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Automation and demographic change

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Automation and demographic change

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Abstract

We analyze the effects of declining population growth on the adoption of automation technology. A standard theoretical framework of the accumulation of traditional physical capital and of automation capital predicts that countries with a lower population growth rate are the ones that innovate and/or adopt new automation technologies faster. We test the theoretical prediction by means of panel data for 60 countries over the time span from 1993 to 2013. Regression estimates provide empirical support for the theoretical prediction and suggest that a 1% increase in population growth is associated with approximately a 2% reduction in the growth rate of robot density. Our results are robust to the inclusion of standard control variables, the use of different estimation methods, the consideration of a dynamic framework with the lagged dependent variable as a regressor, and changing the measurement of the stock of robots.

JEL classification: J11, O14, O33, O40.

Keywords: Automation, Industrial Robots, Demographic Change, Declining Population Growth, Economic Growth.

1 Introduction

Industrialized countries have experienced substantial declines in fertility and in birth rates over the last few 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) in which we depict the situation in the G7 countries). These demographic changes have already had a pronounced effect on the evolution of the labor force. Furthermore, the relatively larger cohorts that entered the labor markets of these countries in the 1960s and 1970s are now starting to reach the retirement age such that a substantial decline in the working-age population is most likely to prevail in the coming decades.

There are many concerns among economists regarding the long-run consequences of the mentioned demographic developments. For example, it is often argued that social security systems and retirement schemes would need to be reformed to ensure that they are accurately financed in the future when fewer and fewer workers will have to support ever more retirees (see Gruber and Wise, 1998; Bloom et al., 2010; The Economist, 2011), there are concerns that investment rates will decline when the retiring cohorts run down their assets (Mankiw and Weil, 1989; Schich, 2008), and some are afraid that the innovative capacity of aging societies will decline (see, for example, Canton et al., 2002; Borghans and ter Weel, 2002; Gehringer and Prettnner, 2014; Irmen and Litina, 2016). Some commentators have even gone so far as to argue that aging is a “threat more grave and certain than those posed by chemical weapons, nuclear proliferation, or ethnic strife” (Peterson, 1999).

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

Country	TFR	TFR	CBR	CBR
	1950-1955	2010-2015	1950-1955	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

As far as the expected labor shortages due to population aging are concerned, there is a silver lining on the horizon. In recent years, robots have started to take over many tasks that have previously been regarded as non-automatable and it is expected that this trend will continue in the future (see Frey and Osborne, 2013; Arntz et al., 2016, for different views on the extent of this development). 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 to rely on the (usually highly imperfect) driving skills of humans (fully automated food deliveries are already present in some cities, see El Pais, 2016); 3D printers are starting to produce highly specialized products – that could not be mass-manufactured before and which therefore required a lot of specialized human labor input – at a large scale; software based on machine learning is now already able to more reliably diagnose diseases than doctors; and even the skills of authors become more and more obsolete as algorithms are able to write newsflashes, reports, and even novels on their own (see, for example, The Economist, 2014; Abeliansky et al., 2015; Lanchester, 2015; Graetz and Michaels, 2015; Brynjolfsson and McAfee, 2016, on different aspects of automation and on new developments). Admittedly, it is still a much bigger pleasure to read “Anna Karenina” than “True Love” (a novel written by an algorithm programmed to rewrite Anna Karenina in the style of the Japanese author Haruki Murakami; see Barrie, 2014). However, things might change quite fast and maybe we will some day be able to find out how “The Trial” or “The Man Without Qualities” end – hopefully in the style of Kafka and Musil, respectively.

The paper is structured as follows. In Section (2), we provide some theoretical considerations on the potential effects of automation in the face of the demographic changes outlined in the introduction and we assess for which countries with a given demographic structure the adoption of robots is most likely to occur at a fast rate. In Section (3) we test the theoretical predictions empirically and in Section (4) we discuss our results and draw some policy conclusions.

2 Declining population growth and automation: Theoretical considerations

2.1 Basic assumptions

Consider an economy with three production factors, human labor, traditional capital (machines, assembly lines, production halls, office buildings, etc.), and automation capital (robots, 3D printers, driverless cars, devices based on machine learning, etc). Time t evolves discretely such that one time step corresponds to approximately 25 years 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 generation. Human labor and traditional physical capital are imperfect substitutes, while automation capital is – by its definition – a perfect substitute for labor. Note the special and non-standard role that automation capital plays in such a setting: on the one hand, it performs the tasks of human labor and therefore constitutes a perfect substitute for this production factor; on the other hand, its accumulation resembles the process of standard physical capital accumulation and the income stream that automation capital generates flows to the capital owners/savers of an economy. Overall, we follow the simplified exposition of Solow (1956) and assume that households save a constant fraction $s \in (0, 1)$ of

their total income. The savings rate could also be endogenized along the lines of Ramsey (1928), Cass (1965), and Koopmans (1965) but this would mainly complicate the exposition without adding substantially new insights regarding the effect of demographic change on automation. In a very interesting contribution, Steigum (2011) analyzes the effects of automation capital that is a (potentially imperfect) substitute for human labor, on long-run economic growth.¹

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. This rate is expected to fall in the future because of the demographic changes outlined in the introduction. We assume that there is inelastic labor supply of households and full employment such that the labor force at time t is also 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 work-force which is realistic, although, of course, it typically requires a certain amount of time. We abstract from this delay and assume that the decline of the population growth rate also represents the decline in the work-force.

Aggregate savings are given by $S_{t+1} = sN_t$ and there are two savings vehicles, traditional physical capital and automation capital. As a consequence, there is a no-arbitrage condition that has to hold in any equilibrium in which individuals are investing in both types of assets. 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

We follow Prettnner (2017) and assume that the production function has a Cobb-Douglas structure with respect to human labor and traditional physical capital. However, the additional non-standard production factor “automation capital” is a perfect substitute for labor 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

¹Endogenizing the savings rate along the lines of Diamond (1965), however, runs into problems because the accumulation of automation capital reduces the wages of households in the first period of their lives and therefore reduces their savings capacity, which leads to a stagnation equilibrium (Sachs and Kotlikoff, 2012; Benzell et al., 2015; Sachs et al., 2015; Gasteiger and Prettnner, 2017). However, it is more realistic that savings are not only made out of wage income but also out of capital income

of economic growth but it would not alter the crucial mechanisms in our framework.² We assume that there is perfect competition on factor markets such that production factors are paid their marginal value product. 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

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

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

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

where R_{t+1}^{autom} is the gross interest rate paid on automation capital, which is equal to the wage rate, and R_{t+1}^{trad} is the gross interest rate paid on traditional physical capital. The no-arbitrage condition states that investments in both types of physical capital have to yield the same rate of return, i.e., it holds that $R_{t+1}^{autom} = R_{t+1}^{trad}$. Setting Equations (2) and (3) equal to each other and solving for K_t and P_t , respectively, yields

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

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

$$Y_t = \left(\frac{\alpha}{1 - \alpha} \right) [L_t + P_t], \quad (5)$$

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 savings rate is large enough such that a positive accumulation rate of automation capital can be sustained (cf. Steigum, 2011; Prettnner, 2017). 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 with respect to physical capital but due to the structure of the production process as derived in the presence of automation capital.³ Allowing for a different rate of depreciation for traditional physical capital and for automation capital would leave our central results unchanged. The only

²For an R&D-based endogenous growth model along the lines of Romer (1990) in which firms can invest in robot technology, see Hémous and Olsen (2016). In Acemoglu and Restrepo (2015) new tasks are constantly created by R&D, while, at the same time, old tasks are automated. Both of these papers focus on a different aspect of the rise of machines than the implications of demographic change for investments in (and the adoption of) automation technology.

³Peretto and Saeter (2013) construct a long-run economic growth model in which firms can invest in technological progress that raises the productivity of physical capital by increasing the elasticity of final output with respect to physical capital. In the long-run limit, their aggregate production function converges to an *AK* type of production function and economic growth is perpetual.

difference would be that an additional constant term (the difference between the rates of depreciation between the two forms of capital) appeared in Equation (4) and in the derivations that are based on this equation.

From Equation (5) it follows that *per capita* GDP is given by

$$y_t = \left(\frac{\alpha}{1 - \alpha} \right) (p_t + 1),$$

where p_t is the automation density in terms of automation capital per capita. We immediately see that the prosperity of a country is positively linked to its automation density. The intuitive explanation for this is clear. For a given population size, automation overcomes the diminishing marginal product of traditional physical capital that acts as a boundary for long-run economic growth in the standard Solow (1956) model (see Prettnner, 2017, for the analysis of the implications of automation for long-run economic growth in such a setting). Once the tasks which could previously only be carried out by human labor are automated, the stock of labor becomes, essentially, a reproducible production factor. At the aggregate level, there are constant returns to scale with respect to all reproducible production factors such that automation creates the potential for long-run growth without additional factor-augmenting technological progress. Next, we analyze how the automation density itself depends on the demographic setting, which is our main question of interest that we analyze empirically in Section (3).

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

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

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

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

From this equation it follows immediately that a country with a lower population growth rate will have a higher density of automation technology. We summarize this 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 (labor income and capital income in the form of traditional physical capital and automation capital), and the no-arbitrage condition (4) holds for both types of investments. In this case a country will have a higher density of automation capital if it has a lower population growth rate (n).*

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

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

Not that this expression 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 robots divided by the population size. \square

The intuition for this finding is the following: A country in which the population – and with it the labor force – grows fast, exhibits a comparably high rate of return on traditional physical capital without the need 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 (think, for example, of African countries with a very fast population growth rate such as Mali and Niger: investing in automation would not be very attractive business strategy). By contrast, in a country in which the population – and with it the labor force – stagnates or even decreases, the rate of return on investment in automation would typically be high and the rate of return on investment in traditional physical capital would be rather low (think, for example, of aging European countries such as Germany and Italy and aging East Asian countries such as Japan and South Korea). Consequently, our theory predicts that the automation density should be higher in the countries in which the growth rate of the population is rather low or even negative.

A first glimpse on whether this is true is provided by Table (2) that shows the robot density as of 2015 in those countries with the highest robot density together with the average population growth rate in the preceding 5-year interval from 2010 to 2015. In general, we observe that the population growth rate in these countries is rather low and in some of them even negative. However, this could just be due to the fact that these countries are richer and are therefore able to invest more in automation technology. In the next section we therefore test whether our theoretical implication is borne out by the data in a more thorough way.

3 Declining population growth and automation: Empirical results

In this section we introduce the data, then we test Proposition (1) empirically, and finally we provide a number of robustness checks.

Table 2: Robot density and population growth in the top 10 countries with the highest robot density (International Federation of Robotics, 2015; United Nations, 2015)

Country	robot density 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%
Taiwan	129	N/A

Note: The robot density is measured in terms of robots per 10,000 employees in manufacturing in 2015. 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).

3.1 Data description

The only available data-set 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 “multipurpose manipulating industrial robots” as defined by the International Organization for Standardization⁴ for several countries, starting from 1993. We use the data until 2013 because the data for the year 2014 seems to be unreliable. There are several zeroes that look like reporting errors in comparison to previous values from the data series. Moreover, since we use 3 year averages this time span provides 7 time periods. We include 60 countries in the sample and report them in Table (9) in the Appendix. We had to combine the NAFTA countries (Canada, the United States, and Mexico) into one country because they only report the values separately starting in 2011. Until this year, the United States reported jointly the values of the three countries.

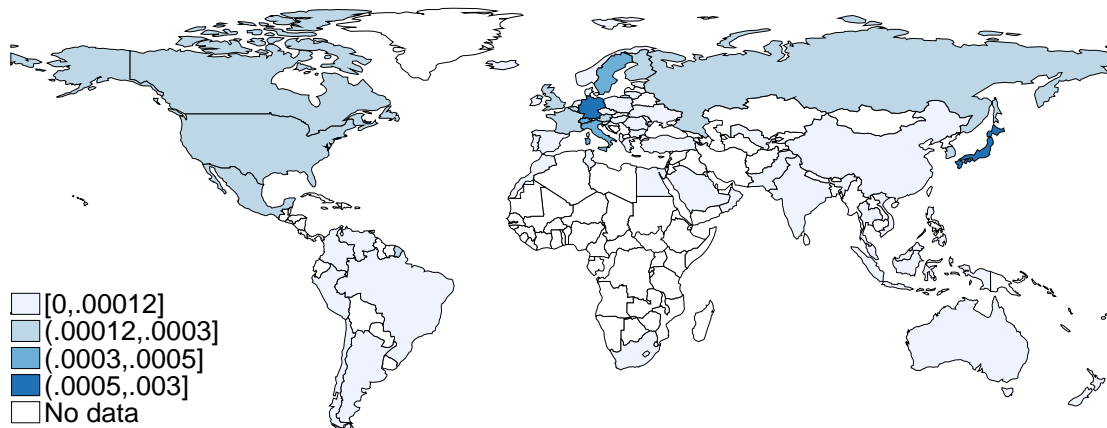
The IFR also reports the deliveries and stock of robots at the industry level. They consider that robots have a life-time horizon of 12 years, after which they are deployed (International Federation of Robotics, 2016). Following Graetz and Michaels (2015), we use an alternative way to calculate the stock of robots (for all robots and for the manufacturing industry) that relies on the perpetual inventory method under the assumption of a depreciation rate of 10%. Similar to Graetz and Michaels (2015), 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

⁴This refers to “Manipulating industrial robot as defined by ISO 8373: An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications” (Graetz and Michaels, 2015; International Federation of Robotics, 2012).

basis. Given that we are mainly interested in the robots used in the manufacturing sector, we follow Graetz and Michaels (2015) and take the average share of deliveries of manufacturing robots over the total deliveries of robots (when data is 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). In Table (8) in the 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 one (2011-2013). We discriminate between percentiles with Figure (1) reporting in the lightest shade of blue for the 75th percentile, proceeding with the 90th percentile, the 95th percentile, and finally the last 5% of the distribution (there are a lot of zeroes in this period so this is why the first cutoff is at the 75th percentile). We had to make this split to show the variation among the adopters. For comparison, in Figure (2) we use the same cutoffs than in the previous figure. We observe a strong increase in robot density, especially in Europe and South Asia. The same figures but only for the manufacturing sector are displayed in the Appendix (Figures (3) and (4)). In the United States we do not see such a strong increase (although it is between 50%-75% of the distribution) due to the reporting issues that we had to create a joint stock with Canada and Mexico.

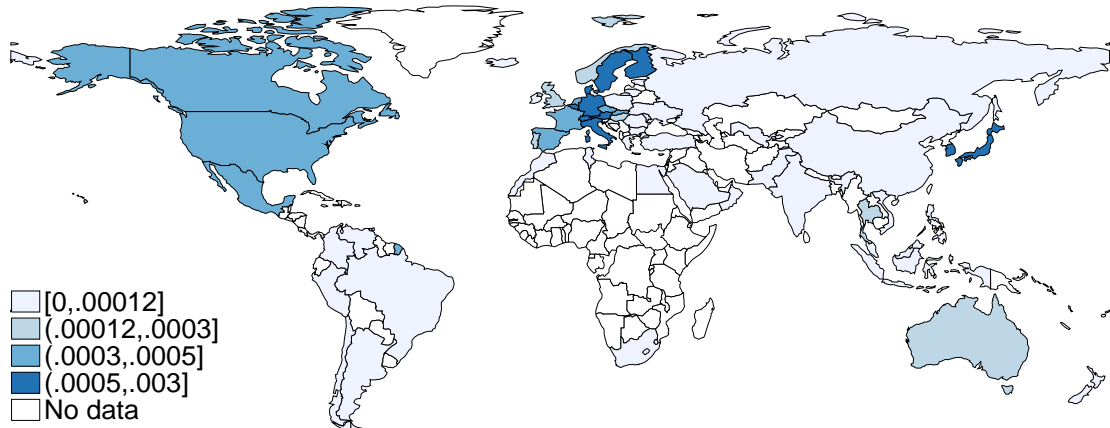
Figure 1: Average robot density for the period 1993-1995



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 in terms of 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. As for other control variables, we included GDP per capita measured in constant US\$ from the year 2010 from the World Development Indicators, openness measured as exports and imports over GDP, and the gross enrollment ratio in

Figure 2: Average 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.

secondary school as in Busse and Spielmann (2006)⁵.

3.2 Empirical estimates

Based on Proposition 1 derived from the theoretical considerations we estimate the relationship between robots adoption and population growth by means of the following equation:

$$\ln(\hat{p}_{i,t}) = c + \alpha \ln(n_{i,t-1}) + \beta \ln(s_{i,t-1}) + \gamma \ln(x_{i,t-1}) + d_t + \epsilon_{i,t}, \quad (7)$$

where $\hat{p}_{i,t}$ is the growth rate of the stock of robots (either manufacturing robots, or the total amount of robots), $n_{i,t-1}$ is the population growth rate between period $t-1$ and $t-2$, $s_{i,t-1}$ is the 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 (i.e. GDP per capita), 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 2007/2008. Since we have zeroes and negative values in the dependent variable and in the population growth rate, we employed an application of the Box-Cox transformation (Box and Cox, 1964) instead of simply applying logs.⁶ We want to apply the logarithmic transformation because this alleviates concerns regarding heteroskedasticity and non-linearities in the non-transformed variables. We relied on 3-year averages to alleviate problems regarding measurement errors and business-cycle effects (the economic growth literature usually relies on 5 year averages

⁵The natural choice of variable would have been mean years of schooling, from (Barro and Lee, 2013). Unfortunately, this variable is only available in 5 year intervals. The alternative would have been to use the literacy rate as a proxy for education but we had a lot of missing values for this variable, so we decided to only employ the gross enrollment ratio (Busse and Spielmann, 2006, also uses this variable).

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

but in this case we would only have 2 consecutive time periods left for estimation).

We first estimate (7) 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 applying various corrected fixed effects estimators (CorrFE) according to Bruno (2005a,b), and a system GMM estimator [GMM (sys)] of Blundell and Bond (1998) as well. Note that both of these types of estimators are seen as remedies for the Nickell (1981) bias in a dynamic panel data setting. We do this exercise for the total amount of robots and for the manufacturing robots separately. Moreover, we assess the robustness of our results by adding a proxy for education, a proxy for GDP per capita, and a proxy for openness. We also consider different depreciation rates (5% and 15% instead of 10%), and a different transformations of the robot adoption and population growth rates (a neglog transformation as employed by Whittaker et al. (2005)).

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 investment rate. When we include the controls, we are not certain regarding the coefficient on openness – on the one hand, as countries become more open, they could 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 automatize the production in search of efficiency gains. Finally, we expect a positive coefficient for GDP per capita because higher income implies a lower return to traditional capital accumulation and therefore a higher incentive to employ robots.

3.2.1 Main Results

Table (3) contains the regression outputs from a baseline specification of Equation (7). As regressors we include the two crucial variables that are suggested by our theoretical considerations in Equation (6), the population growth rate and the investment rate. We observe that there is a negative relationship between population growth and the growth rate of the robot density in all specifications and it is statistically significant in the majority of the cases. Only in column (1), which reports the POLS regression, we find the coefficient not to be statistically significant which is most likely due to the lack of accounting of country-level heterogeneity. Our results are robust to the dynamic specifications using the corrected fixed effects estimator, as well as the system GMM estimator. For the choice between corrected fixed effects and system GMM 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 is therefore the fixed effects regression because the Hausman test suggests that the results from the random effects specification are inconsistent and that

we therefore the 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%, the robot density growth 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.

Table (4) shows the results for the growth rate of the manufacturing robot density. As in the previous case, we document a positive correlation, although not statistically significant, between the investment rate and the growth rate of the manufacturing robots density. We again find a negative association between the population growth rate and the robots density growth rate with the size of the coefficients being similar to the previous table. In this case, there is even less evidence than before of the need of a dynamic specification because the coefficients of the lagged dependent variable are smaller in size and not even statistically significant in the case of the system GMM estimator.

Table 3: The relation between total robots growth and population growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	CorrFE (bb)	CorrFE (ab)	CorrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.316*** (0.779)	0.259*** (0.090)	0.245** (0.0987)	0.226** (0.111)
n_{t-1}	-0.539 (0.328)	-0.694* (0.354)	-2.030** (0.894)	-1.690*** (0.597)	-1.803*** (0.562)	-1.828*** (0.557)	-3.515*** (1.205)
s_{t-1}	0.063 (0.119)	0.090 (0.129)	0.419 (0.495)	0.304 (0.357)	0.324 (0.340)	0.335 (0.341)	0.115 (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: We report 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 Box-Cox 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.

3.2.2 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 because GDP per capita might be correlated with the population growth rate due to the fact that richer countries are more able to invest in new technologies and they are also the ones that are disproportionately affected by declining fertility as outlined in Section (1); 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; and education is highly correlated with GDP per capita, while, at

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	CorrFE (bb)	CorrFE (ab)	CorrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.264*** (0.077)	0.197** (0.086)	0.180** (0.0914)	0.120 (0.120)
n_{t-1}	-0.457 (0.336)	-0.632* (0.368)	-2.185** (0.973)	-1.950*** (0.613)	-2.055*** (0.570)	-2.078*** (0.566)	-3.908*** (1.237)
s_{t-1}	0.026 (0.095)	0.043 (0.101)	0.175 (0.490)	0.132 (0.365)	0.146 (0.343)	0.155 (0.343)	0.311 (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: We report 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 Box-Cox 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.

the same time, a better educated population might be more inclined to invest in (or adapt to) robots.

Table (5), which includes the aforementioned 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 10% level. One reason for this could be that we had 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 we expect that richer countries would be able to invest more in new technologies. However, GDP per capita reverts its sign from column (3) onwards. We believe that the reason for this is the presence of unobserved heterogeneity, as also the Hausman test indicates. Secondary enrollment has the predicted sign, although it is not statistically significant. Finally, openness has a negative sign in most of the specifications although none of the coefficients is statistically significant. Finally, the coefficient size of the lagged dependent variable shows that there is no pressing need to take the dynamics into account in the regression.

Turning to the manufacturing robots (Table (6)), we observe a similar pattern as for the case of total robots. All specifications show a negative correlation between manufacturing robots growth and population growth. In contrast to the previous results, we find no statistical significance in column (7). However, this could be related to the fact that we do not need a dynamic specification and that the system GMM estimator is known to be very

Table 5: Total robots growth including controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	CorrFE (bb)	CorrFE (ab)	CorrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.210** (0.082)	0.137 (0.085)	0.140 (0.088)	0.279 (0.202)
n_{t-1}	-0.565 (0.379)	-0.731* (0.422)	-1.554** (0.689)	-1.377* (0.754)	-1.494** (0.704)	-1.485** (0.708)	-3.247* (1.879)
s_{t-1}	0.092 (0.130)	0.107 (0.134)	-0.416 (0.556)	-0.377 (0.486)	-0.337 (0.443)	-0.336 (0.445)	-0.316 (0.485)
y_{t-1}	-0.172** (0.073)	-0.151** (0.073)	2.535*** (0.911)	2.316*** (0.883)	2.280*** (0.784)	2.283*** (0.787)	-0.080 (0.421)
e_{t-1}	0.148 (0.180)	0.133 (0.176)	0.112 (0.192)	0.106 (0.185)	0.111 (0.171)	0.111 (0.171)	0.334 (0.244)
$open_{t-1}$	0.040 (0.142)	0.034 (0.155)	-0.088 (0.519)	-0.149 (0.552)	-0.136 (0.503)	-0.139 (0.506)	-0.144 (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
Observations	262	262	262	262	262	262	262

Note: We report 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 Box-Cox 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 6: Manufacturing robots growth including controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	CorrFE (bb)	CorrFE (ab)	CorrFE (ah)	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: We report 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 Box-Cox 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.

inefficient in case of a small time dimension. As in the previous, tables we find no evidence of the importance of investment or secondary schooling for robots adoption. Similar to the case of total robots, we find a positive relationship between GDP per capita and the growth rate of manufacturing robots density. A puzzling result is the change in the sign of per capita GDP in the case of the system GMM estimator. However, the estimations performed with the corrected fixed effects estimator still exhibit the significantly positive result. In Tables (10) and (11) in the Appendix we report the same specification but omitting the controls that were not statistically significant (i.e., secondary 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.

As further robustness checks, we used 2-year averages instead of averaging the data over 3 years. Tables (12) and (13) in the Appendix show the baseline 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 (13) 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 can be seen in Tables (14) and (16) (for total robots) and Tables (15) and (16) (for manufacturing robots) in the Appendix. We find no significantly quantitative difference with our previous estimates. As the two final robustness tests we use the neglog transformation for both growth rate variables. This transformation involves making the following adjustments to the variable (which we call x for simplicity). If $x \leq 0$, then we use $-\ln(-x + 1)$ and if $x > 0$, then $\ln(x + 1)$. Results can also be seen in Tables (18) and (19) of the Appendix. Again, results remain fairly the same in terms of sign and statistical significance although the size of the coefficients is higher. The results show some sensitivity with relation of the transformation of the variables that can take the value of 0 or negative values.

4 Conclusions

We propose a theoretical framework of production in the age of automation. In so doing we introduce a new production factor that resembles the properties of labor in the production process, i.e., it is a perfect substitute for labor, while it resembles the properties of capital in the accumulation process, i.e., it is accumulated in the same manner as physical capital due to the savings and investment behavior of households. We show that the standard Solow (1956) framework predicts, under certain circumstances, perpetual growth even without technological progress if full automation of human labor is feasible. Furthermore, we show that countries with a lower population growth rate have a stronger incentive to invest in the adoption of automation. The empirical estimates that we present, subject to several robustness tests, support this theoretical prediction.

As far as the wider policy implications are concerned, our theoretical and empirical findings suggest that countries, which are subject to larger 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 aging imply for long-run economic prosperity, issues that also the media is nowadays heavily concerned with (see, for example, The Washington Post, 2016). Of course, the transition to automation technologies might not be all that smooth because automation capital competes with labor and therefore could act so as to depress wages. If this concern is valid and widespread, it might lead to resistance against automation from labor unions and the population at large. Altogether, it might therefore be in everybody's interest if governments enact policies that alleviate the burden of those who suffer because of automation.

Of course we have to admit that our framework stayed deliberately simple and the results that we present are meant as a first step in the direction of analyzing the interrelations between demography and automation. In reality, there are different skill groups in the population and the tasks that are performed by the different skill groups might be

more or less suited to automation. A more detailed framework should be able to take this into account and to empirically distinguish between the education level of different types of workers, and also the heterogeneity of tasks that workers perform. Furthermore, a more detailed modeling of demographic change is called for that takes survival to old age and changing life expectancy into account. First steps in this direction have been undertaken by Gasteiger and Prettnner (2017).

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5 Appendix

5.1 Summary Statistics

Table 7: 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

5.2 Countries included

Table 8: 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		

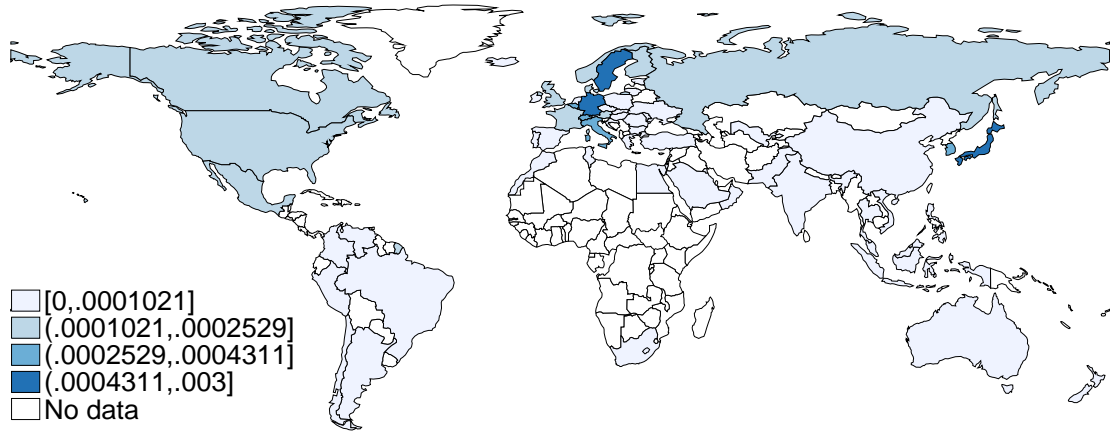
Note: The year indicates the first time that the country reported disaggregated deliveries of robots at the industry level.

Table 9: 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

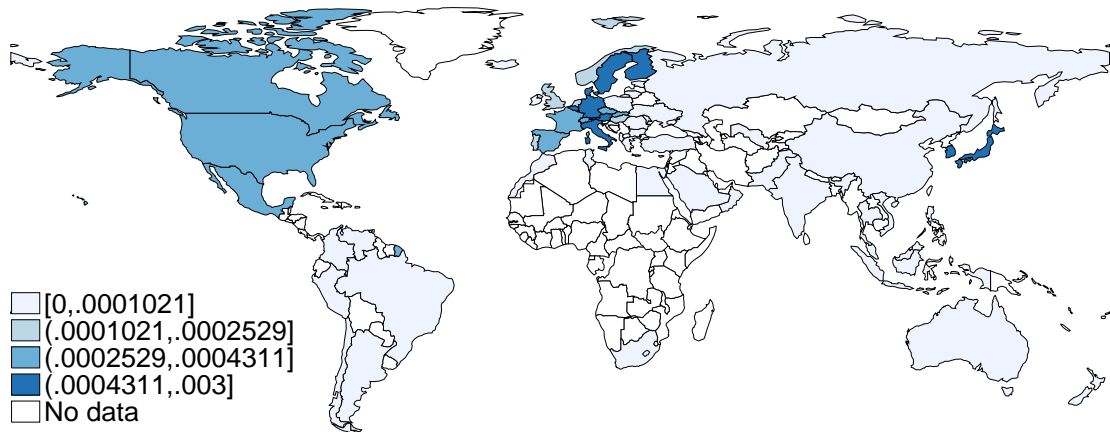
5.3 Distribution of the manufacturing stock of robots

Figure 3: 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 4: 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.

5.4 Estimates with only GDP per capita as control

Table 10: Total robots growth including GDP per capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	CorrFE (bb)	CorrFE (ab)	CorrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.250*** (0.079)	0.197** (0.092)	0.197** (0.100)	0.119 (0.163)
n_{t-1} h	-0.601* (0.320)	-0.732** (0.345)	-1.444* (0.758)	-1.283* (0.659)	-1.430** (0.611)	-1.421** (0.607)	0.565 (8.093)
s_{t-1}	0.102 (0.143)	0.123 (0.148)	0.003 (0.557)	-0.006 (0.400)	0.053 (0.374)	0.052 (0.374)	0.003 (0.420)
y_{t-1}	-0.137*** (0.049)	-0.131*** (0.048)	2.195*** (0.817)	1.944** (0.800)	1.855** (0.737)	1.872** (0.735)	-0.554 (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: We report 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 Box-Cox 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 11: Manufacturing robots growth including GDP per capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	CorrFE (bb)	CorrFE (ab)	CorrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.186** (0.078)	0.124 (0.087)	0.119 (0.091)	0.005 (0.082)
n_{t-1}	-0.525 (0.326)	-0.667* (0.355)	-1.554* (0.806)	-1.468** (0.674)	-1.587*** (0.614)	-1.577*** (0.612)	0.466 (4.403)
s_{t-1}	0.069 (0.119)	0.080 (0.120)	-0.272 (0.533)	-0.229 (0.409)	-0.191 (0.376)	-0.197 (0.376)	0.020 (0.476)
y_{t-1}	-0.152*** (0.046)	-0.145*** (0.046)	2.365*** (0.717)	2.221*** (0.815)	2.174*** (0.740)	2.215*** (0.739)	-0.626 (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: We report 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 Box-Cox 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.

5.5 Baseline estimates using 2-year averages instead of 3-year averages

Table 12: Total robots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	corrFE (bb)	corrFE (ab)	corrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.366*** (0.049)	0.351*** (0.050)	0.393*** (0.051)	0.291*** (0.071)
n_{t-1}	-0.435 (0.294)	-0.606* (0.344)	-1.160* (0.594)	-0.717** (0.359)	-0.736** (0.343)	-0.706* (0.370)	-1.415* (0.760)
s_{t-1}	0.093 (0.099)	0.135 (0.108)	0.380 (0.326)	0.230 (0.214)	0.247 (0.196)	0.257 (0.208)	0.091 (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: We report 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 Box-Cox 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 13: Manufacturing robots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	corrFE (bb)	corrFE (ab)	corrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.341*** (0.049)	0.316*** (0.050)	0.369*** (0.051)	0.297*** (0.083)
n_{t-1}	-0.336 (0.292)	-0.519 (0.347)	-1.142* (0.604)	-0.775** (0.364)	-0.790** (0.346)	-0.754** (0.376)	-1.398* (0.780)
s_{t-1}	0.058 (0.074)	0.088 (0.079)	0.247 (0.316)	0.132 (0.219)	0.148 (0.199)	0.169 (0.213)	-0.033 (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: We report 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 Box-Cox 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.

5.6 Baseline estimates using 5% depreciation rate

Table 14: Total robots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	corrFE (bb)	corrFE (ab)	corrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.339*** (0.077)	0.294*** (0.088)	0.280*** (0.099)	0.299** (0.137)
n_{t-1}	-0.591* (0.332)	-0.718** (0.353)	-2.151** (0.937)	-1.731*** (0.645)	-1.835*** (0.612)	-1.862*** (0.608)	-2.687** (1.291)
s_{t-1}	0.077 (0.125)	0.103 (0.136)	0.545 (0.519)	0.385 (0.387)	0.405 (0.371)	0.419 (0.374)	-0.146 (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: We report 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 Box-Cox 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 15: Manufacturing robots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	corrFE (bb)	corrFE (ab)	corrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.300*** (0.076)	0.246*** (0.085)	0.227** (0.093)	0.200 (0.128)
n_{t-1}	-0.526 (0.345)	-0.673* (0.370)	-2.332** (1.018)	-2.018*** (0.662)	-2.116*** (0.623)	-2.147*** (0.618)	-3.024*** (1.117)
s_{t-1}	0.051 (0.111)	0.070 (0.117)	0.318 (0.517)	0.229 (0.395)	0.244 (0.376)	0.258 (0.376)	0.094 (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: We report 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 Box-Cox 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.

5.7 Baseline estimates using 15% depreciation rate

Table 16: Total robots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	corrFE (bb)	corrFE (ab)	corrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.301*** (0.079)	0.240*** (0.092)	0.227** (0.098)	0.174 (0.106)
n_{t-1}	-0.515 (0.323)	-0.683* (0.353)	-1.945** (0.858)	-1.658*** (0.562)	-1.763*** (0.528)	-1.782*** (0.523)	-4.050*** (1.377)
s_{t-1}	0.055 (0.118)	0.081 (0.126)	0.337 (0.477)	0.247 (0.335)	0.266 (0.319)	0.272 (0.319)	0.291 (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: We report 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 Box-Cox 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 17: Manufacturing robots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	corrFE (bb)	corrFE (ab)	corrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.233*** (0.078)	0.162* (0.085)	0.149* (0.090)	0.071 (0.123)
n_{t-1}	-0.419 (0.328)	-0.605* (0.365)	-2.079** (0.938)	-1.901*** (0.575)	-1.998*** (0.534)	-2.012*** (0.531)	-4.411*** (1.430)
s_{t-1}	0.009 (0.086)	0.022 (0.091)	0.072 (0.469)	0.059 (0.342)	0.071 (0.321)	0.075 (0.320)	0.290 (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: We report 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 Box-Cox 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.

5.8 Baseline estimates using the neglog transformation

Table 18: Total robots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	corrFE (bb)	corrFE (ab)	corrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.496*** (0.068)	0.477*** (0.081)	0.456*** (0.092)	0.473*** (0.105)
n_{t-1}	-12.135* (6.436)	-15.798** (6.399)	-35.286* (18.480)	-20.726** (10.299)	-21.720** (10.138)	-22.657** (9.892)	-40.401*** (14.349)
s_{t-1}	0.321 (0.430)	0.499 (0.475)	2.409** (0.957)	1.275 (0.909)	1.327 (0.916)	1.383 (0.921)	-0.575 (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: We report 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 Box-Cox 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 19: Manufacturing robots

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	POLS	RE	FE	corrFE (bb)	corrFE (ab)	corrFE (ah)	GMM (sys)
\hat{p}_{t-1}				0.257*** (0.077)	0.192** (0.086)	0.174* (0.918)	0.186* (0.110)
n_{t-1}	-4.084 (2.791)	-5.570* (3.069)	-16.691** (7.375)	-14.854*** (4.150)	-15.714*** (3.880)	-15.892*** (3.846)	-23.165*** (8.161)
s_{t-1}	0.030 (0.094)	0.049 (0.100)	0.266 (0.469)	0.219 (0.369)	0.237 (0.347)	0.247 (0.347)	0.152 (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: We report 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 Box-Cox 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.

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