Demographics and Robots*

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Abstract

We argue theoretically and document empirically that aging leads to greater adoption of robotics technology. We first document using US data that robots are most highly substitutable for middle-aged workers, in particular those between the ages of 36 and 55. We then show that demographic change—corresponding to an increasing ratio of older workers to those that are middle-aged—is associated with pronounced increases in the adoption of robots both across countries and US commuting zones. Our directed technological change model 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; these predictions receive support from cross-country, cross-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. 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, as well as several other countries, in the production of robots—a single major producer of industrial robots is headquartered in the United States, compared to six in Germany and six in Japan (Leigh and Kraft, 2017).

In this paper, we advance the hypothesis that much of the cross-country difference in investment in robots is explained by differential demographic trends. Put simply, 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 use robots or other automation technologies to substitute 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 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, documenting a strong correlation between aging and the adoption of robotics technology. 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. 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, 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

[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.

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. We further verify that our results are not driven by the exact age cutoffs used for measuring the overall aging of the population.

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.[2]

As noted above, a sharper prediction of the directed technological change approach to adoption of robots 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.

Robots are, arguably, the tip of the iceberg of a larger set of automation technologies. We provide some suggestive evidence that our demographics variables are also associated with the adoption of other automation technologies, such as numerically controlled machines, weaving and knitting machines, vending machines and ATMs (all measured from the bilateral trade flows data), but not with technologies that appear more labor-augmenting.

Finally, we investigate the implications of demographic change on labor productivity. Even though the theoretical predictions for productivity are ambiguous in view of the induced technology responses, this is an empirically important question that has not received much attention so far. Our results here show no robust country-level effects, but there is a positive impact of demographic change on labor productivity in industries that are most amenable to automation—a result consistent with our theoretical predictions.

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

[2]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.

it reassuring too that the 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 small 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).[3] 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.[4] 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 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.

[3]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).

[4]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 we develop the theoretical implications of demographic change on technology adoption and productivity.

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 simple model of directed technology adoption in which different sectors of the economy combine middle-aged (prime-aged) workers, senior workers and machines to perform the tasks necessary for production. In addition, technology firms (monopolists) invest in the development of new technologies that automate tasks or increase the productivity of middle-aged workers. Following Acemoglu (2007, 2010), we consider a static model, which enables us to derive the main implications of demographic change on the adoption of different types of technologies and productivity in the most transparent manner.[5]

2.1 The Environment

A unique final good Y is produced competitively by combining the output of a continuum of industries using the following Cobb-Douglas aggregate:

$$\ln Y = \int_{i \in \mathcal{I}} \ln Y(i) di,$$

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

In each industry, output is produced by combining production tasks, service (nonproduction) tasks and intermediates embedding different types of technologies. Namely,

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

where $X(i)$ denotes the aggregate of production tasks used by industry i, $S(i)$ denotes service tasks (and with a slight abuse of notation, also the employment of "senior" workers supplying the 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.

The aggregate of production tasks, $X(i)$, is produced from a unit of measure of tasks,

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

[5] 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 on the adoption of the robotics technologies.

where ζ the elasticity of substitution across tasks. Each task $X(i,s)$ is produced either by labor or machines ("robots"). Specifically, we have

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

where $l(i,s)$ denotes employment in the production of task s in industry i, and $m(i,s)$ denotes machines used in industry i to produce task s. Labor and machines are perfect substitutes in automated tasks (those with $s \leq \theta(i)$ in industry i). In addition, $\gamma(i)$ is the exogenous component of the productivity of labor relative to machine in industry i, while $A(i)$ is the endogenous component of this (labor-augmenting) productivity.[6] Finally, $\theta(i)$ designates the automation threshold in industry i such that 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 increases in labor-augmenting productivity (as captured by $A(i)$) is embedded in the intermediate goods, which explains the term $q(\theta(i), A(i))$ in the industry production function (1).

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.[7] 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.[8] Thus, the net output in industry i is given by subtracting the total cost of intermediates, $(1-\eta)q(\theta(i), A(i))$, from the gross output of the industry, $\widetilde{Y}(i)$, i.e.,

$$Y(i) = \widetilde{Y}(i) - (1-\eta)q(\theta(i), A(i)). \tag{2}$$

Finally, we assume that there are two types of workers: middle-aged, with inelastic supply L, and "senior," with inelastic supply S, and we assume that middle-aged workers specialize in production tasks, while senior workers will be employed in service tasks.[9] 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

[6] A more general version of this production technology, similar to that in Acemoglu and Restrepo (2016), allows for $\gamma(i,s)$, so that the productivity of labor relative to the productivity of machines varies across tasks and industries. This more general setup leads to very similar results, and we simplify the technology for expositional reasons.

[7] Since there is a continuum of industries, these technology monopolists will be "monopolistically competitive".

[8] 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.

[9] Allowing both types of workers to work in all tasks with different productivities leads 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.

explicitly

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

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, which we will normalize to 1 below (without any loss of generality given our focus).

2.2 Equilibrium with exogenous technology

Let us denote the set of technologies 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.

In what follows, we impose the following assumption which ensures that machines and middle-aged workers are "gross substitutes"—while machines and senior workers will be complements.

Assumption 1 $\zeta > 1$.

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 the following iso-elastic schedule

$$q(\theta(i), A(i)) = \frac{1}{\eta}X(i)^{\alpha(i)}S(i)^{1-\alpha(i)}\left(\frac{\chi(\theta(i), A(i))}{P_Y(i)}\right)^{-\frac{1}{\eta}}. \quad (3)$$

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

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

Let $L(i) = \int_0^1 l(i,s)dsdi$ and $M(i) = \int_0^1 m(i,s)dsdi$ denote the amount of middle-aged labor and machines employed in industry i, respectively. Then following the same steps as in Acemoglu and Restrepo (2016), we obtain the total supply of production tasks in industry i as

$$X(i) = \left(\widetilde{\theta}(i)^{\frac{1}{\zeta}} M(i)^{\frac{\zeta-1}{\zeta}} + (1-\widetilde{\theta}(i))^{\frac{1}{\zeta}} (A(i)\gamma(i)L(i))^{\frac{\zeta-1}{\zeta}}\right)^{\frac{\zeta}{\zeta-1}}, \tag{4}$$

where $\widetilde{\theta}(i)$ denotes the profit-maximizing threshold below which tasks in industry i are produced by machines. Naturally, this threshold cannot exceed the technological constraints imposed by $\theta(i)$, but firms may prefer not to use machines in all technologically automated tasks (see also Acemoglu and Restrepo, 2016). Whether they do so or not depends on relative factor prices, and in particular, on the cost of performing production tasks in industry i with labor, W, relative to the cost of automation, which is $A(i)\gamma(i)P$. Thus

$$\widetilde{\theta}(i) = \begin{cases} \theta(i) & \text{if } W \geq A(i)\gamma(i)P \\ 0 & \text{if } W < A(i)\gamma(i)P. \end{cases} \tag{5}$$

The demands for factors can then be derived as functions of this equilibrium threshold and factor prices as

$$\begin{aligned} L^d =& Y \int_{i\in\mathcal{I}} (A(i)\gamma(i))^{\zeta-1}\alpha(i)(1-\widetilde{\theta}(i))P_{X(i)}^{\zeta-1}W^{-\zeta}di, \\ M^d =& Y \int_{i\in\mathcal{I}} \alpha(i)\widetilde{\theta}(i)P_{X(i)}^{\zeta-1}P^{-\zeta}di, \\ S^d =& Y \int_{i\in\mathcal{I}} (1-\alpha(i))V^{-1}di, \end{aligned}$$

where $P_{X(i)}$ is the price index for the production tasks in industry i given by

$$P_{X(i)} = \left(\widetilde{\theta}(i)P^{1-\zeta} + (1-\widetilde{\theta}(i))\left(\frac{W}{A(i)\gamma(i)}\right)^{1-\zeta}\right)^{1-\zeta}. \tag{6}$$

The next lemma provides a tractable characterization of aggregate output as a function of the supplies of middle-aged workers, senior workers and machines as well as the set of available technologies in the economy, Θ.

LEMMA 1 *Given a set of technologies Θ and factor supplies $L, S,$ and M, aggregate output is given by a constant returns to scale function $Y(L, S, M; \Theta)$, where*

$$\begin{aligned} \ln Y(L,S,M;\Theta) = & \max_{\{L(i),M(i),S(i),\widetilde{\theta}(i)\}_{i\in\mathcal{I}}} \int_{i\in\mathcal{I}} \ln Y(i)di, \\ & \text{s.t: } Y(i) \leq \frac{2-\eta}{1-\eta}\left(\widetilde{\theta}(i)^{\frac{1}{\zeta}} M(i)^{\frac{\zeta-1}{\zeta}} + (1-\widetilde{\theta}(i))^{\frac{1}{\zeta}} (A(i)\gamma(i)L(i))^{\frac{\zeta-1}{\zeta}}\right)^{\frac{(\zeta-1)\alpha(i)}{\zeta}} S(i)^{1-\alpha(i)}, \\ & \widetilde{\theta}(i) \in [0,\theta(i)], \int_{i\in\mathcal{I}} L(i)di \leq L \int_{i\in\mathcal{I}} M(i)di \leq M \int_{i\in\mathcal{I}} S(i)di \leq S. \end{aligned}$$

The function $Y(L, S, M; \Theta)$ is uniquely defined, and its partial derivatives are equal to factor prices, i.e., $Y_L(L, S, M; \Theta) = W$, $Y_S(L, S, M; \Theta) = V$ and $Y_M(L, S, M; \Theta) = P$.

PROOF. See the Appendix. ■

In this lemma, we took the supply of machines M as given, letting the price of machines, P, adjust. In what follows, this price will be determined competitively given the cost of supplying machines, and in equilibrium, the quantity of machines will adjust. To further simplify the analysis, we assume that machines are produced from the final good subject to constant returns to scale, and without loss of any generality, we normalize their price to $P = 1$. Thus given supplies of middle-aged and senior workers, L and S and a set of technologies Θ, we can represent an *equilibrium with exogenous technology* a supply of machines $M(L, S; \Theta)$ such that the market for machines clears at a rental price of $P = 1$. Then Lemma 1 implies that in an equilibrium with exogenous technology the production of the final good must be given by

$$Y(L, S, M(L, S; \Theta); \Theta).$$

The following proposition shows that an equilibrium with exogenous technology always exists and is unique, and provides a characterization of this equilibrium in terms of the intersection between the market-clearing condition for middle-aged workers and the ideal price index condition (which sets the price of the final good, the numeraire, equal to 1).

PROPOSITION 1 *1. Given supplies of middle-aged and senior workers, L and S, and a set of technologies Θ, an equilibrium with exogenous technology always exists and is unique. The demand for machines is a solution to*

$$Y_M(L, S, M(L, S; \Theta); \Theta) \leq 1,$$

with complementary slackness (i.e., holding as equality if $M(L, S; \Theta) > 0$.

2. Let $\phi = \frac{S}{L+S}$ denote the share of senior workers in the population and $y = Y/(L+S)$ denote aggregate output per worker. Then the equilibrium levels of aggregate output per worker, y, and middle-aged wages, W, are the unique solutions $\{y^E(\phi; \Theta), W^E(\phi, \Theta)\}$ to the system of equations given by: (a) the market-clearing condition for middle-aged workers,

$$W(1-\phi) = y \int_{i \in \mathcal{I}} \alpha(i) \frac{(1-\theta(i)) \left(\frac{W}{A(i)\gamma(i)}\right)^{1-\zeta}}{(1-\theta(i)) \left(\frac{W}{A(i)\gamma(i)}\right)^{1-\zeta} + \theta(i) \min\left\{1, \frac{W}{A(i)\gamma(i)}\right\}^{1-\zeta}} di; \tag{7}$$

and (b) the ideal price index condition,

$$\int_{i \in \mathcal{I}} \alpha(i) \frac{1}{1-\zeta} \ln\left((1-\theta(i)) \left(\frac{W}{A(i)\gamma(i)}\right)^{1-\zeta} + \theta(i) \min\left\{1, \frac{W}{A(i)\gamma(i)}\right\}^{1-\zeta}\right) di \tag{8}$$

$$+ (\ln y - \ln \phi) \int_{i \in \mathcal{I}} (1-\alpha(i)) di = \mu,$$

where μ is a constant. The equilibrium wage of senior workers, V, and the demand for machines, $M(L, S; \Theta)$, can then be derived from $\{y^E(\phi; \Theta), W^E(\phi, \Theta)\}$.

Proof. See the Appendix, where we also provide the exact expression for μ. ■

Figure 1 depicts the characterization of the equilibrium with exogenous technology. The market-clearing condition for middle-aged workers is upward sloping in the (y, W) space because a higher aggregate output per worker will lead to the same demand for middle-aged workers only if the wage is higher. The ideal price index condition is downward sloping because a higher wage for middle-aged workers will necessitate a lower wage for senior workers and thus a lower output per worker given technology. These two curves can thus intersect only once, which corresponds to the unique equilibrium.

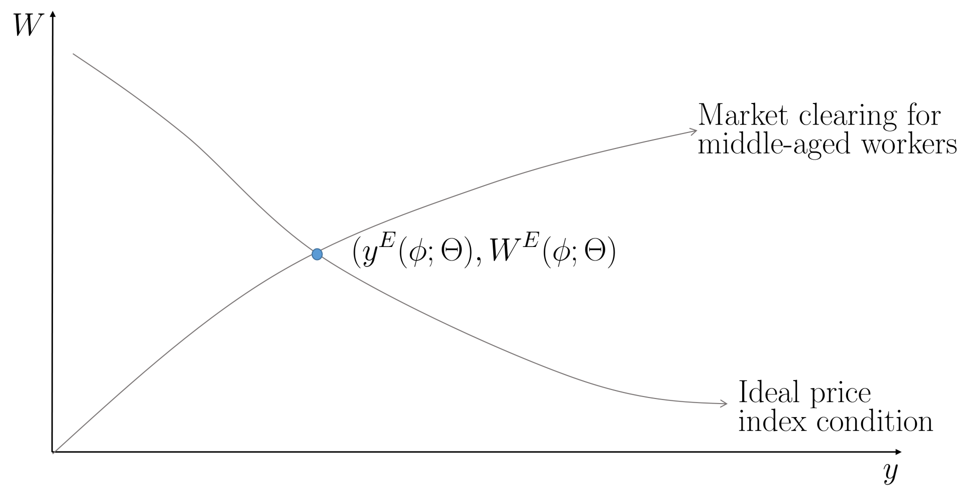

Figure 1: Determination of aggregate output per worker and the wage of middle-aged workers. The upward-sloping curve is for the market-clearing condition for middle-aged workers, (7), while the downward sloping curve is the ideal price index condition, (8).

The comparative statics of the equilibrium with exogenous technology can be illustrated in Figure 1. The most important comparative statics concern the effects of aging and different types of technologies on equilibria factor prices. The next proposition focuses on the implications of aging (and in this proposition and in what follows, we use subscripts to denote partial derivatives when this will cause no confusion).

Proposition 2 *Aging—an increase in ϕ—increases the wage of middle-aged workers, reduces the wage of senior workers and has an ambiguous effect on aggregate output per worker. That is,*

$$W_\phi^E(\phi;\Theta) > 0 \qquad\qquad V_\phi^E(\phi;\Theta) < 0,$$

and

$$y_\phi^E(\phi;\Theta) = \left[V^E(\phi;\Theta) - W^E(\phi;\Theta)\right] + m_\phi^E(\phi;\Theta) \lesseqgtr 0,$$

where $m^E(\phi;\Theta)$ denotes the equilibrium demand of machines per worker.

Proof. See the Appendix. ■

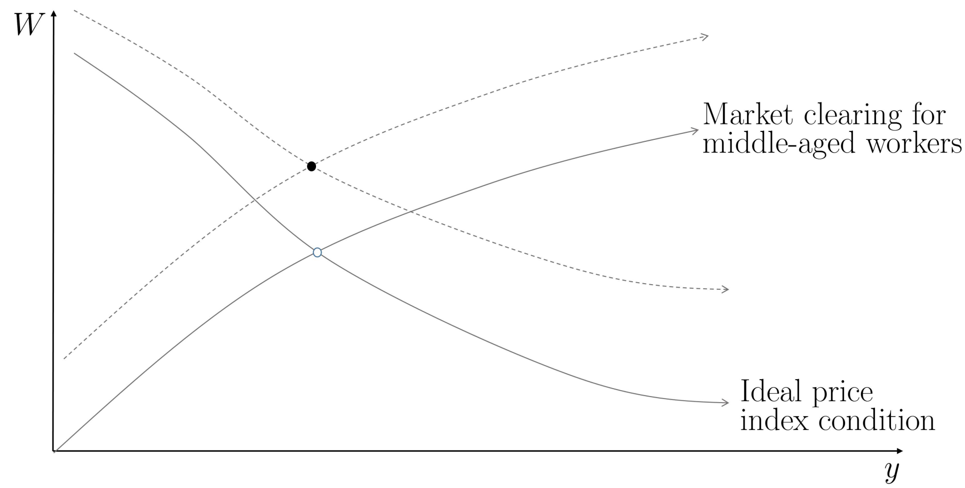

Figure 2: Impact of aging on aggregate output per worker and the wage of middle-aged workers. Aging shifts both curves up, and thus increases the wage of middle-aged workers but has an ambiguous effect on aggregate output per capita.

Figure 2 shows how aging increases the middle-aged wage, W, but has an ambiguous effect on aggregate output per worker. The last expression in Proposition 2 clarifies that this latter effect depends on the wage of middle-aged workers relative to the wage of senior workers. In particular, if $V < W$, there will be a negative effect on productivity (though m_{ϕ}^{E} 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 potential negative effect echoes the concerns raised by Gordon (2016) on the potential for slower growth in the next several decades because of demographic change.site

In the next proposition, we turn to the implications of automation and labor-augmenting technologies on factor prices.

Proposition 3 *1. Consider an increase in automation from $\theta(i)$ to $\theta(i)' > \theta(i)$ for a set of industries with positive measure in which $W > A(i)\gamma(i)$ (so that new automation technologies will be used in these industries). Then, the senior wage, V, increases, and there exists a threshold $\bar{\zeta}$ such that if $\zeta > \overline{\zeta}$, the middle-aged wage, W, decreases, and if $\zeta < \overline{\zeta}$, W increases. Moreover, $\bar{\zeta}$ is decreasing in $\int_{i \in \mathcal{I}} \alpha(i) di$.*

2. Consider an increase in labor-augmenting productivity $A(i)$ to $A(i)' > A(i)$ for a set of industries with positive measure. Then W and V increase.

Proof. See the Appendix. ■

Figure 3 illustrates the comparative statics with respect to the automation technologies in Proposition 3. The forces operating here are the same ones that are emphasized in Acemoglu and Restrepo (2016). Automation creates a negative effect on middle-aged workers because it displaces them from the production tasks they were previously performing. There is, however, a countervailing positive productivity effect as well, because automation, by substituting cheaper machines for middle-aged workers, reduces the costs of production or increases productivity; this greater productivity partly accrues to middle-aged workers. The condition highlighted in Proposition 3 regulates the magnitude of the negative displacement effect relative to the positive productivity effect. In particular, when ζ is high, tasks are highly substitutable, and this reduces the extent of the productivity effect and the upward shift of the ideal price index condition in the figure, thus ensuring a negative effect of automation on the wages of middle-aged workers.

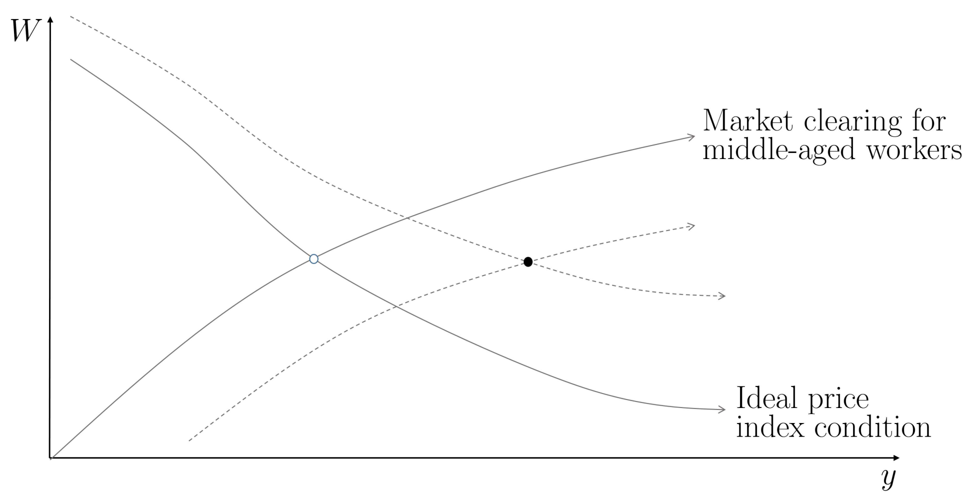

FIGURE 3: Impact of automation on aggregate output per worker and the wage of middle-aged workers. Further automation shifts the market-clearing condition for middle-aged workers up and the ideal price index condition down. Thus it increases aggregate output per capita, but has an ambiguous effect on the middle-aged wage.

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 that in Acemoglu (2007, 2010). We assume that technology monopolists can develop new technologies and sell the intermediates embodying these technologies, the $q(A(i), \theta(i))$'s, to firms producing in different industries. More specifically, recall that for each industry i, there is a single technology monopolist selling these intermediates to firms in that industry. We first assume that the cost of developing a new technology for industry i with automation $\theta(i)$ and labor-augmenting productivity $A(i)$ is

$$\frac{1-\eta}{2-\eta}Y\left[G(\theta(i)+H(A(i))-G(\theta(i))H(A(i)))\right]$$

in terms of the final good of the economy. We assume that H is an increasing and convex function that satisfies $H'(0)=0$, $\lim_{A(i)\to\infty}H(A(i))=1$ and $\lim_{A(i)\to\infty}H'(A(i))=\infty$, and likewise G is increasing and convex, and satisfies $G'(0)=0$, $\lim_{\theta(i)\to 1}G(\theta(i))=1$ and $\lim_{\theta(i)\to 1}G'(\theta(i))=\infty$. This functional form is chosen because it greatly simplifies our analysis of endogenous technology choices, as the next expression will clarify.

Substituting from (3) and using the fact that $P=1$, the (log) profit-maximizing problem of the technology monopolist for industry i can be obtained as

$$\max_{\{\theta(i),A(i)\}}\ln Y(L,S,M;\Theta)+\ln\left[1-G(\theta(i))\right]+\ln\left[1-H(A(i))\right]. \tag{9}$$

Intuitively, because each technology monopolist receives a constant share of the output of the industry it serves, it will receive a constant share of the increase in aggregate output resulting from its technology choices. Moreover, because there is a continuum of industries and each technology monopolist controls the technology for a single industry, in this maximization problem factor prices and machine demands are taken as given.

We can now define an *equilibrium with endogenous technology* as an equilibrium with exogenous technology (as described in the previous subsection) plus technology choices that maximize (9) or equivalently, that are a fixed point $\Theta^*=\{\theta(i)^*,A(i)^*\}_{i\in\mathcal{I}}$ such that

$$\{\theta(i)^*,A(i)^*\}\in\arg\max_{\{\theta(i),A(i)\}}\ln Y(L,S,M^E(L,S;\Theta^*);\Theta)+\ln\left[1-G(\theta(i))\right]+\ln\left[1-H(A(i))\right], \tag{10}$$

for $i\in\mathcal{I}$.

In preparation for the characterization of the equilibrium with endogenous technology, we first study the impact of changes in technologies on aggregate output, which determines the benefit from improving technology in (10).

Proposition 4

$$\frac{d\ln Y(L,S,M;\Theta)}{dA(i)}=\frac{1}{A(i)}\alpha(i)s_{iL}(\phi;\Theta)=\frac{1}{A(i)}\alpha(i)\frac{(1-\theta(i))W^E(\phi;\Theta)^{1-\zeta}}{(1-\theta(i))W^E(\phi;\Theta)^{1-\zeta}+\theta(i)(A(i)\gamma(i))^{1-\zeta}}>0,$$

where $s_{iL}(\phi;\Theta)$ is the share of middle-aged labor in the production of $X(i)$; and

$$\frac{d\ln Y(L,S,M;\Theta)}{d\theta(i)}=\alpha(i)\frac{1}{1-\zeta}\frac{W^E(\phi;\Theta)^{1-\zeta}-(A(i)\gamma(i))^{1-\zeta}}{(1-\theta(i))W^E(\phi;\Theta)^{1-\zeta}+\theta(i)(A(i)\gamma(i))^{1-\zeta}}>0,$$

if $W^E(\phi,\Theta)>A(i)\gamma(i)$, and $\frac{d\ln Y(L,S,M;\Theta)}{d\theta(i)}=0$ otherwise (where we have already substituted for $\widetilde{\theta}(i)=\theta(i)$ when $W^E(\phi;\Theta)\geq A\gamma(i)$).

PROOF. The results follow by differentiating $Y(L, S, M; \Theta)$ and then applying the envelope theorem. The details are provided in the Appendix. ■

To make further progress, let us also define $h(x) = \frac{H'(x)}{1-H(x)}$ and $g(x) = \frac{G'(x)}{1-G(x)}$. Because of the assumptions on H and G introduced above, these functions are increasing and have vertical asymptotes at $x = 1$. Then, given the ratio of senior to middle-aged workers ϕ, an equilibrium with endogenous technology, Θ^*, can be more simply defined by the following set of conditions

$$h(A(i)^*) \geq \frac{d \ln Y(L, S, M; \Theta^*)}{dA(i)} \qquad g(\theta(i)^*) \geq \frac{d \ln Y(L, S, M; \Theta^*)}{d\theta(i)}, \tag{11}$$

with complementary slackness (i.e., with equality for the first equation if $A(i)^* > 0$, and equality for the second equation if $\theta(i)^* > 0$).

The solution to (11) embeds quite rich interactions between the technology choices of different industries. For example, when the productivity effect dominates the displacement effect and automation increases the middle-aged wage (under conditions specified in Proposition 2), automation in one industry, by pushing up wages, encourages further automation in other industries. On the other hand, when the displacement effect is more powerful, automation reduces wages and discourages further automation, though it may in this case encourage improvements in labor-augmenting technologies. These equilibrium technology interactions make the characterization of the fixed points to (10) potentially challenging. However, the problem of characterizing equilibria with endogenous technology can be simplified by noting that all of the equilibrium interactions work through the wage of middle-aged workers, W.

Formally, let $\Theta^R(W) = \{A^R(i, W), \theta^R(i, W)\}_{i \in \mathcal{I}}$ denote equilibrium technology choices given the middle-aged wage, W. These technology choices satisfy

$$\begin{aligned} h(A^R(i, W)) \geq& \frac{1}{A^R(i, W)} \alpha(i) \frac{(1 - \theta^R(i, W)) W^{1-\zeta}}{(1 - \theta^R(i, W)) W^{1-\zeta} + \theta^R(i, W)(A^R(i, W)\gamma(i))^{1-\zeta}}. \\ g(\theta^R(i, W)) \geq& \alpha(i) \frac{1}{1-\zeta} \frac{W^{1-\zeta} - (A^R(i, W)(i)\gamma(i)P)^{1-\zeta}}{(1 - \theta^R(i, W)) W^{1-\zeta} + \theta^R(i, W)(A^R(i, W)\gamma(i))^{1-\zeta}} \end{aligned} \tag{12}$$

again with complementary slackness. The next lemma shows that they are also uniquely determined given W, and establishes a useful supermodularity property for (10).

LEMMA 2 *1. The set of technology choices given W, $\Theta^R(W) = \{A^R(i, W), \theta^R(i, W)\}_{i \in \mathcal{I}}$, is uniquely defined by the global maximum of (10).*

2. The profit-maximization problem of technology monopolists in (10) is supermodular in W, $\theta(i)$ and $-A(i)$, and thus the technology choices of the monopolist for industry i, $\theta^R(i, W)$ and $A^R(i, W)$, are, respectively, increasing and decreasing in W.

3. Moreover, $\lim_{W \to 0} \theta^R(i, W) = 0$ and $\lim_{W \to 0} A^R(i, W) = \overline{A}(i)$, where $h(\overline{A}(i))\overline{A}(i) = \alpha(i)$; and $\lim_{W \to \infty} A^R(i, W) = 0$.

Now, given the definition of $\Theta^R(W)$, the middle-aged wage W is consistent with equilibrium if and only if $W = W^E(\phi, \Theta^R(W))$, where W^E maps the ratio of senior to middle-aged workers and the set of technologies to the equilibrium wage. This formulation enables us to characterize the equilibrium in terms of a fixed point of the wage for middle-aged workers rather than a fixed point in the space of all technologies as in (10). The next proposition establishes the existence of an equilibrium with endogenous technology (when formulated in this manner), and also provides conditions for its uniqueness.

Proposition 5

1. *For any $\phi > 0$ there exists an equilibrium with endogenous technology. In any such equilibrium the wage, W^*, satisfies*

$$W^* = W^E(\phi, \Theta^R(W^*)) \tag{13}$$

Moreover, for each fixed point W^* there is a uniquely defined set of technology choices given by $\Theta^* = \Theta^R(W^*)$.

2. *Let $\bar{\zeta}$ be as defined in Proposition 3. Then there exists $\widetilde{\zeta} < \overline{\zeta}$, such that when $\zeta > \widetilde{\zeta}$, there is a unique fixed point W^* in equation (13) and thus a unique equilibrium with endogenous technology. Moreover, in this equilibrium we have $\frac{dW^E(\phi,\Theta^R(W^*))}{dW} < 1$. In contrast, when $\zeta < \widetilde{\zeta}$, there are multiple fixed points in equation (13) and thus multiple equilibria.*

Proof. See the Appendix. ■

Figures 4 and 5 illustrate the cases with multiple and unique equilibria. The force leading to multiplicity is the one already mentioned above—automation in one industry may encourage further automation in others. Our discussion above clarifies that this will be the case when there is a powerful productivity effect. The condition $\zeta > \widetilde{\zeta}$ ensures that different industries are highly substitutable, which in turn limits the extent of this productivity effect. Figure 4 also underscores that, since every equilibrium corresponds to a unique value of the middle-aged wage, W, and technology choices are monotone in W (in view of the supermodularity in Lemma 2), there always exists a least and a greatest equilibrium.

The next proposition studies the implications of aging—an increase in ϕ—on technology choices, which follows from the supermodularity property established in Lemma 2.

Proposition 6

1. *Suppose $\zeta > \widetilde{\zeta}$. Then an increase in ϕ—aging—increases the equilibrium wage W^*, reduces labor-augmenting technologies, $\{A(i)^*\}_{i\in\mathcal{I}^+}$, and increases automation technologies $\{\theta(i)^*\}_{i\in\mathcal{I}^+}$ where $\mathcal{I}^+$ is the set of industries with $\theta(i)^* > 0$.*

2. *Suppose $\zeta < \widetilde{\zeta}$. Then in the least or the greatest equilibrium, an increase in ϕ—aging—increases the equilibrium wage W^*, reduces labor-augmenting technologies, $\{A(i)^*\}_{i\in\mathcal{I}^+}$, and increases automation technologies $\{\theta(i)^*\}_{i\in\mathcal{I}^+}$ where $\mathcal{I}^+$ is the set of industries with $\theta(i)^* > 0$.*

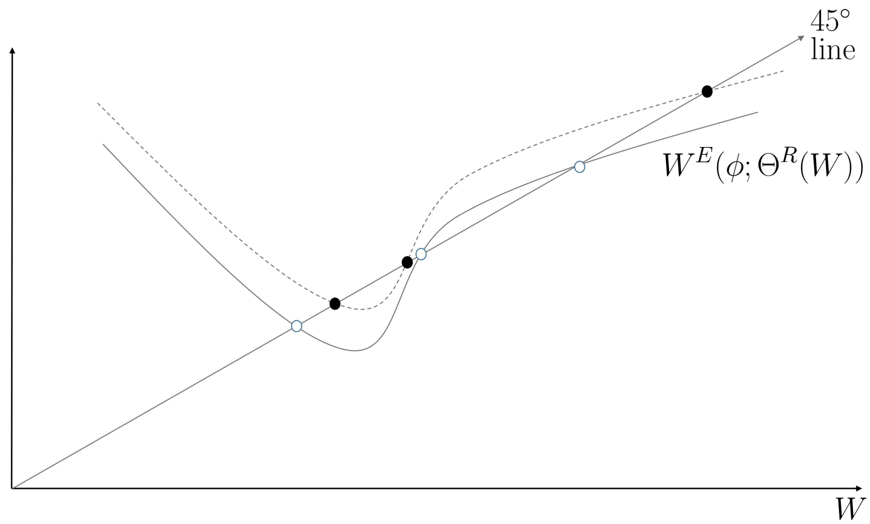

FIGURE 4: Determination of the wage of middle-aged workers in the equilibrium with endogenous technology. Aging shifts the mapping W^E up, and this increases the equilibrium wage in the least and the greatest equilibrium.

This proposition thus provides one of our most important results—aging always encourages automation, and this is regardless of whether 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) and also regardless of whether automation has a positive or negative effect on the wage of middle-aged workers. 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 thus developing automation technologies.

Finally, in the next proposition, we derive how the responsiveness of technologies to aging depends on the importance of middle-aged workers relative to senior workers and the baseline productivity of middle-aged workers when $\theta(i)^* \approx 0$ (where this case is useful for shutting off second-order effects which complicate these comparative statics).

PROPOSITION 7 *For* $\theta(i)^* > 0$*, we have*

$$\frac{d\theta(i)^*}{d\phi} = \frac{\alpha(i)\gamma(i)^{1-\zeta}W^{*\zeta-1}}{g'(0)}\frac{d\ln W^*}{d\phi} + \mathcal{O}(\theta(i)^*).$$

Thus when $\theta(i)^* \approx 0$*, 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 potential for automation (i.e., those with low* $\gamma(i)$*).*

Both of the implications in this proposition will be investigated in our empirical work. Though the latter—that investments in robotics technology will be more pronounced in in-

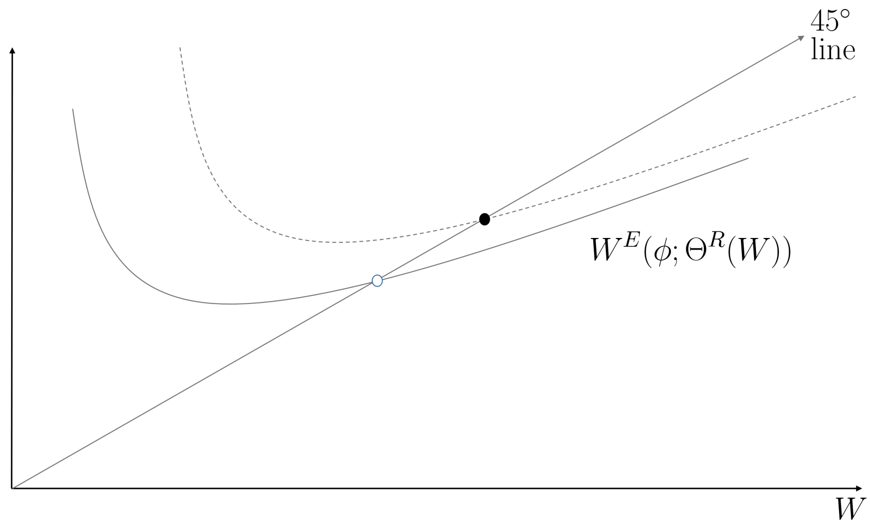

FIGURE 5: Impact of aging on the wage of middle-aged workers when the equilibrium with endogenous technology is unique.

dustries 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 already noted in the context of Proposition 2, the implications of aging for productivity are ambiguous. Nevertheless, when technology is endogenous, the relative changes in productivity across industries can be linked to industry characteristics, providing us with additional empirical predictions. In particular, with endogenous technology, the effect of aging on the output of industry i (with $\theta(i)^* > 0$) can be obtained as

$$\begin{aligned}\frac{d\ln Y(i)}{d\phi} =& \frac{d\ln y^E(\phi;\Theta)}{d\phi} - \frac{d\ln V^E(\phi;\Theta)}{d\phi} + \alpha(i)\left(\frac{d\ln V^E(\phi;\Theta)}{d\phi} - s_{Li}\frac{d\ln W^E(\phi;\Theta)}{d\phi}\right)\\ &+ \alpha(i)\frac{1}{1-\zeta}\frac{W^{1-\zeta}-\gamma(i)^{1-\zeta}}{(1-\theta(i))W^{1-\zeta}+\theta(i)\gamma(i)^{1-\zeta}}\frac{d\theta(i)^*}{d\phi},\end{aligned}$$

where the second line is the endogenous technology effect. The most important observation here is that because of this endogenous technology effect we expect the impact of aging on the change in productivity to be greater in industries that present greater opportunities for automation. To see this, let us compare two industries with different values of $\gamma(i)$—and with the same values for all aggregate variables. The last term on the first line and the term on the second line are greater for the industry with lower $\gamma(i)$ (because aging increases the wage of middle-aged workers and the share of middle-aged labor in production tasks, s_{Li}, is increasing in $\gamma(i)$; and because the numerator of the second line is decreasing and the denominator is increasing in $\gamma(i)$. This implies that, though the aggregate effects of aging are ambiguous, aging should increase productivity in industries with greater opportunities for automation— i.e., those with low $\gamma(i)$—relative to the rest.

On the other hand, the effect of greater reliance on middle-aged workers ($\alpha(i)$) is ambiguous: industries with larger $\alpha(i)$ suffer a greater direct effect, but they may benefit from their greater incentives to adopt robots in response to demographic change.

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.[10]

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 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 6, 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 (55 and older) workers to middle-aged workers (between 20 and 54). This measure is motivated by the patterns of substitution between robots and workers we

[10] 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.

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 7 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.[11] 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 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

[11] 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.

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.[12] 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).[13] 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 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

[12] 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.

[13] 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.

largest increase in the number of robots per thousand workers.

Figure 8 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.[14]

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).[15] We follow the same strategy here and construct the exposure to robots measure as

$$\begin{array}{l}\textit{Exposure to robots} \\ \textit{from 1993 to 2007}_z\end{array} = \sum_{i \in \mathcal{I}} \ell_{zi}^{1970} \left(p_{30}\left(\frac{R_{i,2007}}{L_{i,1990}}\right) - p_{30}\left(\frac{R_{i,1993}}{L_{i,1990}}\right) \right), \tag{14}$$

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.[16]

Figure 9 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

[14] 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.

[15] 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.

[16] 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.

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 (annualized) 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 (annualized) 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.[17] 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.[18] In Figure A1 in the Appendix, we report similar results by five-year age bins, confirming these age thresholds.

Overall, the results in this section 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.

[17] 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).

[18] 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.

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

$$\Delta \frac{R_c}{L_c} = \beta_y \Delta \ln \text{Young}_c + \beta_m \Delta \ln \text{Middle-aged}_c + \beta_o \Delta \ln \text{Old}_c + \Gamma X_{c,1990} + \varepsilon_c, \tag{15}$$

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 (15). 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.[19] 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.[20] Columns 4-6 parallel the first

[19]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.

[20]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 $\ln(1 + R_c)$

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.[21]

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.

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

$$\Delta \frac{R_c}{L_c} = \beta \text{Aging}_c + \Gamma X_{c,1990} + \varepsilon_c, \tag{16}$$

where the key difference from specification (15) 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

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).

[21] 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.

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 (16) 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 10 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 11 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.[22] 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 installations. Table 8 presents estimates of the model

$$\frac{IR_{c,t}}{L_{c,1990}} = \beta \text{Aging}_{c,2025-1990} + \Gamma_t X_{c,1990} + \delta_t + \varepsilon_{c,t}, \tag{17}$$

where the left-hand side variable, in contrast to equation (16), 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

[22] 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).

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 (17) 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 (16) but using log of imports in that category normalized by total intermediate imports as the dependent variable.[23] 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, 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 12.[24] The estimates in column 1 of Table 9 confirm the patterns we have documented so

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

[24] 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

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 13 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.[25] 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 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

since these services are typically provided by local integrators, they do not show up in import statistics).

[25] 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.

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 9 (see footnote 17).

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 14 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 (17) by including interaction effects:

$$\begin{aligned}\frac{IR_{i,c,t}}{L_{i,c,1990}} =& \beta \text{Aging}_c + \beta_R \text{Aging}_c \times \text{Reliance on Middle-Aged Workers}_i \\ &+ \beta_P \text{Aging}_c \times \text{Opportunities for Automation}_i + \Gamma_{i,t} X_{c,1990} + \alpha_i + \delta_t + \varepsilon_{i,c,t},\end{aligned} \tag{18}$$

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. 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.[26] Finally, we report standard

[26] 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).

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 (18) 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 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.[27]

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 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.

[27] 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.

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:

$$\begin{aligned}\Delta \ln VA_{i,c} =& \beta \text{Aging}_c + \beta_R \text{Aging}_c \times \text{Reliance on middle-aged workers}_i \\ &+ \beta_P \text{Aging}_c \times \text{Potential for the use of robots}_i + \Gamma_i X_{c,1995} + \alpha_i + \varepsilon_{i,c},\end{aligned} \tag{19}$$

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 2015 (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 (19) 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 (19) 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

Equilibrium characterization

We start by providing more details on the characterization of the equilibrium with exogenous technology, which was outlined in the text.

The first-order condition for the final good producer yields

$$Y = P_{Y(i)}Y(i),$$

while the first-order conditions for producers in industry i imply

$$\alpha(i)P_{Y(i)}Y(i) = P_{X(i)}X(i) \qquad (1-\alpha(i))P_{Y(i)}Y(i) = VS(i).$$

Using these equations, demand for middle-aged workers, for senior workers and for machines in industry i can be derived as follows

$$\begin{aligned} L(i) =& \int_{\widetilde{\theta}(i)}^{1} l(i,s)ds \\ =& \int_{\widetilde{\theta}(i)}^{1} \frac{X(i,s)}{A(i)\gamma(i)}ds \\ =& \int_{\widetilde{\theta}(i)}^{1} X(i)P_{X(i)}^{\zeta}W^{-\zeta}(A(i)\gamma(i))^{\zeta-1}ds \\ =& (1-\widetilde{\theta}(i))X(i)P_{X(i)}^{\zeta}W^{-\zeta}(A(i)\gamma(i))^{\zeta-1} \\ =& (1-\widetilde{\theta}(i))YP_{X(i)}^{\zeta-1}W^{-\zeta}(A(i)\gamma(i))^{\zeta-1}, \end{aligned}$$

and

$$S(i) = (1-\alpha(i))V^{-1},$$

and

$$\begin{aligned} M(i) =& \int_{0}^{\widetilde{\theta}(i)} m(i,s)ds \\ =& \widetilde{\theta}(i)X(i)P_{X(i)}^{\zeta}P^{-\zeta} \\ =& \widetilde{\theta}(i)YP_{X(i)}^{\zeta-1}P^{-\zeta}. \end{aligned}$$

The expressions for L^d, M^d and S^d in the main text follow by integrating these demands across all industries.

In addition, the wage for middle-aged workers and the price of machines satisfy the following first-order conditions:

$$W = \left[(1-\widetilde{\theta}(i))\frac{X(i)}{L(i)}\right]^{\frac{1}{\zeta}}(A(i)\gamma(i))^{\frac{\zeta-1}{\zeta}}P_{X(i)} \qquad P = \left[\widetilde{\theta}(i)\frac{X(i)}{M(i)}\right]^{\frac{1}{\zeta}}P_{X(i)} \tag{A1}$$

Because $X(i)$ is priced at the marginal cost of production, $P_{X(i)}$ satisfies equation (6). To derive equation (4) in the main text, we replace the expressions for W and P given in equation (A1) into equation (6) and solve for $X(i)$.

Proof of Lemma 1

We first show that any equilibrium allocations satisfies the first-order conditions to the maximization problem in Lemma 1 with the Lagrange multipliers as usual reflecting equilibrium prices. In particular, since the maximization problem in the lemma involves the log of aggregate output, the Lagrange multipliers will correspond to the relevant prices divided by aggregate output— i.e., for the constraint on $Y(i)$, $\frac{P_{Y(i)}}{Y}$; for the constraint on L, $\frac{W}{Y}$; for the constraint on M,$\frac{P}{Y}$; and for the constraint on S, $\frac{V}{Y}$.

Now evaluating the first-order conditions with respect to $Y(i)$ and $S(i)$, and using the values of the Lagrange multipliers given in the previous paragraph, we have that for all $i \in \mathcal{I}$,

$$\frac{1}{Y(i)} = \frac{P_{Y(i)}}{Y},$$

and

$$\frac{P_{Y(i)}}{Y}(1-\alpha(i))\frac{Y(i)}{S(i)} = \frac{V}{Y},$$

which coincide with the optimality conditions for final good producers and the demand for senior workers from industry i

Similarly, using equation (4), the first-order condition with respect to $L(i)$ (again evaluated at the same values of the Lagrange multipliers given above) is

$$\begin{aligned}
\frac{W}{Y} =& \frac{P_{Y(i)}}{Y}\frac{\partial Y(i)}{\partial L(i)} \\
=& \frac{P_{Y(i)}}{Y}\alpha(i)\frac{Y(i)}{X(i)}\left[(1-\widetilde{\theta}(i))\frac{X(i)}{L(i)}\right]^{\frac{1}{\zeta}}(A(i)\gamma(i))^{\frac{\zeta-1}{\zeta}} \\
=& \frac{1}{Y}\frac{\alpha(i)P_{Y(i)}Y(i)}{P_{X(i)}X(i)}\left[(1-\widetilde{\theta}(i))\frac{X(i)}{L(i)}\right]^{\frac{1}{\zeta}}(A(i)\gamma(i))^{\frac{\zeta-1}{\zeta}}P_{X(i)} \\
=& \frac{1}{Y}\left[(1-\widetilde{\theta}(i))\frac{X(i)}{L(i)}\right]^{\frac{1}{\zeta}}(A(i)\gamma(i))^{\frac{\zeta-1}{\zeta}}P_{X(i)},
\end{aligned}$$

which is equivalent to the formula for W derived in equation (A1), thus again matching equilibrium conditions.

Next turning the first-order condition with respect to $M(i)$, we have

$$\begin{aligned}
\frac{P}{Y} =& \frac{P_{Y(i)}}{Y}\frac{\partial Y(i)}{\partial M(i)} \\
=& \frac{P_{Y(i)}}{Y}\alpha(i)\frac{Y(i)}{X(i)}\left[\widetilde{\theta}(i)\frac{X(i)}{M(i)}\right]^{\frac{1}{\zeta}} \\
=& \frac{1}{Y}\frac{\alpha(i)P_{Y(i)}Y(i)}{P_{X(i)}X(i)}\left[\widetilde{\theta}(i)\frac{X(i)}{M(i)}\right]^{\frac{1}{\zeta}}P_{X(i)} \\
=& \frac{1}{Y}\left[\widetilde{\theta}(i)\frac{X(i)}{M(i)}\right]^{\frac{1}{\zeta}}P_{X(i)},
\end{aligned}$$

which is equivalent to the formula for P derived in equation (A1), once again verifying the relevant equilibrium conditions.

Finally, the optimality condition for $\theta(i)$ in the maximization problem is $\widetilde{\theta}(i) = 0$ if $W < A(i)\gamma(i)P$ and $\widetilde{\theta}(i) = \theta(i)$ if $W > A(i)\gamma(i)P$, which coincides with the equilibrium allocation of tasks to factors in equation (5).

Because the objective function in Lemma 1 is strictly concave and the set of constraints is convex, the first-order conditions uniquely define the maximum, which thus coincides with the unique solution to the set of equilibrium conditions provided in the text. ■

Proof of Proposition 1

Part 1: The function $Y(L, S, M; \Theta)$ maximizes a strictly concave function of M subject to a constraint that is linear in M, and thus this function is strictly concave in M. Therefore, $Y_M(L, S, M; \Theta)$ is decreasing in M, and thus there is at most a unique $M(L, S; \Theta)$ such that $Y_M(L, S, M(L, S; \Theta)); \Theta) = 1$ (or $M(L, S; \Theta) = 0$ if $Y_M(L, S, M); \Theta) < 1$ for all M). This establishes the existence and uniqueness of the equilibrium demand for machines, $M(L, S; \Theta)$. Given $M(L, S; \Theta)$, the equilibrium allocation is unique and also given by the unique global maximum of the maximization problem in Lemma 1.

Part 2: Let us rewrite the market-clearing condition for middle-aged workers as

$$\begin{aligned}
L =& Y \int_{i\in\mathcal{I}} (A(i)\gamma(i))^{\zeta-1}\alpha(i)(1-\widetilde{\theta}(i))P_{X(i)}^{\zeta-1}W^{-\zeta}di \\
(1-\phi) =& y \int_{i\in\mathcal{I}} (A(i)\gamma(i))^{\zeta-1}\alpha(i)(1-\widetilde{\theta}(i))P_{X(i)}^{\zeta-1}W^{-\zeta}di \\
W(1-\phi) =& y \int_{i\in\mathcal{I}} \alpha(i)(1-\widetilde{\theta}(i)) {\frac{W}{A(i)\gamma(i)}}^{1-\zeta} P_{X(i)}^{\zeta-1}di \\
W(1-\phi) =& y \int_{i\in\mathcal{I}} \alpha(i) \frac{(1-\widetilde{\theta}(i)){\frac{W}{A(i)\gamma(i)}}^{1-\zeta}}{(1-\widetilde{\theta}(i)){\frac{W}{A(i)\gamma(i)}}^{1-\zeta} + \widetilde{\theta}(i)} di \\
W(1-\phi) =& y \int_{i\in\mathcal{I}} \alpha(i) \frac{(1-\theta(i))W^{1-\zeta}}{(1-\theta(i))W^{1-\zeta} + \theta(i)\min\{A(i)\gamma(i), W\}^{1-\zeta}} di.
\end{aligned}$$

This establishes equation (7). We can verify easily that this is an upward-sloping curve in the (y, W) space.

To derive the ideal price index condition in equation (8), recall that the final good is the numeraire, and thus

$$\int_{i\in\mathcal{I}} \ln P_{Y(i)} di = 0.$$

Moreover, we have

$$\ln P_{Y(i)} = \ln \frac{1-\eta}{2-\eta} + \alpha(i)\ln P_{X(i)} + (1-\alpha(i))\ln V.$$

Now, the market-clearing condition for senior workers implies

$$\ln V = \ln y - \ln \phi + \ln \left(\int_{i \in \mathcal{I}} (1 - \alpha(i)) di \right). \tag{A2}$$

Combining the last three equations we obtain

$$\begin{aligned} 0 &= \int_{i \in \mathcal{I}} \ln P_{Y(i)} di \\ &= \ln \frac{1-\eta}{2-\eta} + \int_{i \in \mathcal{I}} \alpha(i) \frac{1}{1-\zeta} \ln \left((1-\theta(i)) \left(\frac{W}{A(i)\gamma(i)} \right)^{1-\zeta} + \theta(i) \min \left\{ 1, \frac{W}{A(i)\gamma(i)} \right\}^{1-\zeta} \right) di \\ &\quad + \left(\ln y - \ln \phi + \ln \left(\int_{i \in \mathcal{I}} (1-\alpha(i)) di \right) \right) \int_{i \in \mathcal{I}} (1-\alpha(i)) di. \end{aligned}$$

This establishes (8) and also shows that

$$\mu = \ln \frac{2-\eta}{1-\eta} - \ln \left(\int_{i \in \mathcal{I}} (1-\alpha(i)) di \right) \int_{i \in \mathcal{I}} (1-\alpha(i)) di.$$

Moreover, clearly, (8) is a downward-sloping curve in the (y, W) space. Therefore, the two curves (7) and (8) can intersect at most once.

That an intersection must exist follows by noting that equation (7) passes through the point (0,0), and as $y \to \infty$, we have $W \to \infty$ (this follows because otherwise as $y \to \infty$, W would converge to a finite value, but then the right-hand side of equation (7) would diverge, yielding a contradiction) move left. In addition, in (8), as $y \to 0$, we have $W > 0$; and as $y \to \infty$, we have $W \to 0$. Thus, in the (y, W) space, the market-clearing curve for middle-aged workers starts below the ideal price index condition and ends above it, guaranteeing that the two curves intersect.

Finally, for the unique (y^E, W^E) that satisfy (7) and (8), the equilibrium values of the other variables can be computed recursively as follows. Senior wages are given by $V = \frac{y}{\phi} \int_{i \in \mathcal{I}} (1 - \alpha(i)) di$. The threshold tasks $\widetilde{\theta}(i)$ can be computed from equation (5). Prices $P_{X(i)}$ can be computed from equation (6). And finally, the allocation of factors to sectors can be computed using the demand for factors by industry derived above; namely, $L(i) = (1 - \widetilde{\theta}(i)) Y P_{X(i)}^{\zeta-1} W^{-\zeta} (A(i)\gamma(i))^{\zeta-1}$, $M(i) = \widetilde{\theta}(i) Y P_{X(i)}^{\zeta-1} P^{-\zeta}$, and $S(i) = (1 - \alpha(i)) V^{-1}$. ■

Proof of Proposition 2

As shown in Figure 2, an increase in ϕ shifts both the market-clearing condition for middle-aged workers in equation (7) and the ideal price index condition in equation (8) upwards. Thus, ϕ raises the equilibrium wage of middle-aged workers, W.

To derive the impact on V, let us rewrite equation (7) as

$$W \frac{1-\phi}{\phi} = \frac{V}{\int_{i \in \mathcal{I}} (1-\alpha(i)) di} \int_{i \in \mathcal{I}} \alpha(i) \frac{(1-\theta(i)) \left(\frac{W}{A(i)\gamma(i)} \right)^{1-\zeta}}{(1-\theta(i)) \left(\frac{W}{A(i)\gamma(i)} \right)^{1-\zeta} + \theta(i) \min \left\{ P, \frac{W}{A(i)\gamma(i)} \right\}^{1-\zeta}} di; \tag{A3}$$

and also rewrite (8) as

$$\int_{i\in\mathcal{I}} \alpha(i)\frac{1}{1-\zeta}\ln\left((1-\theta(i))\left(\frac{W}{A(i)\gamma(i)}\right)^{1-\zeta}+\theta(i)\min\left\{P,\frac{W}{A(i)\gamma(i)}\right\}^{1-\zeta}\right)di \tag{A4}$$

$$+\ln V\int_{i\in\mathcal{I}}(1-\alpha(i))di=\ln\frac{2-\eta}{1-\eta}$$

In the (V,W) space, an increase in ϕ shifts the market-clearing condition for middle-aged workers in equation (A3) upwards, but does not affect (A4). Thus, ϕ raises the equilibrium wage for middle-aged workers, W, but lowers the wage of senior workers, V.

Finally, because $Y(L,S,M;\Theta)$ exhibits constant returns to scale, we can write

$$y^E(\phi;\Theta)=Y(1-\phi,\phi,m^E(\phi;\Theta);\Theta), \qquad \text{and} \qquad m^E(\phi;\Theta)=M(1-\phi,\phi;\Theta).$$

Thus,

$$\begin{aligned} y^E_\phi(\phi,\Theta)=&Y_S(1-\phi,\phi,m^E(\phi;\Theta);\Theta)-Y_L(1-\phi,\phi,m^E(\phi;\Theta);\Theta)+Y_M m^E_\phi(\phi;\Theta)\\ =&V^E(\phi;\Theta)-W^E(\phi;\Theta)+Pm^E_\phi(\phi;\Theta). \end{aligned}$$

■

Proof of Proposition 3

Part 1: Let $\mathcal{I}^{++}$ denote the set of industries that increase automation. In Figure 3, the increase in automation shifts both the market-clearing condition for middle-aged workers, equation (7), and the ideal price index condition, equation (8), to the right. Therefore, automation always increases aggregate output per worker, y^E, and from equation (A2), it also increases V^E. The characterize the effect on W^E, note that the shift in (8) can be expressed as

$$\begin{aligned} d\ln y\mid_W =&\frac{1}{\int_{i\in\mathcal{I}}(1-\alpha(i))di}\int_{i\in\mathcal{I}^{++}}\alpha(i)\frac{1}{\zeta-1}\frac{P^{\zeta-1}-\left(\frac{W}{A(i)\gamma(i)}\right)^{\zeta-1}}{(1-\theta(i))P^{\zeta-1}+\theta(i)\left(\frac{W}{A(i)\gamma(i)}\right)^{\zeta-1}}di \\ <&\frac{\int_{i\in i\in\mathcal{I}}\alpha(i)di}{\int_{i\in\mathcal{I}}(1-\alpha(i))di}\max_{i\in\mathcal{I}^{++}}\left\{\frac{1}{\zeta-1}\frac{P^{\zeta-1}-\left(\frac{W}{A(i)\gamma(i)}\right)^{\zeta-1}}{(1-\theta(i))P^{\zeta-1}+\theta(i)\left(\frac{W}{A(i)\gamma(i)}\right)^{\zeta-1}}\right\}. \end{aligned} \tag{A5}$$

As $\zeta\to\infty$, $d\ln y\mid_W$ in (A5) converges to zero. By continuing key, this implies that there exists $\bar{\zeta}$, such that the above this threshold is dominated by the shift of the market-clearing condition for middle-aged workers, (7), and thus W decreases. Moreover, (A5) is increasing in $\int_{i\in\mathcal{I}^{++}}\alpha(i)di$, $\bar{\zeta}$ is decreasing in $\int_{i\in\mathcal{I}^{++}}\alpha(i)di$.

Part 2: Increases in $A(i)$ for a set of positive measure industries shift the market-clearing condition for middle-aged workers, equation (7), and the ideal price index condition, (8), upwards. This leads to an increase in the middle-age wage, W^E. We will show in the proof of Proposition 4 that aggregate output per worker, y^E, will also increase, and again from (A2), the wage of senior workers, V^E, also increases. ■

Proof of Proposition 4

Using the envelope theorem, we have

$$\begin{aligned}\frac{d\ln Y(L,S,M;\Theta)}{dA(i)} &= \frac{P_{Y(i)}}{Y}\frac{\partial Y(i)}{\partial A(i)}\Big|_{S(i),L(i),M(i)}\\ &= \frac{1}{A(i)}\frac{\partial \ln Y(i)}{\partial \ln A(i)}\Big|_{S(i),L(i),M(i)}\\ &=\frac{1}{A(i)}\alpha(i)s_{iL}(\phi;\Theta)\\ &=\frac{1}{A(i)}\alpha(i)\frac{(1-\theta(i))W^E(\phi;\Theta)^{1-\zeta}}{(1-\theta(i))W^E(\phi;\Theta)^{1-\zeta}+\theta(i)(A(i)\gamma(i))^{1-\zeta}}>0.\end{aligned}$$

Moreover, for industries $W > A(i)\gamma(i)$, another application of the envelope theorem yields

$$\begin{aligned}\frac{d\ln Y(L,S,M;\Theta)}{d\theta(i)} &= \frac{P_{Y(i)}}{Y}\frac{\partial Y(i)}{\partial \theta(i)}\Big|_{S(i),L(i),M(i)}\\ &= \frac{\partial \ln Y(i)}{\partial \theta(i)}\Big|_{S(i),L(i),M(i)}\\ &=\alpha(i)\frac{1}{1-\zeta}\frac{W^E(\phi;\Theta)^{1-\zeta}-(A(i)\gamma(i)P)^{1-\zeta}}{(1-\theta(i))W^E(\phi;\Theta)^{1-\zeta}+\theta(i)(A(i)\gamma(i)P)^{1-\zeta}}>0.\end{aligned}$$

■

Proof of Lemma 2

Part 1: $\theta^R(i,W)$ and $A^R(i,W)$ are maximizers of (10), which is strictly concave, and thus are uniquely defined, and also satisfy the necessary and sufficient conditions given in the first-order conditions, equation (12).

Part 2: Supermodularity of profits in (10) in W, $\theta(i)$ and $-A(i)$ can be verified directly from the first-order conditions in equation (12). Supermodularity thus ensures that $\theta^R(i,W)$ is nondecreasing in W, while $A^R(i,W)$ is non-increasing in W.

Part 3: From part 1, $\theta^R(i,W)$ and $A^R(i,W)$ are solutions to the set of first-order conditions in equation (12).

Let us define $\overline{A}(i)$ as the unique solution to $h(\overline{A}(i))\overline{A}(i) = \alpha(i)$, which sets the last term in the relevant first-order condition in (12), which is equal to the share of labor and industry i, to 1 Clearly, therefore, $A^R(i,W) \leq \overline{A}(i)$. Suppose that $\frac{W}{\gamma(i)P} < \overline{A}$. Because $A^R(i,W) < \overline{A}$, we have $W < A^R(i,W)\gamma(i)P$, and thus when $W < \overline{A}\gamma(i)P$, we also have $\theta^R(i,W) = 0$.

Finally, suppose that $W \to \infty$. For any $\theta^R(i,W) > 0$ the right-hand side of the first-order condition for $A^R(i,W)$ in equation (12) converges to zero. Thus, we have two possibilities: first, $\lim_{W\to\infty}\theta^R(i,W) = 0$; or second, $\lim_{W\to\infty}A^R(i,W) = 0$. To rule out the first possibility, note that the first-order condition for $A^R(i,W)$ in equation (12) shows that in this case we must have $A^R(i,W) = \overline{A}$. But this implies that eventually $W > \overline{A}\gamma(i)P$ and the first-order condition for

$\theta^R(i,W)$ in equation (12) is violated at $\theta^R(i,W)=0$, yielding a contradiction and establishing that we must be in the second case and thus $\lim_{W\to\infty} A^R(i,W)=0$. ■

Proof of Proposition 5

Part 1: To prove the existence of an equilibrium we analyze the properties of the function $W^E(\phi,\Theta^R(W))$ when $W=0$ and $W\to\infty$.

Lemma 2 shows that for $W<\min_{i\in\mathcal{I}}\overline{A}(i)\gamma(i)P$ we have that $\theta^R(i,W)=0$ and $A^R(i,W)=\overline{A}$. Thus, $W^E(\phi,\Theta^R(0))>0$. It also established that $\lim_{W\to\infty} A^R(i,W)=0$ and $\lim_{W\to\infty}\theta^R(i,W)>0$. The market-clearing condition for middle-aged workers, (7), then implies that if $A(i)=0$ for all $i\in\mathcal{I}$, we must have $W=0$. Thus, $\lim_{W\to\infty} W^E(\phi,\Theta^R(W))=0$

The above observations show that the curve $W^E(\phi,\Theta^R(W))$ starts above the 45 degree line and ends below it. Thus, there exists a solution to $W=W^E(\phi,\Theta^R(W))$.

Part 2: We show that if the wage decreases with automation, the mapping $W^E(\phi,\Theta^R(W))$ is nonincreasing. Suppose that automation reduces W. Lemma 2 also shows that $A^R(i,W)$ is nonincreasing and $\theta^R(i,W)$ is nondecreaing in W (for all i). This implies that the map $W^E(\phi,\Theta^R(W))$ is nonincreasing.

Now recall that Proposition 3 implies that for $\zeta>\overline{\zeta}$, $W^E(\phi,\Theta^R(W))$ is nonincreasing, and must have a unique intersection with the 45 degree line, establishing uniqueness in this case. By continuity, this also implies that there exists another threshold $\widetilde{\zeta}<\bar{\zeta}$ such that, for $\zeta>\widetilde{\zeta}$, the map W^E is no longer nonincreasing, but still intersects the 45 degree line only from above, and thus uniqueness still applies. Conversely, below this threshold, there are multiple intersections and equilibria. In the case of multiple equilibria, the existence of at least and greatest equilibrium follows from the fact that $A^R(i,W)$ is nonincreasing and $\theta^R(i,W)$ is nondecreaing in W (for all i). (Note that we could have $\widetilde{\zeta}=1$, in which case the equilibrium is unique whenever Assumption 1 holds). ■

Proof of Proposition 6

Both parts of this proposition follow directly from Topkis's Monotonicity theorem (Topkis, 1998) given that, from Proposition 2, an increase in ϕ shifts the map $W^E(\phi,\Theta^R(W))$ up (as shown in Figures 5 and 4). ■

Additional References:

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

Main Figures and Tables:

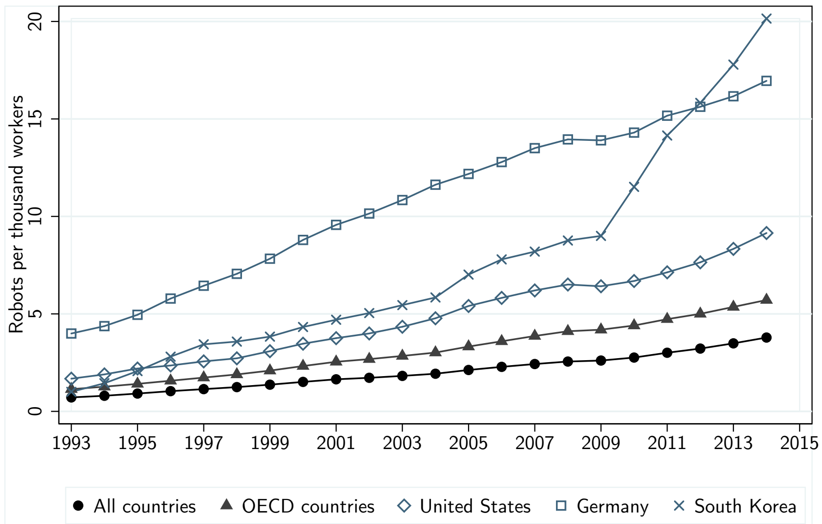

Figure 6: Worldwide trends in robot adoption from the IFR.

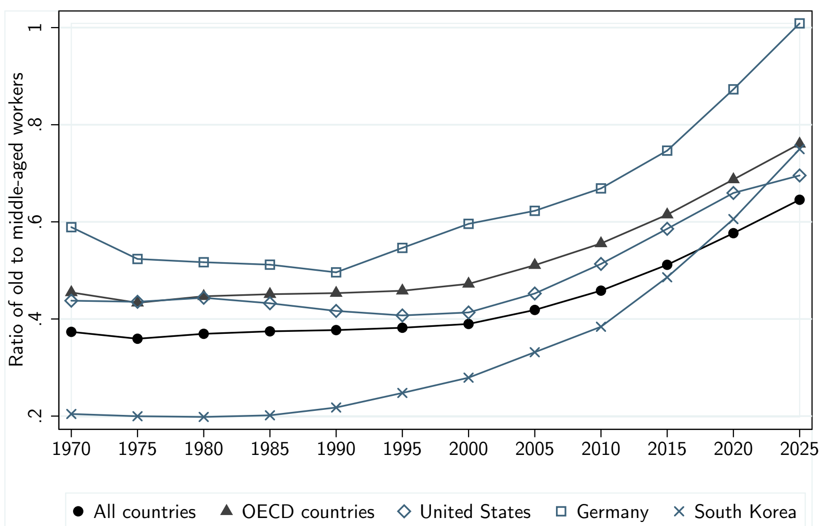

Figure 7: Worldwide aging trends using UN data on population by age groups and forecasts of demographic change.

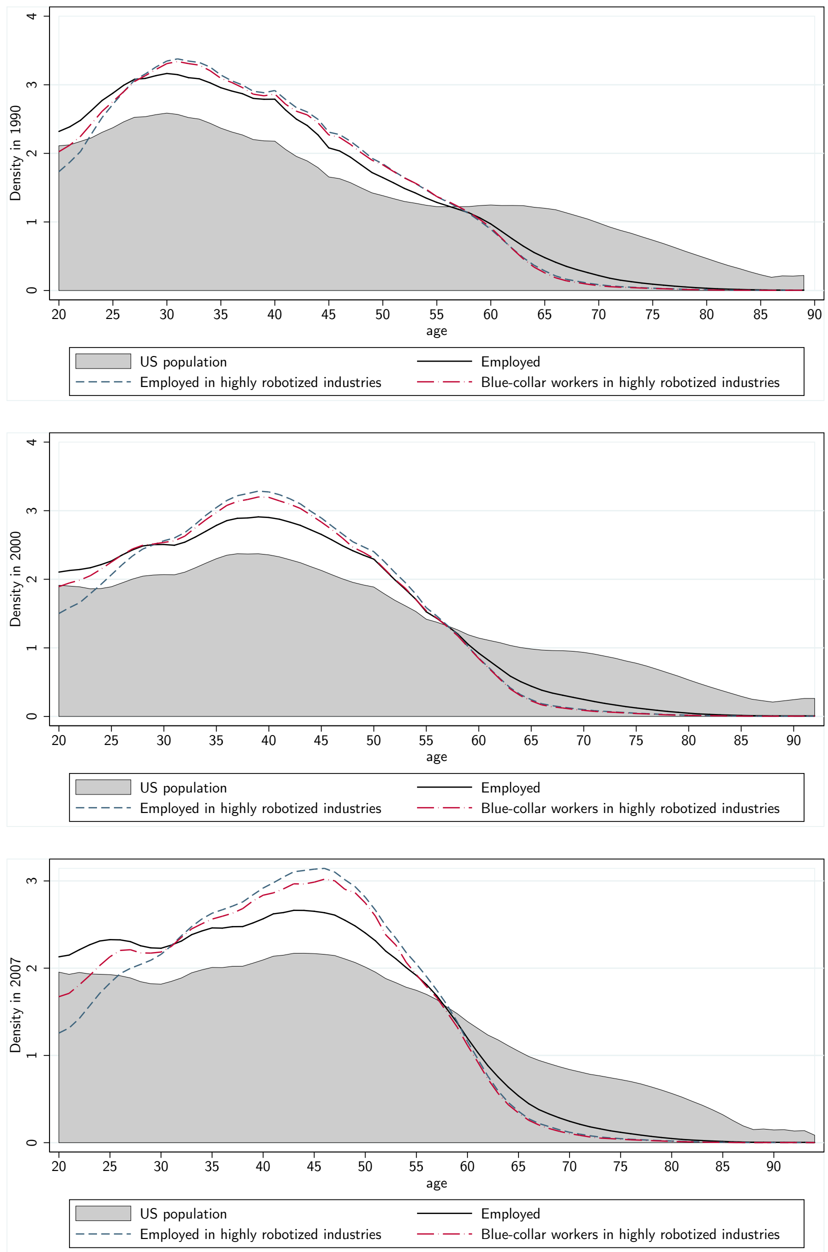

FIGURE 8: U.S. age distribution among the population, employees, and employees in highly robotized industries. The top panel presents the age distributions for 1990. The middle panel presents the age distributions for 2000. The bottom panel presents the age distributions for 2007.

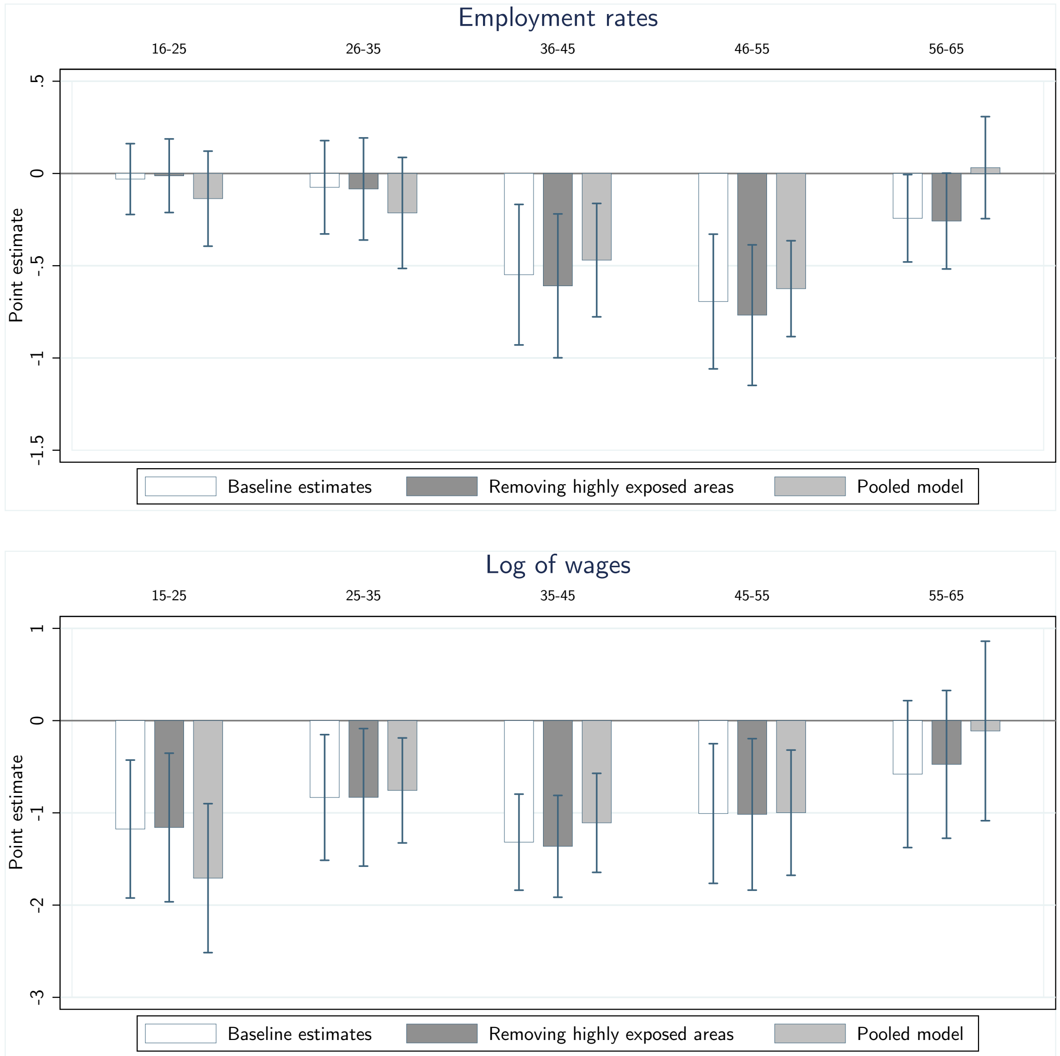

FIGURE 9: Estimated impact of one additional robot per thousand workers on employment. The figure plots the estimates for different age groups and for men separately.

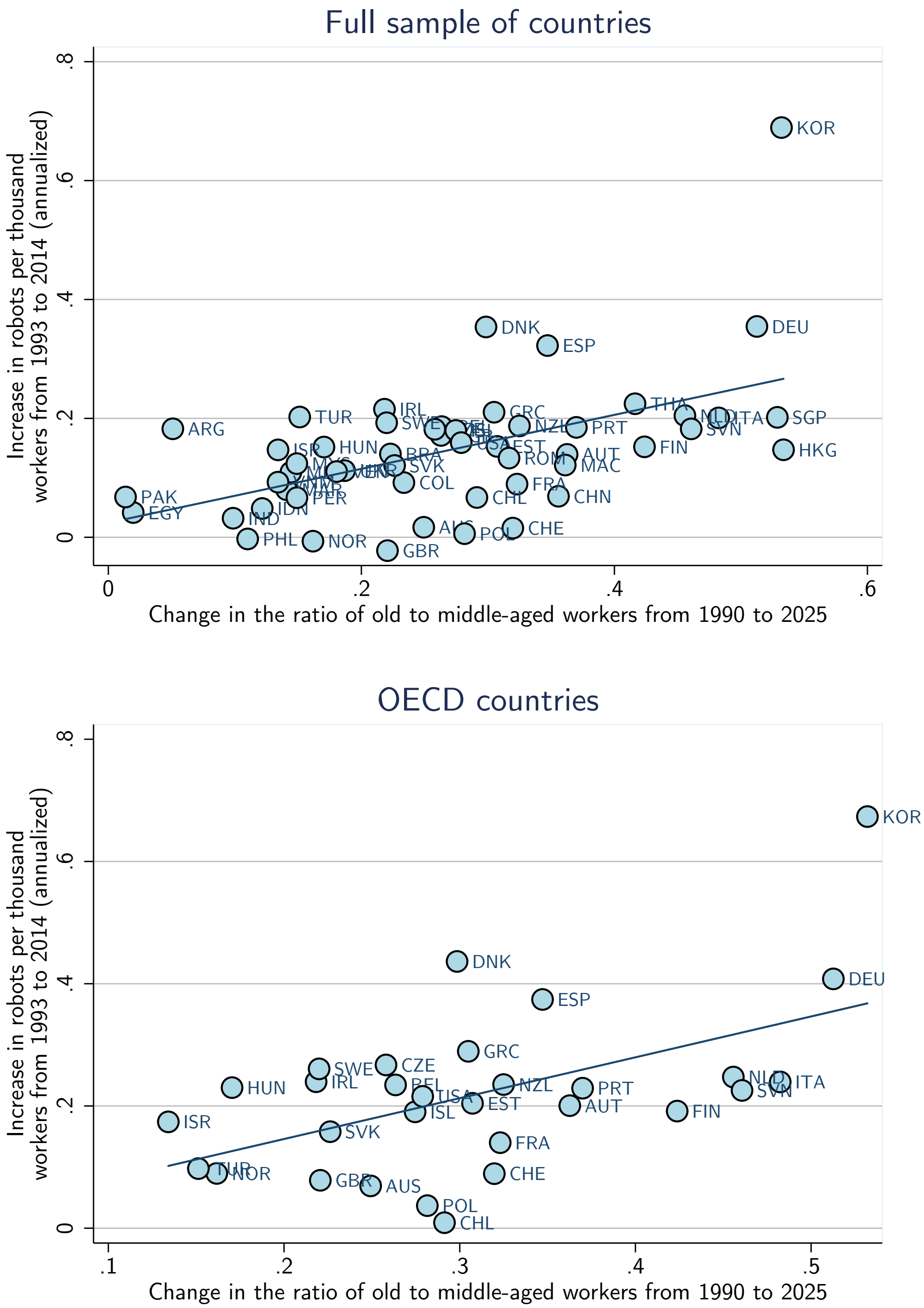

FIGURE 10: Residual plots of the relationship between aging (change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025) and the increase in the number of industrial robots per thousand workers from 1993 to 2014. The plots partial out the covariates included in the regression models in Columns 3 and 6 of Table 4.

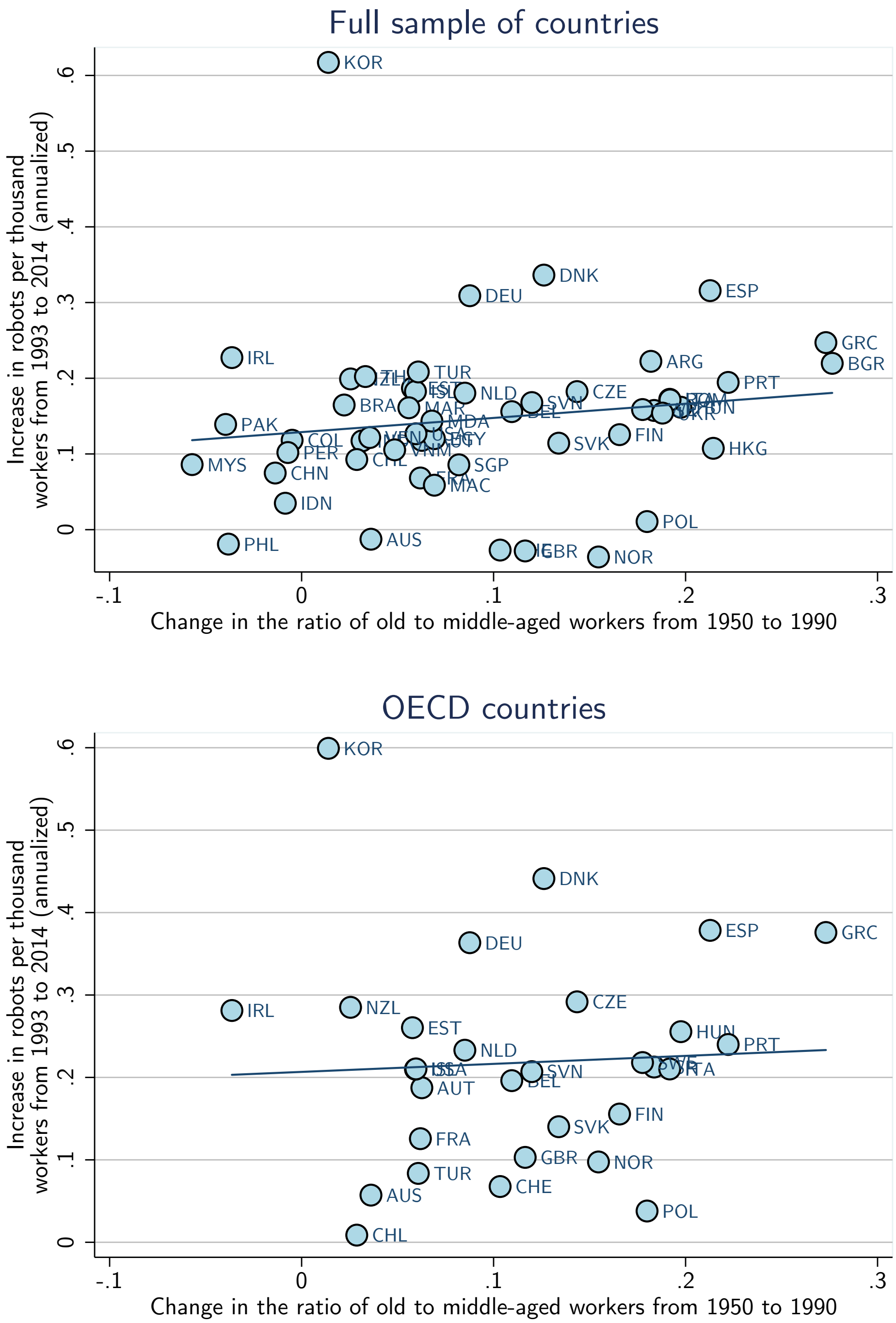

FIGURE 11: Residual plots of the relationship between past aging (change in the ratio of workers above 56 to workers between 21 and 55 between 1950 and 1990) and the increase in the number of industrial robots per thousand workers from 1993 to 2014. The plots partial out the covariates included in the regression models in Columns 4 (top panel) and 9 (bottom panel) of Panel A in Table 5.

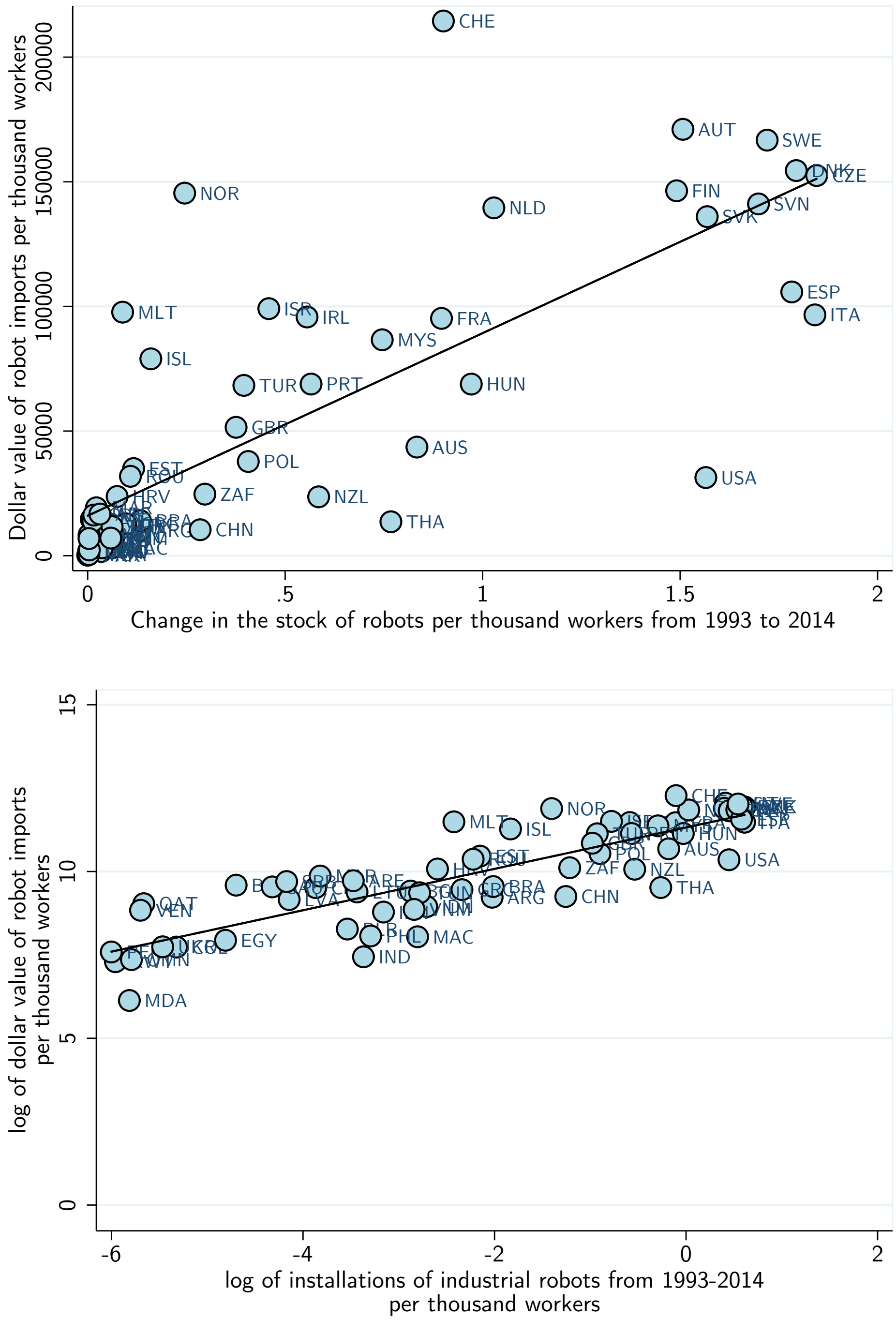

FIGURE 12: Plots of the relationship between the change in the stock of robots provided by the IFR (horizontal axis) and the total dollar value of imports of industrial robots from Comtrade (vertical axis).

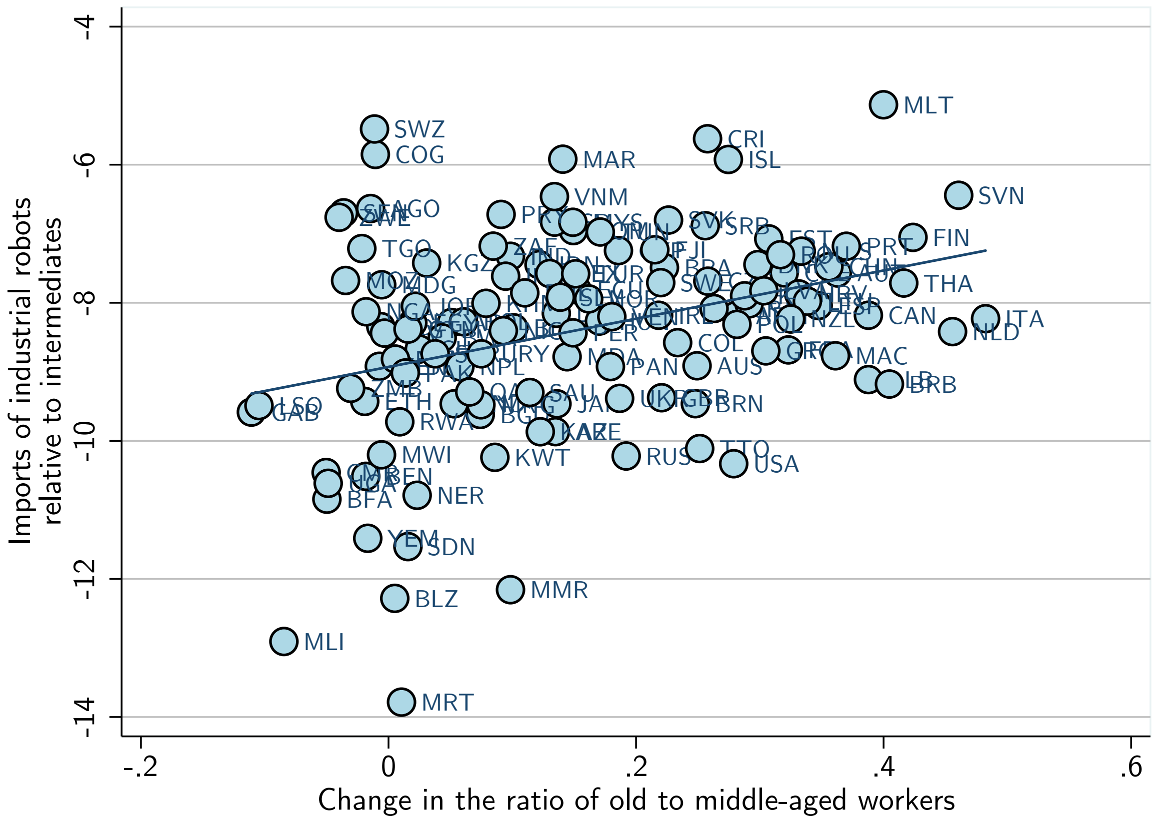

FIGURE 13: Residual plot of the relationship between aging (change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2025) and the log of imports of industrial robots from 1990 to 2016 (relative to total imports of intermediates). The plot partials out the covariates included in the regression models in Column 1 of Table 9.

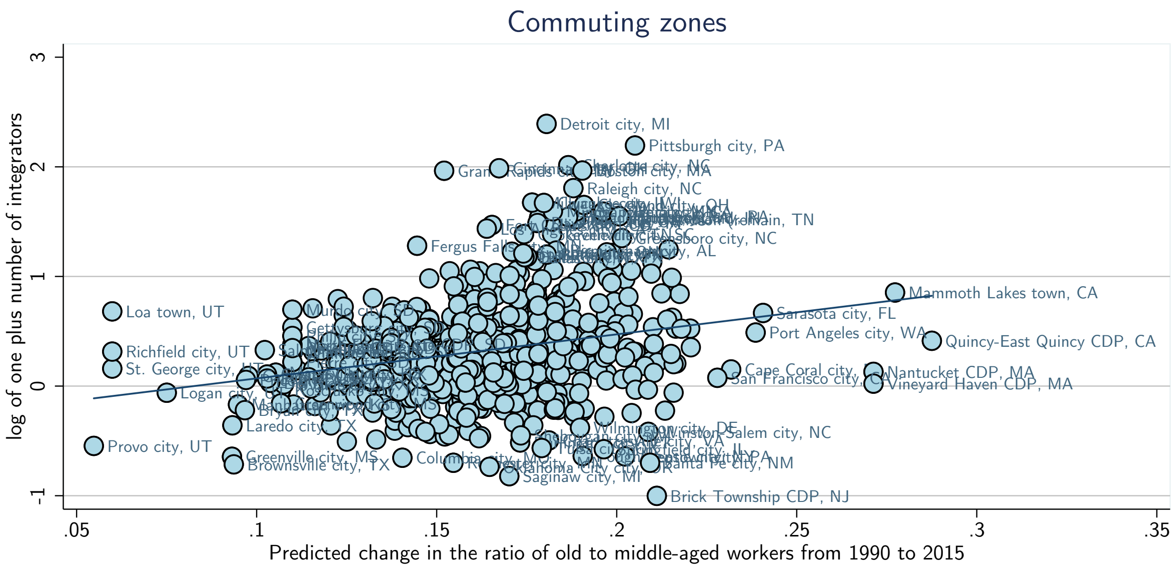

FIGURE 14: Visual IV plot of the relationship between predicted aging (change in the ratio of workers above 56 to workers between 21 and 55 between 1990 and 2015, instrumented using the age composition of a commuting zone in 1990) and the location of robot integrators in the US (from Leigh and Kraft, 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	US ratio middle-aged	Replacea-bility index
	Employment Klems	Employment Unido	in value added	to old workers	Graetz and Michaels
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 old to young 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 old to young 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*	0.559***
	(1.342)	(0.756)	(1.668)	(0.716)	(0.527)	(0.724)	(0.512)	(0.447)	(0.148)
Ratio of old to young workers in 1990	2.019	0.383	0.928	0.317	-0.587	2.131**	1.072	0.826	0.793***
	(1.542)	(0.957)	(1.568)	(0.867)	(0.606)	(1.047)	(0.653)	(0.502)	(0.226)
Log of the GDP per capita in 1990	0.633***	0.146	-0.425**	0.119	0.106	-0.474***	0.020	-0.049	0.049
	(0.196)	(0.113)	(0.201)	(0.116)	(0.071)	(0.125)	(0.069)	(0.061)	(0.041)
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	0.54
					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	0.581***
	(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*	0.790***
	(1.506)	(0.910)	(1.595)	(0.842)	(0.548)	(0.990)	(0.616)	(0.469)	(0.210)
Log of the GDP per capita in 1990	0.602***	0.162	-0.491**	0.134	0.099	-0.456***	0.031	-0.039	0.048
	(0.200)	(0.112)	(0.208)	(0.114)	(0.075)	(0.122)	(0.071)	(0.058)	(0.040)
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	15.21
Overid p-value	0.76	0.25	0.74	0.47	0.60	0.45	0.86	0.72	0.31
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***	3.740***	2.535***		6.731***	4.686***	
	(0.438)	(1.032)	(0.650)		(1.849)	(1.231)	
Aging × Reliance on Middle-Aged Workers		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***	11.807***	7.436***		10.426***	6.195***	
	(1.396)	(4.321)	(2.352)		(3.501)	(2.012)	
Aging × Reliance on Middle-Aged Workers		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***		5.014***	4.641***	
	(0.183)	(1.004)	(0.932)		(1.282)	(1.164)	
Aging × Reliance on Middle-Aged Workers		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***	3.623***	2.299***		6.564***	4.155***	
	(0.476)	(1.189)	(0.707)		(2.169)	(1.351)	
Aging × Reliance on Middle-Aged Workers		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***	13.881***	7.801***		12.349***	6.438***	
	(1.439)	(4.484)	(2.307)		(3.627)	(2.063)	
Aging × Reliance on Middle-Aged Workers		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***	3.814***	3.348***		5.462***	5.084***	
	(0.196)	(1.092)	(0.989)		(1.462)	(1.300)	
Aging × Reliance on Middle-Aged Workers		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 Workers		-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 Workers		-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

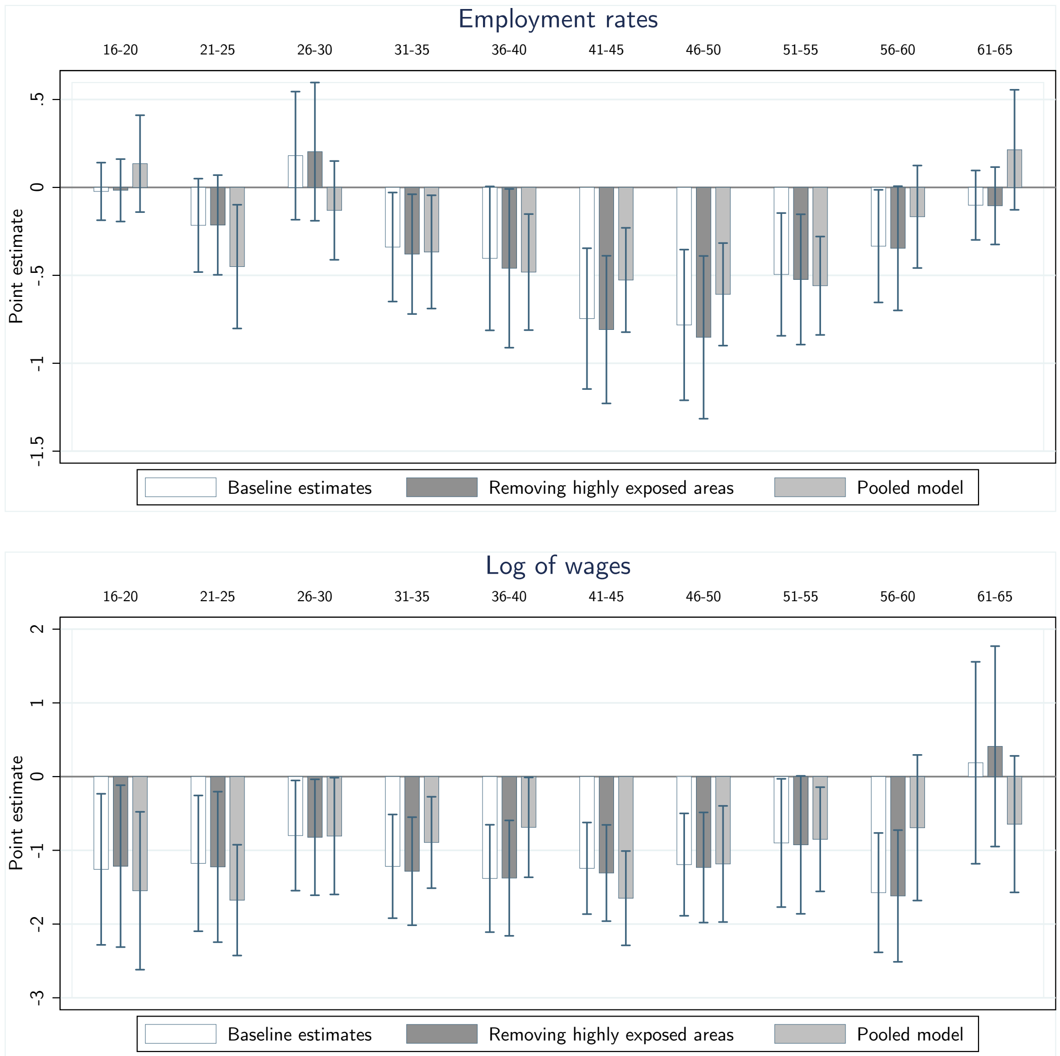

Figure A1: Estimated impact of one additional robot per thousand workers on employment and wages. The figure plots the estimates for different age groups and for men separately.

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	-0.083	-1.694***	-0.705	-0.259
	(0.529)	(0.353)	(0.237)	(0.615)	(0.442)	(0.396)
Observations	22	22	34	22	22	34
R-squared	0.86	0.78	0.69	0.86	0.76	0.68
Instruments F-stat				4.89	3.69	10.21
Overid p-value				0.22	0.38	0.11
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.