained similar results using an alternative unionization series from the Labor Market Data Base (Rama, 1996). The data on wages are from the Penn World Tables, version 9.0 (see Feenstra, Inklaar and Timmer, 2015).

installations. Table 8 presents estimates of the model

$$\frac{IR_{c,t}}{L_{c,1990}} = \beta \text{Aging}_{c,2025-1990} + \Gamma_t X_{c,1990} + \delta_t + \varepsilon_{c,t}, \tag{24}$$

where the left-hand side variable, in contrast to equation (23), denotes the (annual) installation of new robots per thousand workers (with the denominator still corresponding to employment in 1990). Correspondingly, we also allow the covariates in $X_{c,1990}$ to have time-varying coefficients and include year effects δ_t. The sample covers every year between 1993 and 2014, our regressions are again unweighted, and the standard errors are now robust against heteroscedasticity and correlation (clustering) at the country level. Panel A presents OLS estimates and Panel B presents IV estimates. Overall, the estimates are very similar to those of Table 4, with the minor differences explained by 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).

Finally, we also explored models in logs rather than in the number of robots per thousand workers as in our baseline specification. In Appendix Table A4, we present estimates using either $\Delta \ln(1+R_c)$ or $\Delta \ln R_c$ as the dependent variable (in both cases, these are long differences from 1993 to 2014, and we again control for initial stock of robots on the right-hand side). The former specification is motivated by the fact that the initial stock of robots is equal to zero for several countries. We also estimate Poisson regressions for a variant of the model in equation (24) using the number of robot installations per year in each country as the dependent variable. In all cases, the results are very similar to our baseline estimates.

5.3 Alternative Measures of Investment in Robots and Automation

We have so far focused on robots because of the available data, though we believe that similar forces are at work for other automation technologies. In Table 9 we use Comtrade data on the imports of various intermediate goods (embodying different types of technologies) to explore the implications of demographic changes for a different measure of investment in robots and other automation technologies. As noted in Section 3, in these data we can only measure imports of these technologies—not their usage, which varies in countries that produce robots. Despite this shortcoming, we believe it is useful to study this alternative measure of investment in robots as well as the complementary measures of automation technologies.

For different types of imports, we estimate a variant of equation (23) but using log of imports in that category normalized by total intermediate imports as the dependent variable.[30] For each of the import categories indicated in the top row, Panel A presents OLS estimates, while Panel B reports corresponding IV estimates.

In in the first column, as discussed in the Introduction, we look at the imports of industrial robots. The Comtrade data report the total dollar value of imports of industrial robots,

[30]This normalization is important, since total intermediate inputs are correlated with aging.

which enables us to compute the log of the total value of imports relative to total imports of intermediates between 1990 and 2016. As also noted in Section 3, in this case we exclude the major robots producers in our dataset (Germany and South Korea), and countries engaging in significant entrepôt trade (Belgium, Hong Kong, Luxembourg and Singapore). This measure of the change in the value of imports of industrial robots is highly correlated with our IFR measure of the change in the stock of robots per thousand workers, both in levels and in logs, as shown in Figure 11.[31] The estimates in column 1 of Table 9 confirm the patterns we have documented so far—both in the OLS and IV, there is a strong association between aging (measured in exactly the same way as in our main specification) and the change in the imports of robots (relative to total intermediate imports). The IV coefficient estimate is 4.66 (standard error = 2.14) in Panel B, and implies that a 20 percentage point increase in aging, once again corresponding to the difference in expected aging between Germany and the US, leads to a 92 log points increase in the imports of industrial robots relative to total intermediate imports. Figure 12 presents the relationship between imports of industrial robots (relative to total intermediate imports) and aging visually, and confirms that this relationship is not driven by outliers.

The rest of the table looks at the imports of a number of other technologies (or more appropriately, imports of intermediates embodying these technologies). Columns 2-4 consider three other automation technologies, numerically controlled machines, weaving and knitting machines, and vending machines and ATMs. In each case, we see a positive correlation between our aging measure and the imports of these machines relative to total intermediate imports. This evidence supports the presumption that the effect of aging on the adoption of robots is indicative of a broader relationship between demographic change and automation.

Columns 5 and 6 turn to two other classes of technologies, computers and agricultural machinery (including tractors, harvesters and plows), which are interesting in their own right, but a priori may or may not be examples of automation technologies.[32] In both OLS and IV, we see a positive association between aging and computers, and a negative and insignificant relationship between aging and agricultural machinery.

Columns 7 and 8 report results with two technologies that can be considered as broadly labor-augmenting—miscellaneous tools (which includes a wide range of metal hand tools) and general equipment (which includes machinery used in industrial applications that is not autonomous nor

[31] In the level specification, the bivariate regression coefficient is of 73,243 (standard error=7,958). This coefficient is reasonable in view of the fact that the cost of a typical robot ranges between \$50,000 and \$100,000 (This excludes the costs of installation and programming, which often add about \$300,000 to the cost of a robot, but since these services are typically provided by local integrators, they do not show up in import statistics).

[32] Computers are used in a wide range of tasks, and with workers of all ages, so their substitution patterns and effects on the labor market are likely to be broader than those of industrial robots, which we have argued to be more strongly substitutable for middle-aged workers. Indeed, the results in Acemoglu and Restrepo (2017a) suggest that the effects of computer technology on local employment and wages may be quite different than the effects of robots.

numerically controlled). In both cases, our IV estimates show small and non-significant effects of aging on the imports of these technologies relative to total intermediate imports. This pattern is consistent with the presumption that these technologies are closer to our labor-augmenting category than the automation category (though we also do not see a negative impact).

Finally, column 9 estimates the relationship between aging and the capital-output ratio from the Penn World Tables, and shows a positive relationship, which we interpret as partly reflecting the effect on the capital stock of additional investments in robotics and other automation technologies induced by aging.

Overall, the results from the bilateral import data confirm the relationship between demographic change and investment in robotics we have documented so far using a very different data source, and also provide suggestive evidence that a similar relationship may hold for other automation technologies.

6 Demographics and Robots across US Commuting Zones

In this section, we estimate the relationship between aging and the adoption of robots across US commuting zones. Though we do not have direct measures of installations or stocks of robots across US local labor markets, as explained above we proxy for robots-related activity relying on Leigh and Kraft's (2016) measure of the number of integrators (which specialize in installing, programming and maintaining robots). The number of integrators was shown to be related to other measures of exposure to robots in Acemoglu and Restrepo (2017a).

Panel A of Table 10 reports estimates of the model

$$\ln(1 + \text{Integrators}_z) = \beta \text{Aging}_z + \Gamma X_{z,1990} + \upsilon_z$$

across 722 US commuting zones. Here z indexes a commuting zone, Integrators_z is the number of integrators in commuting zone z, and because it is equal to zero in several commuting zones, we formulate the dependent variable as $\ln(1+ \text{Integrators}_z)$. Aging_z now designates the change in the ratio of workers above 56 to those between 21 and 55 between 1990 and 2015 in commuting zone z, constructed from the Census and the American Community Survey, and $X_{z,1990}$ is a vector of additional commuting-zone characteristics measured in 1990, which always includes the exposure to robots measure from Acemoglu and Restrepo (2017a). Panels B and C of the table report estimates from alternative specifications with the number of integrators, Integrators_z, and a dummy variable for the presence of any integrators in the commuting zone as dependent variables. As in our other models, we focus on unweighted regressions and the standard errors are robust against heteroskedasticity and correlation at the state level. In all panels, odd-numbered columns only include census region dummies, while even-numbered columns control for the same set of covariates we included in our analysis of the effects of exposure to robots on workers of different ages reported in Figure 8 (see footnote 24).

In columns 1 and 2, we see in a negative relationship between our demographic change variable and the location of integrators. This is, however, largely because the age composition of the population in a commuting zone is highly endogenous to the economic changes in the area. In the remaining columns of the table, we focus on the source of variation coming from past cohort sizes as in our cross-country IV specifications. More specifically, in columns 3 and 4 we use the size of cohorts in each commuting zone in 1990 to predict the change in aging until 2015. In columns 5 and 6, we use the sizes of cohorts aged 0-5 and 6-10 in 1950, 1960, 1970, 1980 and 1990 to instrument for our aging variable. In contrast to our OLS estimates, the IV estimates in all panels show a positive impact of aging on the location of integrators, which is statistically significant in all cases except in columns 5 and 6 in Panel B, when we look at the number of integrators. Figure 13 depicts the IV relationship between demographic change and robots across commuting zones from the specification in column 4 of Panel A. The positive relationship is clearly visible. Quantitatively, the effects are again sizable. A 10 percentage point increase in our aging variable—which is approximately the average in our sample—is associated with 1.7 additional integrators and a 20 percentage point increase in the probability of having at least one robot integrator.

Overall, even though our proxy for robots-related activity in this section, the number of integrators in the area, is far from perfect, the evidence is broadly supportive of the positive impact of aging on the adoption of robots when we focus on cross-commuting zone variation as well.

7 Demographics and Robots: Industry-Level Results

Our theoretical analysis in Section 2 highlighted that the response of robotics technology to demographic change—an increase in the ratio of older to middle-aged workers—should be more pronounced in industries that rely more on middle-aged workers and also in industries in which these middle-aged workers engage in tasks that can be more productively automated. We now investigate these predictions using the industry-level data from IFR summarized in Table 2.

Table 11 estimates regression models similar to those reported in Table 8, except that our data now vary by country and industry. In particular, our main specification augments equation (24) by including interaction effects:

$$\begin{aligned}\frac{IR_{i,c,t}}{L_{i,c,1990}} =& \beta \text{Aging}_c + \beta_R \text{Aging}_c \times \text{Reliance on Middle-Aged Workers}_i \\ &+ \beta_P \text{Aging}_c \times \text{Opportunities for Automation}_i + \Gamma_{i,t} X_{c,1990} + \alpha_i + \delta_t + \varepsilon_{i,c,t},\end{aligned} \tag{25}$$

where the left-hand side variable denotes the (annual) installation of new robots per thousand workers in industry i, country c and year t, Aging_c is once again defined as the change in the ratio of the population above 56 to those between 21 and 55 from 1990 to 2025, α_i denotes industry effects, δ_t designates time effects, and we also allow the coefficients on the country-level covariates in $X_{c,1990}$ to vary over time and have different effects by industry. The new variables, Reliance on Middle-Aged Workers$_i$ and Opportunities for Automation$_i$, capture industry-characteristics which our theory predicts should impact the response of the adoption of robots to aging. Our sample for this regression covers 50 countries and runs from 1993 to 2014, but is unbalanced since, as indicated in Table A1., data are missing for several country×industry×year combinations.[33] Finally, we report standard errors that are robust against heteroscedasticity and cross-industry and temporal correlation at the country level.

To construct the denominator of our left-hand side variable, we use three approaches. First, in Panel A we use the ILO country data to normalize robot installations by $L_{i,c,1990} = L_{c,1990}/19$ (recall that the IFR reports data for 19 industries). This normalization allows us to use all 50 countries for which there are industry-level robots data. Second, in Panel B we use the UNIDO data on employment by country-industry pair described in Section 3. These data cover 12 manufacturing industries for 46 countries in our sample. Finally, in Panel C we use the EUKLEMS data, also described in Section 3, which cover all the industries in our sample, but only for 22 countries.

Column 1 in all panels presents estimates of equation (25) without any of the interaction terms. Though not reported, our country covariates, $X_{c,1990}$, include region dummies, the log of GDP per capita, log population, average years of schooling and the ratio of older to middle-aged workers in 1990. Except for Panel B, which includes only manufacturing and produces larger estimates, the average effect of aging is comparable to our cross-country estimates.

The remaining columns include the interaction of aging with reliance on middle-aged workers and opportunities for automation. As described in Section 3, the former variable is constructed from the 1990 census as the ratio of middle-aged to senior workers in that industry in the United States. In columns 2-4, the Opportunity for automation$_i$ variable is proxied using Graetz and Michaels's replaceability index, which was also described in Section 3. In columns 5-7, we instead use a dummy variable for the industries identified by BCG (2015). The estimates in columns 2 and 5 show positive and statistically significant interactions with both variables in all panels. The estimates in column 2 of Panel A indicate that a 10 percentage point increase in aging leads to an increase of 0.15 ($= 1.66 \times 0.9 \times 0.1$) annual robot installations per thousand workers in an industry at the 75th percentile of reliance on middle-aged workers compared to an industry at the 25th percentile. More specifically, in electronics, which is at the 75th percentile of reliance on middle-aged workers, a 10 percentage point increase in aging is predicted to increase

[33] In this and subsequent industry-level regressions, we weight country-industry pairs using the baseline share of employment in each industry in that country. This weighting scheme ensures that all countries receive the same weight—as in our unweighted country specifications—while industry weights reflect their relative importance in each country (this is the same weighting scheme used by Graetz and Michaels, 2015 and Michaels, Natraj, and Van Reenen, 2014).

installations of robots by 0.25 per thousand workers per year, while in basic metals, which is at the 25th percentile, the same change is predicted to lead to only 0.1 more robots per thousand workers. Similarly, a 10 percentage point increase in aging is associated with an increase of 0.155 ($= 0.27 \times 5.738 \times 0.1$) annual robot installations per thousand workers in an industry at the 75th percentile of the replaceability index compared to an industry in the 25th percentile. In this instance, automobile manufacturing is approximately at the 75th percentile of the replaceability index, and a 10 percentage point increase in aging is predicted to increase installation of robots by 0.21 per thousand workers per year in this industry, while the same change is predicted to increase installation of robots only by about 0.05 per thousand workers in construction or utilities, which are at the 25th percentile. In summary, aging increases robot installations 3 to 5 times more in the industries with the greatest reliance on middle-age workers and the greatest opportunities for automation than in the average industry in column 1.

In columns 3 and 6, we control for a measure of the baseline extent of robot use in each country-industry pair, which accounts for any unobserved industry characteristics that may be correlated with initial investments and subsequent trends in robotics and/or for mean-reversion (or other) dynamics.[34]

Finally, in columns 4 and 7 we control for a full set of country fixed effects (and we no longer estimate the main effect of aging). In these models the interaction between aging and industry characteristics is identified solely from within country variation. Reassuringly, the size of the interaction coefficients does not change much, and we still find positive and statistically significant interactions in all panels.

Table 12 reports IV estimates for the same specifications as in Table 11. As in our cross-country analysis, we instrument demographic change using past birth rates, and we also include interactions of these birth rates with our measures of reliance on middle-aged workers and opportunities for automation to generate corresponding first-stages for the interaction terms. As before, the first-stages are reasonably strong (the first-stage F-statistic for excluded instruments ranges from 7.33 to 15.35 in the most demanding specifications; and moreover, our estimates always comfortably pass Hansen's overidentification test). The IV estimates confirm the patterns reported in Table 11, and most importantly, show more pronounced responses to aging from industries that rely more on middle-aged workers and have greater opportunities for automation. In fact, these estimates are quantitatively quite similar to the OLS ones.

Table 13 reports placebo exercises for our industry-level results similar to those in Table 5. To save space we focus on estimates that use the country employment from ILO to normalize

[34] Because we do not observe the stock of robots for all country-industry pairs in 1993, we follow Graetz and Michales (2015) and impute these stocks when they are missing in 1993. To do so, we deflate the first observation of the stock of robots in a country-industry pair back in time using the growth rate of the stock of total robots in the country during the same period. Including this control reduces the heterogeneous impact of aging slightly, but does not alter our qualitative conclusions.

the installation of robots, which yields the largest sample. Reassuringly, neither the main effects nor the interaction terms involving past demographic changes are significant in this case; although some of the interaction terms have positive coefficients in Panel A, they are statistically insignificant and about half the size of their counterparts in Table 11. These coefficients become even smaller, and continue to be insignificant, when we add expected aging in Panel B.

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

8 Productivity

In this section, we turn to the relationship between demographic change and change in labor productivity (real value-added per worker). As highlighted in our theoretical analysis in Section 2, this relationship is on in general ambiguous. On the one hand, demographic change might reduce the number of high-productivity middle-aged workers relative to lower-productivity older workers. On the other hand, demographic change might increase productivity because of the technology adoption it induces. Nevertheless, our model also makes some unambiguous predictions: because of the induced increase in automation, industries with the greatest potential for automation should increase their value added per worker relative to other industries that cannot rely on automation to substitute for middle-aged workers.

This issue is investigated in Table 14, where we present estimates of the following equation:

$$\begin{aligned}\Delta \ln VA_{i,c} =& \beta \text{Aging}_c + \beta_R \text{Aging}_c \times \text{Reliance on middle-aged workers}_i \\ &+ \beta_P \text{Aging}_c \times \text{Potential for the use of robots}_i + \Gamma_i X_{c,1995} + \alpha_i + \varepsilon_{i,c},\end{aligned} \tag{26}$$

where the left-hand side variable denotes the change in log value added per worker in industry i in country c between 1995 and 2007. In Panels A and B, we measure this variable from the EUKLEMS data, which cover the same 19 industries we have used throughout, but only for 22 countries. Because the productivity measure is only available from 1995 onwards, we adjust our aging variable to be between 1995 and 2025 (rather than starting in 1990 as we had before). In addition, we allow the baseline covariates in $X_{c,1995}$ to affect industries differently and include industry effects, α_i. In Panel C, we instead use the OECD STAN database, which includes 27 countries, but with patchier coverage of industries. In all cases, we use the same weighting scheme as in our industry-level analysis of installation of robots, corresponding to unweighted regressions across countries, and the standard errors are again robust against heteroscedasticity and correlation at the country level.

The structure of Table 14 is similar to that of Table 11. Panel A presents OLS estimates and Panel B reports IV estimates of equation (26) with the EUKLEMS data, while Panel C shows

IV results using the OECD STAN data. Column 1 in Panel A shows that aging reduces the average growth of value added per worker. A 10 percentage point increase in aging is associated with a 14.5% decline in value-added per worker (standard error=5.6%) in the top panel and a 17.3% decline in value-added per worker (standard error=6.2%). These results differ from the findings in Acemoglu and Restrepo (2017b), where we showed that there was no negative effect of aging on growth in GDP per capita. The negative estimates in column 1 here are driven by the smaller samples in the EUKLEMS and OECD datasets, and are not robust to using other measures of economic activity. For instance, as reported in Table A5 in the Appendix, if we estimate the analogue of equation (26) at the country level for the larger sample, there is no significant negative relationship.

Of greater interest given the theoretical predictions highlighted in Section 2 are the interaction effects, especially the interaction between aging and opportunities for automation. Here, we find a robust and sizable positive interaction, indicating that in the presence of aging, industries with greater opportunities for automation are experiencing relative productivity gains. The magnitudes are sizable. For example, the IV estimate in column 2 of Panel B shows that a 10 percentage points increase in aging causes an increase of 12% ($= 0.27 \times 4.498 \times 0.1$) in the growth of value added per worker in an industry at the 75th percentile of the replaceability index compared to an industry at the 25th percentile. This implies that in industries at the 25th percentile of the replaceability index, such as construction of utilities, a 10 percentage point increase in aging Is predicted to reduce the growth of value added by 19.5% between 1995 and 2007, while the same change reduces the growth of value added only by 7.5% in industries at the 75th percentile, such as automobiles. This result confirms the basic premise from our theoretical analysis of productivity effects—that the endogenous automation response tends to increase productivity in industries with greater opportunities for automation relative to industries with lesser opportunities for automation or robotics.

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

Overall, consistent with our theoretical predictions, the evidence suggests that aging increases relative productivity in industries that have the greatest opportunities for automation—and has ambiguous effects on aggregate (or average) productivity.

9 Conclusion

The populations of most developed and many developing countries are aging rapidly. Many economists see these demographic changes as major "headwinds" potentially slowing down or even depressing economic growth in the decades to come (e.g., Gordon, 2016, Summers, 2013).

However, a reasoning based on directed technological change models—which highlight the effects of changing scarcity of different types of labor on the adoption and development of technologies substituting for these factors—suggests that these demographic changes should be associated with major technological responses.

We have documented in this paper that this is indeed the case; countries and US labor markets undergoing more major demographic change have invested significantly more in new robotic technologies (and more broadly in a variety of automation technologies). We have argued that this is because ongoing demographic changes are increasing the scarcity of middle-aged workers and robots are most substitutable with middle-aged workers (which can be seen both in the age composition of employment across industries with different investments in robotics, and the causal effects of the exposure to robots on the employment and wages of workers of different ages). The effects of demographic change on investment in robots are highly robust and quantitatively sizable. For example, differential aging alone accounts for about 40% of the cross-country variation in investment in robotics.

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

The technology responses to aging mean that the productivity implications of demographic changes are more complex than previously recognized. Especially in industries most amenable to automation, aging can trigger significantly more adoption of new robots and as a result, lead to greater productivity—even if the direct effect of aging might be negative. Using industry-level productivity data, we find that the main effect of aging on productivity is ambiguous, but consistent with our theoretical predictions, in the face of demographic change industries with the greatest opportunities for automation are experiencing more rapid growth of productivity relative to other industries.

Several questions raised in this paper call for greater research. First, it is important to investigate the effects of aging on technology adoption and productivity using more disaggregated industry data and even more preferably firm-level data, to which we do not have access in this paper. Second, it would be interesting to study whether the effects of demographic change on technology adoption are being mediated through wages and whether other factors affecting wages, such as differences in labor market institutions, also have similar effects on technology. Third, our theoretical framework makes specific predictions about how aging may reduce investments in labor-augmenting technologies even as it is encouraging further automation. This is another theoretical implication that we investigated with the data available to us, but can better be studied using more disaggregated data on industries and technologies. Finally, motivated by industrial robots, our focus has been on the substitution of machines for middle-aged workers in production tasks (and mostly in manufacturing). Though it is well-known that with the advent of artificial intelligence, a broader set of tasks can be automated, there is currently little research on incentives for the automation of nonproduction tasks and their productivity implications.

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Appendix: Omitted Proofs

Proof of Proposition 1

1. Existence and uniqueness of equilibrium.

Recall that $C(W,V,P)$ is the cost of producing one unit of aggregate output. Let $P_Y(i)$ denote the price of good $Y(i)$ and $P_X(i)$ denote the price of $X(i)$.

The Cobb-Douglas production function for $Y(i)$ in equation (2) implies that

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

Solving for $P_Y(i)$ yields equation (5). Equation (1) then implies

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

where $P_X(i)$ is given in equation (8) in the main text.

The demand for labor from production and service tasks then follows from Shepherd's Lemma and takes the form

$$L^d = C_W(W,V,P)\frac{Y}{2-\eta}, \qquad S^d = C_V(W,V,P)\frac{Y}{2-\eta},$$

where $2-\eta$ in the denominator accounts for the intermediate goods, $q(i)$, and the cost of producing these goods.

From these equations, conditions (13) and (14) can be written as

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

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

We now show that, for any $\phi \in (0,1)$ there is a unique pair $\{W^E(\phi,\Theta), V^E(\phi,\Theta)\}$ that solves (A1) and (A2).

Consider the iso-cost $C(W,V,P) = 1$. The market equilibrium occurs at a point where the tangent to this curve has slope $-\frac{\phi}{1-\phi}$ as shown in Figure 1.

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

$$\frac{C_W(W,V,P)}{C_V(W,V,P)} = \frac{V}{W}\frac{\int \alpha(i)s_L(i)\lambda(i)^{1-\sigma}P_X(i)^{\alpha(i)(1-\sigma)}V^{(1-\alpha(i))(1-\sigma)}di}{\int (1-\alpha(i))\lambda(i)^{1-\sigma}P_X(i)^{\alpha(i)(1-\sigma)}V^{(1-\alpha(i))(1-\sigma)}di}.$$

Letting $\alpha_{min} = \inf_{i\in\mathcal{I}} \alpha(i)$ and $\alpha_{max} = \sup_{i\in\mathcal{I}} \alpha(i)$, we get

$$\begin{aligned} 0 \leq \frac{C_W(W,V,P)}{C_V(W,V,P)} &\leq \frac{V}{W}\frac{\alpha_{max}}{1-\alpha_{min}}\frac{\int \lambda(i)^{1-\sigma}P_X(i)^{\alpha(i)(1-\sigma)}V^{(1-\alpha(i))(1-\sigma)}di}{\int \lambda(i)^{1-\sigma}P_X(i)^{\alpha(i)(1-\sigma)}V^{(1-\alpha(i))(1-\sigma)}di} \\ &= \frac{V}{W}\frac{\alpha_{max}}{1-\alpha_{min}}. \end{aligned}$$

Therefore, as $\frac{V}{W} \to 0$, $\frac{C_W(W,V,P)}{C_V(W,V,P)} \to 0$ (recall that $\alpha_{min}, \alpha_{max} \in (0,1)$).

Likewise, along the iso-cost $C(W,V,P) = 1$, $C_W(W,V,P)/C_V(W,V,P) = \infty$ as $\frac{V}{W} \to \infty$. Hence,

$$\frac{C_W(W,V,P)}{C_V(W,V,P)} \geq \frac{V}{W}\frac{\alpha_{min}}{1-\alpha_{max}}[\min_{i\in\mathcal{I}} s_L(i)]\frac{\int \lambda(i)^{1-\sigma}P_X(i)^{\alpha(i)(1-\sigma)}V^{(1-\alpha(i))(1-\sigma)}di}{\int \lambda(i)^{1-\sigma}P_X(i)^{\alpha(i)(1-\sigma)}V^{(1-\alpha(i))(1-\sigma)}di}$$
$$= \frac{V}{W}\frac{\alpha_{min}}{1-\alpha_{max}}[\min_{i\in\mathcal{I}} s_L(i)].$$

Since $\frac{V}{W} \to \infty$, $W \to 0$ and so $\theta^A(i) = 0$ for all tasks, which implies that $s_L(i) = 1$ for all i. Therefore, as $\frac{V}{W} \to \infty$, we must have $\frac{C_W(W,V,P)}{C_V(W,V,P)} \to \infty$.

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

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

Finally, aggregate output per worker is given by

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

while machinery per worker is given by

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

and the threshold $\theta^A(i)$ can be computed from equation (7).■

2. Comparative statics with respect to ϕ.

Because the iso-cost curve $C(W,V,P) = 1$ is convex, an increase in ϕ raises $W^E(\phi,\Theta)$ and reduces $V^E(\phi,\Theta)$.

To complete the proof, we derive the formula for $y^E_\phi(\phi,\Theta)$ given in the main text. National income accounting implies

$$\frac{1}{2-\eta}y^E(\phi,\Theta) = \phi V^E(\phi,\Theta) + (1-\phi)W^E(\phi,\Theta) + m^E(\phi,\Theta)P, \tag{A3}$$

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

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

Next differentiating $C(W,V,P) = 1$ with respect to ϕ, and recalling that $\frac{C_W}{C_V} = \frac{1-\phi}{\phi}$, we obtain $\phi V^E_\phi(\phi,\Theta) + (1-\phi)W^E_\phi(\phi,\Theta) = 0$. Substituting this into the previous expression, we obtain (15).■

Proof of Proposition 2

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

Part 2: Let $W^P(\phi, A)$ denote the middle-aged wage that would result if $\theta(i) = 0$ and there were no automation technologies. From Proposition 1, we can conclude immediately that $W^P(\phi, A)$ is increasing in ϕ, $W^P(\phi, A) \to 0$ when $\phi \to 0$, and $W^P(\phi, A) \to \infty$ when $\phi \to \infty$. Then define $\widetilde{\phi}(A)$ as the maximum level of ϕ such that $W^P(\phi, A) \leq A(i)P$ for almost all i. For $\phi \leq \widetilde{\phi}(A)$, we have that the unique equilibrium is given by $\theta(i) = 0$ for almost all i and $W^P(\phi, A) = W^E(\phi, \Theta)$. Thus, for $\phi \leq \widetilde{\phi}(A)$, the set $\mathcal{I}^+(\phi, A)$ has measure zero.

For $\phi > \widetilde{\phi}(A)$, we have $W^E(\phi, \Theta) > W^E(\widetilde{\phi}(A), \Theta) = W^P(\phi, A)$. Thus, the equilibrium must involve a positive measure of industries that are adopting automation technologies. That is, $W^E(\phi, \Theta) > W^P(\phi, A) \geq A(i)P$ and $\theta^A(i) = \theta(i)$ for a positive measure of industries.■

Proof of Proposition 3

We first state and prove the following lemma.

Lemma A2 *Suppose that for almost all industries*

$$\pi(i) < \overline{\pi} = \frac{1}{\sigma}\frac{1-\alpha_{max}}{\alpha_{max}}.$$

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

Proof. Let $\chi(i)$ denote the share of expenditure going to industry i, $\chi_L(i)$ the share of payments to middle-aged workers going to those in industry i, and $\chi_S(i)$ the share of payments to senior workers going to those in industry i. Finally, let $s_L(i)$ denote the labor share of production tasks in industry i.

We have

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

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

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

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

- From the ideal price condition, (13):

$$d \ln V \int_{i\in\mathcal{I}} \chi(i)(1-\alpha(i))di + d \ln W \int_{i\in\mathcal{I}} \chi(i)\alpha(i)s_L(i)di = \int_{i\in\mathcal{I}} \chi(i)\alpha(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di; \quad \text{(A5)}$$

- From the demand for middle-aged workers, (10):

$$
\begin{aligned}
0 = d\ln Y - d\ln W &\int_{i\in\mathcal{I}} \chi_L(i)(\zeta - (\zeta-1)s_L(i))di \\
&+ d\ln W \int_{i\in\mathcal{I}} \chi_L(i)(1-\sigma)\alpha(i)s_L(i)di + d\ln V \int_{i\in\mathcal{I}} \chi_L(i)(1-\sigma)(1-\alpha(i))di \\
&- \int_{i\in\mathcal{I}} \chi_L(i)(\alpha(i)(1-\sigma)+\zeta-1)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di \\
&- \int_{i\in\mathcal{I}} \chi_L(i)\frac{d\theta^A(i)}{1-\theta^A(i)}; \qquad \text{(A6)}
\end{aligned}
$$

- From the demand for senior workers, (12):

$$
\begin{aligned}
0 = d\ln Y - d\ln V& \\
&+ d\ln W \int_{i\in\mathcal{I}} \chi_S(i)((1-\sigma)\alpha(i)s_L(i)di + d\ln V \int_{i\in\mathcal{I}} \chi_S(i)(1-\sigma)(1-\alpha(i)di \\
&- \int_{i\in\mathcal{I}} \chi_S(i)\alpha(i)(1-\sigma)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di. \qquad \text{(A7)}
\end{aligned}
$$

Using equations (A5), (A6), and (A7), we can solve for $d\ln W$ and $d\ln S$ as

$$
\begin{aligned}
d\ln W =& \frac{1}{\Lambda}\Bigg[(\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di \\
&-(\zeta-1)\int_{i\in\mathcal{I}}\chi_L(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di - \int_{i\in\mathcal{I}}\chi_L(i)\frac{d\theta^A(i)}{1-\theta^A(i)} \\
&+\frac{\left[1+(\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)di\right]}{\int_{i\in\mathcal{I}}\chi(i)(1-\alpha(i))}\int_{i\in\mathcal{I}}\chi(i)\alpha(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di.\Bigg], \qquad \text{(A8)}
\end{aligned}
$$

where[35]

$$
\begin{aligned}
\Lambda =& \left[\int_{i\in\mathcal{I}}\chi_L(i)(\zeta-(\zeta-1)s_L(i))di + (\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)s_L(i)di\right] \\
&+\left[1+(\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)di\right]\frac{\int_{i\in\mathcal{I}}\chi(i)\alpha(i)s_L(i)di}{\int_{i\in\mathcal{I}}\chi(i)(1-\alpha(i))} > 0.
\end{aligned}
$$

Note that, because $\zeta > \sigma$, we have

$$
(\zeta-1)\int_{i\in\mathcal{I}}\chi_L(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di > (\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di.
$$

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

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

which corresponds to the determinant of the bordered Hessian of $C(V,W,P)$ (holding P constant)

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

being positive. Since $C(V,W,P)$ is strictly concave in its first two arguments, we always have $\Lambda > 0$.

In addition, we also have

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

Using equation (A8) and these two inequalities, we have

$$d\ln W<\frac{1}{\Lambda}\left[-\int_{i\in\mathcal{I}}\chi_L(i)\frac{d\theta^A(i)}{1-\theta^A(i)}+\frac{\sigma}{\int_{i\in\mathcal{I}}\chi(i)(1-\alpha(i))}\int_{i\in\mathcal{I}}\chi(i)\alpha(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di.\right].$$

The last inequality shows that the condition

$$\frac{\sigma}{\int_{i\in\mathcal{I}}\chi(i)(1-\alpha(i))}\chi(i)\alpha(i)s_L(i)\pi(i)<\chi_L(i)$$

is sufficient to ensure $d\ln W<0$. This condition can be rewritten as

$$\pi(i)<\frac{1}{\sigma}\frac{\chi_L(i)\int_{i\in\mathcal{I}}\chi(i)(1-\alpha(i))}{\chi(i)\alpha(i)s_L(i)}=\frac{1}{\sigma}\frac{\int_{i\in\mathcal{I}}\chi(i)(1-\alpha(i))di}{\int_{i\in\mathcal{I}}\chi(i)\alpha(i)s_L(i)di},$$

where we have used the fact that $\chi_L(i)=\frac{\chi(i)\alpha(i)s_L(i)}{\int_{i\in\mathcal{I}}\chi(i)\alpha(i)s_L(i)di}$.

This follows because
$$\frac{1}{\sigma}\frac{1-\alpha_{max}}{\alpha_{max}}<\frac{1}{\sigma}\frac{\int_{i\in\mathcal{I}}\chi(i)(1-\alpha(i))di}{\int_{i\in\mathcal{I}}\chi(i)\alpha(i)s_L(i)di}.$$

■

With this lemma at hand, we now turn to the proof of the proposition.

1. Impact of an increase in automation.

The definition of $\widetilde{\phi}(A)$ implies that for $\phi<\widetilde{\phi}(A)$, we have $\theta^A(i)=0$. Therefore, changes in automation technologies do not lead to their adoption and there is no impact on equilibrium wages.

For $\phi>\widetilde{\phi}(A)$, automation has an ambiguous effect on W as shown in equation (A8). Turning to V, we have

$$\begin{aligned}d\ln V=&d\ln W\frac{\int_{i\in\mathcal{I}}\chi_L(i)(\zeta-(\zeta-1)s_L(i))di+(\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)s_L(i)di}{1+(\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)di}\\&+\int_{i\in\mathcal{I}}\chi_L(i)\frac{d\theta^A(i)}{1-\theta^A(i)}\\&+(\zeta-1)\int_{i\in\mathcal{I}}\chi_L(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di\\&-(\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di\\>&d\ln W+\int_{i\in\mathcal{I}}\chi_L(i)\frac{d\theta^A(i)}{1-\theta^A(i)}.\end{aligned}$$

Here we used the fact that, because $\zeta>\sigma$, we have $\int_{i\in\mathcal{I}}\chi_L(i)(\zeta-(\zeta-1)s_L(i))di>1$, and

$$(\zeta-1)\int_{i\in\mathcal{I}}\chi_L(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di>(\sigma-1)\int_{i\in\mathcal{I}}(\chi_L(i)-\chi_S(i))\alpha(i)\frac{s_L(i)}{1-\theta^A(i)}\pi(i)d\theta^A(i)di.$$

This inequality implies that $d \ln V > d \ln W$, and W/V declines with automation. Moreover, substituting for $d \ln V > d \ln W$ in equation (A5), we get

$$
\begin{aligned}
& d \ln V \int_{i \in \mathcal{I}} \chi(i)(1-\alpha(i)) di \\
& + d \ln V \int_{i \in \mathcal{I}} \chi(i)\alpha(i) s_L(i) di > \int_{i \in \mathcal{I}} \chi(i)\alpha(i) \frac{s_L(i)}{1-\theta^A(i)} \pi(i) d\theta^A(i) di,
\end{aligned}
$$

which implies $d \ln V > 0$.

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

2. Impact of an increase in labor-augmenting technologies. To be completed.

Proof of Lemma 1

Part 1: The first-order conditions directly follow by differentiating equation (16).

Part 2: Supermodularity of profits in (16) in W, $\theta(i)$ and $-A(i)$ can be verified directly from the first-order conditions in equations (19) and (20). This supermodularity then ensures that $\theta^R(W, i)$ is nondecreasing in W, while $A^R(W, i)$ is non-increasing in W.

Part 3: Because $\theta^R(W, i)$ is non-decreasing in W and $\theta^R(W, i) \geq 0$, and because $A^R(W, i)$ is non-increasing in W and $A^R(W, i)$, there exist $\underline{\theta}$ and $\overline{A}$ such that $\lim_{W \to 0} \theta^R(W, i) = \underline{\theta}$ and $\lim_{W \to 0} A^R(W, i) = \overline{A}$.

We now show that $\underline{\theta} = 0$. Taking the limit of the first-order condition for $\theta^R(W, i)$ in equation (19) as $W \to 0$ we get

$$
h(\underline{\theta}) \geq \lim_{W \to 0} (\sigma - 1)\alpha(i)\rho(i) \frac{s_L(i)}{(1-\underline{\theta})} \frac{1}{\zeta - 1} \left[\left(\frac{W}{\overline{A} P} \right)^{\zeta - 1} - 1 \right] = 0,
$$

but this condition can only hold for $\underline{\theta} = 0$.

Also, plugging $\underline{\theta} = 0$ in the first-order condition for $A^R(W, i)$ in equation (20), we can conclude that

$$
g(\overline{A}) = \lim_{W \to 0} (\sigma - 1)\alpha(i)\mu(i) s_L(i) \frac{1}{\overline{A}} = (\sigma - 1)\alpha(i)\mu(i) \frac{1}{\overline{A}},
$$

which implies $\overline{A} = \widetilde{A}(i)$. ■

Proof of Proposition 4

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

Part 3 of Lemma 1 shows that for $W \to 0$, we have that $\theta^R(W, i) = 0$ and $A^R(W, i) = \widetilde{A}(i)$. Thus, $W^E(\phi, \Theta^R(0)) > 0$.

In addition, as W increases, both $\theta^R(W,i)$ and $A^R(W,i)$ converge to some finite values (the former is nondecreasing and bounded above by one, and the latter is nonincreasing and bonded below by zero). Thus, $W^E(\phi,\Theta^R(W))$ converges to a finite limit. This implies that the curve $W^E(\phi,\Theta^R(W))$ starts above the 45 degree line and ends below it. Thus, there exists at least one solution to $W = W^E(\phi,\Theta^R(W))$. This establishes existence. If there are multiple intersections, the smallest and the largest give the least and the greatest equilibria in view of the supermodularity established in Lemma 1.■

Proof of Proposition 5

Both parts of this proposition follow directly from Topkis's Monotonicity theorem (Topkis, 1998) since, from Proposition 1, an increase in ϕ shifts the map $W^E(\phi,\Theta^R(W))$ up (as shown in Figures 3 and 4). ■

Proof of Proposition 6

To economize on space, we prove this proposition only for the case in which technology choices are differentiable and thus we can apply the implicit function theorem. The proof in the more general case has a similar idea, but also explicitly allows for the equilibrium to change discontinuously.

The first-order condition for a monopolist that chooses an interior solution for $\theta(i)$ is given by:

$$h(\theta^R(W,i)) = (\sigma-1)\alpha(i)\rho(i)\frac{s_L(i)}{1-\theta(i)}\pi(i),$$

where $\pi(i) > 0$. The implicit function theorem implies that we can differentiate this expression to obtain:

$$d\theta^R(W,i) = \frac{(\zeta-1)h(\theta^R(W,i)) + \frac{(\sigma-1)\alpha(i)\rho(i)}{1-\theta^R(W,i)}}{h'^R(W,i)) + \frac{\zeta-1}{(\sigma-1)\alpha(i)\rho(i)}h(\theta^R(W,i))^2}s_L(i)\left[d\ln W - d\ln A^R(W,i)\right]. \tag{A9}$$

This expression shows that, for industries in $\mathcal{I}^+(\phi,\Theta)$, the (semi) elasticity of $\theta^R(W,i)$ with respect to effective wages (given by $W/A(i)$) is

$$\Gamma(\alpha(i)\rho(i)) = \frac{(\zeta-1)h(\theta^R(W,i)) + \frac{(\sigma-1)\alpha(i)\rho(i)}{1-\theta^R(W,i)}}{h'^R(W,i)) + \frac{\zeta-1}{(\sigma-1)\alpha(i)\rho(i)}h(\theta^R(W,i))^2}s_L(i) > 0.$$

The first-order condition for a technology monopolist that chooses an interior solution for $A(i)$ is:

$$g(A^R(W,i))A^R(W,i) = (\sigma-1)\alpha(i)\mu(i)s_L(i).$$

The implicit function theorem implies that we can differentiate this expression to obtain:

$$\begin{aligned}(1+\varepsilon_g+(1-\zeta)(1-s_L(i)))d\ln A^R(W,i) = &-(1+(\zeta-1)s_L(i)\pi(i))\frac{d\theta^R(W,i)}{1-\theta^R(W,i)}\\ &-(\zeta-1)(1-s_L(i))d\ln W\end{aligned} \tag{A10}$$

(where recall that ε_g is the elasticity of the g function with respect to A).

Using equations (A9) and (A10), we obtain:

$$\frac{d\theta^R(W,i)}{d\ln W} = \frac{(1+\varepsilon_g)\Gamma(\alpha(i)\rho(i))}{1+\varepsilon_g+(1-\zeta)(1-s_L(i)) - \frac{1}{1-\theta^R(W,i)}\Gamma(\alpha(i)\rho(i))\left[1+(\zeta-1)s_L(i)\pi(i)\right]},$$

which then implies that

$$\Gamma_i = \frac{(1+\varepsilon_g)\Gamma(\alpha(i)\rho(i))}{1+\varepsilon_g+(1-\zeta)(1-s_L(i)) - \frac{1}{1-\theta^R(W,i)}\Gamma(\alpha(i)\rho(i))\left[1+(\zeta-1)s_L(i)\pi(i)\right]} > 0.$$

The denominator in this expression coincides with the determinant of the Hessian matrix associated with the monopolist problem. Because the monopolist maximizes profits, this determinant is positive, and $\Gamma_i > 0$.

The results then follows by observing that the (semi-) elasticity $\Gamma(\alpha(i)\rho(i))$ is increasing in $\alpha(i)\rho(i)$, which implies that Γ_i is increasing in $\alpha(i)\rho(i)$. ■.

Proof of Proposition 7

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

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

Equation (A10) shows that, as $\varepsilon_g \to \infty$, $\frac{d\ln A^R(W,i)}{d\phi} \to 0$. In this limit case, we have

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

The term $\sigma\alpha(i)\frac{s_L(i)}{1-\theta(i)^*}\pi(i)\Gamma(\alpha(i)\rho(i))\frac{d\ln W^*}{d\phi}$ captures the productivity benefits to industry i arising from the endogenous response of automation. Because of the term $\Gamma(\alpha(i)\rho(i))$, theses productivity benefits are larger for industries with a larger $\rho(i)$, which implies that aging raises output in industries with a greater $\rho(i)$ relative industries with lower $\rho(i)$. Because the elasticities Γ_i and $\frac{d\ln A^R(W,i)}{d\ln W}$ are smooth in ε_g, there exists $\bar{\varepsilon}_g < \infty$ such that, for $\varepsilon_g < \bar{\varepsilon}_g$, aging raises output in industries with a greater $\rho(i)$ relative industries with lower $\rho(i)$. ■.

Additional References:

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

Main Figures and Tables:

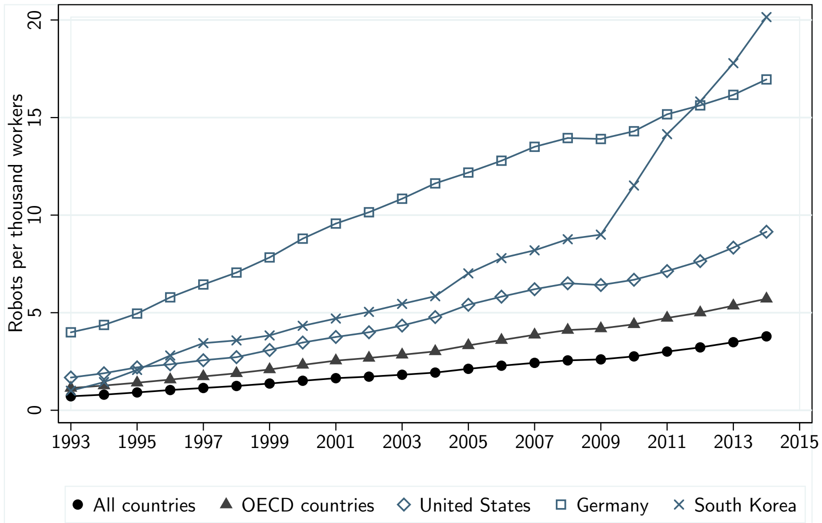


Figure 5: Worldwide trends in robot adoption from the IFR.

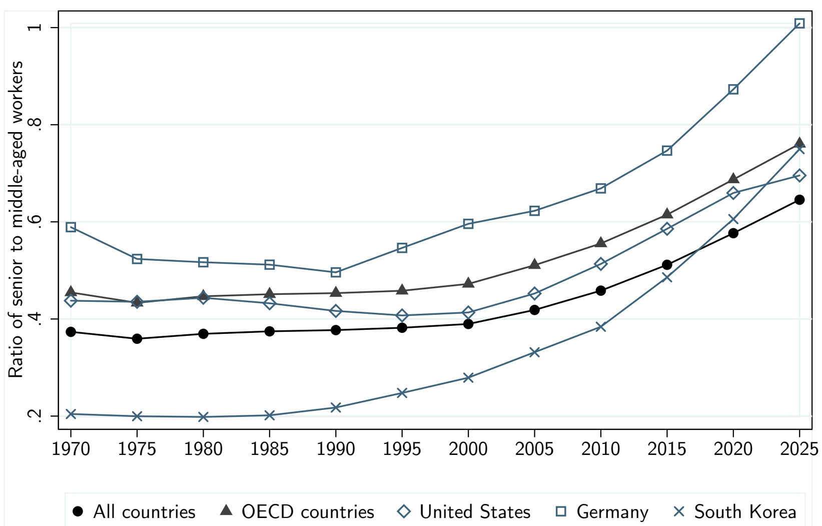


Figure 6: Worldwide aging trends using UN data on population by age groups and forecasts of demographic change.

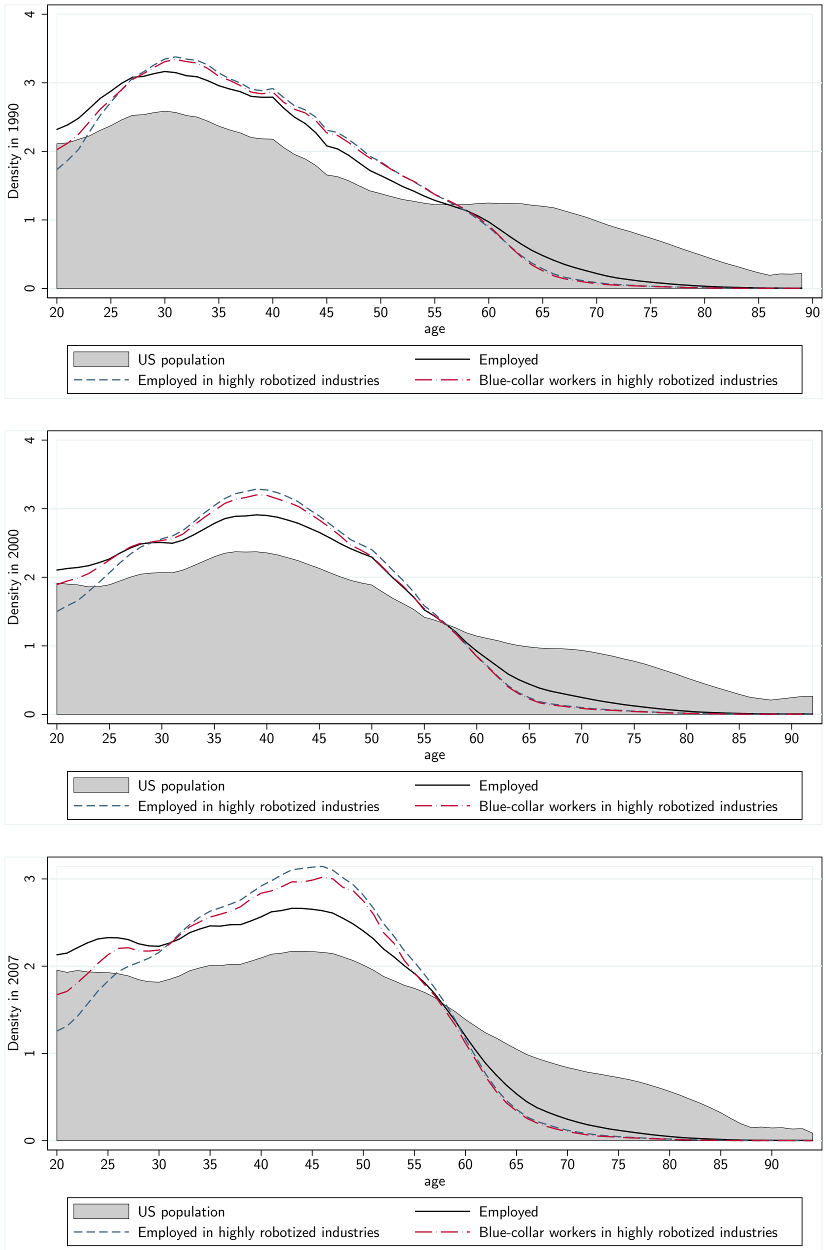


FIGURE 7: U.S. age distribution among the population, employees, and employees in highly robotized industries. The top panel presents the age distributions for 1990. The middle panel presents the age distributions for 2000. The bottom panel presents the age distributions for 2007.

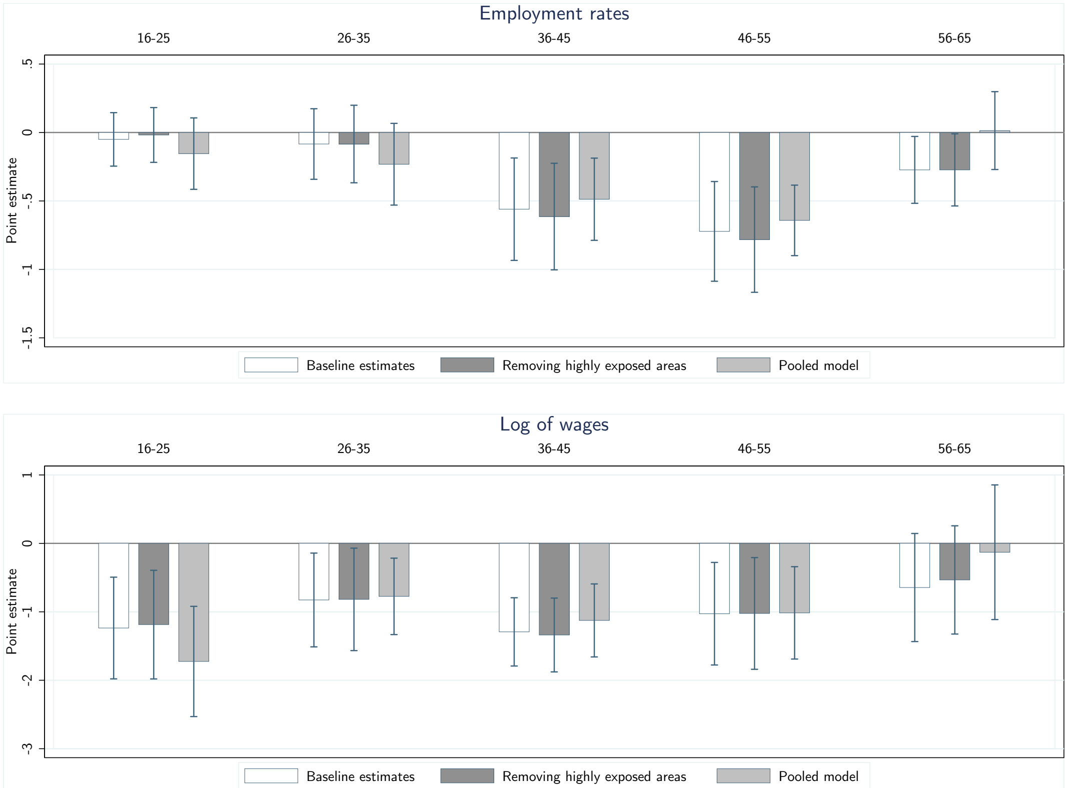


FIGURE 8: Estimated impact of one additional robot per thousand workers on employment and wages. The figure plots the estimates for different age groups and for men separately.

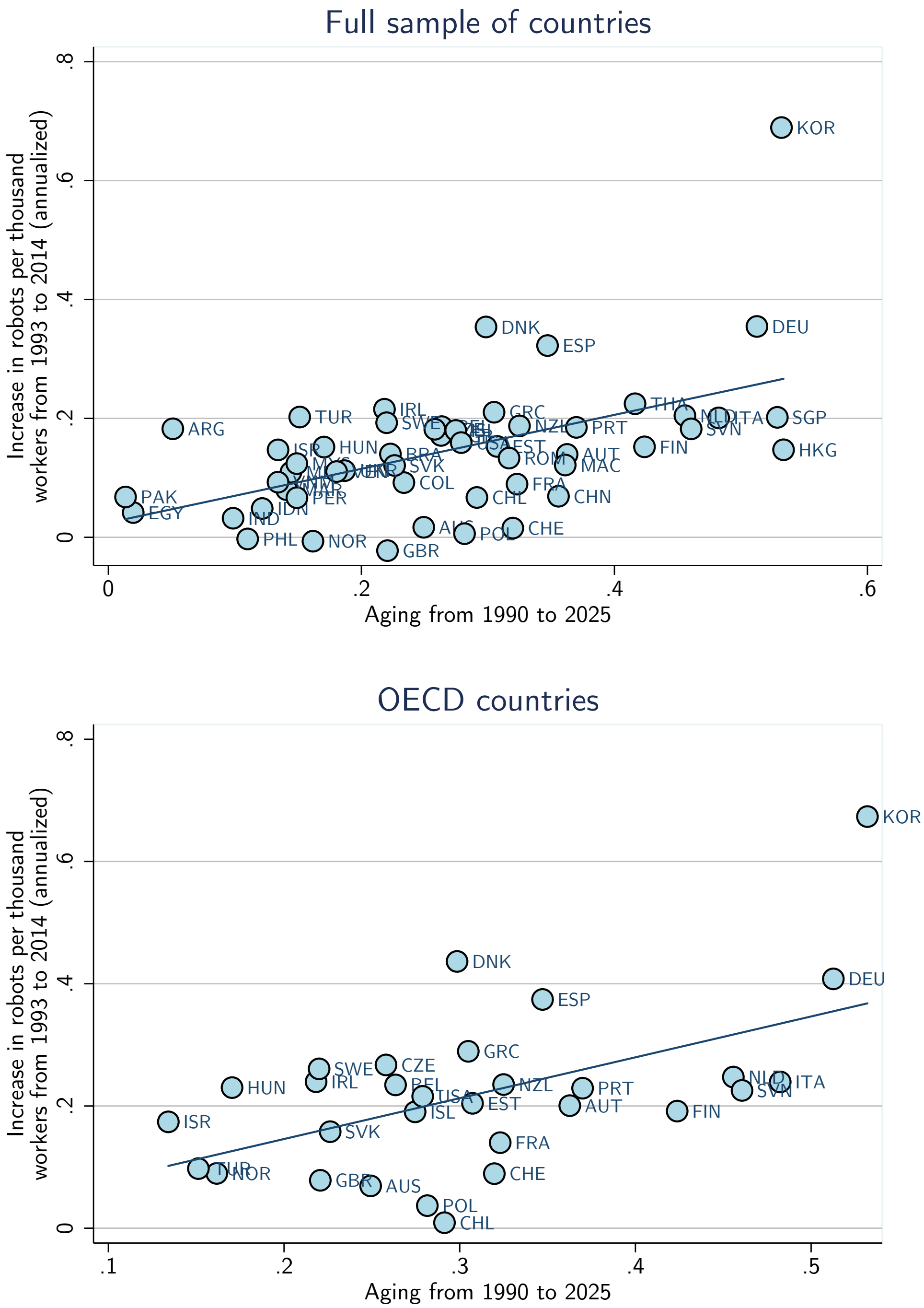


FIGURE 9: Residual plots of the relationship between aging (change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025) and the increase in the number of industrial robots per thousand workers from 1993 to 2014. The plots partial out the covariates included in the regression models in Columns 3 and 6 of Table 4.

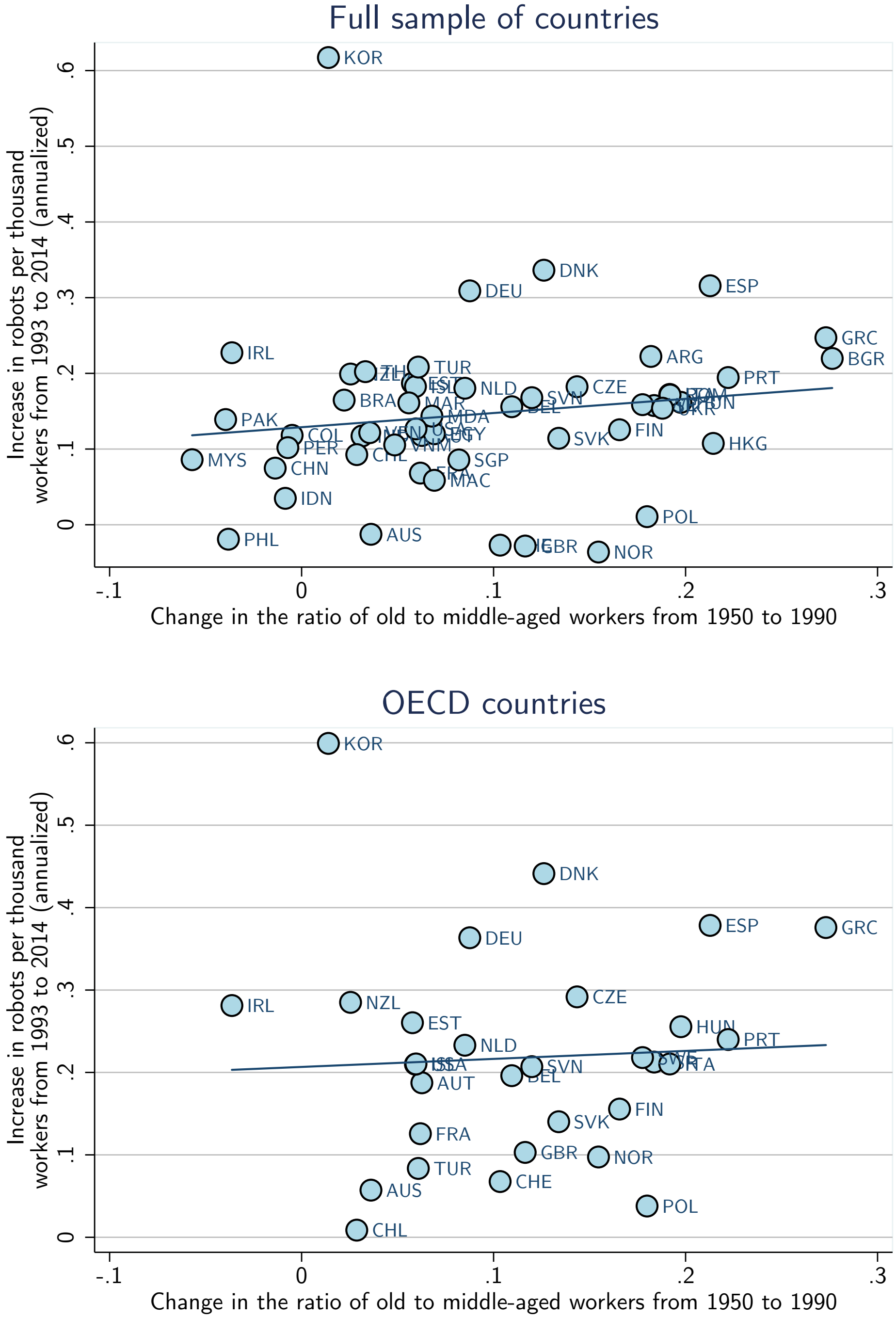


FIGURE 10: Residual plots of the relationship between past aging (change in the ratio of workers above 56 to workers between 21 and 55 between 1950 and 1990) and the increase in the number of industrial robots per thousand workers from 1993 to 2014. The plots partial out the covariates included in the regression models in Columns 4 (top panel) and 9 (bottom panel) of Panel A in Table 5.

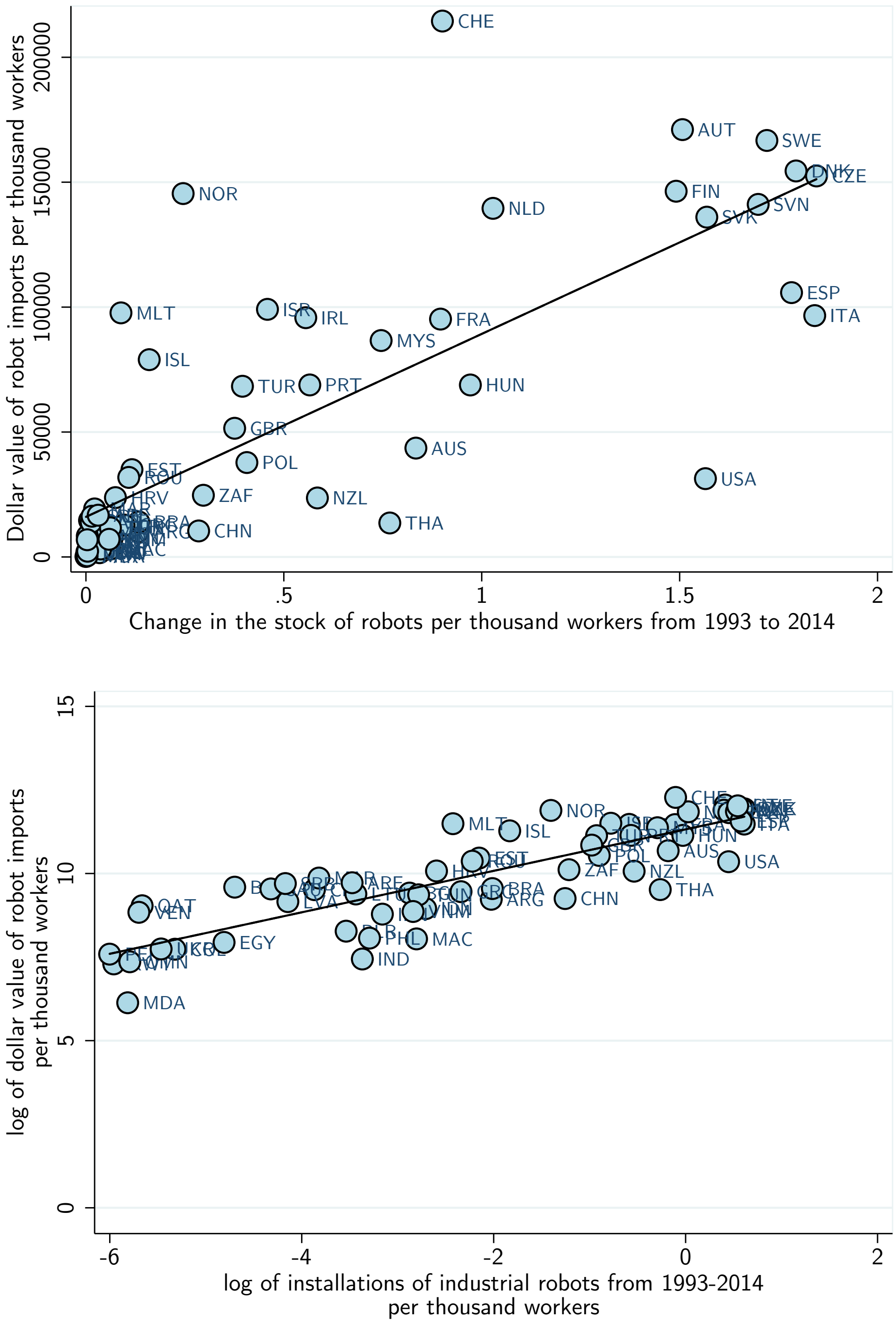


Figure 11: Plots of the relationship between the change in the stock of robots provided by the IFR (horizontal axis) and the total dollar value of imports of industrial robots from Comtrade (vertical axis).

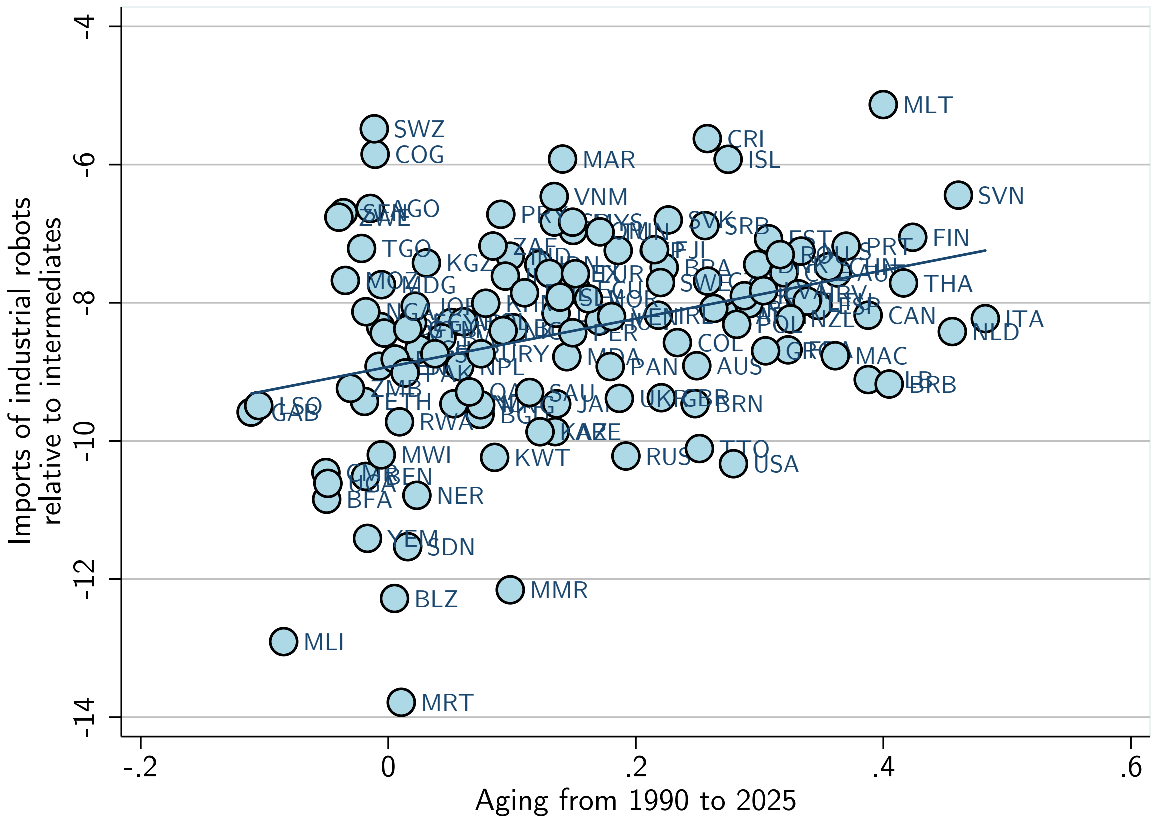


FIGURE 12: Residual plot of the relationship between aging (change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025) and the log of imports of industrial robots from 1990 to 2016 (relative to total imports of intermediates). The plot partials out the covariates included in the regression models in Column 1 of Table 9.

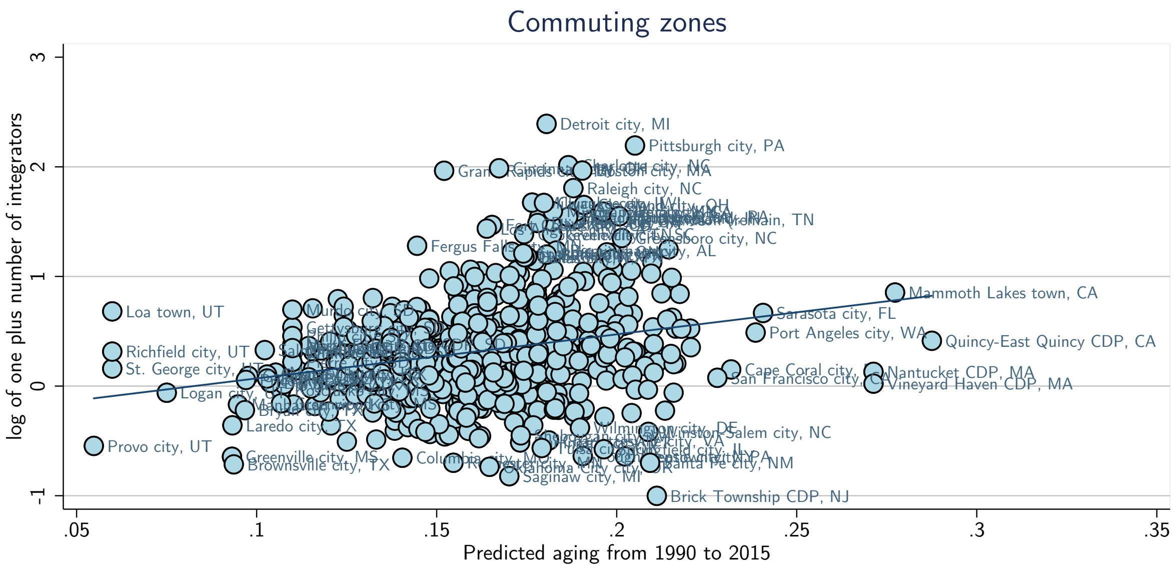


FIGURE 13: Visual IV plot of the relationship between predicted aging (change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015, instrumented using the age composition of a commuting zone in 1990) and the location of robot integrators in the US (from Leigh and Kraft, 2016). The plots partial out the covariates included in the regression models in Column 4 in Table 10.

Table 1: Summary statistics for countries

	All countries	OECD	Rapidly-aging countries	Slowly-aging countries
IFR sample:				
Robots per thousand workers in 2014	3.79	5.71	5.76	1.81
	(4.60)	(4.83)	(5.29)	(2.64)
Robots per thousand workers in 1993	0.72	1.14	1.09	0.34
	(1.13)	(1.22)	(1.24)	(0.87)
Annualized increase from 1993 to 2014	0.15	0.22	0.22	0.07
	(0.18)	(0.19)	(0.21)	(0.09)
Robot installations per year (1993-2014)	0.24	0.36	0.37	0.10
	(0.31)	(0.32)	(0.36)	(0.18)
Ratio of old to middle-aged workers	0.38	0.45	0.41	0.34
in 1990	(0.13)	(0.09)	(0.12)	(0.14)
Change in old to middle-aged workers	0.26	0.31	0.37	0.16
from 1990 to 2025	(0.13)	(0.11)	(0.09)	(0.07)
Change in old to middle-aged workers	0.13	0.16	0.19	0.08
from 1990 to 2015	(0.08)	(0.06)	(0.05)	(0.08)
	$N = 52$	$N = 30$	$N = 26$	$N = 26$
Comtrade sample:				
Dollar value of robot imports from 1996	24.6K	93.7K	44.6K	4.4K
to 2015 per thousand workers	(45.9K)	(56.0K)	(56.8K)	(13.7K)
Change in old to middle-aged workers	0.15	0.29	0.27	0.03
from 1990 to 2025	(0.15)	(0.09)	(0.10)	(0.06)
	$N = 145$	$N = 30$	$N = 73$	$N = 72$

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

Table 2: Summary statistics for industries

	Robot installations per thousand workers		Percent increase in value added	US ratio middle-aged to old workers	Replaceability index Graetz and Michaels
	Employment Klems	Employment Unido			
Prone to the use of robots:					
Automotive	7.62	5.01	54.6%	7.78	.
Electronics	0.75	0.67	54.2%	8.10	.
Metal machinery	0.45	0.41	49.7%	6.79	.
Metal products	1.14	0.84	43.4%	6.44	.
Plastic, Chemicals, and Pharmaceuticals	1.30	1.15	39.8%	8.15	.
Other manufacturing:					
Food and Beverages	0.46	0.30	30.7%	7.80	.
Furniture	0.38	0.09	38.5%	7.78	.
Glass and Ceramics	0.26	0.13	52.4%	6.94	.
Basic metals	0.49	0.29	56.3%	6.13	.
Paper and printing	0.05	0.03	33.8%	7.10	.
Textiles and leather	0.07	0.03	34.1%	5.88	.
Other vehicles	0.30	0.15	61.8%	6.48	.
Other manufacturing industries	0.37	.	37.2%	6.34	.
Nonmanufacturing:					
Agriculture	0.02	.	21.6%	3.85	.
Construction	0.01	.	41.6%	8.08	.
Education	0.04	.	34.4%	5.94	.
Mining	0.09	.	61.0%	8.52	.
Other nonmanufacturing industries	0.00	.	38.3%	6.91	.
Utilities	0.01	.	52.3%	8.04	.
Average	0.22	0.59	38.5%	6.92	0.24
Interquantile range	0.45	0.65	19.8%	1.66	0.27
Standard deviation	(0.95)	(1.03)	(11.2%)	(1.13)	(0.14)
Countries	22	50	22	US	US
Country*years	312	542	.	.	.

Notes: The table presents summary statistics for each of the 19 industries covered in the IFR data. The bottom rows present summary statistics for each variable over all these industries. The replaceability index is not reported by industry, but can be obtained directly from Graetz and Michaels (2015). Section 3 in the main text describes the sources and data in detail.

Table 3: OLS estimates of the impact of population change on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Population in three age brackets					
Change in the log of population ≤ 35 years	0.075	-0.048	-0.190	-0.054	-0.310	-0.315
from 1990 to 2025	(0.137)	(0.208)	(0.183)	(0.158)	(0.249)	(0.217)
Change in the log of population between 36-55 years	-0.640***	-0.514*	-0.369	-0.798***	-0.428	-0.422
from 1990 to 2025	(0.197)	(0.282)	(0.242)	(0.222)	(0.307)	(0.363)
Change in the log of population ≥ 56 years	0.461***	0.476**	0.184	0.746**	0.553*	0.434
from 1990 to 2025	(0.151)	(0.177)	(0.151)	(0.271)	(0.311)	(0.279)
Baseline number of robots per thousand workers			0.061***			0.074**
			(0.020)			(0.027)
Observations	52	52	52	30	30	30
R-squared	0.49	0.59	0.76	0.44	0.61	0.74
	Panel B. Population in three age brackets					
Change in the log of population	0.200	-0.246	-0.314	-0.011	0.376	0.124
from 1990 to 2025	(0.327)	(0.619)	(0.636)	(0.657)	(0.843)	(0.877)
Change in the log of population between 21-35 years	-0.021	0.072	-0.007	-0.372	-0.855	-0.684
from 1990 to 2025	(0.204)	(0.332)	(0.366)	(0.301)	(0.669)	(0.640)
Change in the log of population between 36-55 years	-0.737***	-0.712**	-0.442	-0.536***	-0.691*	-0.689*
from 1990 to 2025	(0.243)	(0.308)	(0.285)	(0.176)	(0.331)	(0.393)
Change in the log of population between 56-65 years	0.428**	0.824**	0.552*	0.701**	0.535	0.577
from 1990 to 2025	(0.212)	(0.342)	(0.316)	(0.322)	(0.555)	(0.550)
Baseline number of robots per thousand workers			0.040*			0.048*
			(0.021)			(0.027)
Observations	52	52	52	30	30	30
R-squared	0.48	0.57	0.71	0.50	0.64	0.75
	Panel C. Population in two age brackets					
Change in the log of population between 21-55 years	-0.473***	-0.641*	-0.668**	-0.756***	-1.202**	-1.170***
from 1990 to 2025	(0.175)	(0.366)	(0.306)	(0.213)	(0.447)	(0.399)
Change in the log of population > 55 years	0.339**	0.440**	0.343*	0.605**	0.478	0.473
from 1990 to 2025	(0.142)	(0.217)	(0.175)	(0.237)	(0.328)	(0.306)
Baseline number of robots per thousand workers			0.049**			0.057**
			(0.020)			(0.024)
Observations	52	52	52	30	30	30
R-squared	0.42	0.58	0.74	0.42	0.63	0.76
Covariates included:						
Country covariates in 1990		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

Notes: The dependent variable is change in the stock of industrial robots per thousand workers from 1993 to 2014 (from IFR). The explanatory variables include the (projected) change in the log of population in different age groups between 1990 and 2025 (from the UN population statistics). Columns 1-3 use the full sample, while columns 4-6 are for the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5, in addition, include the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 4: Estimates of the impact of aging on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging from 1990 to 2025	0.762***	0.651***	0.453**	1.117***	0.983***	0.667**
	(0.252)	(0.221)	(0.194)	(0.366)	(0.298)	(0.240)
Ratio of senior to middle-aged workers in 1990		-0.177	-0.403		-0.339	-0.835*
		(0.295)	(0.253)		(0.471)	(0.471)
Log of the GDP per capita in 1990		0.047	-0.011		0.037	-0.018
		(0.035)	(0.030)		(0.052)	(0.054)
Robots per thousand workers in 1993			0.047**			0.062**
			(0.023)			(0.024)
Observations	52	52	52	30	30	30
R-squared	0.43	0.57	0.71	0.38	0.54	0.67
	Panel B. IV estimates					
Aging from 1990 to 2025	0.803***	0.672***	0.516***	1.576***	1.018***	0.807***
	(0.264)	(0.203)	(0.171)	(0.473)	(0.316)	(0.271)
Ratio of senior to middle-aged workers in 1990		-0.180	-0.406*		-0.337	-0.785**
		(0.264)	(0.225)		(0.413)	(0.369)
Log of the GDP per capita in 1990		0.046	-0.015		0.036	-0.016
		(0.033)	(0.027)		(0.047)	(0.048)
Robots per thousand workers in 1993			0.046**			0.058**
			(0.020)			(0.023)
Observations	52	52	52	30	30	30
Instruments F-stat	23.13	15.70	13.67	7.66	7.12	8.12
Overid p-value	0.79	0.49	0.10	0.75	0.34	0.04
Covariates included:						
Country covariates in 1990		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

Notes: The dependent variable is change in the stock of industrial robots per thousand workers from 1993 to 2014 (from IFR). The aging variable is the (projected) change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Columns 1-3 use the full sample, while columns 4-6 are for the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5, in addition, include the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 5: OLS estimates of the impact of past and expected aging on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Placebo test					
Aging from 1950 to 1990	-0.004	-0.097	0.187	-0.357	0.095	0.097
	(0.265)	(0.318)	(0.224)	(0.587)	(0.456)	(0.344)
Observations	52	52	52	30	30	30
R-squared	0.21	0.44	0.65	0.02	0.26	0.56
	Panel B. Past vs. expected aging					
Aging from 1950 to 1990	-0.261	-0.243	0.040	-0.243	0.192	0.176
	(0.329)	(0.324)	(0.255)	(0.436)	(0.315)	(0.331)
Aging from 1990 to 2025	0.795***	0.664***	0.450**	1.105***	0.988***	0.673**
	(0.263)	(0.221)	(0.198)	(0.348)	(0.306)	(0.246)
Observations	52	52	52	30	30	30
R-squared	0.44	0.58	0.71	0.38	0.54	0.67
	Panel C. Current vs. expected aging					
Aging from 1990 to 2015	0.949***	0.636**	0.407	0.861**	0.688*	0.366
	(0.350)	(0.303)	(0.304)	(0.366)	(0.347)	(0.328)
Aging from 2015 to 2025	0.530	0.671	0.510	1.398**	1.320**	1.007*
	(0.385)	(0.439)	(0.423)	(0.527)	(0.564)	(0.543)
Test for equality of coefficients	0.43	0.95	0.87	0.31	0.38	0.40
Observations	52	52	52	30	30	30
R-squared	0.43	0.57	0.71	0.38	0.55	0.68
Covariates included:						
Country covariates in 1990		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

Notes: The dependent variable is change in the stock of industrial robots per thousand workers from 1993 to 2014 (from IFR). In panel A, the aging variable is the past change in the ratio of workers above 56 to workers between 21 and 55 between 1950 and 1990 (from the UN Population Statistics). In panel B we also include the (projected) aging variable between 1990 and 2025 (from the UN Population Statistics). In panel C, we estimate the impact of the aging variable between 1990 and 2015 and the projected aging between 2015 and 2025. Columns 1-3 use the full sample, while columns 4-6 are for the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5, in addition, include the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 6: 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					
Aging during period	2.494***	1.583***	1.509**	2.907***	1.923***	1.905*
	(0.704)	(0.483)	(0.703)	(1.020)	(0.636)	(1.019)
Observations	104	104	104	60	60	60
R-squared	0.32	0.55	0.08	0.18	0.46	0.10
	Panel B. IV estimates					
Aging during period	3.182***	2.116***	2.385*	4.486***	2.279***	2.827**
	(0.904)	(0.649)	(1.243)	(1.547)	(0.810)	(1.402)
Observations	104	104	104	60	60	60
Countries in sample	52	52	52	30	30	30
Instruments F-stat	10.57	6.12	2.49	6.59	8.49	4.46
Overid p-value	0.41	0.15	0.22	0.64	0.26	0.37
Covariates included:						
Country covariates in 1990		✓	✓		✓	✓
Initial robot density in 1993		✓	✓		✓	✓
Country trends			✓			✓

Notes: The dependent variable is the change in the stock of industrial robots per thousand workers for two periods: from 1993 to 2005 and from 2005 to 2014 (from IFR). The aging variable is the contemporary change in the ratio of workers above 56 to workers between 21 and 55 for each of these periods: between 1990 and 2005 and between 2005 and 2015 (from the UN Population Statistics). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Columns 1-3 use the full sample, while columns 4-6 are for the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5, in addition, include the 1990 values of log GDP per capita, log of population, average years of schooling, the ratio of workers above 56 to workers between 21 and 55, and the baseline (1993) value of robots per thousand workers. Columns 3 and 6 include a full set of country fixed effects. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 7: Estimates of the impact of aging, unions, and the wage level on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging from 1990 to 2025	0.800***	0.782***	0.698**	1.240***	1.142***	0.860**
	(0.200)	(0.204)	(0.270)	(0.343)	(0.390)	(0.356)
Baseline unionization rate	0.198	0.224*	0.203	0.416**	0.398**	0.263
	(0.125)	(0.118)	(0.132)	(0.177)	(0.175)	(0.193)
log of the hourly wage in 1993		0.178	0.145		0.144	0.036
		(0.107)	(0.127)		(0.199)	(0.206)
Robots per thousand workers in 1993			0.013			0.048*
			(0.038)			(0.026)
Observations	38	38	38	30	30	30
R-squared	0.71	0.73	0.74	0.62	0.63	0.70
	Panel B. IV estimates					
Aging from 1990 to 2025	0.732***	0.706***	0.725***	1.389***	1.404***	1.261***
	(0.167)	(0.162)	(0.209)	(0.333)	(0.394)	(0.365)
Baseline unionization rate	0.189*	0.215**	0.208**	0.459***	0.467***	0.386**
	(0.105)	(0.097)	(0.103)	(0.165)	(0.172)	(0.172)
log of the hourly wage in 1993		0.181**	0.146		0.057	-0.051
		(0.091)	(0.102)		(0.195)	(0.198)
Robots per thousand workers in 1993			0.011			0.032
			(0.029)			(0.025)
Observations	38	38	38	30	30	30
Instruments F-stat	12.64	14.14	14.73	5.29	4.86	5.74
Overid p-value	0.10	0.15	0.06	0.47	0.42	0.18
Covariates included:						
Country covariates in 1990	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓			✓

Notes: The dependent variable is change in the stock of industrial robots per thousand workers from 1993 to 2014 (from IFR). The aging variable is the (projected) change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). In addition, we also estimate the impact of the baseline unionization rate (from the ILO) and wage level (from the Penn World Tables) in a country. Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Columns 1-3 use the full sample, while columns 4-6 are for the OECD sample. All columns include region dummies, and the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 8: Estimates of the impact of aging on robot installations per year.

	Dependent variable: Installations of industrial robots per thousand workers per year					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging from 1990 to 2025	1.228***	0.999***	0.538**	1.785***	1.519***	0.845***
	(0.395)	(0.347)	(0.231)	(0.489)	(0.427)	(0.276)
Observations	1144	1144	1144	660	660	660
Countries in sample	52	52	52	30	30	30
R-squared	0.42	0.54	0.76	0.34	0.55	0.74
	Panel B. IV estimates					
Aging from 1990 to 2025	1.336***	0.931***	0.612***	2.619***	1.472***	1.042***
	(0.426)	(0.332)	(0.202)	(0.533)	(0.459)	(0.314)
Observations	1144	1144	1144	660	660	660
Countries in sample	52	52	52	30	30	30
Instruments F-stat	26.59	18.36	16.14	9.67	9.45	11.14
Overid p-value	0.79	0.93	0.13	0.89	0.75	0.04
Covariates included:						
Country covariates in 1990		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

Notes: The dependent variable is installations of industrial robots per thousand workers for each country-year pair between 1993 and 2014 (from IFR). The aging variable is the (projected) change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Columns 1-3 use the full sample, while columns 4-6 are for the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5, in addition, include the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. All regressions are unweighted and the standard errors are robust against heteroscedasticity and serial correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 9: Estimates of the impact of aging on imports of intermediate goods.

	Dependent variable: log of value of imports from 1990 to 2016 (normalized by intermediate imports)								
Intermediate goods:	Industrial robots	Numerically controlled machines	Weaving and Knitting machines	Vending machines and ATMS	Computers	Agricultural machinery	Miscellaneous tools	General equipment	Increase in Capital from PWT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A. OLS estimates				
Aging from 1990 to 2025	3.492**	2.296***	3.042*	2.442***	1.724***	-0.939	0.500	0.835*	0.676***
	(1.342)	(0.756)	(1.668)	(0.716)	(0.527)	(0.724)	(0.512)	(0.447)	(0.155)
Ratio of old to young workers in 1990	2.019	0.383	0.928	0.317	-0.587	2.131**	1.072	0.826	0.794***
	(1.542)	(0.957)	(1.568)	(0.867)	(0.606)	(1.047)	(0.653)	(0.502)	(0.251)
Log of the GDP per capita in 1990	0.633***	0.146	-0.425**	0.119	0.106	-0.474***	0.020	-0.049	0.048
	(0.196)	(0.113)	(0.201)	(0.116)	(0.071)	(0.125)	(0.069)	(0.061)	(0.033)
Observations	125	130	131	129	131	131	131	130	143
R-squared	0.55	0.64	0.36	0.50	0.42	0.41	0.38	0.25	0.51
					Panel B. IV estimates				
Aging from 1990 to 2025	4.656**	1.726*	5.087*	1.870	1.940***	-1.504	0.151	0.457	0.866***
	(2.139)	(0.968)	(2.942)	(1.393)	(0.621)	(1.214)	(0.749)	(0.493)	(0.223)
Ratio of old to young workers in 1990	1.920	0.421	0.657	0.359	-0.615	2.206**	1.119*	0.851*	0.769***
	(1.506)	(0.910)	(1.595)	(0.842)	(0.548)	(0.990)	(0.616)	(0.469)	(0.225)
Log of the GDP per capita in 1990	0.602***	0.162	-0.491**	0.134	0.099	-0.456***	0.031	-0.039	0.041
	(0.200)	(0.112)	(0.208)	(0.114)	(0.075)	(0.122)	(0.071)	(0.058)	(0.033)
Observations	125	130	131	129	131	131	131	130	143
Instruments F-stat	16.70	15.79	16.49	16.32	16.49	16.49	16.49	15.79	15.12
Overid p-value	0.76	0.25	0.74	0.47	0.60	0.45	0.86	0.72	0.11
Other covariates included:									
Country covariates in 1990	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the log of total imports from 1990 to 2016 of the intermediate indicated in each column header, normalized by total imports of intermediate goods. The aging variable is the (projected) change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. All columns include region dummies and the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 10: Estimates of the impact of aging on the location of robot integrators in the US.

	OLS estimates		IV using predicted aging from 1990 demographics		IV using predicted aging based on past cohort sizes	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. log of 1+the number of integrators			
Aging from 1990 to 2015	-0.745**	-0.453	4.281***	4.017**	2.213*	1.946*
	(0.324)	(0.310)	(1.039)	(1.645)	(1.148)	(1.062)
Exposure to robots measure	0.186***	0.112***	0.105***	0.067**	0.138***	0.088***
	(0.025)	(0.030)	(0.036)	(0.031)	(0.030)	(0.028)
Observations	722	722	722	722	722	722
R-squared	0.10	0.61	-0.28	0.43	-0.03	0.56
Instruments F-stat			70.40	17.83	4.57	5.35
Overid p-value					0.00	0.60
			Panel B. Number of integrators			
Aging from 1990 to 2015	-5.364**	-3.327	16.221***	16.990*	4.842	8.949
	(2.436)	(2.393)	(4.371)	(10.104)	(8.034)	(6.248)
Exposure to robots measure	1.170***	1.427**	0.822**	1.226**	1.005**	1.306**
	(0.395)	(0.692)	(0.340)	(0.559)	(0.446)	(0.655)
Observations	722	722	722	722	722	722
R-squared	0.09	0.42	-0.07	0.34	0.05	0.39
Instruments F-stat			70.40	17.83	4.57	5.35
Overid p-value					0.00	0.75
			Panel C. Dummy for the presence of integrators			
Aging from 1990 to 2015	-0.140	0.043	2.406***	2.501***	1.845**	1.661**
	(0.180)	(0.201)	(0.711)	(0.944)	(0.721)	(0.704)
Exposure to robots measure	0.107***	0.029	0.066**	0.005	0.075***	0.013
	(0.017)	(0.019)	(0.028)	(0.026)	(0.022)	(0.021)
Observations	722	722	722	722	722	722
R-squared	0.09	0.47	-0.18	0.32	-0.07	0.40
Instruments F-stat			70.40	17.83	4.57	5.35
Overid p-value					0.00	0.60
Other covariates included:						
Regional dummies	✓	✓	✓	✓	✓	✓
Commuting zone covariates		✓		✓		✓

Notes: The dependent variable is the number of robot integrators in each US commuting zone (from Leigh and Kraft, 2016). The aging variable is the change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015 (from the US CEnsus and American Community Survey). Panel A presents estimates using the log of 1+the number of integrators as the dependent variable. Panel B presents estimates using the number of integrators as the dependent variable. Panel C presents estimates using a dummy for whether a commuting zone has an integrator as the dependent variable. Columns 1-2 present OLS estimates. Columns 3-4 present IV estimates where the aging variable is instrumented using the projected aging based on the age distribution of a commuting zone in 1990. Columns 5-6 present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts in past Censuses. Even columns include census region dummies and the mesure of exposure to robots from Acemoglu and Restrepo (2017a). Odd columns, in addition, control for commuting-zone covariates, including log population, share of working-age population, share of population by race, share of population with highschool and college, and the share of employment in broad industry categories in 1990. All estimates are unweighted, and in parenthesis we report standard errors that are robust against heteroscedasticity and correlation in the error terms within states. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 11: OLS estimates of the impact of aging on robot installations by country-industry pairs per year.

	Dependent variable: Installation of robots in country-industry pairs per year						
		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Normalizing by average employment in an industry.						
Aging from 1990 to 2025	1.558***	1.565***	0.961***		0.686***	0.430**	
	(0.438)	(0.441)	(0.330)		(0.217)	(0.164)	
Aging × reliance on middle-aged		0.900***	0.601***	0.598***	0.264***	0.177**	0.174**
		(0.252)	(0.171)	(0.167)	(0.090)	(0.077)	(0.074)
Aging × opportunities for automation		5.738***	4.150***	4.211***	6.045***	4.256***	4.281***
		(1.751)	(1.083)	(1.079)	(1.680)	(1.090)	(1.094)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
R-squared	0.36	0.37	0.46	0.47	0.39	0.47	0.49
	Panel B. Normalizing by employment from UNIDO.						
Aging from 1990 to 2025	3.934***	-20.698**	-14.853***		-2.413***	-1.592	
	(1.396)	(8.434)	(4.997)		(0.877)	(1.074)	
Aging × reliance on middle-aged		3.979***	2.392***	2.584***	1.043***	0.646	0.849**
		(1.377)	(0.818)	(0.831)	(0.360)	(0.390)	(0.413)
Aging × opportunities for automation		36.725**	29.320***	27.123***	7.970***	4.771***	4.768***
		(17.072)	(10.329)	(9.573)	(2.827)	(1.415)	(1.444)
Observations	5974	5974	5974	5974	5974	5974	5974
Countries in sample	46	46	46	46	46	46	46
R-squared	0.33	0.35	0.44	0.47	0.37	0.44	0.47
	Panel C. Normalizing by employment from KLEMS.						
Aging from 1990 to 2025	0.783***	3.667***	3.148***		0.513***	0.462***	
	(0.183)	(1.004)	(0.932)		(0.135)	(0.135)	
Aging × reliance on middle-aged		0.365**	0.419***	0.378***	0.108*	0.136*	0.106
		(0.130)	(0.124)	(0.125)	(0.062)	(0.067)	(0.070)
Aging × opportunities for automation		8.094***	6.375***	6.780***	4.502***	4.180***	4.223***
		(2.427)	(2.164)	(2.164)	(1.187)	(1.053)	(1.041)
Observations	5928	5928	5928	5928	5928	5928	5928
Countries in sample	22	22	22	22	22	22	22
R-squared	0.56	0.56	0.57	0.57	0.56	0.57	0.58
Covariates included:							
Country covariates in 1990	✓	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The dependent variable is installations of industrial robots in each country-industry-year cell with available data between 1993 and 2014 (from IFR). The aging variable is the (projected) change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). We also estimate the interaction of aging with an industry reliance on young workers (proxied using 1990 US Census data on the age distribution of workers in each industry), and the two measures for opportunities for automation: the replaceability index from Graetz and Michaels (2015) in columns 2-4; and a measure of potential for the use of robots from the BCG in columns 5-7. Panel A presents estimates where we normalize robot installations by the average employment in an industry from the ILO. Panel B presents estimates where we normalize robot installations by employment in an industry from UNIDO. Panel C presents estimates where we normalize robot installations by employment in an industry from EUKLEMS. All columns include region dummies, and the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. Columns 4 and 7 include a full set of country fixed effects. All regressions weigh industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 12: IV estimates of the impact of aging on robot installations by country-industry pairs per year.

	Dependent variable: Installation of robots in country-industry pairs per year						
		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Normalizing by average employment in an industry.						
Aging from 1990 to 2025	1.424***	-2.832***	-1.800***		-0.846**	-0.465*	
	(0.476)	(0.938)	(0.593)		(0.356)	(0.282)	
Aging × reliance on middle-aged		0.950***	0.548***	0.546***	0.327***	0.186**	0.181**
		(0.311)	(0.189)	(0.185)	(0.112)	(0.086)	(0.083)
Aging × opportunities for automation		5.325***	4.058***	4.037***	5.883***	3.750***	3.785***
		(1.932)	(1.190)	(1.188)	(1.981)	(1.212)	(1.221)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
Instruments F-stat	19.01	.	6.01	7.82	.	6.37	7.99
Overid p-value	0.86	0.21	0.39	0.72	0.17	0.60	0.47
	Panel B. Normalizing by employment from UNIDO.						
Aging from 1990 to 2025	4.476***	-24.684***	-16.560***		-3.205***	-1.416	
	(1.439)	(8.935)	(5.209)		(1.016)	(0.978)	
Aging × reliance on middle-aged		4.875***	2.461***	2.776***	1.243***	0.530	0.847**
		(1.427)	(0.780)	(0.848)	(0.384)	(0.348)	(0.409)
Aging × opportunities for automation		41.672**	33.939***	30.569***	9.751***	5.380***	5.402***
		(18.597)	(11.523)	(10.885)	(3.126)	(1.591)	(1.618)
Observations	5974	5974	5974	5974	5974	5974	5974
Countries in sample	46	46	46	46	46	46	46
Instruments F-stat	15.04	9.58	10.06	7.62	9.50	9.46	7.33
Overid p-value	0.67	0.25	0.34	0.47	0.26	0.40	0.27
	Panel C. Normalizing by employment from KLEMS.						
Aging from 1990 to 2025	0.837***	0.381**	0.338***		0.266**	0.225***	
	(0.196)	(0.149)	(0.110)		(0.114)	(0.085)	
Aging × reliance on middle-aged		0.424***	0.404***	0.367***	0.167**	0.122	0.096
		(0.136)	(0.143)	(0.139)	(0.068)	(0.078)	(0.079)
Aging × opportunities for automation		8.139***	6.910***	7.283***	4.832***	4.595***	4.646***
		(2.762)	(2.224)	(2.232)	(1.398)	(1.168)	(1.155)
Observations	5928	5928	5928	5928	5928	5928	5928
Countries in sample	22	22	22	22	22	22	22
Instruments F-stat	21.33	28.15	96.13	15.35	31.36	32.88	9.07
Overid p-value	0.06	0.26	0.35	0.16	0.32	0.40	0.16
Covariates included:							
Country covariates in 1990	✓	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The dependent variable is installations of industrial robots in each country-industry-year cell with available data between 1993 and 2014 (from IFR). The aging variable is the (projected) change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). We also estimate the interaction of aging with an industry reliance on young workers (proxied using 1990 US Census data on the age distribution of workers in each industry), and the two measures for opportunities for automation: the replaceability index from Graetz and Michaels (2015) in columns 2-4; and a measure of potential for the use of robots from the BCG in columns 5-7. Panel A presents estimates where we normalize robot installations by the average employment in an industry from the ILO. Panel B presents estimates where we normalize robot installations by employment in an industry from UNIDO. Panel C presents estimates where we normalize robot installations by employment in an industry from EUKLEMS. We instrument aging and its interactions using the size of five-year birth cohorts between 1950 and 1985. All columns include region dummies, and the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. Columns 4 and 7 include a full set of country fixed effects. All regressions weigh industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 13: OLS estimates of the impact of aging and past aging on robot installations by country-industry pairs per year.

	Dependent variable: Installation of robots in country-industry pairs per year						
		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Placebo test						
Aging from 1950 to 1990	-0.038	0.407	1.326		0.894	2.402	
	(0.746)	(1.797)	(1.121)		(2.958)	(1.958)	
Past Aging × Reliance on Middle-Aged Workers		0.325	0.255	0.265	0.125	0.022	0.028
		(0.448)	(0.268)	(0.268)	(0.172)	(0.117)	(0.111)
Past Aging × Opportunities for Automation		-0.334	2.740	2.398	1.604	2.307	2.291
		(3.220)	(2.040)	(2.056)	(2.828)	(1.787)	(1.818)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
R-squared	0.35	0.35	0.45	0.47	0.36	0.46	0.47
	Panel B. Past vs. expected aging						
Aging from 1950 to 1990	-0.562	-0.862	0.435		-0.866	0.753	
	(0.739)	(1.713)	(1.106)		(2.917)	(1.955)	
Past Aging × Reliance on Middle-Aged Workers		0.021	0.056	0.064	0.036	-0.029	-0.024
		(0.400)	(0.256)	(0.255)	(0.155)	(0.113)	(0.108)
Past Aging × Opportunities for Automation		-2.329	1.190	0.939	-0.455	0.812	0.796
		(3.105)	(1.998)	(2.054)	(2.576)	(1.781)	(1.808)
Aging from 1990 to 2025	1.595^{***}	3.796^{***}	2.504^{***}		6.787^{***}	4.633^{***}	
	(0.420)	(0.988)	(0.631)		(1.774)	(1.202)	
Aging × Reliance on Middle-Aged Workers		0.899^{***}	0.597^{***}	0.594^{***}	0.262^{***}	0.179^{**}	0.175^{**}
		(0.240)	(0.167)	(0.163)	(0.085)	(0.076)	(0.073)
Aging × Opportunities for Automation		5.884^{***}	4.071^{***}	4.150^{***}	6.074^{***}	4.200^{***}	4.228^{***}
		(1.682)	(1.053)	(1.048)	(1.616)	(1.066)	(1.071)
Observations	10602	10602	10602	10602	10602	10602	10602
Countries in sample	50	50	50	50	50	50	50
R-squared	0.36	0.37	0.46	0.47	0.39	0.47	0.49
Covariates included:							
Country covariates in 1990	✓	✓	✓	✓	✓	✓	✓
Initial robot density in 1993			✓	✓		✓	✓
Country fixed effects				✓			✓

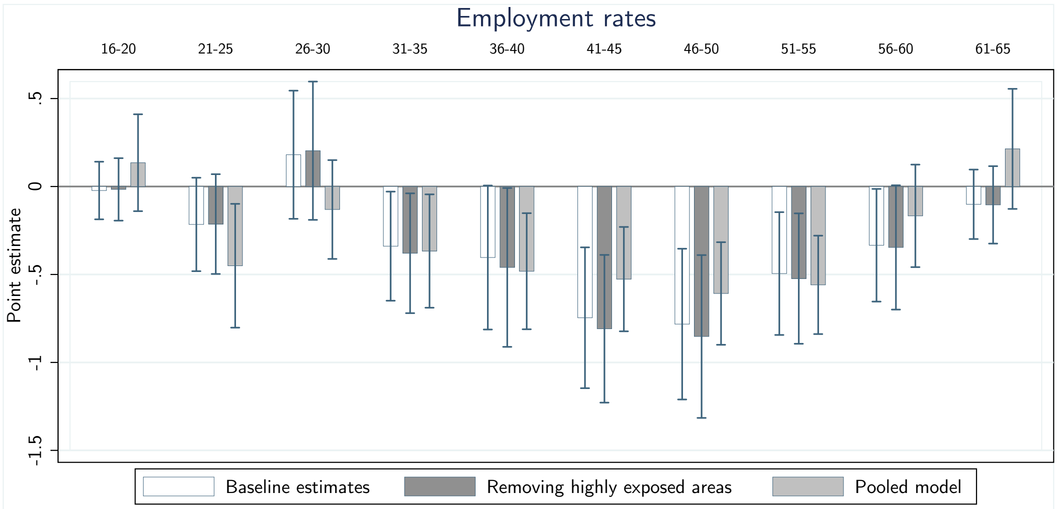
Notes: The dependent variable is installations of industrial robots in each country-industry-year cell with available data between 1993 and 2014 (from IFR). We normalize installations using the average employment by industry from the ILO. In Panel A, the aging variable is the past change in the ratio of workers above 56 to workers between 21 and 55 between 1950 and 1990 (from the UN Population Statistics). In Panel B, we also include (projected) aging between 1990 and 2025 (from the UN Population Statistics). We also estimate the interaction of past and (projected) aging with an industry reliance on young workers (proxied using 1990 US Census data on the age distribution of workers in each industry), and the two measures for opportunities for automation: the replaceability index from Graetz and Michaels (2015) in columns 2-4; and a measure of potential for the use of robots from the BCG in columns 5-7. All columns include region dummies, and the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. Columns 4 and 7 include a full set of country fixed effects. All regressions weigh industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table 14: Estimates of the impact of aging on the value added of country-industry pairs per year.

	Dependent variable: Change in value-added per worker from 1995 to 2007						
		Potential for the use of robots					
		Replaceability index			BCG measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. OLS estimates						
Aging from 1995 to 2025	-1.455**	0.124	0.317		0.306	0.523	
	(0.559)	(1.259)	(1.159)		(1.216)	(1.138)	
Aging × reliance on middle-aged		-0.253	-0.296	-0.253	-0.248	-0.291	-0.255
		(0.256)	(0.242)	(0.238)	(0.251)	(0.239)	(0.244)
Aging × opportunities for automation		2.900**	3.069**	3.019***	1.141**	1.220**	1.219**
		(1.238)	(1.192)	(0.936)	(0.501)	(0.483)	(0.469)
Observations	418	418	418	418	418	418	418
Countries in sample	22	22	22	22	22	22	22
R-squared	0.77	0.77	0.78	0.91	0.77	0.78	0.91
	Panel B. IV estimates						
Aging from 1995 to 2025	-1.728***	1.290	1.334		1.232	1.348	
	(0.622)	(1.270)	(1.162)		(1.422)	(1.319)	
Aging × reliance on middle-aged		-0.597**	-0.624**	-0.597*	-0.558*	-0.592**	-0.593*
		(0.295)	(0.279)	(0.326)	(0.305)	(0.290)	(0.354)
Aging × opportunities for automation		4.498***	4.510***	4.149***	1.512***	1.570***	1.559***
		(1.313)	(1.476)	(1.007)	(0.427)	(0.442)	(0.398)
Observations	418	418	418	418	418	418	418
Countries in sample	22	22	22	22	22	22	22
Instruments F-stat	8.20	27.62	16.20	6.16	51.22	12.66	5.38
Overid p-value	0.18	0.58	0.71	0.55	0.41	0.45	0.35
	Panel C. IV estimates (STAN data)						
Aging from 1995 to 2025	-2.030***	0.530	0.878		0.528	0.732	
	(0.471)	(0.999)	(0.838)		(1.059)	(0.920)	
Aging × Reliance on Middle-Aged Workers		-0.477**	-0.424*	-0.373*	-0.434*	-0.379	-0.336
		(0.231)	(0.233)	(0.224)	(0.231)	(0.238)	(0.232)
Aging × Opportunities for Automation		3.894***	3.861***	3.080***	1.407***	1.255***	1.049***
		(1.425)	(1.180)	(0.766)	(0.509)	(0.423)	(0.407)
Observations	462	462	462	462	462	462	462
Countries in sample	27	27	27	27	27	27	27
Instruments F-stat	18.97	23.42	11.29	10.69	14.72	10.06	12.64
Overid p-value	0.98	0.55	0.47	0.33	0.45	0.32	0.28
Covariates included:							
Country covariates in 1990	✓	✓	✓	✓	✓	✓	✓
Initial value added in 1995			✓	✓		✓	✓
Country fixed effects				✓			✓

Notes: The dependent variable is the change in value-added per worker from in each country-industry pair between 1995 and 2007 (from EUKLEMS in Panels A and B, and STAN in Panel C). The aging variable is the (projected) change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025 (from the UN Population Statistics). We also estimate the interaction of aging with an industry reliance on young workers (proxied using 1990 US Census data on the age distribution of workers in each industry), and the two measures for opportunities for automation: the replaceability index from Graetz and Michaels (2015) in columns 2-4; and a measure of potential for the use of robots from the BCG in columns 5-7. Panel A presents OLS, and Panel B presents IV estimates where we instrument aging and its interactions using the size of five-year birth cohorts between 1950 and 1985. Panel C presents additional estimates using data from STAN. All columns include region dummies, and the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. Columns 4 and 7 include a full set of country fixed effects. All regressions weigh industries by their share of employment in a country, and the standard errors are robust against heteroscedasticity and correlation within countries. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Appendix Figures and Tables



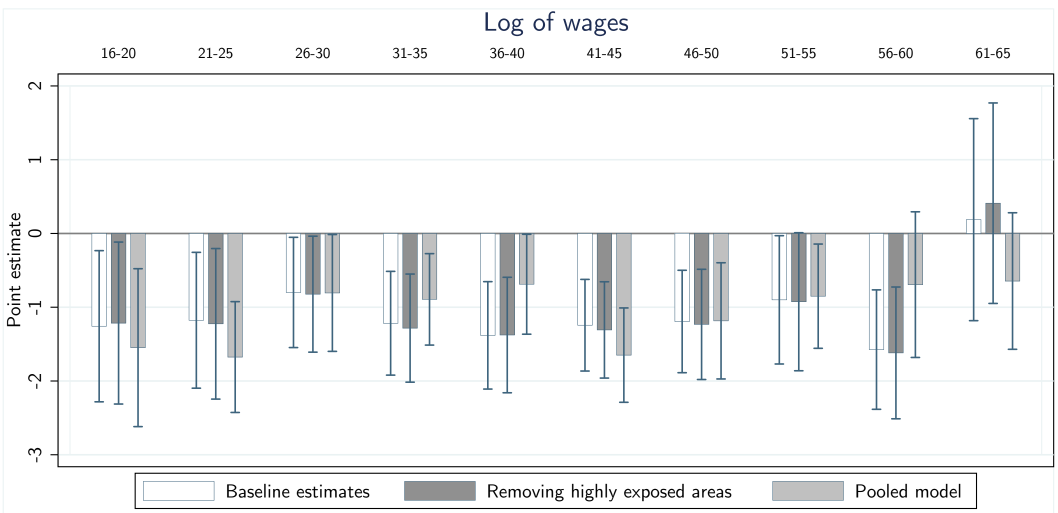


Figure A1: Estimated impact of one additional robot per thousand workers on employment and wages. The figure plots the estimates for different age groups and for men separately.

Table A1: Set of countries in our sample and availability of industry data.

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

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

Table A2: Estimates of the impact of aging from 1990 to 2015 on the adoption of industrial robots.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)					
	Full sample			OECD sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
Aging from 1990 to 2015	1.229***	0.975***	0.657**	1.463**	1.295**	0.763*
	(0.408)	(0.338)	(0.300)	(0.616)	(0.478)	(0.368)
Ratio of old to young workers in 1990		-0.074	-0.341		-0.342	-0.913
		(0.285)	(0.238)		(0.546)	(0.582)
Log of the GDP per capita in 1990		0.059	-0.004		0.076	-0.004
		(0.035)	(0.030)		(0.057)	(0.053)
Robots per thousand workers in 1993			0.050**			0.073***
			(0.023)			(0.023)
Observations	52	52	52	30	30	30
R-squared	0.42	0.55	0.70	0.24	0.44	0.61
	Panel B. IV estimates					
Aging from 1990 to 2015	1.381***	1.110***	0.814***	2.574***	1.305***	0.708**
	(0.390)	(0.317)	(0.263)	(0.941)	(0.450)	(0.350)
Ratio of old to young workers in 1990		-0.073	-0.330		-0.342	-0.924*
		(0.262)	(0.222)		(0.487)	(0.519)
Log of the GDP per capita in 1990		0.053	-0.008		0.076	-0.005
		(0.034)	(0.027)		(0.050)	(0.045)
Robots per thousand workers in 1993			0.048**			0.074***
			(0.020)			(0.020)
Observations	52	52	52	30	30	30
Instruments F-stat	14.98	11.59	10.15	3.20	3.90	6.77
Overid p-value	0.77	0.47	0.10	0.68	0.45	0.08
Covariates included:						
Country covariates in 1990		✓	✓		✓	✓
Initial robot density in 1993			✓			✓

Notes: The dependent variable is change in the stock of industrial robots per thousand workers from 1993 to 2014 (from IFR). The aging variable is the observed change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015 (from the UN Population Statistics). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Columns 1-3 use the full sample, while columns 4-6 are for the OECD sample. Columns 1 and 4 include region dummies. Columns 2 and 5, in addition, include the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. Columns 3 and 6 add the baseline (1993) value of robots per thousand workers. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A3: Estimates of the impact of aging on the adoption of industrial robots using different definitions of middle-aged and senior workers.

	Dependent variable: Change in the stock of industrial robots per thousand workers (annualized)			
	OLS estimates		IV estimates	
	All countries	OECD	All countries	OECD
	(1)	(2)	(3)	(4)
	Panel A. Middle-aged from 21-60; Senior from 61 onwards			
Aging from 1990 to 2025	0.594**	0.731**	0.738***	0.827***
	(0.268)	(0.302)	(0.236)	(0.286)
Observations	52	30	52	30
Instruments F-stat			16.03	13.29
Overid p-value			0.14	0.05
	Panel B. Middle-aged from 21-50; Senior from 51 onwards			
Aging from 1990 to 2025	0.326**	0.614**	0.376***	0.834***
	(0.144)	(0.223)	(0.132)	(0.248)
Observations	52	30	52	30
Instruments F-stat			12.29	9.92
Overid p-value			0.13	0.03
	Panel C. Middle-aged from 21-55; Senior from 56-70			
Aging from 1990 to 2025	0.828**	1.429***	0.815**	1.674***
	(0.367)	(0.488)	(0.347)	(0.610)
Observations	52	30	52	30
Instruments F-stat			18.55	19.12
Overid p-value			0.06	0.03
	Panel D. Middle-aged from 36-55; Senior from 56 onwards			
Aging from 1990 to 2025	0.313**	0.391**	0.319***	0.347**
	(0.130)	(0.155)	(0.121)	(0.162)
Observations	52	30	52	30
Instruments F-stat			13.47	5.69
Overid p-value			0.15	0.08
Covariates included:				
Country covariates in 1990	✓	✓	✓	✓
Initial robot density in 1993	✓	✓	✓	✓

Notes: The dependent variable is change in the stock of industrial robots per thousand workers from 1993 to 2014 (from IFR). The aging variable is the (projected) change in the ratio of senior to middle-aged workers between 1990 and 2025 (from the UN Population Statistics). In panel A we define middle-aged workers as those between 21 and 60, and senior workers as those above 61. In panel A we define middle-aged workers as those between 21 and 50, and senior workers as those above 51. In panel C we define middle-aged workers as those between 21 and 55, and senior workers as those between 56 and 70. In panel D we define middle-aged workers as those between 36 and 55, and senior workers as those above 56. Columns 1-2 present OLS estimates, while columns 3-4 present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Columns 1 and 3 use the full sample, while columns 2 and 4 are for the OECD sample. All columns include region dummies, the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55, and the baseline (1993) value of robots per thousand workers. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A4: Estimates of the impact of aging on robot installations per year and additional specifications.

	Full sample			OECD sample		
	Dependent variable:					
	$\Delta \ln(1+R)$	$\Delta \ln R$	Poisson	$\Delta \ln(1+R)$	$\Delta \ln R$	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. OLS estimates					
main						
Aging from 1990 to 2025	4.609**	2.830***	1.364***	1.140	2.099*	0.821**
	(1.843)	(0.860)	(0.481)	(1.396)	(1.058)	(0.396)
Observations	52	23	1144	30	22	660
Countries in sample			52			30
R-squared	0.85	0.79		0.89	0.71	
	Panel B. IV estimates					
main						
Aging from 1990 to 2025	5.570**	3.493***	1.364***	-1.211	2.527**	0.821**
	(2.172)	(1.032)	(0.481)	(2.730)	(1.172)	(0.396)
Observations	52	23	1144	30	22	660
Countries in sample			52			30
R-squared	0.85	0.79		0.88	0.71	
Instruments F-stat	16.80	3.28		6.19	5.36	
Overid p-value	0.02	0.26		0.11	0.08	
Country covariates in 1990	✓	✓	✓	✓	✓	✓
Initial robot density in 1993	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is: in Panel A, the change in log of 1+ the number of robots in a country from 1993 to 2014 (from IFR); in Panel B, the change in the log of the number of robots in a country from 1993 to 2014 (from IFR); and in Panel C, the the number of robot installations in each country-year pair from 1993 to 2014 (from IFR)—and in this case we estimate a Poisson model. The aging variable is the observed change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015 (from the UN Population Statistics). Panel A presents OLS estimates. Panel B presents IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. Columns 1-3 use the full sample, while columns 4-6 are for the OECD sample. All columns include region dummies, the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55, and the baseline (1993) value of robots per thousand workers. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table A5: Estimates of the impact of aging on economic activity at the country level.

	OLS estimates			IV estimates		
	EUKLEMS sample		OECD	EUKLEMS sample		OECD
	Value added	GDP	GDP	Value added	GDP	GDP
	(1)	(2)	(3)	(4)	(5)	(6)
Aging from 1995 to 2025	-1.307**	-0.306	-0.110	-1.694***	-0.705	-0.378
	(0.529)	(0.353)	(0.214)	(0.615)	(0.442)	(0.374)
Observations	22	22	35	22	22	35
R-squared	0.86	0.78	0.70	0.86	0.76	0.69
Instruments F-stat				4.89	3.69	6.83
Overid p-value				0.22	0.38	0.24
Country covariates in 1990	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is: in columns 1 and 4, the change in value added per worker from 1995 to 2007 (from EUKLEMS); in columns 2-3 and 5-6, the change in the log of GDP per capita from 1995 to 2007 (from the Penn World Tables). The aging variable is the observed change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015 (from the UN Population Statistics). Columns 1-3 presents OLS estimates. Columns 4-6 present IV estimates where the aging variable is instrumented using the size of five-year birth cohorts between 1950 and 1985. All columns include the 1990 values of log GDP per capita, log of population, average years of schooling and the ratio of workers above 56 to workers between 21 and 55. All regressions are unweighted and the standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.