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POPULATION GROWTH AND AUTOMATION DENSITY: THEORY AND CROSS-COUNTRY EVIDENCE*

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ABSTRACT

We analyze the effects of declining population growth on automation. Theoretical considerations imply that countries with lower population growth introduce automation technologies faster. We test the theoretical implication on panel data for 60 countries over the time span 1993-2013. Regression estimates support the theoretical implication, suggesting that a 1% increase in population growth is associated with an approximately 2% reduction in the growth rate of robot density. Our results are robust to the inclusion of standard control variables, different estimation methods, dynamic specifications, and changes with respect to the measurement of the stock of robots.

JEL classification: J11, O33, O40.

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1 INTRODUCTION

Industrialized countries have experienced substantial declines in fertility and in birth rates over the last decades. For example, in the United States, the total fertility rate (TFR) fell from 3.33 children per woman in the period 1950-1955 to 1.89 children per woman in the period 2010-2015. Over the same time span, the crude birth rate (CBR) decreased from 24.4 children per 1000 inhabitants to 12.6 children per 1000 inhabitants (see The United Nations, 2015, and Table 1 displaying the numbers for the G7 countries). These demographic changes have already slowed down the growth rate of the labour force in the corresponding countries and will likely lead to a decline in the working-age population in the coming decades. Overall, declining fertility is the central driver of population aging, contributing much more than increasing life expectancy or changing migration patterns (Weil, 1997; Bloom and Luca, 2016; Prettner and Bloom, 2020).

Many economists are concerned regarding the long-run consequences of these described demographic trends (for an overview, see Bloom et al., 2010). For example, social security systems and retirement schemes might be underfunded when fewer and fewer workers have to support ever more retirees (see Gruber and Wise, 1998; Bloom et al., 2007; The Economist, 2011); investment rates might decline when the retiring cohorts run down their assets (Mankiw and Weil, 1989; Schich, 2008); and the innovative capacity of aging societies might decrease (see, for example, Canton et al., 2002; Borghans and ter Weel, 2002; Gehringer and Prettner, 2019).

Table 1: TFR and CBR in the G7 countries 1950-1955 and 2010-2015 (United Nations, 2015)

Country	TFR 1950-1955	TFR 2010-2015	CBR 1950-1955	CBR 2010-2015
Canada	3.65	1.61	27.4	10.9
France	2.75	2.00	19.1	12.4
Germany	2.13	1.39	15.6	8.3
Italy	2.36	1.43	18.2	8.6
Japan	3.00	1.40	23.8	8.3
U.K.	2.18	1.92	15.1	12.6
USA	3.33	1.89	24.4	12.6

Despite these concerns, behavioral reactions to declining fertility might mitigate some of its negative economic effects. For example, if families have fewer children, they will invest more in the education of each child, such that average human capital increases (Strulik et al., 2013). Similarly, labour supply of parents will increase in case of falling fertility because of the reduction in the time required for child care (see, for example, Bloom et al., 2009; Lee and Mason, 2010; Ashraf et al., 2013).

Regarding the expected labour shortages due to population aging, there is another silver lining on the horizon. In recent years, robots have started to take over many tasks that were previously regarded as non-automatable. Economists expect that this trend will continue in the future (see Frey and Osborne, 2017; Arntz et al., 2017; Acemoglu and Restrepo, 2017b; The Economist, 2019). Very prominent examples that have received an extensive media coverage in recent years are autonomous cars and lorries that could soon transport passengers and goods without the need for human drivers; 3D printers producing customized products that otherwise require specialized human labour input; and software based on machine learning making strides in diagnosing diseases, and writing newsflashes, reports, and even novels on their own.[1]

The effects of automation on employment, wages, and productivity have recently started to catch the attention of economists. From a theoretical perspective, Acemoglu and Restrepo (2018), Chu et al. (2020), Prettner and Strulik (2020), and Hémous and Olsen (2021) propose R&D-based growth models in which robots can easily perform the tasks of low-skilled workers and show the pathways by which automation affects economic outcomes in the long run. From an empirical perspective, Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) investigate the effects of automation on productivity, wages, and unemployment. In general, this literature finds that automation has the potential to increase productivity and thereby economic growth. However, there are also potential inequality-enhancing effects. Since robots compete with labour more closely than other types of machines and the income of robots flows to the capital owners that invested in them, automation contributes to the declining labour income share as observed since the 1980s (see Elsby et al., 2013; Karabarbounis and Neiman, 2014; Prettner, 2019).[2] In addition to its effect on the labour income share, automation can also partly explain why the real wages of low-skilled workers have been decreasing in the United States since the 1970s (Autor and Dorn, 2013; Lankisch et al., 2019). This is because low-skilled workers are (still) easier to substitute by robots than high-skilled workers.

As far as the employment effects of automation and new technologies are concerned, the evidence to date is mixed. While Acemoglu and Restrepo (2020) find negative employment effects of the use of industrial robots for the United States, Dauth et al. (2017) focus on Germany and find a small negative effect of industrial robots on employment in manufacturing. This effect is, however, fully compensated by employment gains in the service sector. Gregory et al. (2016) find a positive overall employment effect of automation in Europe, which is in line with automation-augmented search-and-matching models of the labour market (Guimarães and Mazeda Gil, 2019; Cords and Prettner, 2021).

In our contribution we aim to complement the analysis of the labour market impact of automation by focusing on the incentives to automate in the first place. We therefore focus on the reverse question whether countries in which the population growth rate is lower and which are, thus, aging faster, invest more in automation. While all the contributions mentioned above are related to our paper because they are dealing with some of the causes

[1] See, for example, The Economist (2014), Abeliansky et al. (2020), Lanchester (2015), Brynjolfsson and McAfee (2016), and Prettner and Strulik (2020) on different aspects of automation and on new developments.

[2] Apart from automation, demographic change can also explain a part of the declining labour income share mechanically (d'Albis et al., 2020; Glover and Short, 2020).

and consequences of automation, only the independent and parallel works by Acemoglu and Restrepo (2017a) and Acemoglu and Restrepo (2021) investigate the relationship between automation and ageing. Acemoglu and Restrepo (2021) document a positive correlation between the change in the ratio of old workers to young workers between 1990 and 2015 and the change in the number of robots per million hours worked between 1993 and 2014. Acemoglu and Restrepo (2021) focus on the age composition of workers and its relationship with automation, also considering the industry dimension. They find that a larger share of older workers has a positive effect on the adoption of automation. We provide a complementary analysis by i) showing how a simple general equilibrium growth model that is augmented by automation predicts that demographic changes affect the adoption of robots; and ii) empirically testing the implications of the theoretical model on panel data of robot adoption and population growth for a broad group of countries. We show that – from a theoretical point of view – countries with lower population growth have higher incentives to invest in automation. Regression estimates support the theoretical prediction, suggesting that a 1% increase in population growth is associated with an approximately 2% reduction in the growth rate of the automation density as measured by the number of robots per thousand inhabitants.

Our paper is structured as follows. In Section 2, we suggest a simple general equilibrium framework to highlight the main effect of demographic change on automation. In Section 3, we test the theoretical prediction empirically and in Section 4, we discuss our results and draw some policy conclusions.

2 DECLINING POPULATION GROWTH AND AUTOMATION: THEORETICAL CONSIDERATIONS

The purpose of this section is to outline a simple general equilibrium model of automation that captures the basic channel by which demographic change affects automation and to derive the corresponding hypothesis that we test in the empirical part.

2.1 BASIC ASSUMPTIONS

Following Prettner (2019) and Antony and Klarl (2020), we consider an economy with three production factors, human labour, traditional capital (machines, assembly lines, etc.), and automation capital (robots, 3D printers, etc). Time t evolves discretely and the population grows at rate n between time t and time $t+1$. Traditional capital and automation capital can be accumulated and they fully depreciate over the course of one time period (which is one generation or approximately 20 years). In the baseline version of the model we assume that human labour and traditional physical capital are imperfect substitutes, while automation capital is a perfect substitute for labour. In addition and consistent with Solow (1956), we assume that households save a constant fraction $s \in (0,1)$ of their total income. We show in extensions that the main implication of the theory does not change in case of imperfect substitution between robots and workers as in Lankisch et al. (2019) or an endogenous saving rate as in Gasteiger and Prettner (2020).

2.2 HOUSEHOLDS AND POPULATION GROWTH

The population size is given by N_t and its evolution is governed by the difference equation

$$N_{t+1} = (1+n)N_t,$$

where n is the population growth rate. Because of the demographic changes outlined in the introduction, this rate is expected to fall in the future – in some countries to negative values. As is standard, the labour force at time t is given by $L_t \equiv N_t$. Consequently, a reduction in the population growth rate translates into a reduction in the growth rate of the workforce, which is realistic in the long run.

Aggregate savings are given by $S_{t+1} = sN_t$, where s is the saving rate. There are two saving vehicles, traditional physical capital and automation capital. A no-arbitrage condition holds ensuring that rational investors would like to hold both types of capital in equilibrium. This condition states that the rates of return on traditional physical capital and on automation capital have to be equal.

2.3 PRODUCTION AND AUTOMATION

As in Prettner (2019), the production function has a Cobb-Douglas structure with respect to human labour and traditional physical capital. However, the additional non-standard production factor "automation capital" is a perfect substitute for labour such that aggregate output is given by

$$Y_t = K_t^{\alpha}(L_t + P_t)^{1-\alpha},$$

where K_t refers to traditional physical capital, P_t denotes automation capital, and $\alpha \in (0,1)$ is the elasticity of output with respect to traditional physical capital. We abstract from factor-augmenting technological progress that would only act as an additional source of economic growth but it would not alter the crucial mechanisms in our framework. Perfect competition on factor markets implies that the production factors are paid their marginal value products. Normalizing the price of final output to 1, the wage rate and the rates of return on the two types of capital are given by

$$w_t = (1-\alpha)\left(\frac{K_t}{L_t+P_t}\right)^{\alpha}, \tag{1}$$

$$R_{t+1}^{autom} = w_t = (1-\alpha)\left(\frac{K_t}{L_t+P_t}\right)^{\alpha}, \tag{2}$$

$$R_{t+1}^{trad} = \alpha\left(\frac{L_t+P_t}{K_t}\right)^{1-\alpha}, \tag{3}$$

where R^{autom}_{t+1} is the gross interest rate paid on automation capital, which is equal to the wage rate, and R^{trad}_{t+1} is the gross interest rate paid on traditional physical capital. While the *ceteris paribus* effects of K_t and L_t on factor remuneration are straightforward, we have non-standard *ceteris paribus* effects of the accumulation of automation capital: As P_t increases, the wage rate decreases because workers compete with automation capital, whereas the rate of return on traditional physical capital increases because automation capital substitutes for workers and therefore raises the marginal product of traditional physical capital. It is important to note at this point that, while automation reduces the marginal product of labour and thereby the wage rate, labour productivity as measured by output per worker *increases* with automation.

The no-arbitrage condition states that investments in both types of capital yield the same rate of return, i.e., $R^{autom}_{t+1} = R^{trad}_{t+1} \equiv R_{t+1}$ holds in equilibrium. Setting Equations (2) and (3) equal to each other and solving for P_t and K_t yields

$$P_t = \frac{1-\alpha}{\alpha} K_t - L_t \qquad \Leftrightarrow \qquad K_t = \frac{\alpha}{1-\alpha}(P_t + L_t). \tag{4}$$

It would be tempting to conclude from the *ceteris paribus* effects above that the accumulation of automation capital raises the interest rate. Such a claim, however, would be based on an isolated interpretation of Equation (3) without taking the compensating negative effect of automation on the interest rate, which is obvious from Equation (2), into account. Due to the no-arbitrage relationship, the net effect of automation on the interest rate is zero in equilibrium and, thus, negligible from an empirical point of view. As a consequence, the argument that we observe low interest rates together with automation cannot be used to refute the validity of the theoretical arguments sketched out above.

Plugging the expression for traditional physical capital from Equation (4) into the aggregate production function provides

$$Y_t = \left(\frac{\alpha}{1-\alpha}\right)^{\alpha} (L_t + P_t), \tag{5}$$

where it is immediately clear that the standard convergence process to a stationary equilibrium with no long-run growth that we know from the Solow (1956) model without technological progress does not hold anymore. Instead, the production function has the potential to lead to long-run growth if the saving rate is high enough so as to sustain a positive accumulation rate of automation capital (cf. Steigum, 2011; Prettner, 2019; Lankisch et al., 2019). Note that Equation (5) resembles the properties of an AK type of production structure. However, in contrast to standard AK type of growth models, this is not due to an assumption that removes the diminishing marginal product of physical capital but due to the structure of the production process in the presence of automation capital.

2.4 THE EFFECT OF DEMOGRAPHIC CHANGE ON AUTOMATION DENSITY

Since households save a constant fraction $s \in (0,1)$ of their total income Y_t and the economy is closed, aggregate investment is $I_t = sY_t$ such that

$$K_{t+1} + P_{t+1} = sY_t.$$

Substituting for K_{t+1} by the no-arbitrage relationship (4), for Y_t by Equation (5), and dividing by the population size N_{t+1} provides the following expression

$$\frac{\alpha(p_{t+1}+1)}{1-\alpha} + p_{t+1} = s\left(\frac{\alpha}{1-\alpha}\right)^{\alpha} \frac{1+p_t}{1+n},$$

where p_t is the automation density, i.e., the number of robots in relation to the population. Solving this equation for the automation density in period $t+1$ as a function of the automation density in period t and the parameter values of the model yields the dynamic evolution of the automation density

$$p_{t+1} = s(1-\alpha)\left(\frac{\alpha}{1-\alpha}\right)^{\alpha} \frac{1+p_t}{1+n} - \alpha. \tag{6}$$

From this equation it follows immediately that a country with a lower population growth rate will have a higher automation density. It is important to note that i) this result is not a partial equilibrium but a general equilibrium result in the sense that both investors and firms behave optimally and ii) that the effect of population growth is stronger than than if it were solely due to the capital delusion mechanism. We summarize the theoretical insight — that we aim to test empirically in the second part of the paper — in the following proposition.

Proposition 1. *Consider a country in which the production structure is described by an aggregate production function of the form of Equation (5). Households save a constant fraction $s \in (0,1)$ of their total income (labour income plus capital income in the form of traditional physical capital and automation capital), and the no-arbitrage condition (4) holds for both types of investments. Ceteris paribus, a country will experience faster growth in automation density between periods t and $t+1$ if it exhibits a lower population growth rate (n).*

Proof. Taking the derivative of Equation (6) with respect to n we get

$$\frac{\partial p_{t+1}}{\partial n} = -s(1-\alpha)\left(\frac{\alpha}{1-\alpha}\right)^{\alpha} \frac{1+p_t}{(1+n)^2} < 0. \tag{7}$$

This implies that, given p_t, the automation density of the next period and therefore its growth rate will be lover if n is higher. Note that the derivative is, in general, not equal to -1 such that our result is not just due to the fact that automation density is defined as the aggregate stock of automation capital divided by the population size.

□

The intuition for this finding is the following: A country in which the population — and with it the workforce — grows fast, exhibits a comparatively high rate of return on traditional physical capital and a low wage rate such that there is no incentive to invest in automation capital. In fact, in such a country, the rate of return on investment in automation capital tends to be rather low. Examples are African countries with fast population growth such as Mali and Niger: investing in automation would not be an attractive business strategy in these countries because of the abundance of labour and the correspondingly low wages. By contrast, in a country in which the population — and with it the labour force — stagnates or even decreases, the rate of return on investment in automation capital is comparatively high and the rate of return on investment in traditional physical capital is rather low. Examples are ageing European countries such as Germany and Italy and ageing East Asian countries such as Japan and South Korea in which labour is scarce, wages are high, and the interest rate is low.

2.5 ROBUSTNESS OF THE THEORETICAL RESULTS

2.5.1 HOUSEHOLD'S SAVING DECISIONS

To show the robustness of our results with respect to relaxing the assumption of an exogenously given saving rate, we now introduce a standard endogenous consumption-savings choice. In doing so, we follow the exposition of Gasteiger and Prettner (2020) and assume that households live for two time periods, adulthood and retirement. Households derive utility from consumption in both time periods but they only earn a labour income in the first period (cf. Diamond, 1965). Denoting consumption in the first period by $c_{1,t}$, consumption in the second period by $c_{2,t+1}$, and the discount factor by $\beta = 1/(1+\rho)$, with ρ being the discount rate, household's lifetime utility (U_t) is given by

$$U_t = \log(c_{1,t}) + \beta \log(c_{2,t+1}). \tag{8}$$

As is standard, the logarithmic utility function ensures analytical tractability. The central result would not change, however, in case of a more general specification in which the elasticity of intertemporal substitution was different from one but households were still risk averse (see the calculations and numerical results in the extensions of Gasteiger and Prettner, 2020). The budget constraint is given by

$$c_{1,t} + \frac{c_{2,t+1}}{R_{t+1}} = w_t, \tag{9}$$

such that discounted lifetime consumption expenditures are equal to lifetime income (consisting only of income in period t because the household is retired in period $t+1$). As is well-known in this setting, the optimal consumption-savings choice amounts to consuming a constant fraction of income in the first period and saving the rest for consumption in retirement. With $\tilde{s}_t$ denoting savings, optimal choices are given by

$$c_{1,t} = \frac{1}{1+\beta} w_t, \qquad \tilde{s}_t = \frac{\beta}{1+\beta} w_t. \tag{10}$$

The law of motion for the aggregate stock of assets in the overlapping generations model with automation capital is given by

$$K_{t+1} + P_{t+1} = \tilde{s}_t L_t \tag{11}$$

as in Gasteiger and Prettner (2020). Plugging in savings ($\tilde{s}_t$), wages (w_t), and the traditional physical capital stock as a function of automation capital as given in (4), we get

$$\frac{\alpha}{1-\alpha}(P_{t+1} + L_{t+1}) + P_{t+1} = \frac{\beta(1-\alpha)}{1+\beta}\left(\frac{\alpha}{1-\alpha}\right)^{\alpha} L_t. \tag{12}$$

Dividing by the size of the adult cohort $L_{t+1} = (1+n)L_t$ and rearranging, we arrive at

$$p_{t+1} = \frac{\beta}{1+\beta}\left(\frac{\alpha}{1-\alpha}\right)^{\alpha} \frac{1}{1+n} - \alpha. \tag{13}$$

It is immediately clear by inspection that an increase in the population growth rate (n) reduces the automation density (p_{t+1}). Thus, our central result from the case of an exogenous saving choice carries over to a standard setting in which the saving rate is endogenously chosen by households.[3]

To show that our result is not a mere capital dilution effect, we now use Equation (11) to derive the expression of the traditional physical capital stock (the other saving vehicle) depending on population growth. To this end, we plug in savings ($\tilde{s}_t$), wages (w_t), and the automation capital stock as a function of traditional physical capital as given in (4). This yields

$$k_{t+1} = \alpha + \alpha\left(\frac{\beta}{1+\beta}\right)\left(\frac{1-\alpha}{1+n}\right)\left(\frac{\alpha}{1-\alpha}\right)^{\alpha}. \tag{14}$$

Now we take the derivatives of p_{t+1} [Equation (13)] and k_{t+1} [Equation (14)] with respect to n, which are, respectively,

$$\frac{\partial p_{t+1}}{\partial n} = -\frac{[\alpha/(1-\alpha)]^{\alpha}\beta}{(\beta+1)(n+1)^2}, \qquad \frac{\partial k_{t+1}}{\partial n} = -\frac{(1-\alpha)\alpha\,[\alpha/(1-\alpha)]^{\alpha}\beta}{(\beta+1)(n+1)^2}. \tag{15}$$

As expected, both expressions are negative. In addition, however, we can show that automation capital per capita declines by more than traditional physical capital per capita.

[3] For the implications of an overlapping generations structure on economic growth in the context of automation, see Gasteiger and Prettner (2020).

To see this, we use (15) to derive the following relationship

$$\frac{\partial k_{t+1}}{\partial n} = (1-\alpha)\alpha \cdot \frac{\partial p_{t+1}}{\partial n}. \tag{16}$$

Since $(1-\alpha)\alpha < 1$, this implies that the traditional physical capital stock is less affected by a marginal increase in n than the automation capital stock. Thus, our results regarding the effects of population growth on automation adoption cannot be explained solely by a capital dilution effect. We summarize these insights in the following proposition.

Proposition 2.

- *The negative effect of population growth on the adoption of automation capital is robust to a standard extension in which households choose their saving rate endogenously.*

- *The negative effect of population growth on automation density cannot be explained as originating solely in a capital dilution effect.*

Proof. The proof follows directly from the derivations and explanations above. □

2.5.2 SKILL-SPECIFIC HETEROGENEITIES OF WORKERS

Next, we show that our results are robust to the introduction of different skill levels of workers in the production function. To this end, we assume that the representative firm can now employ both low-skilled workers ($L_{u,t}$) and high-skilled workers ($L_{s,t}$) in addition to the two types of capital according to the CES production function

$$Y_t = \left[L_{s,t}^{\gamma} + (P_t + L_{u,t})^{\gamma}\right]^{\frac{1-\alpha}{\gamma}} K_t^{\alpha}, \tag{17}$$

where $\gamma \in (-\infty, 1]$ determines the elasticity of substitution between low-skilled workers and high-skilled workers as $\sigma = 1/(1-\gamma)$. Note that workers with different skills are perfect substitutes for $\gamma = 1$ and perfect complements for $\gamma \to -\infty$. The empirically relevant range for this parameter is $\gamma \in (0, 0.5)$ such that low-skilled and high-skilled workers are gross substitutes and σ lies in the range $\sigma \in (1, 2)$ (Autor, 2002; Acemoglu, 2009). Overall, robots are perfect substitutes for low-skilled workers only but imperfect substitutes for high-skilled workers. Now the size of the workforce is given by $L_t = L_{u,t} + L_{s,t}$ and the shares of high-skilled and low-skilled workers are $l_{s,t} = L_{s,t}/(L_{s,t} + L_{u,t})$ and $l_{u,t} = L_{u,t}/(L_{s,t} + L_{u,t})$. Output per worker then follows in a straightforward way as

$$y_t = \left[l_{s,t}^{\gamma} + (p_t + l_{u,t})^{\gamma}\right]^{\frac{1-\alpha}{\gamma}} k_t^{\alpha}. \tag{18}$$

From the modified production function (17) and the assumption of perfect competition on the factor markets it follows that

$$R_{t+1}^{trad} = \alpha K_t^{\alpha-1}\left[L_{s,t}^{\gamma} + (L_{u,t} + P_t)^{\gamma}\right]^{\frac{1-\alpha}{\gamma}}, \tag{19}$$

$$R_{t+1}^{autom} = (1-\alpha)K_t^{\alpha}(L_{u,t} + P_t)^{\gamma-1}\left[L_{s,t}^{\gamma} + (L_{u,t} + P_t)^{\gamma}\right]^{\frac{1-\alpha-\gamma}{\gamma}}. \tag{20}$$

Again, for rational investors, a no-arbitrage condition $R_{t+1}^{autom} = R_{t+1}^{trad} \equiv R_{t+1}$ holds that allows to derive the equilibrium stock of traditional physical capital depending on automation capital and employment of both types of workers as

$$K_t = \frac{\alpha(L_{u,t} + P_t)^{1-\gamma}\left[(L_{u,t} + P_t)^{\gamma} + L_{s,t}^{\gamma}\right]}{1-\alpha}. \tag{21}$$

Dividing Equation (21) by the number of workers yields the traditional physical capital stock per worker ($k_t = K_t/L_t$) as a function of automation capital per worker ($p_t = P_t/L_t$) and the shares of skilled and unskilled workers, $l_{s,t}$ and $l_{u,t}$:

$$k_t = \frac{\alpha(l_{u,t} + p_t) + \alpha l_{s,t}^{\gamma}(l_{u,t} + p_t)^{1-\gamma}}{1-\alpha}. \tag{22}$$

Aggregate investment is again given by $I_t = sY_t$ and — under full depreciation over the course of one generation — the accumulation equation for both types of capital follows as

$$P_{t+1} + K_{t+1} = sY_t. \tag{23}$$

Dividing by $L_{t+1} = (1+n)L_t$ and plugging (18) and the optimal factor input relationship (22) from above into this result yields

$$p_{t+1} + \frac{\alpha(l_{u,t+1} + p_{t+1}) + \alpha l_{s,t+1}^{\gamma}(l_{u,t+1} + p_{t+1})^{1-\gamma}}{1-\alpha}$$
$$= \frac{s}{1+n}\left[l_{s,t}^{\gamma} + (p_t + l_{u,t})^{\gamma}\right]^{\frac{1-\alpha}{\gamma}}\left[\frac{\alpha(l_{u,t} + p_t) + \alpha l_{s,t}^{\gamma}(l_{u,t} + p_t)^{1-\gamma}}{1-\alpha}\right]^{\alpha}.$$

Due to its complexity, this equation cannot be solved analytically, so we resort to a numerical illustration of the effects of population growth on the adoption of automation capital. For this illustration, we use the parameter values in Table 2 and an initial stock of automation capital of $p_t = 1$. Note that the population growth rate refers to a yearly value and is converted into generational terms under the assumption that one period in our setting lasts for 20 years.

Overall, our results show that an increase of the population growth rate from 0.9% per year to 1% per year decreases the stock of automation capital in period $t+1$ from 1.496 to 1.464. Consequently, our central result from the baseline version of the model is robust to the introduction of different skill types of which only low-skilled workers can be perfectly substituted by robots.

At this stage, a remark on two aspects related to the empirical implementation of the

Table 2: Parameter values for the numerical illustration

Parameter	Value	Source
s	21%	Grossmann et al. (2013)
n	0.9%	World Bank (2016)
α	1/3	Acemoglu (2009); Grossmann et al. (2013)
l_s	23%	Lankisch et al. (2019)
γ	0.15	Plausible estimate according to Autor (2002) and Acemoglu (2009) that still allows for growth in robots

model is in order.

Remark 1.

- *The closed economy assumption of the model might not be fulfilled in reality. However, the empirical results do not depend on whether or not the model refers to a closed economy. The reason is that population growth, which is used as a proxy for n, also includes migration, while the gross investment rate, which is used as a proxy for the saving rate s, includes international capital flows.*

- *A potential endogeneity of the saving rate s to demographic change is not an issue for the analysis of the effect of changing population growth on automation because we control for the gross saving rate in the regressions.*

3 DECLINING POPULATION GROWTH AND AUTOMATION: EMPIRICAL RESULTS

In this section we first introduce the data, then we test Proposition 1 empirically, and finally we provide a number of robustness checks. Table 3 provides a first glimpse on whether the result implied by Proposition 1 is consistent with the data. The table depicts the number of industrial robots per 10,000 employees as of 2015 together with the average population growth rate in the preceding 5-year interval from 2010 to 2015 for the nine countries with the highest robot usage. In general, we observe that the population growth rate in these countries is rather low and in some of them it is even negative. However, this could just be due to the fact that these countries are richer, implying that they have a lower fertility rate and that they are, at the same time, able to invest more in automation. In the next section we therefore test whether our theoretical implication is borne out by the data in a more thorough way.

3.1 DATA DESCRIPTION

The only available dataset so far to study the adoption of robots is the one collected by the International Federation of Robotics (IFR). The IFR reports the yearly delivery of

Table 3: Robots per 10,000 employees in manufacturing and population growth in the top 9 countries in terms of robot usage (International Federation of Robotics, 2015; United Nations, 2015)

Country	robots per 10,000 employees in manufacturing	average population growth between 2010 and 2015
South Korea	347	0.48%
Japan	339	-0.12%
Germany	261	0.16%
Italy	159	0.07%
Sweden	157	0.83%
Denmark	145	0.42%
United States	135	0.75%
Spain	131	-0.21%
Finland	130	0.50%

Note: The population growth rate is calculated as the average population growth rate from 2010 to 2015. The data sources are (International Federation of Robotics, 2015; United Nations, 2015).

"multipurpose manipulating industrial robots" as defined by the International Organization for Standardization for several countries, starting in 1993. We use the data until 2013 because the data for the year 2014 are unreliable: there are several zeroes that seem to be reporting errors in comparison to previous values in the data series. In the baseline specification we use 3 year averages of the data which provides us with 7 time periods for estimation. The sample includes 60 countries for which the data are available (for the list of countries see Table A.3 in the Online Appendix). We had to combine the NAFTA countries (Canada, the United States, and Mexico) into one country because they report the values jointly until 2011.[4]

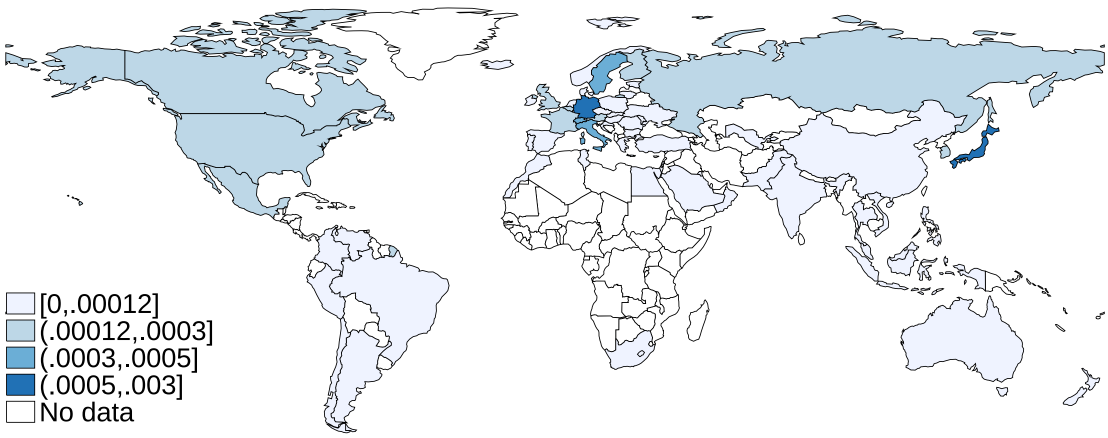
The IFR also reports the deliveries of robots and the stock of robots at the industry level. They consider that robots have a lifetime horizon of 12 years, after which they are deployed (International Federation of Robotics, 2016). Following Graetz and Michaels (2018), we use an alternative way to calculate the stock of robots (for all robots and for robots in the manufacturing industry separately) that relies on the perpetual inventory method under the assumption of a depreciation rate of 10%. In robustness checks we also use alternative depreciation rates of 5% and 15%. Similar to Graetz and Michaels (2018), we prefer this method over the one used by the IFR because it is more in line with the standard economics literature. Since the IFR reports the stock of robots in 1993, this is our first value for the constructed series. Although all countries report the total stock of robots, not all of them report the stock nor the deliveries disaggregated at the industry level on a yearly basis. Given that we are mainly interested in the robots used in the manufacturing sector, we follow Graetz and Michaels (2018) and take the average share of deliveries of manufacturing robots over the total deliveries of robots (when the data were available), construct an average share, and impute the values for deliveries of

[4]In total, we have a sample size of 300 observations that we can use for the empirical analysis (60 countries over 5 time periods). Since we are using a lag of one period and since we compute the (log) growth rate, we lose two periods of observations.

manufacturing robots, as well as for the initial stock of robots (when the corresponding data were not available). In Table A.2 in the Online Appendix we show the first reported year of robots' data disaggregated by the industry level for the countries for which there were gaps in the reported data.

In the following figures we show how the robot density has evolved between the first period of the sample (1993-1995) and the last period (2011-2013). We discriminate between percentiles with Figure 1 (covering the period 1993-1995) reporting in the lightest shade of blue the 75th percentile, proceeding with the 90th percentile, the 95th percentile, and finally with the remaining 5% of the distribution (there are many countries with zeroes in this period which is why we use the 75th percentile as the first cutoff). For comparison, we show the same data for the period 2011-2013 in Figure 2 and use the same cutoffs as in the previous figure. We observe a strong increase in robot density, especially in Europe and East Asia. Similar figures but only for robots used in the manufacturing sector are displayed in the Online Appendix (Figures A.1 and A.2).

Figure 1: Average robot density for the period 1993-1995

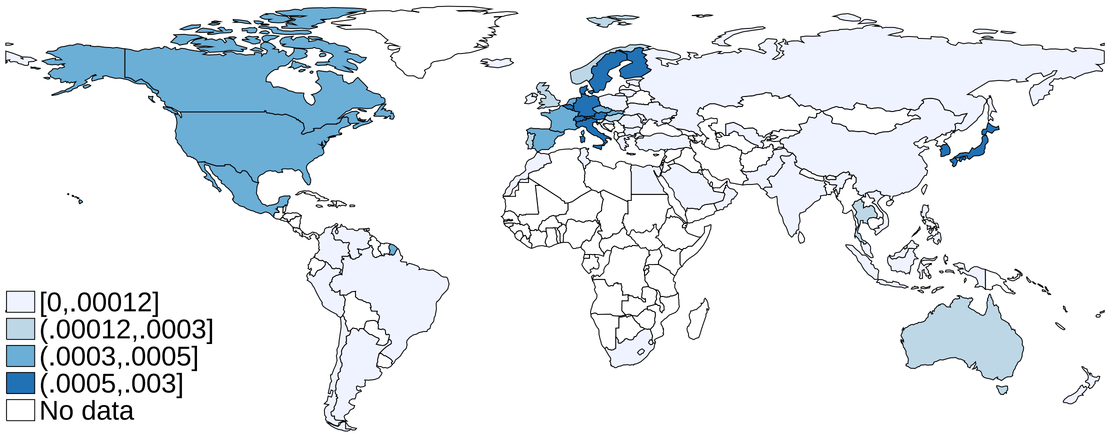


Source: IFR and World Development Indicators. Note: The USA, Canada and Mexico have the same values because of the joint reporting.

We also collected information from the International Monetary Fund (IMF) on the investment share (over GDP). We constructed our investment variable summing the reported values of private investment, public investment, and joint ventures between the state and the private sector. Regarding the other control variables, we included GDP per capita measured in constant US$ with a base year of 2010 from the World Development Indicators, openness measured as exports and imports over GDP, the gross enrollment ratio in secondary schools as in Busse and Spielmann (2006)[5] and the contribution of the service sector to total GDP. Finally, we have retrieved life expectancy and the dependency ratio from the World Development Indicators, and the exports of industrial robots from UN Comtrade, standardized by GDP. The construction of the variables is described in

[5]The natural choice of a proxy variable for education would have been the mean years of schooling as reported by Barro and Lee (2013). However, this variable is only available in 5 year intervals.

Figure 2: Average robot density in the period 2011-2013



Source and Note: See Figure 1.

Table A.4 in the Appendix.

3.2 EMPIRICAL SPECIFICATION

Based on Proposition 1, we estimate the relationship between robots adoption and population growth based on the following equation:

$$\ln(\hat{p}_{i,t}) = c + \alpha \ln(n_{i,t-1}) + \beta \ln(s_{i,t-1}) + \gamma \ln(x_{i,t-1}) + d_t + \epsilon_{i,t}, \qquad (24)$$

where $\hat{p}_{i,t}$ is the growth rate of the robot density (either manufacturing robots, or the total amount of robots per 1000 inhabitants), $n_{i,t-1}$ is the population growth rate between period $t-1$ and $t-2$, $s_{i,t-1}$ is the gross investment rate in period $t-1$, $x_{i,t-1}$ is a vector of further control variables that will be used in the robustness analysis (e.g., GDP per capita, openness, etc), and d_t are time-specific effects to control for events and trends that affect all countries in the same manner, for example, the global economic and financial crisis that started in 2007. Since we have zeroes and negative values in the dependent variable and in the population growth rate, we employed the zero-skewness log transformation (Box and Cox, 1964).[6] We apply the logarithmic transformation because this alleviates concerns regarding heteroscedasticity and non-linearities in the non-transformed variables. We relied on 3-year averages to reduce problems regarding measurement errors and business-cycle effects. While the economic growth literature usually relies on 5 year averages, we would be left with only 2 consecutive time periods for estimation in this case.

We first estimate Equation (24) using pooled OLS (POLS) and then proceed with a random-effects (RE) and a fixed-effects (FE) specification. Finally, we take the potential dynamics into account by including the lagged dependent variable in the regressions and

[6] We created a new variable in the following manner: $z = \ln(\text{growth rate} - k)$, choosing k such that the skewness of z is zero. The correlation between the non-transformed variables and the variables in logarithms (naturally omitting the zeroes and the negative values) is 0.89.

by applying various corrected fixed effects estimators (CorrFE) following Bruno (2005a,b), and the system GMM estimator [GMM (sys)] of Blundell and Bond (1998). Note that both of these types of estimators are seen as remedies for the Nickell (1981) bias in a dynamic panel data setting. We report the results for the total amount of robots and then also separately for the subset of manufacturing robots. Moreover, we assess the robustness of our results by adding proxies for education, GDP per capita, openness, life expectancy, the dependency ratio, and the value of exported robots. In other robustness checks reported in the Online Appendix, we consider different depreciation rates in the construction of the robot data series (5% and 15% instead of 10%), a different transformation of robot adoption and population growth rates [a neglog transformation as used by Whittaker et al. (2005)], and finally considering percentile changes as in Graetz and Michaels (2018).

Based on the theoretical considerations we expect to find a negative coefficient for the population growth rate that is smaller than -1 and a positive sign for the gross investment rate that is the standard proxy used for the gross saving rate s. Again, it is important to note that the population growth rate takes migration into account and that the gross investment rate includes international capital flows. When we include the controls, we expect a positive coefficient for GDP per capita because higher incomes imply a stronger incentive to employ robots. Furthermore, a better educated population might be more inclined to invest in (or adapt to) robots such that the coefficient of education should also be positive. However, we have no a priori expectation regarding the sign of the coefficient for openness — on the one hand, as countries become more open, they might need fewer robots because domestic production could easier be substituted by imports; on the other hand, open economies are also subject to stronger international competition such that there is an incentive to automate the production in search of efficiency gains. Regarding the dependency ratio, we would expect that higher dependency is associated with faster robot growth; higher robot exports with lower national sales of industrial robots; and the coefficient on life expectancy is ambiguous — while higher life expectancy would suggest a lower need for replacing humans with robots, given the demand for healthcare of the elderly and the potential of robots in its supply, the coefficient could be positive.

3.3 EMPIRICAL ESTIMATES

3.3.1 BASELINE ESTIMATES

Table 4 contains the regression outputs from a baseline specification of Equation (24). As regressors we include the two crucial variables that are suggested by our theoretical considerations, the population growth rate and the investment rate. We observe a negative relationship between population growth and the growth rate of the robot density in all specifications and, with one exception, it is statistically significant. Only in column (1), which reports the POLS regression, we find the coefficient not to be statistically significant. This is most likely due to the lack of accounting for country-level heterogeneity. Our results are robust to the dynamic specifications using the corrected fixed effects estimators, as well as the system GMM estimator which also controls for endogeneity of the regressors using internal instruments. As far as the choice between corrected fixed effects and system GMM is concerned, we prefer the corrected fixed effects specifications because Judson and Owen (1999) report that this estimator performs better when the amount of time periods is smaller than 10, which is the case in our sample. Although the lagged dependent variable is statistically significant, the size of the coefficient does not suggest strong evidence for the use of a dynamic specification. Our preferred specification among the non-dynamic panel data estimators is the fixed effects regression because the Hausman test indicates that the results from the random effects specification are inconsistent. Thus, we need to control for unobserved heterogeneity. The coefficient estimate for the population growth rate in case of the fixed-effects specification suggests that when population growth increases by 1%, growth of the robot density will decrease by 2%. As far as the main control variable (the investment share) is concerned, we find the expected positive relationship, although it is not statistically significant.

Since one might not be able to rule out a positive relationship between population growth and savings, we also estimate the indirect effect of population growth on automation via the saving rate. To this end, we ran an auxiliary regression of the form

$$\ln s_{i,t-1} = c_2 + \alpha_2 \ln n_{i,t-1} + d_t + \epsilon_{i,t-1}. \tag{25}$$

With this new specification, the effect of population growth on automation growth is given by α (from the baseline regression) plus $\beta \cdot \alpha_2$. Retrieving the coefficient α_2 from Table A.5 in the Appendix and α and β from Table 4, we can calculate the overall effect of population growth (taking the values of column (3)) as $-2.030 + 0.387 \cdot 0.419 = -1.868$, which is smaller than zero.[7]

Table 5 shows the results for the growth rate of the manufacturing robot density (instead of all robots). We again find the negative association between population growth and growth of the robot density as suggested by Proposition 1 with the size of the coefficients being similar to the ones reported in Table 4. As in the previous case, we document an insignificant positive correlation between the investment rate and the growth rate of the manufacturing robots density. In this case, there is even less evidence for the need of a dynamic specification because the coefficients of the lagged dependent variable are smaller in size and not even statistically significant in case of the system GMM estimator.

[7]We thank an anonymous referee for suggesting this robustness check.

Table 4: The relation between total robots growth and population growth

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.316***	0.259***	0.245**	0.226**
				(0.779)	(0.090)	(0.0987)	(0.111)
n_{t-1}	-0.539	-0.694*	-2.030**	-1.690***	-1.803***	-1.828***	-3.515***
	(0.328)	(0.354)	(0.894)	(0.597)	(0.562)	(0.557)	(1.205)
s_{t-1}	0.063	0.090	0.419	0.304	0.324	0.335	0.115
	(0.119)	(0.129)	(0.495)	(0.357)	(0.340)	(0.341)	(0.473)
Country FE	no	no	yes	yes	yes	yes	-
Time FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.922
Hansen test	-	-	-	-	-	-	0.623
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table 5: The relation between manufacturing robots growth and population growth

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.264***	0.197**	0.180**	0.120
				(0.077)	(0.086)	(0.0914)	(0.120)
n_{t-1}	-0.457	-0.632*	-2.185**	-1.950***	-2.055***	-2.078***	-3.908***
	(0.336)	(0.368)	(0.973)	(0.613)	(0.570)	(0.566)	(1.237)
s_{t-1}	0.026	0.043	0.175	0.132	0.146	0.155	0.311
	(0.095)	(0.101)	(0.490)	(0.365)	(0.343)	(0.343)	(0.401)
Country FE	no	no	yes	yes	yes	yes	-
Time FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.623
Hansen test	-	-	-	-	-	-	0.506
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

3.3.2 ROBUSTNESS ANALYSIS

In Section A.4 in the Online Appendix we show the robustness of our empirical estimates. As a first robustness check, we control for three potential omitted variables: GDP per capita, openness of the economy, and secondary school enrollment (Tables A.6 and A.7). Regression results show again a negative correlation between robot density growth and population growth. In Tables A.8 and A.9 we report the same specification as before but omitting the controls that were not statistically significant (i.e., secondary school enrollment and openness). The results do not change dramatically but the significance of the puzzling negative sign of per capita GDP in case of the system GMM estimator vanishes. To control for structural change, we report the results of adding the (log) of the size of the service sector as a percentage of overall value added with the results remaining fairly unchanged (refer to Table A.10 for total robots and Table A.11 for manufacturing robots). Next, as alternatives to the saving rate we use two different proxies for investment —ä the capital stock (in 2005 US$) and gross fixed capital formation as a fraction of GDP (Tables A.12 and A.14; and Tables A.13 plus A.15 show the results for the total robots and manufacturing robots, respectively). The tables show that the stock of capital is not significantly correlated with the pace of robot adoption. Moreover, the estimates of population growth remain close in value to our previous estimates and statistically significant in all relevant specifications. The same applies for the regressions where we inlcude a different set of control variables: the dependency ratio, life expectancy and the exports of industrial robots (Tables A.16 and A.17).

Furthermore, we use 2-year averages instead of averaging the data over 3 years (Tables A.18 and A.19) and the results remain unchanged. We also constructed two alternative robot stocks using 5% and 15% as alternative depreciation rates (results shown in Tables A.20 and A.22 (for the total stock of robots) and Tables A.21 and A.23 (for manufacturing robots)). We find no substantial differences with our previous estimates. In another sensitivity analysis, we exclude Germany, South Korea, the NAFTA countries, Japan, and China because these are the countries with the highest (manufacturing) robot density and also very low fertility rates. However, the results are rather stable (see Tables A.24 and A.25). We then did a further change in the sample to include two extra available years (2014 and 2015) and we replaced population growth with labour force growth (see Tables A.26 and A.27).

Another concern might be that our results depend on the zero-skewness log transformation. A further robustness check therefore relies on using the neglog transformation for both the population growth rate and the robot density growth rate. Results are shown in Tables A.30 and A.31 of the Online Appendix and again they remain similar to the baseline specification. In our last robustness check, we follow Graetz and Michaels (2018) and convert the dependent variable into percentiles. Tables A.32 and A.33 show the results. Again, the qualitative relationships between the variables remains the same as in case of our baseline regressions.[8]

4 CONCLUSIONS

We propose a simple theoretical framework of production in the age of automation for countries that are subject to declining population growth. In so doing, we introduce automation as a new production factor that resembles the properties of labour in the production process, while it resembles the properties of traditional physical capital in the accumulation process. We show that lower population growth implies a stronger incentive to invest in the adoption of automation. Our empirical estimates and several robustness checks support this theoretical prediction.

As far as policy implications are concerned, our findings suggest the following. Countries that are subject to substantial demographic challenges will be the first to adopt and/or invent new automation technologies. This, in turn, might help them to overcome some of the negative effects that declining population growth and population ageing imply for long-run economic prosperity, issues that also the media is heavily concerned with (see, for example, The Washington Post, 2016).

Our framework stayed deliberately simple. In reality, there are several aspects that our stylized model does not capture. For example, i) different (manufacturing) sectors in the economy might use robots with different intensities and ii) innovation and automation are endogenous. Analyzing the extent to which the differences across sectors in robot use change with declining population growth is definitely a worthwhile research question in and of itself. In addition, it would be interesting to analyze the effects of changing population growth on the incentives to invest in innovation and automation within the frameworks of Acemoglu and Restrepo (2018), Chu et al. (2020), Prettner and Strulik (2020), and Hémous and Olsen (2021). Since these aspects are beyond the scope of our paper, we have to leave them as promising avenues for future research.

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[8] Section A.4 in the Online Appendix further elabourates on the robustness analysis.

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A ONLINE APPENDIX

A.1 SUMMARY STATISTICS

Table A.1: Summary statistics

Variable (in logs)	Observations	Mean	Std. Dev.	Minimum	Maximum
$\hat{p}_{t-1}$	300	4.300	0.909	-2.126	8.249
n_{t-1}	300	-2.057	0.239	-2.788	-1.179
$s_{i;t-1}$	300	2.879	0.609	-1.697	3.815
y_{t-1}	300	9.351	1.262	6.539	11.408
e_{t-1}	267	4.368	0.540	1.616	5.065
$open_{t-1}$	295	4.262	0.523	2.789	6.033

A.2 DATA DESCRIPTION

Table A.2: Countries with adjusted values to create manufacturing stock

Country	Year	Country	Year
Argentina	2004	South Korea	2001 (gap in 2002)
Australia	2006	Malaysia	2006
Austria	2003	Mexico	2011
Belgium	2004	Netherlands	2004
Brazil	2004	New Zealand	2006
Bulgaria	2006	Philippines	2006
Canada	2011	Poland	2004
Chile	2005	Portugal	2004
China	2006	Romania	2004
Denmark	1996	Russia	2004
Greece	2006	Singapore	2005
Hungary	2004	Slovakia	2004
Iceland	2006	Slovenia	2005
Malta	2006	South Africa	2005
Peru	2006	Switzerland	2004
India	2006	Thailand	2005
Indonesia	2006	Turkey	2005
Ireland	2006	USA	2004
Israel	2005	Vietnam	2005
Japan	1996		

Note: The year indicates the first time that the country reported disaggregated deliveries of robots at the industry level.

Table A.3: Countries included in the sample

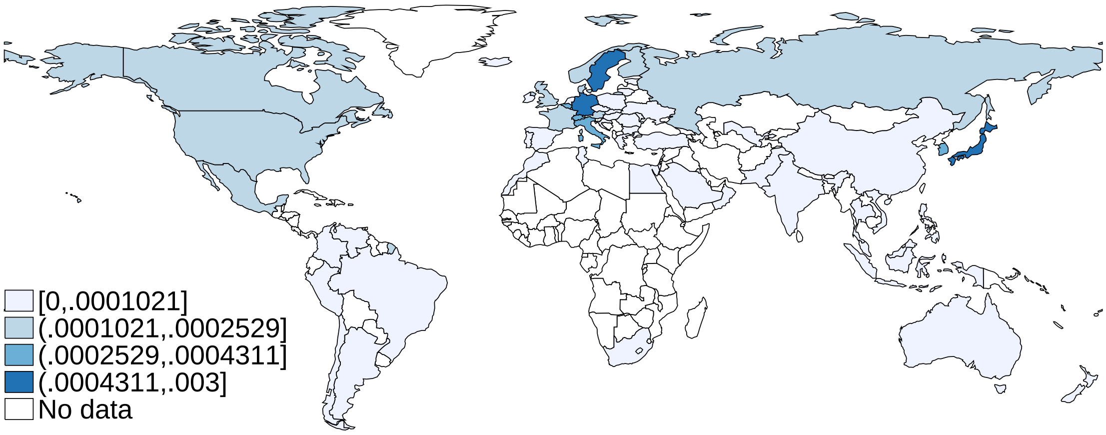
Argentina	France	Moldova	Serbia
Australia	Germany	Morocco	Singapore
Austria	Greece	NAFTA	Slovakia
Belgium	Hungary	Netherlands	South Africa
Brazil	Iceland	New Zealand	Spain
Bulgaria	India	Norway	Sweden
Chile	Indonesia	Oman	Switzerland
China	Ireland	Pakistan	Thailand
Colombia	Israel	Peru	Tunisia
Croatia	Italy	Philippines	Turkey
Czech Republic	Japan	Poland	Ukraine
Denmark	South Korea	Portugal	United Kingdom
Egypt	Kuwait	Romania	Uzbekistan
Estonia	Lithuania	Russia	Venezuela
Finland	Malaysia	Saudi Arabia	Vietnam

Table A.4: Description of the variables used in the empirical analysis

Variable	Source	Construction of the variable used in the empirical regression
Robots	International Federation of Robotics	The variable is standardized by population. Then we calculate the growth rate. Later we use the zero-skewness log transformation, which allows us to smooth the variable in a similar vain to a log transformation but including the negative values and zeroes. Not all countries report the stock nor the deliveries of industrial robots disaggregated at the industry level on a yearly basis. We follow Graetz and Michaels (2018) and take the average share of deliveries of manufacturing robots over the total deliveries of robots (when the data were available), construct an average share, and impute the values for deliveries of manufacturing robots, as well as for the initial stock of robots (when the corresponding data were not available). Please see Table A.2. in the Appendix for further details. With the initial value of the stock of industrial robots we create the stock of robots using the perpetual inventory method and assume a depreciation rate of 10%.
Population	World Development Indicators	Total population. We calculate the growth rate. Later we use the zero-skewness log transformation, which allows us to smooth the variable in a similar vain to a log transformation but including the negative values and zeroes.
Saving Rate	International Monetary Fund	Since we are not able to find a comprehensive dataset on saving rate we instead use the investment share over GDP. We sum the reported values of private investment, public investment, and joint ventures between the state and the private sector. We take logs.
GDP per Capita	World Development Indicators	GDP per capita measured in constant US$ with a base year of 2010. We take logs.
Openness	World Development Indicators	Openness is measured as exports and imports over GDP. We take logs.
Education	World Development Indicators	Gross enrollment ratio in secondary schools. We take logs.
Service Sector	World Development Indicators	Contribution of the service sector to total GDP. We take logs.
Capital Stock	Penn World Tables	Capital stock measured in 2005 US$. We take logs.
Gross Fixed Capital Formation	World Development Indicators	Gross fixed capital formation as a fraction of GDP. We take logs.
Labour Force	World Development Indicators	labour force. Then we calculate the growth rate. Later we use the zero-skewness log transformation, which allows us to smooth the variable in a similar vain to a log transformation but including the negative values and zeroes.
Life Expectancy	World Development Indicators	"Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life" (metadata description). We take logs.
Robot Exports	UN COMTRADE	We consider the code 847950 (HS96) for the data, divide it by GDP, and we use the zero-skewness log transformation, which allows us to smooth the variable in a similar vain to a log transformation but including the zero values.
Dependency Ratio	World Development Indicators	Age dependency ratio is the ratio of dependents–people younger than 15 or older than 64–to the working-age population–those ages 15-64. Data are shown as the proportion of dependents per 100 working-age population (metadata description). We take logs.

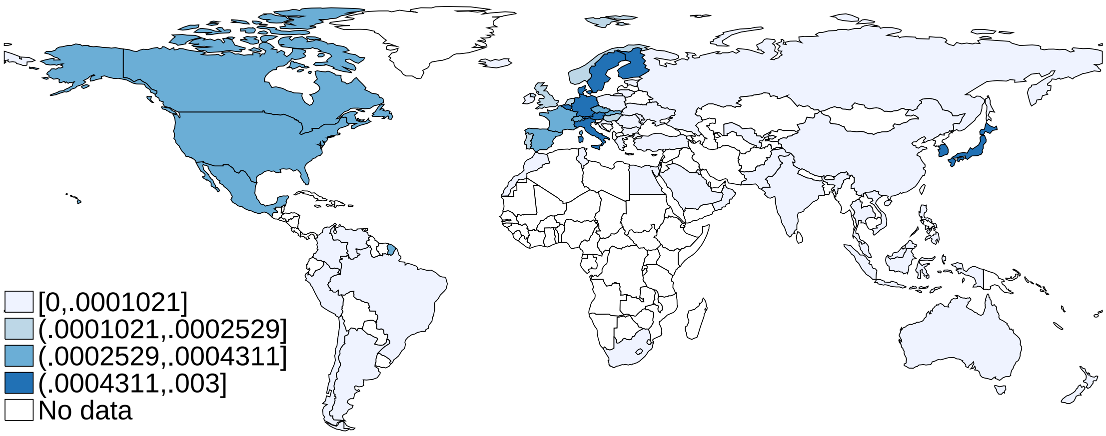
A.3 DISTRIBUTION OF THE MANUFACTURING STOCK OF ROBOTS

Figure A.1: Average manufacturing robot density for the period 1993-1995



Source: IFR and World Development Indicators. Note: The USA, Canada and Mexico have the same values because of the joint reporting.

Figure A.2: Average manufacturing robot density in the period 2011-2013



Source: IFR and World Development Indicators. Note: The USA, Canada and Mexico have the same values because of the joint reporting.

A.4 SAVING RATE AND POPULATION GROWTH

Table A.5: Saving rate and population growth, same period

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
s_{t-1}				0.673***	0.573***	0.581***	0.779***
				(0.039)	(0.043)	(0.044)	(0.132)
n_t	0.712**	0.426***	0.387**	0.125	0.152	0.150	0.126
	(0.326)	(0.153)	(0.172)	(0.119)	(0.102)	(0.103)	(0.164)
Country FE	no	no	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test		-	-	-	-	-	0.637
Hansen Test		-	-	-	-	-	0.126
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth was transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

A.5 ROBUSTNESS ANALYSIS

As a first robustness check, we control for three potential omitted variables: GDP per capita, openness of the economy, and secondary school enrollment. Omitting these variables could be a source of bias for the following reasons. As far as GDP per capita is concerned, richer countries are more able to invest in new technologies and they are also the ones that are disproportionally affected by declining fertility as outlined in Section 1. As far as openness is concerned, an open economy might be under more pressure to stay competitive, and, at the same time, smaller economies by means of the population size tend to be more open. Finally, education has a negative effect on fertility and a positive effect on GDP per capita, while, at the same time, a better educated population might be more inclined to invest in (or adapt to) robots.

Table A.6, which includes the mentioned control variables, shows again a negative correlation between robot density growth and population growth. The magnitude of the coefficients in the different specifications are marginally smaller than in the previous tables. However, except for the pooled OLS specification, they are statistically significant at the 5% or at the 10% level. One reason for the lower significance levels might be that we have to accept a reduction in the sample size because of several missing observations for the openness and the secondary enrollment variables. The coefficient estimate of the investment rate is still not statistically significant across the specifications, as in the previous case. In columns (1) and (2), GDP per capita has a negative sign, which is surprising given that richer countries would be able to invest more in new technologies. However, GDP per capita reverts its sign from column (3) onwards. Again, we believe that the reason for this is the presence of unobserved heterogeneity correlated with the regressors and therefore the estimation of a misspecified regression in columns (1) and (2), as also suggested by the Hausman test. Secondary enrollment has the predicted sign, although it is not statistically significant. Openness has a negative sign in most of the specifications, although none of the coefficients is statistically significant. Moreover, the coefficient size of the lagged dependent variable shows no need for taking the dynamics into account in the regressions.

Table A.6: Total robots growth including controls

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.210**	0.137	0.140	0.279
				(0.082)	(0.085)	(0.088)	(0.202)
n_{t-1}	-0.565	-0.731*	-1.554**	-1.377*	-1.494**	-1.485**	-3.247*
	(0.379)	(0.422)	(0.689)	(0.754)	(0.704)	(0.708)	(1.879)
s_{t-1}	0.092	0.107	-0.416	-0.377	-0.337	-0.336	-0.316
	(0.130)	(0.134)	(0.556)	(0.486)	(0.443)	(0.445)	(0.485)
y_{t-1}	-0.172**	-0.151**	2.535***	2.316***	2.280***	2.283***	-0.080
	(0.073)	(0.073)	(0.911)	(0.883)	(0.784)	(0.787)	(0.421)
e_{t-1}	0.148	0.133	0.112	0.106	0.111	0.111	0.334
	(0.180)	(0.176)	(0.192)	(0.185)	(0.171)	(0.171)	(0.244)
$open_{t-1}$	0.040	0.034	-0.088	-0.149	-0.136	-0.139	-0.144
	(0.142)	(0.155)	(0.519)	(0.552)	(0.503)	(0.506)	(0.795)
Country FE	no	no	yes	yes	yes	yes	-
Time FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.979
Hansen test	-	-	-	-	-	-	0.156
Countries	57	57	57	57	57	57	57
Observations	262	262	262	262	262	262	262

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.7: Manufacturing robots growth including controls

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.148*	0.064	0.60	0.043
				(0.078)	(0.079)	(0.081)	(0.131)
n_{t-1}	-0.472	-0.636	-1.726**	-1.599**	-1.700**	-1.697**	-1.833
	(0.382)	(0.422)	(0.702)	(0.771)	(0.703)	(0.706)	(1.218)
s_{t-1}	0.061	0.067	-0.646	-0.586	-0.567	-0.570	-0.241
	(0.109)	(0.108)	(0.558)	(0.496)	(0.441)	(0.442)	(0.349)
y_{t-1}	-0.197***	-0.181***	2.617***	2.531***	2.551***	2.580***	-0.523***
	(0.068)	(0.067)	(0.841)	(0.899)	(0.785)	(0.787)	(0.169)
e_{t-1}	0.187	0.182	0.174	0.171	0.174	0.173	0.352*
	(0.175)	(0.166)	(0.174)	(0.189)	(0.171)	(0.171)	(0.180)
$open_{t-1}$	0.024	0.021	0.000	-0.059	-0.033	-0.036	-0.392
	(0.148)	(0.158)	(0.515)	(0.566)	(0.504)	(0.507)	(0.659)
Country FE	no	no	yes	yes	yes	yes	-
Time FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.720
Hansen test	-	-	-	-	-	-	0.234
Countries	57	57	57	57	57	57	57
Observations	262	262	262	262	262	262	262

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Turning to the results regarding manufacturing robots as displayed in Table A.7, we observe a similar pattern as for the case of the total amount of robots. All specifications show a negative correlation between manufacturing robot density growth and population growth. In contrast to the previous results, we find no statistical significance in case of the system GMM estimator reported in column (7). However, this could be related to the fact that the system GMM estimator is inefficient in case of a small time dimension. As in the previous tables, we find no evidence for the importance of investment or secondary schooling for robots adoption. Similar to the case of the total stock of robots, we find a positive relationship between GDP per capita and the growth rate of the manufacturing robots density. A puzzling result is the change in the sign of per capita GDP in case of the system GMM estimator. However, the estimations performed with the corrected fixed effects estimators still exhibit a significantly positive coefficient estimate.

In Tables A.8 and A.9 we report the same specification as before but omitting the controls that were not statistically significant (i.e., secondary school enrollment and openness). The results do not change dramatically but the significance of the puzzling negative sign of per capita GDP in case of the system GMM estimator vanishes. Additionally, we report the results of adding the (log) of the size of the service sector as a percentage of overall value added to control for structural change. The results remaining fairly unchanged (see Table A.10 for total robots and Table A.11 for manufacturing robots). As alternatives to the saving rate we used two different proxies for investment – the capital stock (in 2005 US$) from the Penn World Tables version 8.1 and gross fixed capital formation as a fraction of GDP from the World Development Indicators. Tables A.12 and A.14 show the results for the total stock of robots, while Tables A.13 and A.15 show the results for the manufacturing robots only. The tables show that the stock of capital is not significantly correlated with the pace of robot adoption. Moreover, the estimates of population growth remain close in value to our previous estimates and statistically significant in the relevant specifications. The same conclusion holds when we include alternative controls such as the dependency ratio, the stock of exported robots, and life expectancy (results available in Tables A.16 and A.17 for total robots and manufacturing robots, respectively).

Table A.8: Total robots growth including GDP per capita

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.250***	0.197**	0.197**	0.119
				(0.079)	(0.092)	(0.100)	(0.163)
n_{t-1}	-0.601*	-0.732**	-1.444*	-1.283*	-1.430**	-1.421**	0.565
	(0.320)	(0.345)	(0.758)	(0.659)	(0.611)	(0.607)	(8.093)
s_{t-1}	0.102	0.123	0.003	-0.006	0.053	0.052	0.003
	(0.143)	(0.148)	(0.557)	(0.400)	(0.374)	(0.374)	(0.420)
y_{t-1}	-0.137***	-0.131***	2.195***	1.944**	1.855**	1.872**	-0.554
	(0.049)	(0.048)	(0.817)	(0.800)	(0.737)	(0.735)	(1.130)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.438
Hansen test	-	-	-	-	-	-	0.591
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.9: Manufacturing robots growth including GDP per capita

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.186**	0.124	0.119	0.005
				(0.078)	(0.087)	(0.091)	(0.082)
n_{t-1}	-0.525	-0.667*	-1.554*	-1.468**	-1.587***	-1.577***	0.466
	(0.326)	(0.355)	(0.806)	(0.674)	(0.614)	(0.612)	(4.403)
s_{t-1}	0.069	0.080	-0.272	-0.229	-0.191	-0.197	0.020
	(0.119)	(0.120)	(0.533)	(0.409)	(0.376)	(0.376)	(0.476)
y_{t-1}	-0.152***	-0.145***	2.365***	2.221***	2.174***	2.215***	-0.626
	(0.046)	(0.046)	(0.717)	(0.815)	(0.740)	(0.739)	(0.511)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.250
Hansen test	-	-	-	-	-	-	0.427
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.10: Total robots growth including the service sector

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.314***	0.267***	0.252***	0.159
				(.083)	(.089)	(0.090)	(0.146)
n_{t-1}	-0.470	-0.594*	-1.907*	-1.617**	-1.699**	-1.726**	-2.330
	(0.320)	(0.347)	(1.137)	(0.774)	(0.719)	(0.724)	(1.727)
s_{t-1}	0.067	0.097	0.590	0.446	0.466	0.478	0.626
	(0.132)	(0.146)	(0.443)	(0.370)	(0.355)	(0.357)	(0.763)
$serv_{t-1}$	-0.590	-0.533	1.155	0.931	0.972	1.004	-3.872**
	(0.596)	(0.675)	(1.911)	(1.006)	(0.943)	(0.943)	(1.759)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.957
Hansen test	-	-	-	-	-	-	0.443
Countries	58	58	58	58	58	58	58
Observations	288	288	288	288	288	288	288

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator. *serv* stands for the contribution of the service sector to overall GDP.

Table A.11: Manufacturing robots growth including the service sector

	(1) POLS	(2) RE	(3) FE	(4) CorrFE (bb)	(5) CorrFE (ab)	(6) CorrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.342***	0.328***	0.306***	0.047
				(0.076)	(.074)	(0 .078)	(0 .121)
n_{t-1}	-0.405	-0.516	-2.286*	-1.774**	-1.790**	-1.854**	-4.526**
	(0.300)	(0.323)	(1.257)	(0.795)	(0.769)	(0.775)	(2.291)
s_{t-1}	0.033	0.050	0.370	0.187	0.194	0.209	1.023
	(0.103)	(0.112)	(0.423)	(0.375)	(0.366)	(0.367)	(1.010)
$serv_{t-1}$	-0.559	-0.535	1.010	0.830	0.839	0.874	-4.106**
	(0.577)	(0.636)	(1.893)	(1.022)	(0.981)	(0.977)	(1.967)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.281
Hansen test	-	-	-	-	-	-	0.372
Countries	58	58	58	58	58	58	58
Observations	288	288	288	288	288	288	288

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator. *serv* stands for the contribution of the service sector to overall GDP.

Table A.12: Total robots - capital stock as control

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.322***	0.263***	0.248***	0.290*
				(0.078)	(0.092)	(0.096)	(0.172)
n_{t-1}	-0.513	-0.665*	-1.877**	-1.565**	-1.669***	-1.691***	-1.664
	(0.338)	(0.364)	(0.814)	(0.617)	(0.592)	(0.596)	(1.319)
s_{t-1}	0.046	0.074	0.471	0.348	0.371	0.382	0.225
	(0.113)	(0.124)	(0.429)	(0.320)	(0.299)	(0.300)	(0.521)
$capital\ stock_{t-1}$	-0.022	-0.027	-0.518	-0.455	-0.450	-0.458	-0.189
	(0.048)	(0.044)	(0.547)	(0.366)	(0.338)	(0.337)	(0.184)
Country FE	no	no	yes	yes	yes	yes	-
Year Dummies	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.345
Hansen test	-	-	-	-	-	-	0.090
Number of Countries	59	59	59	59	59	59	59
Observations	295	295	295	295	295	295	295

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.13: Manufacturing robots - capital stock as control

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.361***	0.340***	0.316***	0.047
				(0.079)	(0.086)	(0.094)	(0.108)
n_{t-1}	-0.501	-0.640*	-2.211**	-1.669***	-1.715***	-1.772***	-5.383***
	(0.338)	(0.360)	(0.931)	(0.639)	(0.631)	(0.637)	(1.255)
s_{t-1}	0.011	0.026	0.241	0.074	0.089	0.102	0.452
	(0.084)	(0.091)	(0.415)	(0.323)	(0.310)	(0.310)	(0.590)
$capital\ stock_{t-1}$	0.003	0.000	-0.416	-0.429	-0.401	-0.411	-0.404
	(0.049)	(0.047)	(0.541)	(0.371)	(0.352)	(0.352)	(0.246)
Country FE	no	no	yes	yes	yes	yes	-
Year Dummies	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.255
Hansen test	-	-	-	-	-	-	0.774
Number of Countries	59	59	59	59	59	59	59
Observations	295	295	295	295	295	295	295

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.14: Total robots - gross fixed capital formation (as a fraction of GDP) as control

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.312***	0.262***	0.247**	0.109
				(0.072)	(0.092)	(0.097)	(0.134)
n_{t-1}	-0.430	-0.586	-2.006**	-1.667**	-1.761**	-1.787**	-2.743**
	(0.342)	(0.370)	(0.884)	(0.775)	(0.752)	(0.757)	(1.249)
s_{t-1}	-0.006	0.013	0.247	0.077	0.115	0.132	-0.527
	(0.088)	(0.099)	(0.849)	(0.577)	(0.532)	(0.532)	(0.918)
$capital\ formation_{t-1}$	0.678**	0.579*	0.267	0.342	0.323	0.313	1.385
	(0.311)	(0.311)	(0.726)	(0.678)	(0.640)	(0.637)	(1.322)
Country FE	no	no	yes	yes	yes	yes	-
Year Dummies	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.311
Hansen test	-	-	-	-	-	-	0.973
Number of Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.15: Manufacturing robots - gross fixed capital formation (as a fraction of GDP) as control

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.351***	0.335***	0.312***	0.154
				(0.068)	(0.078)	(0.084)	(0.110)
n_{t-1}	-0.410	-0.547	-2.301**	-1.754**	-1.782**	-1.842**	-2.907**
	(0.329)	(0.357)	(0.977)	(0.783)	(0.773)	(0.780)	(1.356)
s_{t-1}	-0.036	-0.026	-0.113	-0.342	-0.306	-0.293	-0.338
	(0.054)	(0.060)	(0.779)	(0.580)	(0.551)	(0.548)	(0.695)
$capital\ formation_{t-1}$	0.682**	0.596**	0.495	0.576	0.553	0.553	1.460
	(0.297)	(0.292)	(0.641)	(0.687)	(0.664)	(0.659)	(1.210)
Country FE	no	no	yes	yes	yes	yes	-
Year Dummies	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.677
Hansen test	-	-	-	-	-	-	0.419
Number of Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.16: Total robots - life expectancy, dependency ratio and exports of robots as extra controls

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.169**	0.095	0.092	0.025
				(0.078)	(0.087)	(0.087)	(0.144)
n_{t-1}	-0.731	-0.986**	-2.105*	-1.614*	-1.899**	-1.913**	-2.363
	(0.515)	(0.477)	(1.206)	(0.901)	(0.897)	(0.923)	(1.810)
s_{t-1}	0.122	0.138	0.440	0.506	0.529	0.530	-1.183
	(0.177)	(0.192)	(0.750)	(0.575)	(0.550)	(0.550)	(1.598)
Dependency	-0.097	-0.164	0.116	0.342	0.170	0.144	-1.186
	(0.364)	(0.321)	(1.516)	(1.968)	(1.827)	(1.833)	(1.519)
Life Exp.	-2.571	-2.023	4.791	2.255	3.005	3.058	-1.620
	(1.798)	(1.608)	(9.615)	(9.025)	(8.550)	(8.493)	(16.852)
Robo. Expo.	0.025	0.002	-0.101	-0.105	-0.112	-0.112	-0.286
	(0.047)	(0.042)	(0.100)	(0.100)	(0.097)	(0.098)	(0.194)
Country FE	no	no	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.521
Hansen Test	-	-	-	-	-	-	0.531
Countries	60	60	60	60	60	60	60
Observations	240	240	240	240	240	240	240

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator. "Dependency" stands for the dependency ratio, "life exp." for life expectancy and "robo. expo." for the exports of industrial robots.

Table A.17: Manufacturing robots - life expectancy, dependency ratio and exports of robots as extra controls

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$			0.134*	0.049	0.043	-0.061	
				(0.074)	(0.082)	(0.082)	(0.111)
n_{t-1}	-0.622	-0.976**	-2.577*	-2.178**	-2.463***	-2.481***	-2.095
	(0.509)	(0.477)	(1.288)	(0.921)	(0.904)	(0.910)	(2.138)
s_{t-1}	0.081	0.086	0.244	0.360	0.374	0.375	-0.843
	(0.138)	(0.143)	(0.754)	(0.590)	(0.557)	(0.554)	(1.599)
Dependency	-0.104	-0.247	-0.499	-0.334	-0.458	-0.488	-1.079
	(0.373)	(0.326)	(1.382)	(2.017)	(1.847)	(1.842)	(1.667)
Life Exp.	-2.886	-2.255	8.150	5.841	6.805	6.914	-4.852
	(1.842)	(1.607)	(9.383)	(9.282)	(8.698)	(8.579)	(15.850)
Robo. Expo.	0.044	0.038	0.028	0.017	0.015	0.015	-0.098
	(0.048)	(0.045)	(0.111)	(0.102)	(0.098)	(0.099)	(0.191)
Country FE	no	no	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.979
Hansen Test	-	-	-	-	-	-	0.799
Countries	60	60	60	60	60	60	60
Observations	240	240	240	240	240	240	240

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator. "Dependency" stands for the dependency ratio, "life exp." for life expectancy and "robo. expo." for the exports of industrial robots.

As further robustness checks, we used 2-year averages instead of averaging the data over 3 years. Tables A.18 and A.19 show the corresponding results. As before, we observe a statistically significant negative correlation of the population growth rate with the growth of robot density (either of the total stock of robots or the ones employed in the manufacturing sector). However, the magnitude of the correlation is smaller in absolute value. The investment rate coefficient continues to be statistically insignificant in both tables, having a positive sign in most of the cases. Only in column (7) of Table A.19 the coefficient of the investment rate is negative, although this estimate should be considered with caution because the AR(2) test cannot rule out remaining autocorrelation of the residuals at the 10% significance level. Moreover, we also constructed two alternative robot stocks using 5% and 15% as alternative depreciation rates. The estimates for the baseline model are shown in Tables A.20 and A.22 (for the total stock of robots) and Tables A.21 and A.23 (for manufacturing robots). We find no substantial differences with our previous estimates.

Table A.18: Total robots - 2-year averages instead of 3-year averages

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.366***	0.351***	0.393***	0.291***
				(0.049)	(0.050)	(0.051)	(0.071)
n_{t-1}	-0.435	-0.606*	-1.160*	-0.717**	-0.736**	-0.706*	-1.415*
	(0.294)	(0.344)	(0.594)	(0.359)	(0.343)	(0.370)	(0.760)
s_{t-1}	0.093	0.135	0.380	0.230	0.247	0.257	0.091
	(0.099)	(0.108)	(0.326)	(0.214)	(0.196)	(0.208)	(0.155)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.143
Hansen test	-	-	-	-	-	-	0.276
Countries	60	60	60	60	60	60	60
Observations	539	539	539	539	539	539	539

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.19: Manufacturing robots - 2-year averages instead of 3-year averages

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.341***	0.316***	0.369***	0.297***
				(0.049)	(0.050)	(0.051)	(0.083)
n_{t-1}	-0.336	-0.519	-1.142*	-0.775**	-0.790**	-0.754**	-1.398*
	(0.292)	(0.347)	(0.604)	(0.364)	(0.346)	(0.376)	(0.780)
s_{t-1}	0.058	0.088	0.247	0.132	0.148	0.169	-0.033
	(0.074)	(0.079)	(0.316)	(0.219)	(0.199)	(0.213)	(0.195)
Country FE	no	no	yes	yes	yes	yes	-
Year Dummies	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.055
Hansen test	-	-	-	-	-	-	0.155
Countries	60	60	60	60	60	60	60
Observations	539	539	539	539	539	539	539

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.20: Total robots - 5% depreciation rate

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.339***	0.294***	0.280***	0.299**
				(0.077)	(0.088)	(0.099)	(0.137)
n_{t-1}	-0.591*	-0.718**	-2.151**	-1.731***	-1.835***	-1.862***	-2.687**
	(0.332)	(0.353)	(0.937)	(0.645)	(0.612)	(0.608)	(1.291)
s_{t-1}	0.077	0.103	0.545	0.385	0.405	0.419	-0.146
	(0.125)	(0.136)	(0.519)	(0.387)	(0.371)	(0.374)	(0.622)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.783
Hansen test	-	-	-	-	-	-	0.177
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.21: Manufacturing robots 5% depreciation rate

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.300***	0.246***	0.227**	0.200
				(0.076)	(0.085)	(0.093)	(0.128)
n_{t-1}	-0.526	-0.673*	-2.332**	-2.018***	-2.116***	-2.147***	-3.024***
	(0.345)	(0.370)	(1.018)	(0.662)	(0.623)	(0.618)	(1.117)
s_{t-1}	0.051	0.070	0.318	0.229	0.244	0.258	0.094
	(0.111)	(0.117)	(0.517)	(0.395)	(0.376)	(0.376)	(0.458)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.884
Hansen test	-	-	-	-	-	-	0.119
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.22: Total robots - 15% depreciation rate

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.301***	0.240***	0.227**	0.174
				(0.079)	(0.092)	(0.098)	(0.106)
n_{t-1}	-0.515	-0.683*	-1.945**	-1.658***	-1.763***	-1.782***	-4.050***
	(0.323)	(0.353)	(0.858)	(0.562)	(0.528)	(0.523)	(1.377)
s_{t-1}	0.055	0.081	0.337	0.247	0.266	0.272	0.291
	(0.118)	(0.126)	(0.477)	(0.335)	(0.319)	(0.319)	(0.542)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.790
Hansen test	-	-	-	-	-	-	0.891
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.23: Manufacturing robots 15% depreciation rate

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.233***	0.162*	0.149*	0.071
				(0.078)	(0.085)	(0.090)	(0.123)
n_{t-1}	-0.419	-0.605*	-2.079**	-1.901***	-1.998***	-2.012***	-4.411***
	(0.328)	(0.365)	(0.938)	(0.575)	(0.534)	(0.531)	(1.430)
s_{t-1}	0.009	0.022	0.072	0.059	0.071	0.075	0.290
	(0.086)	(0.091)	(0.469)	(0.342)	(0.321)	(0.320)	(0.491)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.481
Hansen test	-	-	-	-	-	-	0.813
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

In another sensitivity analysis, we exclude Germany, South Korea, the NAFTA countries, Japan, and China because these are the countries with the highest (manufacturing) robot density and also very low fertility rates. Irrespective of this substantial reduction in the sample, the results are stable, as can be seen is Tables A.24 and A.25. We did a further change in the sample to include two extra available years (2014 and 2015 – although creating the last value as an average of two and not three years). Furthermore, we replaced population growth with labour force growth. Tables A.26 and A.27 show the results including the two extra years for the total stock of robots. The point estimates are slightly smaller (in absolute value) but not statistically significantly different from each other. Tables A.28 and A.29 show the baseline estimates using labour force growth instead of population growth. As before, the results differ only slightly from the baseline estimates.

Table A.24: Total robots - reduced sample

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				.306***	0.250***	0.237***	0.184
				(0.068)	(0.083)	(0.088)	(0.123)
n_{t-1}	-0.614*	-0.766**	-2.098**	-1.756**	-1.869***	-1.893***	-3.630***
	(0.326)	(0.353)	(0.904)	(0.692)	(0.664)	(0.671)	(1.303)
s_{t-1}	0.074	0.098	0.373	0.291	0.304	0.313	0.498
	(0.123)	(0.132)	(0.510)	(0.369)	(0.350)	(0.348)	(0.599)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.785
Hansen test	-	-	-	-	-	-	0.504
Countries	55	55	55	55	55	55	55
Observations	275	275	275	275	275	275	275

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.25: Manufacturing robots - reduced sample

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.247***	0.179**	0.163*	0.076
				(0.070)	(0.081)	(0.086)	(0.104)
n_{t-1}	-0.530	-0.704*	-2.264**	-2.038***	-2.147***	-2.170***	-4.138***
	(0.336)	(0.368)	(0.983)	(0.711)	(0.674)	(0.680)	(1.164)
s_{t-1}	0.035	0.050	0.123	0.111	0.117	0.124	0.531
	(0.098)	(0.103)	(0.502)	(0.376)	(0.352)	(0.351)	(0.569)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.429
Hansen test	-	-	-	-	-	-	0.565
Countries	55	55	55	55	55	55	55
Observations	275	275	275	275	275	275	275

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with “bb” indicating initialization by the Blundell and Bond (1998) estimator, “ab” initialization by the Arellano and Bond (1991) estimator, and “ah” initialization by the Anderson and Hsiao (1982) estimator.

Table A.26: Total robots - sample with two extra years

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.2452***	0.2207***	0.2395***	0.1326
				(0.064)	(0.073)	(0.076)	(0.094)
n_{t-1}	-0.533*	-0.629**	-1.101**	-0.897*	-0.936**	-0.908**	-1.888***
	(0.281)	(0.294)	(0.440)	(0.459)	(0.445)	(0.456)	(0.570)
s_{t-1}	0.073	0.093	0.268	0.191	0.210	0.213	-0.006
	(0.120)	(0.127)	(0.400)	(0.299)	(0.281)	(0.289)	(0.530)
Country FE	no	no	yes	yes	yes	yes	-
Year Dummies	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.685
Hansen test	-	-	-	-	-	-	0.138
Number of Countries	60	60	60	60	60	60	60
Observations	360	360	360	360	360	360	360

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with “bb” indicating initialization by the Blundell and Bond (1998) estimator, “ab” initialization by the Arellano and Bond (1991) estimator, and “ah” initialization by the Anderson and Hsiao (1982) estimator.

Table A.27: Manufacturing robots - sample with two extra years

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.2932***	0.2899***	0.2917***	0.1719
				(0.060)	(0.059)	(0.061)	(0.106)
n_{t-1}	-0.520*	-0.638**	-1.342***	-0.814*	-0.815*	-0.813*	-1.675***
	(0.297)	(0.306)	(0.452)	(0.460)	(0.456)	(0.461)	(0.628)
s_{t-1}	0.038	0.048	0.097	-0.059	-0.040	-0.038	-0.303
	(0.088)	(0.093)	(0.411)	(0.306)	(0.297)	(0.298)	(0.431)
Country FE	no	no	yes	yes	yes	yes	-
Year Dummies	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.750
Hansen test	-	-	-	-	-	-	0.235
Number of Countries	60	60	60	60	60	60	60
Observations	360	360	360	360	360	360	360

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.28: Total robots - labour force growth

	(1) POLS	(2) RE	(3) RE	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
$\hat{p}_{t-1}$				0.321***	0.262***	0.248**	0.199**	
				(0.072)	(0.094)	(0.097)	(0.094)	
n_{t-1}	-0.805*	-0.959**	-1.541**	-1.379***	-1.424***	-1.430***	-2.763***	
	(0.403)	(0.454)	(0.635)	(0.465)	(0.447)	(0.449)	(0.714)	
s_{t-1}	0.062	0.090	0.493	0.385	0.393	0.402	-0.150	
	(0.103)	(0.113)	(0.451)	(0.353)	(0.330)	(0.331)	(0.532)	
Country FE	no	no	yes	yes	yes	yes	-	
Year Dummies	yes	yes	yes	yes	yes	yes	yes	
AR(2) test	-	-	-	-	-	-	0.387	
Hansen test	-	-	-	-	-	-	0.123	
Number of Countries	60	60	60	60	60	60	60	
Observations	300	300	300	300	300	300	300	

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.29: Manufacturing robots - labour force growth

	(1) POLS	(2) RE	(3) RE	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
$\hat{p}_{t-1}$				0.372***	0.363***	0.3446***	0.194**	
				(0.066)	(0.069)	(0.074)	(0.097)	
n_{t-1}	-0.811*	-0.971**	-1.747**	-1.506***	-1.518***	-1.531***	-2.924***	
	(0.448)	(0.491)	(0.673)	(0.471)	(0.468)	(0.467)	(0.692)	
s_{t-1}	0.037	0.051	0.272	0.103	0.103	0.112	-0.087	
	(0.080)	(0.084)	(0.469)	(0.352)	(0.344)	(0.343)	(0.268)	
Country FE	no	no	yes	yes	yes	yes	-	
Year Dummies	yes	yes	yes	yes	yes	yes	yes	
AR(2) test	-	-	-	-	-	-	0.713	
Hansen test	-	-	-	-	-	-	0.411	
Number of Countries	60	60	60	60	60	60	60	
Observations	300	300	300	300	300	300	300	

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

A concern could arise that our results are dependent on the zero-skewness log transformation. A further robustness check therefore relies on using the neglog transformation for both the population growth rate and the robot density growth rate. The neglog transformation involves the following adjustments to a variable (which we call x for simplicity). If $x <= 0$, then we use $-\ln(-x+1)$ instead of x and if $x > 0$, then we use $\ln(x+1)$ instead of x. The results are shown in Tables A.30 and A.31. Again, the results remain similar to the baseline specification in terms of the sign and the statistical significance, although the size of the coefficients is much larger.

Table A.30: Total robots - neglog transformation

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.496***	0.477***	0.456***	0.473***
				(0.068)	(0.081)	(0.092)	(0.105)
n_{t-1}	-12.135*	-15.798**	-35.286*	-20.726**	-21.720**	-22.657**	-40.401***
	(6.436)	(6.399)	(18.480)	(10.299)	(10.138)	(9.892)	(14.349)
s_{t-1}	0.321	0.499	2.409**	1.275	1.327	1.383	-0.575
	(0.430)	(0.475)	(0.957)	(0.909)	(0.916)	(0.921)	(1.030)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.100
Hansen test	-	-	-	-	-	-	0.186
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

Table A.31: Manufacturing robots - neglog transformation

	(1) POLS	(2) RE	(3) FE	(4) corrFE (bb)	(5) corrFE (ab)	(6) corrFE (ah)	(7) GMM (sys)
$\hat{p}_{t-1}$				0.257***	0.192**	0.174*	0.186*
				(0.077)	(0.086)	(0.918)	(0.110)
n_{t-1}	-4.084	-5.570*	-16.691**	-14.854***	-15.714***	-15.892***	-23.165***
	(2.791)	(3.069)	(7.375)	(4.150)	(3.880)	(3.846)	(8.161)
s_{t-1}	0.030	0.049	0.266	0.219	0.237	0.247	0.152
	(0.094)	(0.100)	(0.469)	(0.369)	(0.347)	(0.347)	(0.355)
Country FE	no	no	yes	yes	yes	yes	-
Year FE	yes	yes	yes	yes	yes	yes	yes
AR(2) test	-	-	-	-	-	-	0.798
Hansen test	-	-	-	-	-	-	0.219
Countries	60	60	60	60	60	60	60
Observations	300	300	300	300	300	300	300

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are bootstrapped with 50 iterations. Column (7) uses collapsed instruments and an orthogonal transformation. All of the variables are in logarithms, while population growth and robots growth were transformed with the zero-skewness log transformation. CorrFE refers to the corrected fixed effects with "bb" indicating initialization by the Blundell and Bond (1998) estimator, "ab" initialization by the Arellano and Bond (1991) estimator, and "ah" initialization by the Anderson and Hsiao (1982) estimator.

In our last robustness check, we follow Graetz and Michaels (2018) and convert the dependent variable into percentiles. Consequently, we include the population growth rate without the logarithmic transformation as regressor. We estimate, as before, a pooled OLS and a random effects specification. To the latter we also add continent dummies to further control for differences related to the geographical location. Finally, we also include several cross-sectional regressions for different time periods. Tables A.32 and A.33 show the results. Naturally, the coefficient estimates cannot anymore be interpreted as elasticities. We observe that the qualitative relationships between the variables remains the same as in case of our baseline regressions and that the coefficients are statistically significant in most of the specifications (sometimes also the investment rate is significant as can be seen in Table A.32). We refrain from using the fixed effects estimator given the nature of the dependent variable. In this scenario the preferred specification is the one obtained with the random effects estimator. Both tables show that a one percent increase of the population growth rate is associated with a decrease of approximately two percentiles in the growth of the robot density. The addition of the continent dummies does not add much additional explanatory power and the magnitude of the coefficient of interest barely changes. With regards to the cross-sections, we rank the robot density growth rates to avoid dividing them into percentiles with only 60 observations. The coefficient of interest is still significant in most specifications and has the predicted negative sign. In columns (5) and (7) of both tables, however, the coefficient looses statistical significance. This could be due to the dot-com crisis and the global financial crisis because these columns correspond to the periods including 2001 and 2008, respectively.

Table A.32: Total robots - percentiles as the dependent variable

	(1) POLS	(2) RE	(3) RE	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
n_{t-1}	-1.862***	-2.053***	-2.144**	-3.323***	-0.142	-1.027**	-0.870	-1.671***
	(0.653)	(0.651)	(0.996)	(0.387)	(0.355)	(0.369)	(1.061)	(0.316)
s_{t-1}	0.649	0.721*	0.765*	0.741	0.392	0.687*	0.213	0.434
	(0.415)	(0.395)	(0.404)	(0.422)	(0.301)	(0.323)	(0.290)	(0.365)
Period	All	All	All	1999-2001	2002-2004	2005-2007	2008-2010	2011-2013
FE	Year	Year	Year + Continent	-	-	-	-	-
Observations	300	300	300	60	60	60	60	60

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are clustered at the continent level. The dependent variable of columns (1) to (3) is the percentile of the distribution of the robot density growth, while the one of columns (3) to (6) is the country rank.

Table A.33: Manufacturing robots - percentiles as the dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
n_{t-1}	-1.689**	-1.863**	-2.080*	-3.011***	0.183	-0.820**	-0.880	-1.537***
	(0.748)	(0.729)	(1.064)	(0.537)	(0.360)	(0.287)	(0.758)	(0.292)
s_{t-1}	0.594	0.612	0.647	0.670	0.345	0.817**	0.004	0.427
	(0.415)	(0.393)	(0.403)	(0.338)	(0.284)	(0.305)	(0.347)	(0.360)
Period	All	All	All	1999-2001	2002-2004	2005-2007	2008-2010	2011-2013
FE	Year	Year	Year + Continent	-	-	-	-	-
Observations	300	300	300	60	60	60	60	60

Note: Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. The standard errors of columns (1), (2), and (3) are clustered at the country level, while the ones from (4) to (6) are clustered at the continent level. The dependent variable of columns (1) to (3) is the percentile of the distribution of the robot density growth, while the one of columns (3) to (6) is the country rank.