Digital Transformation and Growth Models

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Abstract The digital transformation of economic systems has become an established trend. One piece of evidence for this is that some of the empirical laws formulated by N. Kaldor, which accompanied the process of long-term economic growth in the twentieth century, have ceased to act. Another feature of modern development is that digital technologies, having an intensive labor-saving property, which makes their use "toxic" for the labor market. This fact raises the importance of assessing the potential number of jobs, taking into account technological substitution under various scenarios of real wage formation. In close connection with such an assessment is the determination of the gross product and the level of decline in aggregate consumer demand caused by a reduction in the number of jobs and the increasing role of intelligent machines in the economy. For a more accurate description of the above features of modern economic development, we have proposed a set of economic growth models that take into account the new stylized facts of economic development formulated by J. Stiglitz and T. Piketty. The developed models are verified using the US statistics.

Keywords Digital transformation · Economic system · Mathematical model

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1 Introduction

In the twentieth century, there were a number of empirical laws accompanying the process of economic growth, which were to be valid in the long term. N. Kaldor (1961) formulated a number of them, but not all of them remain valid at present. A number of works devoted to the central issue of economics—the distribution of income between factors of production and the distribution of income and welfare among people, taking into account the widespread diffusion of artificial intelligence (AI) (Korinek & Stiglitz, 2017; Stiglitz, 2016)—showed that it is necessary to use new models. One reason for this rethinking has been the rapid growth of the NBIC technology sector (Bainbridge & Roko, 2006; Roco, 2011).

The technologies of the fourth industrial revolution have become a new reality, which makes it possible to fully automate the manufacturing process of products, practically crowding out people from the sphere of production and even services. Digital technologies have an intensive laborsaving property, which makes them "toxic" for the labor market. The utilization of digital platforms, computers, and robots at a large scale will accelerate the process of technological replacement of labor by capital in the coming decades.

In relation to today, negative expectations for the labor market are largely associated with the development of digital technologies, where the effects of wide automation are estimated to be from an employment reduction of 9% in the European economy (Arntz et al., 2016) to 47% in the US economy (Frey & Osborne, 2017). The acute discussion of this issue is also largely due to the growing income inequality over the past 30 years (Piketty, 2014; Stiglitz, 2012) and the long-term downtrend in the manufacturing share (OECD, 2017) in developed countries.

The McKinsey Global Institute experts' forecast (2017) shows that by 2055, half of the existing jobs around the world can be eliminated due to full automation of production.

One of the consequences of digital technologies development is a decrease in average wages (Brynjolfsson & McAfee, 2014), which is due to the widespread use of information and communication technologies, and as a result, their gradual reduction in cost. Acemoglu and Restrepo (2017) noted that the use of industrial robots between 1990 and 2007 in local US labor markets had reduced employment and wages: one robot per thousand workers reduces the employment-to-population ratio by about 0.18–0.34 percent and reduces wages by about 0.25–0.5 percent. According to other estimates for the EU countries, one robot per thousand workers reduces the level of employment by 0.16–0.2 percent (Chiacchio et al., 2018). The use of industrial robots on a global economic scale also poses significant threats: the obtained estimates indicate a long-term reduction in employment by about 1.3% (Carbonero et al., 2018). The impact of automation on labor market transformation is lasting: automation is very good for economic growth and very bad for equality (Berg et al., 2018).

Not all assessments are so pessimistic. Analyzing the American labor market for the period from 1850 to 2015, Atkinson and Wu (2017) argue that the level of professional outflow in the USA is now at a historic low, and no more than 10% of jobs in the US economy are exposed to a real threat of automation. In many cases, machines replace and complement human labor; they add value to tasks requiring the unique abilities of workers (Autor, 2015). Autor and Dorn (2013) noted that due to the imbalance of technological progress when it is impossible to replace routine tasks with information technology, there is an increase in wages and employment in the low-skilled services sector. Some researchers in Europe are also not inclined to dramatize the consequences of widespread job automation (Arntz et al., 2016; Pouliakas, 2018). In Germany, according to research, no more than 13–15 percent of employees are at risk of automation (Arnold et al., 2016; Dengler & Matthes, 2018). OECD researchers also tend to believe that no more than 10% of those employed in the American economy are at risk of automation (Nedelkoska & Quintini, 2018). Exploring the practical application of robots and AI (Vermeulen et al., 2018), a team of authors notes that this is “a common structural change.” Analyzing German industrial practice regarding the use of robots from 1994 to 2014 (Wolfgang et al., 2018), the authors note that the use of robots resulted in job losses in manufacturing, but this was offset by successes in the business services sector.

An important attribute of the digital economy is a qualitatively new role of technological progress contributing to an uneven increase in productivity of the main factors of economic growth (capital and labor). At the same time, the fourth industrial revolution, along with the complete production automation and acceleration of the growth of productivity and GDP, may have very negative social consequences. One of the possible effects is the sharp reduction in the number of middle-class jobs and a further increase in income inequality in society. Therefore, a scenario in which the reduction of the middle class can lead to social upheaval in developed countries is possible.

Due to the growth of total factor productivity (TFP), national income (GDP) will also grow. However, empirical evidence over the past 40 years shows that median income in a number of developed countries stopped growing as far back as the 1980s, although until then, it had grown proportionally to productivity for decades (Brynjolfsson & McAfee, 2014). This process accelerated after the 2000s. If stagnation of the median salary was observed before 2000, now it has already begun to decline, although TFP in developed economies has been growing steadily all this time (Brynjolfsson & McAfee, 2014). Such inequality is increasing because of a growing gap a) between labor income and capital income and b) between high-income and low-income families (Leipziger & Dodev, 2016). Referring to the data on the US economy, they emphasize that the share of domestic income that goes to wages has been declining since the early 1970s, since the share that goes to capital has increased. This trend in the ever-decreasing share of gross domestic income earmarked for labor (wages) since its peak in 1970 explains the expansion of inequality in the USA in recent decades.

One of the options for maintaining aggregate demand at the level of potential output of goods and services may be the introduction of a universal basic income (UBI) for all adult citizens. In a number of states, such as Switzerland and Finland, the idea of UBI has not find widespread support (Gotev, 2016; Valero, 2019). In the

Netherlands, experiments, although they do not have a direct reference to basic income, are being carried out in about twenty municipalities. Similar projects are under development in Denmark, France, Catalonia, Scotland, Corsica, and Portugal (De Wispelaere & Haagh, 2019). In February 2017, the European Parliament voted with 328 votes against using UBI to offset losses from the use of robots in the labor market. However, the idea of basic income is gaining considerable popularity among the public: support for basic income in the last wave of the European Social Survey (ESS) averages to just over 50 percent (Lee, 2018). The idea of UBI is negatively perceived by US researchers (Hoynes & Rothstein, 2019; Kearney & Mogstad, 2019), although they admit that the motivation for using UBI is a labor market situation, where adequate wage and income growth is not provided for a long time for those workers who are at the bottom of the income distribution curve.

Our research is devoted to the development of mathematical models describing the influence of digital transformation on the economic system. The models consider human capital, the new nature of technological progress in the digital economy, and capital income as endogenous factor. In addition, we present the simplest model for determining the unconditional basic income (UBI), which provides a balance of real demand and supply in the economy. The US economy data from 1982 to 2018 is used to verify developed models and to forecast dynamics of the US GDP, employment and UBI needed.

The paper is organized into the following sections that build off each other. Section 1 provides an overview of the literature on digital transformation and modern economic development studies. The data and the set of models are presented in Sect. 2. Section 3 contains models' validation, analysis of the results and the main points of discussion. The last section concludes the research with recommendations for future analysis.

2 Stylized Facts and the Model Theoretical Foundations

A number of recent works (Korinek & Stiglitz, 2017; Stiglitz, 2016) showed that new models must take into account the following: firstly, human capital in the production function; secondly, the new nature of technological progress in the digital economy, which will be determined mainly by the amount of technological information necessary for the production of goods and services; thirdly, capital income, which should be considered as an endogenous factor in describing the growth of the physical capital share in national income.

In the twentieth century, there were a number of empirical laws accompanying the process of long-term economic growth and N. Kaldor (1961) was the first to formulate a number of them. The following Kaldor laws are of interest for our further analysis: (a) the ratio of physical capital to output is approximately constant; (b) the shares of labor and physical capital in national income are approximately constant; (c) the wages of workers grow in proportion to labor productivity.

Stiglitz (2016) formulated new stylized (empirical) facts in the modern economy development, and some of them differ from the Kaldor laws. Among them are the following: (a) the average wage no longer grows in proportion to productivity, so the share of capital is growing; (b) there is growing inequality, both in terms of wages and capital income, as well as growing inequality in general.

Stiglitz only needed a small technical modification of classical models in order to take into account new empirical facts. Nevertheless, his models made it possible to formulate new theoretical foundations that explain the stagnation of workers' wages in recent decades, despite productivity and GDP continuing to grow. In Korinek and Stiglitz (2017), AI is seen as an absolute form of technological progress, replacing skilled workers and leading to technological unemployment. The same work also analyzed how technological labor substitution affects the workers' wages in the short and long term. It is shown that in the general case, the addition of machine labor creates a redistribution of income from human labor to additional factors.

T. Piketty studied new trends in capital accumulation, economic growth and income inequality, which emerged at the beginning of the twenty-first century and obtained interesting results. First, Picketty showed that capital intensity of developed countries followed a large U-curve and at the beginning of the twenty-first century and returned to maximum values close to those observed at the end of nineteenth at (Piketty, 2014, Ch. 2, 3). The return of capital intensity in developed countries in the twenty-first century to its maximum value means that it is now stabilizing again, at least until the middle of the century (Piketty, 2014, Ch.5). Therefore, it follows that in the first half of the twenty-first century, Kaldor's first empirical regularity remains valid.

Kaldor's second empirical regularity will cease to operate in practice in the twenty-first century: the share of capital income in GDP will not remain constant but will grow, as Piketty (2014) shows. Piketty suggests that the share of capital income at the global level will reach 30–40% by the middle of the current century, i.e., a level close to the indicators of the eighteenth–nineteenth centuries (Piketty, 2014, Ch.6). As for the share of labor, it should accordingly fall. For example, in the USA, the share of labor in GDP has already fallen from 65% to 55% between 1970 and 2015. This was precisely the reason for the stagnation of the workers' wages observed during this period.

Kaldor's third regularity ceased to work since the mid-1970s, when the growth paths of labor productivity and real average wages of workers diverged: the first continued and continues to grow steadily, while the second—at first stagnated, and from the beginning of the twenty-first century started to decline (Ford, 2015).

B. Arthur (1996) was the first to note that in the high-tech sectors of the knowledge-based economy, there are increasing returns to scale, while in traditional industries, including manufacturing, decreasing returns to scale remains dominant. As changes took place, the main mechanisms determining the behavior of the economy have shifted: from decreasing to increasing returns to scale.

We also took into account the presence of long waves in the economy, although not all economists support the theory of long waves, primarily because of the difficulty of confirming their regular nature. Among economists who share this theory, there is no consensus regarding the periodization of these waves, but the prevailing opinion is that the rise of the 4th cycle was seen in 1948–1973 (Van Duijn, 2006). In this regard, we will adhere to the same periodization, assuming that the rise of the 5th cycle occurred at the beginning of the 1980s, approximately between 1982 and 2019.

Based on the above and taking into account the new stylized facts established by Stiglitz and Piketty, we have proposed models to forecast the dynamics of potential jobs, employment of people in the economy, as well as the dynamics of UBI required to ensure a guaranteed level of aggregate demand. These models can serve as a useful complement to the theoretical results obtained by J.Stiglitz and T. Piketty.

3 Data and Model

3.1 Data

The main data used in our set of models are data on GDP (Y), physical (K) and human capital (H), labor (L) and technological progress (A).

The numerical values of production factors (K, L) and GDP (Y) for the US economy were taken from the US Bureau of Economic Analysis (2020b, 2020c, 2020d). TFP data (A) was taken from the University of Groningen and the University of California. The human capital (H) data was obtained from an article by M. Christian (2017).

Auxiliary data involved in our calculations include data from the International Federation of Robotics (2019) on the number of robots and statistics on the US population dynamics (US Bureau of Economic Analysis, 2020a).

3.2 The Basic Model of Long-Term Economic Growth

As a basic model for describing long-term economic growth, we adopted a modified neoclassical model (Mankiw et al., 1992), which takes into account human capital:

$$\mathrm{Y(t)} = \gamma \times \mathrm{K}^{\alpha}(\mathrm{t}) \times \mathrm{H}^{\beta}(\mathrm{t}) \times \left[\mathrm{A(t)} \times \mathrm{L_p(t)}\right]^{1-\alpha-\beta+\delta} \tag{1}$$

where $Y(t)$—gross domestic product (GDP); $K(t)$—physical capital; $H(t)$—human capital; $A(t)$—technological progress; $L_p(t)$—potential number of jobs in the economy; α and β—physical and human capital shares in GDP; δ—parameter characterizing increasing returns to scale ($\delta > 0$); γ—constant rate factor.

We introduced the parameter δ into the production function in Eq. (1) to account for the increasing returns generated in high-tech science-intensive sectors of the economy according to Arthur (1996).

Kaldor's second regularity means that in Eq. (1) α and β, characterizing the shares of physical and human capital, as well as $(1 - \alpha - \beta + \delta)$, characterizing the share of effective labor, are constant values.

Kaldor's third regularity is formalized in the form:

$$\bar{w}(t) = a_0 \times A(t) \tag{2}$$

where $\bar{w}(t)$ —current average workers' wage; a_0—normalization coefficient. Such an increase in workers' wages was observed in the "golden era" of the global economy (1950–1970).

In order to take into account the new empirical pattern of increasing capital income share in GDP, we propose an endogenous calculation mechanism for $\alpha(t)$, taking advantage of the fact that the marginal product of labor is equal to the real wage rate in a perfectly competitive market (Kurzenev & Matveenko, 2018, Ch.3):

$$\frac{\partial Y}{\partial L} = \frac{W}{P} = w \tag{3}$$

where W—nominal wage; P—price level. Accordingly, the marginal product of capital is generally equal to the interest rate r (average return on capital) plus the capital depreciation rate (Kurzenev & Matveenko, 2018, Ch.3):

$$\frac{\partial Y}{\partial K} = r + \mu_K \tag{4}$$

Since the production function is given in Eq. (1), for the real wage rate in Eq. (3), we obtain the formula:

$$w = \frac{\partial Y}{\partial L} = [1 - \alpha(t) - \beta(t) + \delta]\frac{Y_P}{L_P} \tag{5}$$

where Y_P—potential GDP. The formula for calculating the combined physical and human capital share in national income is below:

$$\alpha(t) + \beta\,(t) = 1 + \delta - \frac{wL_p}{Y_p} \tag{6}$$

Calculating the marginal product of capital in Eq. (4) for the production function in Eq. (1), we obtain:

$$\begin{aligned} &\text{a) } r + \mu_K = \tfrac{\partial Y}{\partial K} = \alpha \tfrac{Y}{K}; \\ &\text{b) } \alpha = (r + \mu_K) \times \sigma_K \end{aligned} \tag{7}$$

It follows that the physical capital share in GDP is proportional to the average return on capital (r) and capital intensity of income (σ_K). This, according to Piketty

(2014), is the first fundamental law of capitalism that defines the national income distribution between capital and labor.

Based on the equality of the net marginal products of physical and human capital (Barro & Sala-i-Martin, 2003), in accordance with the production function in Eq. (1), $\frac{\partial Y}{\partial K} = \alpha æ_K = \frac{\partial Y}{\partial H} = \beta æ_H$, we get the ratio:

$$\alpha = \beta \frac{æ_H}{æ_K} \tag{8}$$

Therefore, from formula in Eq. (6), using relation in Eq. (8), we can distinguish the dynamics of the physical capital share:

$$\widetilde{\alpha} = \alpha(t) = \frac{æ_H}{æ_H + æ_K}\left(1 + \delta - \frac{wL_p}{Y_p}\right) \tag{9}$$

Thus, the inclusion of human capital in in Eq. (1) allows us to assess the physical capital share in national income in Eq. (9) more accurately.

3.3 The Basic Model of Long-Term Economic Growth

The accumulation of capital and innovative technologies of the 4th industrial revolution will become the driving force of economic development. Capital growth was the most important feature of capitalism in the nineteenth–twentieth centuries. It will accelerate in the twenty-first century, according to Piketty.

We assume that Kaldor's first empirical law is formalized as follows:

$$\begin{aligned} &\text{a)}\ K = \sigma_K \times Y, \quad \sigma_K = \text{const}; \\ &\text{b)}\ Y = æ_K \times K, \quad æ_K = \text{const} \end{aligned} \tag{10}$$

where σ_K—physical capital intensity ratio; $æ_K$—physical capital productivity ratio.

For human capital, similar equations are obtained:

$$\begin{aligned} &\text{a)}\ H = \sigma_H \times \ Y, \sigma_H = \text{const}; \\ &\text{b)}\ Y = æ_H \times H, \quad æ_H = \text{const} \end{aligned} \tag{11}$$

where σ_H—human capital intensity ratio; $æ_H$—human capital productivity ratio.

The movement of physical $K(t)$ and human $H(t)$ capital is described by the classical equation of capital accumulation (Kurzenev & Matveenko, 2018, Ch.3; Barro & Sala-i-Martin, 2003, Ch.1):

$$\begin{aligned} &\text{a) } \dot{K}(t) = I_K(t) - \mu_K \times K(t); \\ &\text{b) } \dot{H}(t) = I_H(t) - \mu_H \times H(t) \end{aligned} \tag{12}$$

where $I_K(t)$ and $I_H(t)$—gross investment in physical and human capital; μ_K and μ_H—physical and human capital depreciation rates.

Since $I_K(t) = s_K \cdot Y(t)$, $I_H(t) = s_H \cdot Y(t)$, where s_K and s_H—the rate of investment in physical and human capital, respectively, Eq. (12) are transformed in:

$$\begin{aligned} &\text{a) } \dot{K}(t) = s_K \times Y(t) - \mu_K \times K(t); \\ &\text{b) } \dot{H}(t) = s_H \times Y(t) - \mu_H \times H(t) \end{aligned} \tag{13}$$

Given Kaldor's first empirical regularity in Eq. (10), Eq. (13) will be simplified further:

$$\begin{aligned} &\text{a) } \dot{K}(t) = (s_K \times æ_K - \mu_K) \times K(t); \\ &\text{b) } \dot{H}(t) = (s_H \times æ_H - \mu_H) \times H(t) \end{aligned} \tag{14}$$

The solution of differential Eq. (14) has the form:

$$\begin{aligned} &\text{a) } K(t) = K_0 \times \exp\left[(s_K \times æ_K - \mu_K) \times (t - T_0)\right]; \\ &\text{b) } H(t) = H_0 \times \exp\left[(s_H \times æ_H - \mu_H) \times (t - T_0)\right] \end{aligned} \tag{15}$$

where K_0 and H_0—physical and human capital volumes at the initial moment T_0.

Therefore, in the first half of the twenty-first century, there will be an exponential increase in accumulated capital. However, given that, in accordance with the theory of long waves, at its lower stage, the effect of capital saturation should occur in the 2020–2030, the accumulation of capital will occur along the logistic path:

$$K(t) = \frac{K_1}{1 + u_K \times \exp\left[-\vartheta_K \times (t - T_0)\right]} \tag{16}$$

where K_1, u_K and ϑ_K are constant parameters.

Similarly, to describe the process of human capital accumulation, we obtain the following equation:

$$H(t) = \frac{H_1}{1 + u_H \times \exp\left[-\vartheta_H \times (t - T_0)\right]} \tag{17}$$

where H_1, u_H and ϑ_H are constant parameters.

Knowing the trajectory of capital accumulation in Eq. (16) and using relation in Eq. (10b), we can calculate the growth trajectory of potential output:

$$\mathrm{Y_p(t) = æ_K \times K(t)} \tag{18}$$

We use the set of Eqs. (15)–(17) to predict the physical and human capital dynamics in the first half of the twenty-first century.

3.4 The Model of the Dynamics of Technological Progress in the Era of the Digital Economy

Next, we need to decide on a model for calculating technological progress $A(t)$, which is expressed by the total factor productivity (TFP) of capital and labor. TFP plays the key role in economic development and provides for more than 60% of productivity growth (Easterly & Levine, 2019).

In Akaev and Sadovnichy (2018), we derived a formula for calculating the rate of technological progress for the era of the digital economy:

$$\begin{aligned} &\mathrm{a)}\ q_{Ad}(t) = \frac{\dot{A}_d(t)}{A_d(t)} = \xi\sqrt{\psi_d(t) \times \dot{g}(t)}; \\ &\mathrm{b)}\ \psi_d(t) = \frac{I_d(t)}{K_d(t)};\ \ S_d(t) = S_{do} \times \exp\left[g(t)\right] \end{aligned} \tag{19}$$

where $A_d(t)$—technological progress (TFP) in the era of the digital economy; ξ—calibration factor ($\xi = 0.07$); $I_d(t)$—current investment in fixed assets $K_d(t)$ of information and digital industries; $S_d(t)$—volume of technological production knowledge (information) in the digital economy, which is growing exponentially. Therefore, $\dot{g}(t)$ represents the growth rate of technological production information.

In Akaev and Sadovnichy (2018), we showed that the function $\psi_d(t)$ can be approximated by a linear function and extrapolated for predictive purposes:

$$\begin{aligned} &\psi_d(t) = \psi_0 + \psi_1 \times (t - T_0); \\ &T_0 = 1982; \psi_0 = 0.09; \psi_1 = 0.002 \end{aligned} \tag{20}$$

The growth rate of production technological information $\dot{g}(t)$ for the forecast period of 2020–2030 is described by the following function (Akaev & Sadovnichy, 2018):

$$\text{a) } \dot{g}(t) = \frac{1}{\varsigma_g} \times \left(1 - \frac{e^{-\rho \times \varsigma_g \times g(t)}}{1-\rho} + C_1 \times e^{-\varsigma_g \times g(t)}\right)^{-1}; \quad \text{b) } C_1 = e^{\varsigma_g \times g_1}\left(\frac{1}{\nu_1} - 1 + \frac{e^{-\varsigma_g \times g_1}}{1-\rho}\right); \tag{21}$$

$$\text{c) } t = \varsigma_g \times g(t) + \frac{e^{-\rho \times \varsigma_g \times g(t)}}{\rho(1-\rho)} - C_1 \times e^{-\varsigma_g \times g(t)} + C_2;$$

$$\text{d) } C_2 = \frac{1}{\nu_1} - 1 - \varsigma_g \times g_1 - \frac{1}{\rho} \times e^{-\rho \times \varsigma_g \times g_1}$$

The values of all parameters included in the above formulas were estimated in Akaev and Sadovnichy (2018):

$$g_1 = 5.3; \varsigma_g = 14; \rho = 0.008; \nu_1 = \frac{1}{14} \tag{22}$$

Solving the differential Eq. (19a) with respect to $A_d(t)$, we get:

$$A_d(t) = A_{do} \times \exp\left\{\xi \times \int_t^{To} \sqrt{\psi_d(\tau)\dot{g}(\tau)}d\tau\right\} \tag{23}$$

Since the functions $\psi_d(t)$ and $\dot{g}(t)$ are given, we can calculate the growth path of technological progress $A(t)$ in the era of the digital economy using formula (23).

3.5 *Models of Employment and Income, Taking into Account Technological Substitution of Jobs*

Substituting relations in Eqs. (10) and (11) in formula (1) and resolving it with respect to $L(t)$, we obtain the following formula for calculating employment:

$$L(t) = \lambda \times \frac{K(t)^{\frac{1-\widetilde{\alpha}-\widetilde{\beta}}{1-\widetilde{\alpha}-\widetilde{\beta}+\delta}}}{A(t)}, \lambda = \left(\frac{æ_K^{1-\beta} \times æ_H^{\beta}}{\gamma}\right)^{\frac{1}{1-\widetilde{\alpha}-\widetilde{\beta}+\delta}} \tag{24}$$

Here λ—constant normalization factor. In this formula, the parameters $æ$, γ, δ are constant, and the share of expanded capital $\widetilde{\alpha} + \widetilde{\beta}$ in GDP will increase in accordance with the formula (6). Therefore, the parameters $\widetilde{\alpha}$ and $\widetilde{\beta}$ are marked with an $\widetilde{\alpha}$ (i.e. combining grave-acute-grave) at the top, indicating that they are variable. If in formula (24), we fix the constant current values to $\widetilde{\alpha} = \alpha_0$ and $\widetilde{\beta} = \beta_0$, then the formula can be used to forecast the dynamics of the potential number of jobs in the economy.

Having predicted growth paths of potential GDP (Y_p) and potential jobs L_p, we can calculate the growth of the total share of physical and human capital $\widetilde{\alpha}+\widetilde{\beta}$ depending on the given growth scenarios of the real worker's wage rate (w) using formula (6). Two practically interesting scenarios come to mind: first, empirical growth and second, growth proportional to labor productivity. The first scenario is based on the continuation of the trend in the movement of the wage rate that has developed over the past decades. In the second scenario, the real salary paid by firms is determined by the formula (Blanchard, 2016, Ch.3), which expresses Kaldor's third law in Eq. (2):

$$w = \frac{A}{1+\eta}; \eta \geq 0 \tag{25}$$

where η—cost overrun. If markets were perfectly competitive, then $\eta = 0$. We will describe this scenario as hypothetical.

Next, we consider the impact of the technological substitution of jobs. Their reduction due to the intensive use of robots will occur in various sectors of the economy, the growth of which can be predicted using the logistic function:

$$\mathrm{R(t)} = \mathrm{R}_1 + \frac{\mathrm{R}_2}{1 + \mathrm{u_R} \times \exp\left[-\vartheta_\mathrm{R} \times (\mathrm{t} - \mathrm{T_{BR}})\right]} \tag{26}$$

where R_1, R_2, u_R, ϑ_R—constant parameters.

Automation using robots increases the demand for more skilled labor. However, the overall balance is negative for employment and wages: they are both declining, as it is claimed in Acemoglu and Restrepo (2017). The empirical laws for the US economy established by Acemoglu and Restrepo are formalized as follows:

$$\begin{gathered}\text{a) } \mathrm{L_H(t)} = \mathrm{L_p(t)} \times \{1 - \varepsilon_\mathrm{L} \times [\mathrm{R(t)} - \mathrm{R}_0]\}; \\ \text{b) } \bar{\mathrm{w}}(\mathrm{t}) = \bar{\mathrm{w}}_0 \times \{1 - \varepsilon_\mathrm{w} \times [\mathrm{R(t)} - \mathrm{R}_0]\} \times \exp\left[\bar{\mathrm{q}}_\mathrm{p} \times (\mathrm{t} - \mathrm{T}_0)\right]\end{gathered} \tag{27}$$

where $L_H(t)$—jobs (number) occupied by people; $\bar{w}_0$—average annual employee wage; $\bar{q}_p$—average projected inflation; R_0—the number of robots operating in the economy at the time T_0; $\varepsilon_L = (0.18 + 0.34) \cdot 10^{-7}$ и $\varepsilon_w = (0.25 + 0.5) \cdot 10^{-7}$—empirical coefficients.

Thus, we will have the following equations for calculating the dynamics of increasing the total capital share in Eq. (6) and the physical capital share in Eq. (9), according to the two scenarios:

1. empirical

$$\begin{aligned}&a)\ \widetilde{\alpha}_e+\widetilde{\beta}_e=1+\delta-\bar{w}_0\times\{1-\varepsilon_w\times[R(t)-R_0]\}\times\exp\left[\bar{q}_p\times(t-T_0)\right]\times\tfrac{L_p}{Y_p};\\&b)\ \widetilde{\alpha}_e=\tfrac{æ_H}{æ_H+æ_K}\left[1+\delta-\bar{w}_0\times\{1-\varepsilon_w\times[R(t)-R_0]\}\times\exp\left[\bar{q}_p\times(t-T_0)\right]\times\tfrac{L_p}{Y_p}\right]\end{aligned}\tag{28}$$

2. hypothetical

$$\begin{aligned}&c)\ \widetilde{\alpha}_w+\widetilde{\beta}_w=1+\delta-\tfrac{A(t)}{1+\eta}\times\tfrac{L_p}{Y_p}\times\exp\left[\bar{q}_p\times(t-T_0)\right];\\&d)\ \widetilde{\alpha}_w=\tfrac{æ_H}{æ_H+æ_K}\left\{1+\delta-\tfrac{A(t)}{1+\eta}\times\tfrac{L_p}{Y_p}\times\exp\left[\bar{q}_p\times(t-T_0)\right]\right\}\end{aligned}\tag{29}$$

By substituting dependencies in Eqs. (28a) and (29c) alternately into formula (24), we obtain forecast trajectories L_{pe} and L_{pw} for the growth in the number of real jobs in the US economy, corresponding to the two scenarios adopted above. Further, using the formula (27a), we calculate the predicted trajectories of the number of jobs for people L_{He} and L_{Hw}.

Therefore, if $\bar{w}(t)$ is the nominal average forecast wage of one employee, then the forecast of the dynamics of the total income of all workers employed in the economy can be calculated using both empirical laws in Eq. (27):

$$\bar{Y}_{ph}(t)=\bar{w}(t)\times L_H(t)\tag{30}$$

In order to establish a relationship between the private households' incomes $\bar{Y}_{ph}(t)$ in Eq. (30) and the real aggregate demand for goods and services, we turn to the main economic identity:

$$Y=C+I+G+NX\tag{31}$$

where $C(t)$—total household consumption; $I(t)$—gross investment; $G(t)$—government spending; $NX(t)$—net exports.

Assuming that in this equation $C(t)=c\bar{Y}_{ph}$ (c—households average consumption coefficient), $I=s\cdot Y$, $G=\tau\cdot Y$ (τ—average tax rate) and $NX=0$ (case of balanced foreign trade), we obtain the following relationship linking aggregate real demand for goods and services (Y_{rd}) and real total annual household income $\bar{Y}_{ph}$:

$$Y_{rd}(t)=c'\times\bar{Y}_{ph}(t);\quad c'=\frac{c}{1-s-\tau}\tag{32}$$

The question arises, how can consumer demand be ensured at the level of potential output of goods and services? We have already noted above that one of the solution options is the introduction of UBI. To assess the UBI, first, it is necessary to calculate the predicted dynamics of population growth, which can best be set by the logistic function:

$$\mathrm{N(t)} = \mathrm{N}_1 + \frac{\mathrm{N}_2}{1 + \mathrm{u_N} \times \exp\left[-\vartheta_\mathrm{N} \times (\mathrm{t} - \mathrm{T_{bN}})\right]} \tag{33}$$

where N_1, N_2, u_N, ϑ_N—constant parameters, T_{bN}—year of the beginning of the population growth dynamics approximation.

We also approximate the dynamics of the UBI by the logistic function:

$$\mathrm{r_b(t)} = \frac{\mathrm{r_{bo}}}{1 + \mathrm{u_b} \times \exp\left[-\vartheta_b(\mathrm{t} - \mathrm{T_{b0}})\right]} \tag{34}$$

where r_{b0}, u_b, ϑ_b—constant parameters; T_{b0}—year of UBI commencement.

The total UBI received by the entire adult population is determined by the formula:

$$\mathrm{Y_{Nb}(t)} = \phi \times \mathrm{N(t)} \times \mathrm{r_b(t)} \tag{35}$$

where ϕ—coefficient taking into account the adult population receiving UBI ($\phi \le 1$). Then, the aggregate demand of households, taking into account both labor income $\bar{Y}_{ph}$ in Eq. (30) and UBI in Eq. (35):

$$\mathrm{Y_{rdb}(t)} = \mathrm{c}'\left[\bar{\mathrm{Y}}_\mathrm{ph}(\mathrm{t}) + \mathrm{Y_{Nb}(t)}\right] \tag{36}$$

So, we have compiled the model of economic growth in Eq. (1), taking into account both physical and human capital, and endogenous formation mechanisms of physical and human capital shares in national income in Eq. (6), as well as technical progress (Eqs. 19 and 23). We use the model to forecast the potential GDP and the number of jobs under given scenarios of the wage rate changes and the level of UBI necessary to ensure the sustainability of the economy.

4 Results and Discussion

4.1 Results

The article (Christian, 2017) presents a study on the assessment of the US economy human capital from 1975 to 2013, and therefore calculations using H are limited to this period.

The verification of the production function (1) for the US economy in the period from 1982 to 2013 are presented in Table 1:

The approximation of US GDP using the formula (1) is presented in Fig. 1. Actual values are marked in black, simulated in red.

Table 1 Results of calculations for the model (1)

Parameter Estimates	Accuracy ratings
$\gamma = 0.101;\ \alpha = 0.439;\ \beta = 0.183;\ \delta = 0.081$	The average approximation error is 0.59%; Normalized coefficient of determination 0.964

Source: calculated by the authors based on data from M. Christian (2017), US Bureau of Economic Analysis (2020b, 2020c, 2020d), The University of Groningen and University of California, Davis (2020)

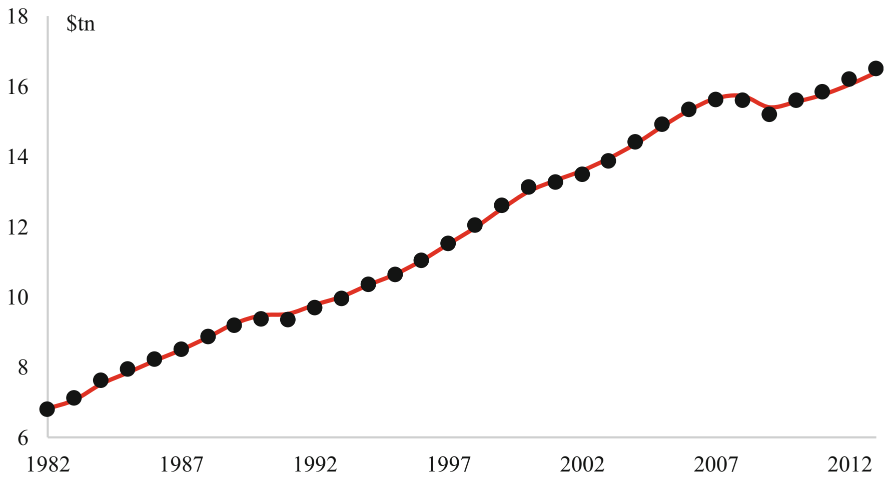

Fig. 1 US GDP growth dynamics (1982–2013). Source: Authors' creation

Table 2 Estimates of the model (1) parameters quality

Parameters	Standard error	t-statistic
α	0.0587	8.832
β	0.0282	4.986
δ	0.0176	25.028

Source: calculated by the authors based on data from M. Christian (2017), US Bureau of Economic Analysis (2020b, 2020c, 2020d), The University of Groningen and University of California, Davis (2020)

Table 2 shows the parameters' statistical estimates for production factors (significance level of 95%).

Based on data for the $K(t)$ (from 1982 to 2018) and for the $H(t)$ (from 1982 to 2013), coefficient estimates were obtained for capital accumulation models in the twenty-first century. The results are summarized in Table 3:

By extrapolating in accordance to formula (15b) for 2014–2018, using values of human capital and taking into account available statistical data on other production factors, Fig. 1 can be supplemented with simulated GDP values (highlighted in green in Fig. 2).

Table 3 Calculation results for capital accumulation models (15–17)

Parameter Estimates	Accuracy ratings
$\sigma_K = 3.31$; $æ_K = 0.302$; $\mu_K = 0.035$; $s_K = 18.6\%$ $K_1 = 163.6$ trillion dollars; $u_k = 1.782$; $\vartheta_k = 0.038$ $\sigma_H = 13.12$; $æ_H = 0.076$; $s_H = 29.5\ \%$; $\mu_H = 1.04\%$ $H_1 = 567.5$ trillion dollars; $u_H = 1.399$; $\vartheta_H = 0.02$	R^2 are close to 1; The observed F-test values are more than critical (significance level of 95%)

Source: calculated by the authors based on data from M. Christian (2017), US Bureau of Economic Analysis (2020b, 2020c, 2020d), The University of Groningen and University of California, Davis (2020)

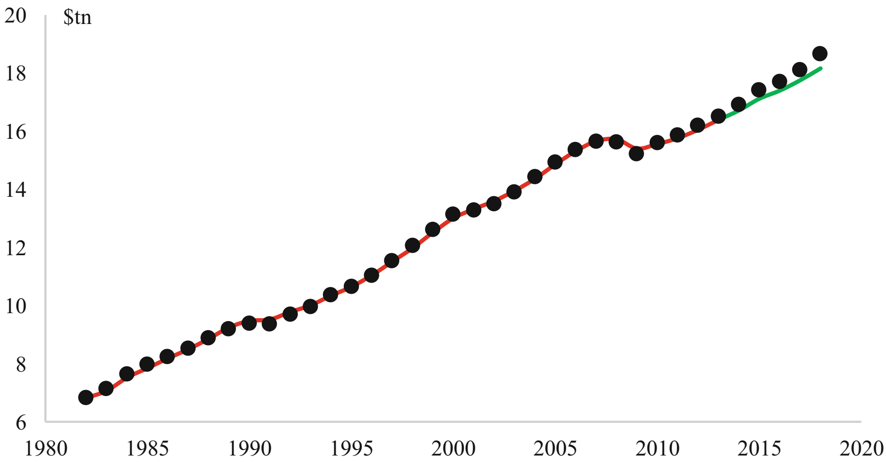

Fig. 2 US GDP growth dynamics (1982–2018). Source: Authors' creation

Let us note that we do not present the results for the technological progress model (19–23), since it was studied in detail in Akaev and Sadovnichy (2018).

According to the International Federation of Robotics (2019), on the number of robots operating in the US economy, the parameters values of Eq. (26) were found: $R_1 = 0.17$ million; $R_2 = 17.5$ million; $u_R = 132$; $\vartheta_R = 0.121$; $T_{BR} = 1995$.

The predicted dynamics of the potential number of jobs in the US economy as a whole is $L_p(t)$ and, for the two varying scenarios $L_{pe}(t)$ and $L_{pw}(t)$, which are calculated by formula (24), are shown in Fig. 3a. The corresponding trajectories of the number of employees, taking into account production and management robots—L_{He} and L_{Hw}, are presented in Fig. 3b.

Predicted growth paths of potential US GDP until 2030, calculated using the formula (1) under various scenarios of the labor employment reduction L_{pe}, L_{pw}, L_{He}, L_{Hw}, (see Figs. 3a, 3b) and accelerated capital accumulation K (16), are presented in

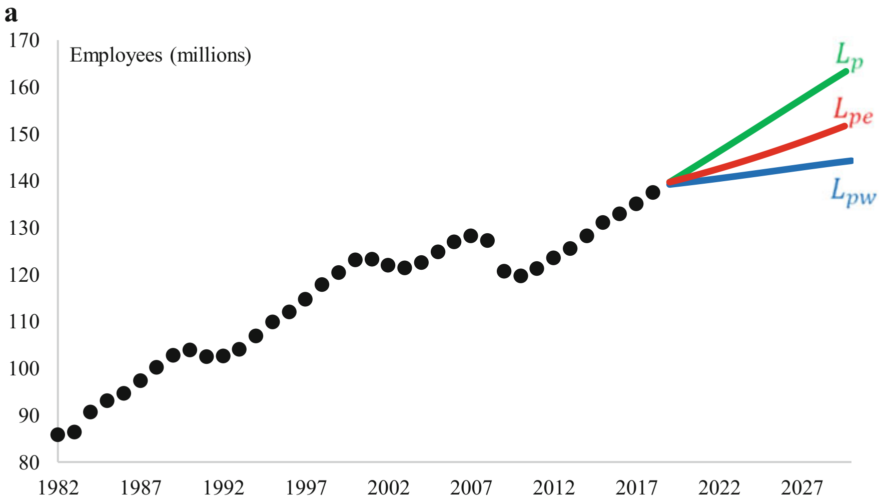

Fig. 3a Forecasts of the number of employed in the US economy, taking into account technological substitution of jobs (L_p—potential number of employees; L_{pe}, L_{pw}—number of employees in the empirical and hypothetical scenarios). Source: Authors' creation

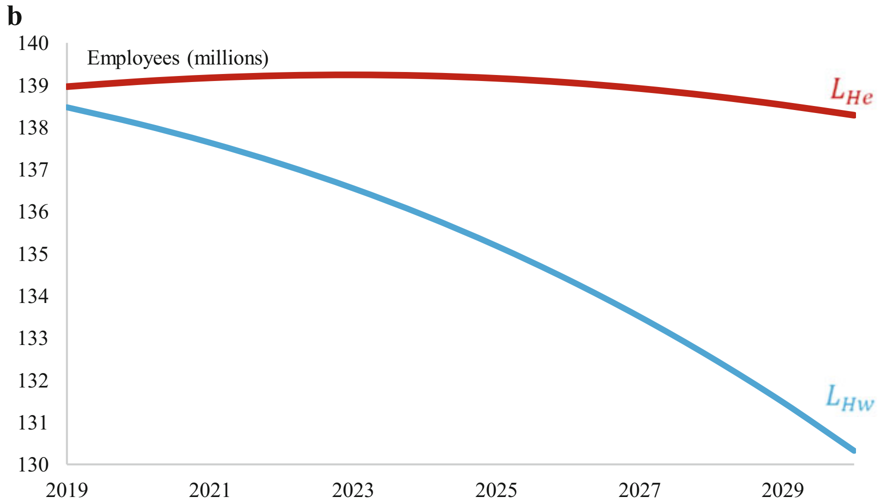

Fig. 3b Forecasts of the number of employees in the US economy, taking into account production and management robots (L_{He}, L_{Hw}—number of employees in the empirical and hypothetical scenarios). Source: Authors' creation

Figs. 4a and 4b. Note that the current values for USA hold as follows: $c = 0.82$; $s = 0.18$; $\tau = 0.11$; $c^{'} = 1.16$.

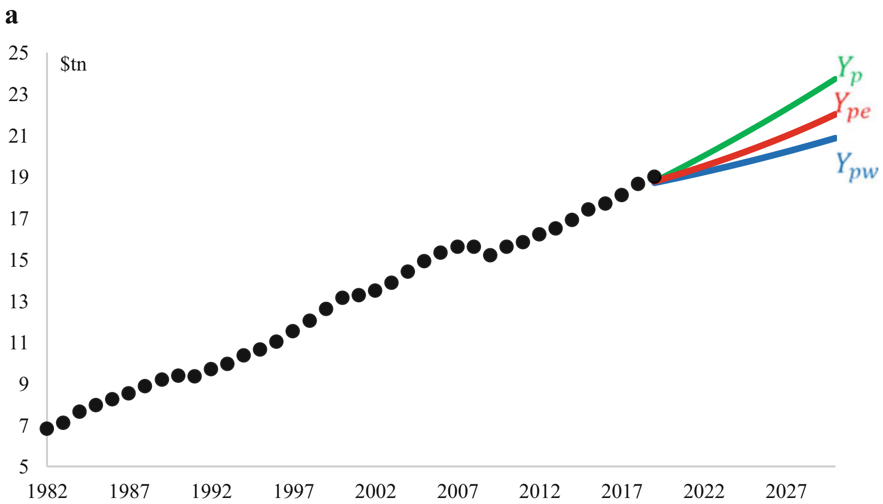

Fig. 4a Forecasts of GDP dynamics taking into account technological substitution of jobs (Y_p—potential GDP; Y_{pe}, Y_{pw}—GDP in the empirical and hypothetical scenarios). Source: Authors' creation

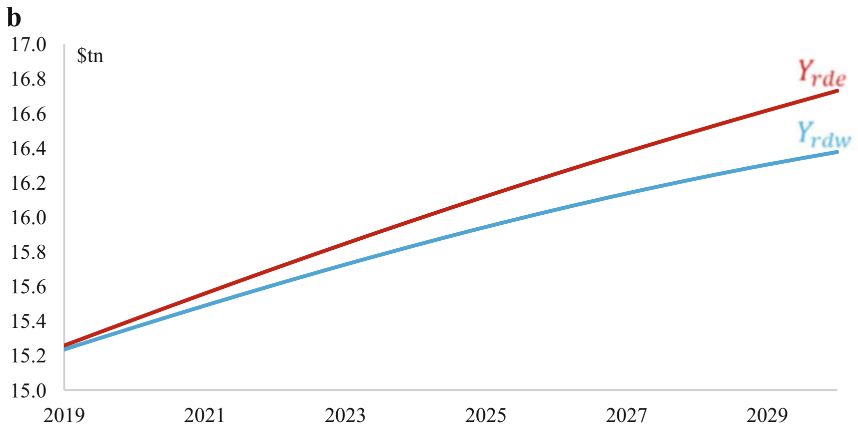

Fig. 4b Forecasts of the dynamics of real household demand (Y_{rde}, Y_{rdw}—real demand in the empirical and hypothetical scenarios). Source: Authors' creation

According to estimates, the GDP potential value (Y_p) for 2030 is 23.7 trillion dollars with the number of employees L_p equal to 164.1 million jobs. Table 4 shows the US economy forecasts for 2030 under the considered scenarios.

To describe the dynamics of the US population growth, the numerical values of the parameters are determined: $N_1 = 0.009$ million people; $N_2 = 617.76$ million people; $u_N = 2.93$; $\vartheta_N = 0.018$; $T_{bN} = 1950$.

Table 4 USA Economic Forecast 2030

Indicator	Scenario	
	Empirical	Hypothetical
Number of employees (million), including:		
technological substitution of jobs	152.2	144.3
production and management robots	138.3	130.3
GDP, taking into account technological substitution of jobs (trillion dollars)	22	20.9
Households real demand (trillion dollars)	16.7	16.3

Source: calculated by the authors based on data from M. Christian (2017), International Federation of Robotics (2019), US Bureau of Economic Analysis (2020b, 2020c, 2020d), The University of Groningen and University of California, Davis (2020)

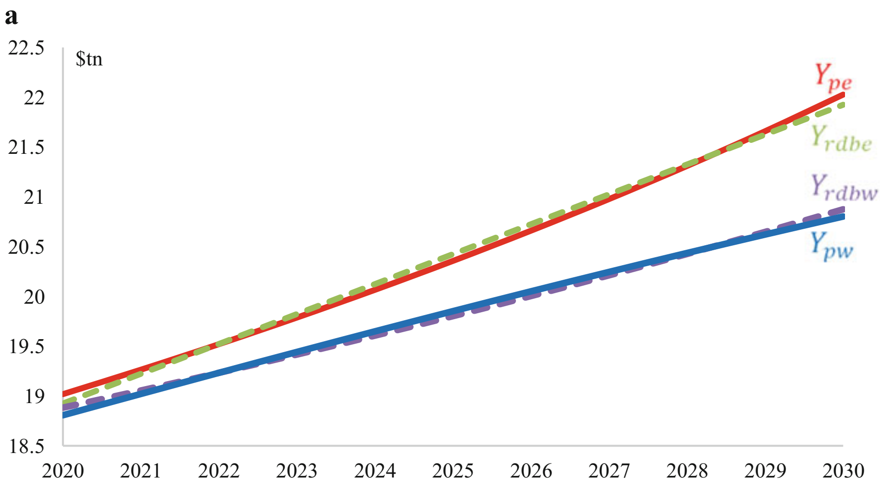

Fig. 5a Recovery of the aggregate household demand potential volume (Y_{rdbe}—aggregate demand, Y_{pe}—GDP in the empirical scenario; Y_{rdbw}—aggregate demand, Y_{pw}—GDP in the hypothetical scenario) by introducing the UBI. Source: Authors' creation

Under the condition $T_{b0} = 2020$, $\phi = 0.85$, we calculated the parameters of the predicted UBI growth function (34): for the empirical scenario, they are $r_{b0e} = 0.04$; $u_{be} = 2.46$; $\vartheta_{be} = 0.047$; for the hypothetical one, they are $r_{b0w} = 0.19$; $u_{bw} = 17.03$; $\vartheta_{bw} = 0.018$

The growth trajectory of the aggregate household demand, including UBI in Eq. (36) and the growth curve of the UBI itself in Eq. (34) are presented in Figs. 5a and 5b.

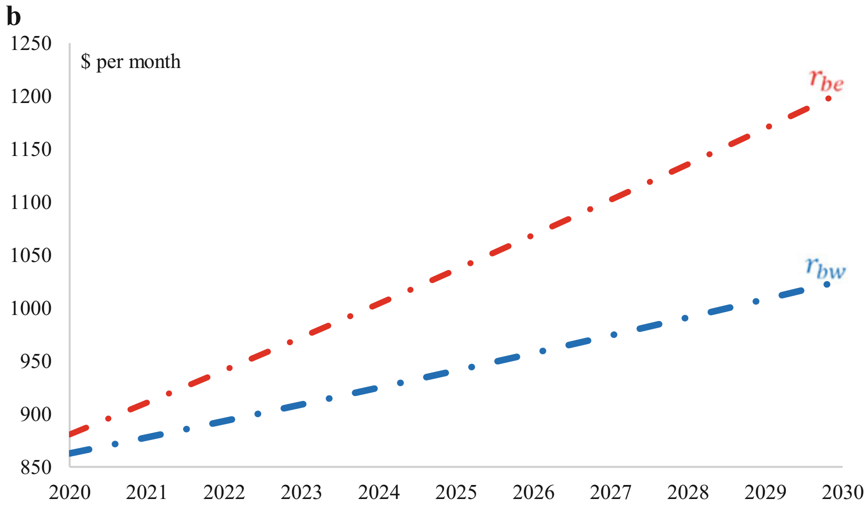

Fig. 5b Dynamics of basic income r_b (r_{be}, r_{bw}—number of monthly payments in the empirical and hypothetical scenarios). Source: Authors' creation

4.2 *Analysis of the Results*

Verification of the production function (1), carried out on the example of the US economy, shows that the model works well. This can be seen in Fig. 1, where the calculated and actual values of GDP almost coincide. The correspondence of model values to real ones is confirmed by high-quality assessments and statistical significance of the parameters (see Tables 1 and 2). Thus, the proposed modification of the simplest production function based on economic development modern ideas—taking into account human capital and increasing returns generated by high-tech science-intensive sectors of the economy—is adequately realistic and can be used in practice.

One of the key points is the accurate assessment of the parameters of the physical and human capital accumulation models (15–17) for making forecasts for the first half of the twenty-first century. Using the obtained statistically significant estimates (Table 3), factors K and H are simulated close to real values. The proposed capital models correspond to the ideas of Piketty and Stiglitz and can be used both to determine the average annual growth rate of potential GDP (in our calculations, it is 2.15%) and in related studies of the future dynamics of the capital resources of the economy.

Of greatest interest for analysis are the calculation results for two scenarios—hypothetical and empirical. As can be seen from Fig. 3a, in the case of a hypothetical scenario, the potential number of jobs is lower than the empirical option (on average, 2.9% per year). Moreover, judging by Fig. 3b, in the hypothetical scenario, there is a sharper decrease in the number of jobs occupied by people (–5.89%), compared with the empirical scenario (–0.49%). In the empirical scenario, despite technological substitution, there is even a slight increase in the number of jobs occupied by people in the first half of the forecast period (2020–2025).

At the same time, the average difference in forecast GDP values for the considered scenarios is equivalent to the difference in the potential number of jobs (2.9%), and the average growth rates are 1.6% and 1.1% for empirical and hypothetical options, respectively. Figure 4b indicates that the wage growth under the hypothetical scenario partially offsets the negative impact of declining employment on real demand for goods and services—the average discrepancy between Y_{rde} and Y_{rdw} curves is 1.1%.

The difference in approaches to the nominal wage determination between the 2 scenarios is also manifested at the level of UBI calculations. The calculations confirm the conclusion that there is a smaller gap between real demand and supply under the hypothetical scenario—the amount of funds needed to restore demand is on average 18.19% of the projected GDP for the empirical scenario and 17.01% for the hypothetical one. This fact affects the value of the UBI. According to our calculations for 10 years, in the hypothetical scenario, it is enough to increase the initial UBI ($860 / month per person) by about $160. While in the empirical scenario, a higher initial level of UBI ($880 / month per person) is required, alongside annual increases of the amount of payments to a level of $1200 / month in 2030.

In general, the forecasts obtained correspond to the hypotheses about the impact of digital transformation on the economy and new stylized facts. Acceleration of technological progress, automation, and robotization have a negative impact on the labor factor. Under these conditions, the dynamics of economic development indicators (GDP, real demand, and number of jobs) are inversely proportional to the change in the real wage rate. On the other hand, an increase in wages has a positive effect on smoothing inequality and reduces the required UBI value.

4.3 Discussion

It is necessary to compare the modeled results with the currently available estimates. According to forecasts of the US Congressional Budget Office (2020), the US potential real GDP by the end of 2030 will be 23.3 trillion dollars. That differs 1.7% from the values obtained using our model. An alternative estimate proposed by the OECD (2020) is 21.9 trillion dollars, which practically coincides with our empirical scenario projection. Hence, taking into account various scenarios of wage rate dynamics allows us to form a space of adequate estimates of future GDP.

On the other hand, according to the calculations of the US Department of Labor, Bureau of Labor Statistics (2019), the number of jobs in the US economy by 2028 will be 169.4 million, which is 6% higher than our forecast for the same year. In our opinion, this discrepancy once again emphasizes the complexity of the digital transformation process and the importance of finding tools to describe it.

Information and knowledge have become the main resources of the modern economy. The particularity of these resources lies in the fact that they are the result of human intellectual activity and information activities of the society. In this regard, the areas of production associated with the generation, transmission, processing, and use of information are becoming increasingly important in modern economic systems. This raises the question of using the concept of "intellectual capital" instead of human capital in future models of economic dynamics. The concept of intellectual capital (Edvinsson & Malone, 1997) is wider and deeper than the concept of human capital and includes information as an independent production resource.

In the scenarios of wage changes, both empirical and hypothetical, the forecasts about the decrease in the number of jobs due to automation and robotization of production, and, therefore, the prospect of a decrease in demand for goods and services, are confirmed. According to the model, in both scenarios, a gradual decrease in employment because of crowding out of human labor by intelligent machines can lead to a drop in real demand in the next decade. The identified problem poses a potential threat to the economic well-being of the USA. In this regard, as one of the solutions, the introduction of the UBI is proposed in order to create a balance between supply and demand. Estimating the level of UBI using our model, we got an initial value of \$860–880 per month per person in 2020 and forecast values for 2030. Calculations within the framework of our model have shown that annual costs per person should be approximately 10–12 thousand dollars. This amount is close to what is currently voiced in a research environment, for example, in Kearney and Mogstad (2019). These calculations show that, depending on the selected UBI scenario, federal budget spending will range from \$1.2 to \$2.49 trillion (i.e., from 5.85% to 12.15% of GDP). This is significantly higher than the current payments for various social programs of the federal government (about \$ 1 trillion). Nevertheless, as shown by the actions of the US administration to support the population in the context of the COVID-19 pandemic, macroeconomic instruments can be used to maintain consumer demand (Fabian & Sink, 2020). The model we have proposed is the simplest and, for special cases, may require a more accurate mechanism for tuning the UBI parameters.

5 Conclusion

In this work, we proposed a set of economic growth models, built in accordance with the new stylized facts of economic development formulated by J. Stiglitz and T. Piketty, and taking into account the endogenous nature of the formation of physical and human capital shares in national income, and technological progress.

The practical significance of the presented models lies in the wide possibilities of their application in predicting the dynamics of the potential number of jobs, taking into account technological substitution under various scenarios of real wage formation. In addition, with the help of models, we estimate the corresponding GDP volume and the level of decline in aggregate consumer demand caused by the reduction in the number of jobs occupied by people and the increasing role of robots in the economy.

Verification of our developed models with existing US statistics indicates their high accuracy, compliance of the calculated values with actual ones and low approximation error. In the considered scenarios of wage changes—empirical and hypothetical, the forecasts of economists of a decrease in the number of jobs due to automation and robotization of production, and, as a consequence, the prospect of a decrease in demand for goods and services, are confirmed. Based on this, we also presented the simplest model for determining the UBI, which provides a balance of real demand and supply in the economy.

Our proposed set of mathematical models is a useful decision-making tool in the areas of economic and social policy to ensure the stable development of the state.

Recommendations for further development of models can be divided into three groups. Firstly, a further complication is possible, for example, by introducing additional factors and parameters when calculating the UBI. Secondly, models should be verified on the statistics of other countries in order to identify possible shortcomings of the presented economic and mathematical apparatus, as well as to formulate recommendations for managing various national economies. Thirdly, a separate direction for the study is finding the optimal scenario for the formation of real wages for given criteria.

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