NEW TECHNOLOGIES, POTENTIAL UNEMPLOYMENT AND 'NESCIENCE ECONOMY' IN THE RUSSIAN REGIONS

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The use of unmanned technologies can cause a decrease in the level of employment. The article discusses the compensation mechanisms and conflicting results of empirical studies. On the basis of internationally comparable methods (Frey, Osborne, 2017; Manyika et al, 2017), it was estimated that about 44% of the workers in Russia can be replaced, which is lower than in most developed countries. In the regions, specializing in the manufacturing industry, this value is higher, the least values are in the least developed regions. Long-term mismatch between the exponential increase in automation rate, the compensating effect of retraining and new jobs creation is possible. Some people will be not ready for life-long learning, development and creation of new ideas, technologies and products, competition with robots, and accordingly there is a possibility of their social exclusion in the future. The term 'nescience economy' was proposed to describe these processes. In some southern regions, low rate of potential automation combined with high levels of potential exclusion, that is, in the future they can combine low labor productivity, and therefore lower budget revenues, with high social risks and costs.

Keywords: automation, new technologies, diffusion of innovations, ICT, R&D, innovations, Russian regions, technological exclusion

Introduction

A number of authors document the beginning of a new industrial revolution, or «industry 4.0» (Hawken et al 2013; Schwab, 2017), which features are universal digitalization, robotization (Ford, 2015) and the formation of smart networks. Many of the new technologies are disruptive, capable of completing the development of entire sub-sectors, and therefore potentially leading to an increase in the level of structural (technological) unemployment. For example, in the USA in the last 10 years there has been an increasing gap between the positive dynamics of labor productivity and stagnant employment (Brynjolfsson, McAfee, 2014). This may be partly because of robots development. They are automatic devices intended for carrying out production and other operations previously performed by humans (Rifkin, 1995): complex computer programs (bots), industrial robots, smart homes, smartphones, etc. According to the previous estimates (Brynjolfsson, McAfee 2014; Manyika et al., 2017), about half of the jobs in the world can be automated by 2030-35. At the same time, compensation mechanisms operate in the economy (Vivarelli, 2014), jobs are created in new industries (Berger, Frey, 2015; World Bank, 2016). Therefore, it is important to understand how the threats to automation (The Future of Jobs, 2016) are related to the formation of long-term technological unemployment and the exclusion of citizens from modern economic activities. In different countries and regions, the automation potential and subsequent social consequences are different (Berger, Frey, 2016a; Manyika et al., 2017).

The purpose of the work is to raise awareness and intensify scientific discussion about the possible social consequences of robotization in the Russian regions and developing countries. To do this, the paper suggests methods and describes the results of preliminary assessments of the potential level of employment automation and the possible social exclusion from modern economic activity. The approach used in this work does not solve the problem of predicting these phenomena, but may serve the task of determining the pessimistic scenario.

The first paragraph describes the existing theoretical models of the impact of technology on employment, the second part presents empirical estimates of the potential of employment automation. Next, the research methodology is described, a preliminary assessment of robotization in the Russian regions is given, and the scales of the 'nescience economy' are assessed.

Technological change and employment: theoretical approaches

The effect of technological change on employment is devoted to the work of major scientists and thinkers (Keynes, 1933; Pigou, 1933; Ricardo, 1951; Marx, 1961; Marshal, 1961, and others). Based on the review of works (Vivarelli, 2014), several main mechanisms compensate for the decline in employment as a result of innovation, but each of them has its own limitations in modern conditions in Russia.

Creation of new machines (Say, 1964). New technologies contribute to the appearance of jobs in sectors that create and maintain robots and other mechanisms. This does not compensate for the number of retired workers (Freeman et al., 1982). In the conditions of weak development of robotics in Russia, this effect will have a weak effect. In the future, robots will be able to repair and recreate themselves.

Reduced prices (Pigou, 1933; Stoneman, 1995; Vivarelli, 1995). New technologies contribute to lower prices for products, as they increase production efficiency. Lower prices stimulate demand, which leads to an increase in production and employment. However, prices fall under conditions of perfect competition, in Russia in many markets monopolies and oligopolies are being formed. Under conditions of structural unemployment, demand will remain only for essential goods, and for new products will decrease (Zubarevich, 2010).

Investments (Ricardo, 1951; Marshal 1961; Stoneman, 1995). The accumulation of investments in the period between the reduction of costs due to innovation and the subsequent decrease in prices. Capital investments in production and jobs. In conditions of high risks in Russia, investors prefer to accumulate or withdraw capital abroad. Investments can also be directed to the creation of industries with low employment.

Reduction of wages (Pigou, 1933; Venables, 1985). Reduction of costs by reducing wages, working hours, underemployment. Labor and capital are not always interchangeable. In Russia, there are administrative restrictions on staff cuts (Zubarevich, 2015).

Increased incomes (Vivarelli, 2014). Increased incomes due to increased labor productivity should lead to increased demand and employment in other sectors. Increased incomes in Russia can be spent on acquiring foreign durable goods, as well as real estate. It may have limited impact, including due to possible inflation.

Creation of new products and services (Nelson, Phelps, 1966; Aghion, Howitt 1994; Endquist et al., 2001). The emergence of new industries, new products and services will lead to increased demand for labor. Low entrepreneurial and innovative activity in Russia limits the development opportunities for new industries and new products.

On a downtrend of Kondratieff wave, the factors of economic growth are depleting and the unemployment rate may increase (Freeman et al., 1982; Perez, 1983), but then the technologies of the next cycle form new activities and increase the demand for labor force. According to (Bainbridge, Roco, 2006), the new order will be based on NBIC convergence, that is, on the interaction of nano- (N), bio- (B), information technologies (I) and cognitive science (C). The main characteristic of the new way of life will be the formation of smart systems, in which a person will take less and less participation. The problem of potential unemployment is associated with the emergence of systems such as “robot-robot”: algorithms with elements of artificial intelligence, internet of things, autopilot vehicles, etc. At the previous stage of automation, non-adaptive mechanical tools were used (Banham, 1980), which were limited in their functions and covered some branches of the economy. At the new stage (Brynjolfsson, McAfee, 2014) a fundamentally different environment is being formed in which the surrounding materials, equipment and even the human body will be integrated and able to adapt.

If the beginning of a new technological paradigm in Russia is 2015, then it will be formed by 2035 (Baburin, 2010). In accordance with the diffusion model (Rogers, 2010), robotization will occur along an S-shaped curve (Fig. 1), and by 2035 the process may be exponential (Baburin, 2010; Brynjolfsson, McAfee, 2014; Manyika et al., 2017).

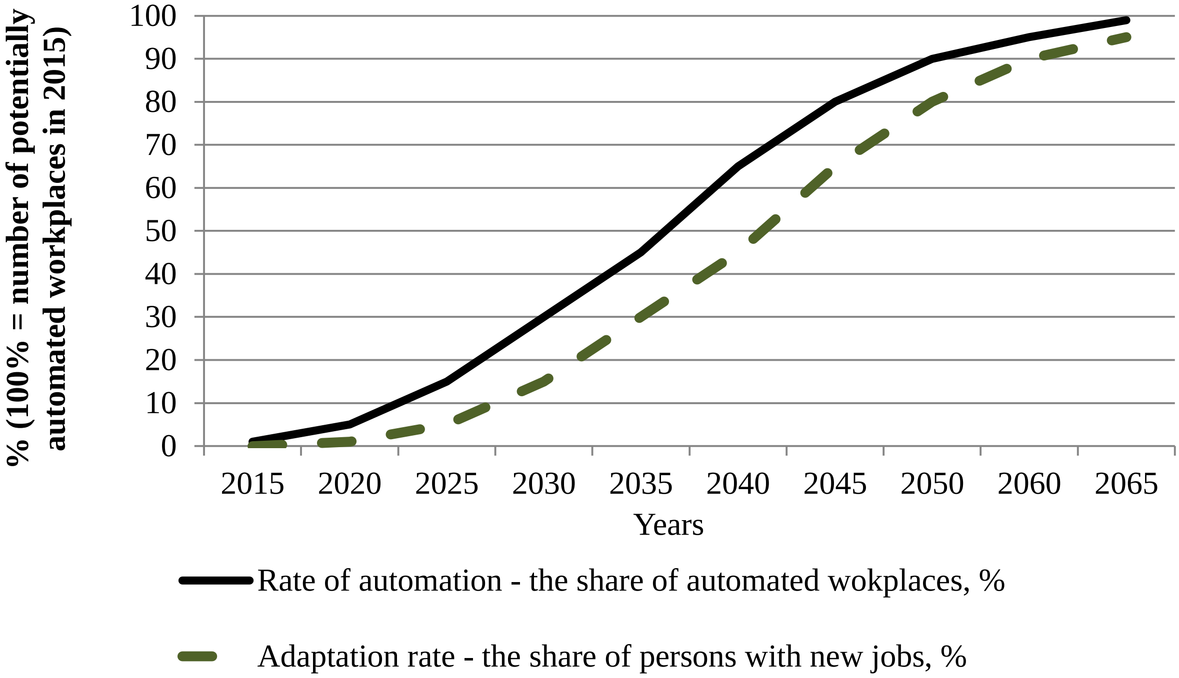

Figure 1 - The curves of potential robotization (automation) and adaptation of the labor market

To save employment, it will be necessary to introduce retraining programs for new professions, to develop creative industries and realize entrepreneurial initiatives. It is highly possible that Russian Government and the labor market will respond to technological challenges with a delay of several years, since the introduction of new training programs, development of startups takes time. That is, there will be a gap between the increasing number of unemployed people and the appearance of new vacancies (see similar argumentation in Brynjolfsson, McAfee, 2014). At the same time, the described model (fig. 1) is intentionally simplified and does not take into account possible demographic changes (aging of the population, increase in pension age, etc.). For some regions, a situation of long-term decline in employment is more possible.

The impact of robotization on socio-economic processes can be described using the model proposed in the work (Autor et al., 2003)

$$Q = (\mathrm{L}_s + C)^{1-\beta} \times L_{NS}^{\beta}\text{, with } 0 \leq \beta \geq 1 \qquad (1),$$

where Q is the output, L_S and L_{NS} are the number of automated and not automated workforce, C is the computer capital (robots). The model predicted an increase in the share of highly qualified specialists performing non-routine activities.

Previous empirical evaluations of potential automation

Starting with the book (Rifkin, 1995), dozens of papers tried to explain an effect of modern technology on employment. M. Vivarelli (Vivarelli, 2014), after conducting a detailed review of econometric studies, notes that the selection of adequate indicators of technological change is a non-trivial task. The following indicators are related to product innovations: the number of patents, research and development (R & D) expenditures. There were several indicators of process innovations: equipment acquisition, software updates, introduction of information and communication technologies (ICT), etc. (Parisi et al., 2006). Each of the indicators have its limitations and disadvantages. At the same time, the estimates obtained at the level of countries, regions and industries have biases related to undercounting of macroeconomic cycles, changes in working hours and other factors, while at the level of firms, intersectoral movements of employment are not taken into account. The results are ambiguous for process innovations, which predominantly reduce employment, but compensating mechanisms (Table 1) is also revealed, associated with new products, lower prices and higher incomes. Technical progress leads to an increase in demand for more qualified specialists (Bekman et al., 1998).

Historically, periods of major technological change have not led to a long-term increase in unemployment. For example, the increase in labor productivity in agriculture due to mechanization was compensated by the migration of the rural population to the city and appearance of new professions. But there was a temporary surge in unemployment in certain industries and regions, and accordingly social protests. The most widespread is the movement of the Luddites in England during the 1st Industrial Revolution, when the workers destroyed looms because of unemployment and famine, engaged in battles with regular troops (Johnes, 2006). Today, opponents of the proliferation of new technologies are often called “neoluddits” (Johnes, 2006).

In recent years, dozens of studies have been published to assess the potential automation of workplaces. A start was made by the article (Frey, Osborne, 2013), in which the appropriate methodology was proposed:

$$L_{NS} = \sum_{i=1}^{n}\left(L_{PM,i} + L_{C,i} + L_{\mathrm{SI},i}\right) \tag{2}$$

where L_{NS} is the estimate of the number of the least susceptible to robotization employees; L_{PM}, L_C and L_{SI} - the number of employed in professions i (n = 702 professions in the United States), which have different automation potential based on three criteria (Table 2).

Table 2 - Criteria that determine the potential degree of automation

Criterion	Variable	Description
PM - perception and manipulation.	Dexterity of fingers and hands.	Ability to perform coordinated movements, collect small objects.
	Constrained space	Ability to work in uncomfortable positions

C - creative intelligence (David, 2015)	Originality	Ability to come up with unusual ideas, develop creative solutions to problems
	Art	Knowledge of the theory and methods of art
SI - Social Intelligence	Social Susceptibility	Aware of the reactions of others
	Negotiation and persuasion	Attraction and reconciliation of the parties. Ability to convince
	Help and care for others	The ability to provide personal, medical, emotional support

Source: Autor et al., 2003; Frey, Osborne, 2017

Based on these criteria, the authors proposed a function of automation probability for each profession. Several professional groups have a low probability (less than 0.01): doctors, social workers, creative and STEM professions, scientists, mentors and top managers. Among the most vulnerable professions (above 0.99) are: telemarket hosts, seamstresses, technicians, insurance and tax agents, bank clerks, librarians. The automation probability accountants and auditors is about 0.94. In the US, about 47% of employees are vulnerable, that is, they have a probability higher than 0.7. Firstly, routine, but the most crucial areas, such as logistics and production, will be automated, then an increasing number of services, sales, construction, and with the development of artificial intelligence - science, engineering. The two main personal factors that reduce the likelihood of robotization are high salaries and the level of competence.

Robotization processes will have high spatial differentiation (Berger et al., 2015). For example, in the USA, the greatest vulnerability is observed in the cities of Las Vegas, Los Angeles, Houston, where the entertainment sphere is developed (the hotel sector and restaurant business are most susceptible), and the least vulnerable: Boston, Washington, New York, San Francisco, where R&D, ICT and other creative industries are represented (Florida, 2002).

Using a similar technique, studies have been conducted in many countries (Table 3). The lower potential of automation in developed countries is associated with a higher level of ICT implementation (World Bank, 2016) and the quality of human capital. On average, in the Organization for Economic Cooperation and Development (OECD) countries, the proportion of vulnerable workers is about 57%, in Thailand - 72%, and in Ethiopia - about 85%.

Table 3 - Estimates of the proportion of potentially automated workforce,%

Country	Methods of [Frey, Osborne, 2013]	Methods of [Arntz et al., 2016]	Methods of [Manyika et al., 2017]
China	77,1	-	51
Индия	68,9	-	52
Germany	59	12	48
Italy	56.2	10	50
Poland	56.3	7	49

Japan	49	7	56
USA	47	9	46
France	49.5	9	43
Canada	45	9	47
Sweden	46.7	7	46
United Kingdom	35	10	43
Korea	-	6	52
Russia	26.5 [Zemtsov, 2017]	2	44.8 [Zemtsov, 2017]

Additional sources: Knowles-Cutler et al., 2014; Pajarinen, Rouvinen, 2014; Schattorie et al., 2014; Bowles, 2014; Wakao, Osborne, 2015; Brzeski, Burk, 2015; Chang, Huynh, 2016; Lamp, 2016; World Bank 2016

OECD researchers (Arntz et al., 2016), criticizing the approach (Frey, Osborne, 2017), believe that whole professions cannot be eliminated and only individual tasks are automated. Evaluation results of (Frey, Osborne, 2017) were used as a dependent variable. Then, according to surveys, factors affecting the probability of automation were assessed (Bonin et al. 2015; Chang, Huynh, 2016). It is higher for women employed between the ages of 25-29 and 60-65, for those with a low level of education, but lower for employees of the largest firms with high incomes and managers. Based on a combination of these criteria, the share of the most vulnerable professions was identified: about 9% of employed in OECD member countries, 6% in South Korea, and 2% in Russia. But in Russia there is a low level of implementation of labor-saving technologies, so one would expect a higher value than in developed countries. The result obtained (Arntz et al., 2016) may be associated with a lack of methodology based on the strong assumption that similar positions have similar correlation of tasks and similar characteristics of respondents regarding the level of automation in different countries.

Experts at the McKinsey Global Institute (Chui et al., 2015; Manyika et al., 2017), also criticizing the approach (Frey, Osborne, 2017), looked at 2000 production tasks in 800 US occupations and estimated the proportion of time workers spend on performing routine operations (tab. 4). About 49% of work time can be automated, but fully robotized - only 5% of professions.

According to surveys of top managers of the largest companies in 15 countries (The Future of Jobs, 2016), by 2020 their employment will decrease by 5 million people: 7 million jobs will be automated, 2 million can be created in the field of STEM-technologies, in the financial sector and in sales. At the same time, the ratio of eliminated and created jobs for men will be 3 to 1, and for women - 5 to 1, that is, gender inequality will increase.

According to expert polls (Le Clair et al., 2016), smart technologies are capable of eliminating about 16% of jobs in the US by 2025, and will create only 9% (13.9 million people), mainly in the field of data analysis and robots maintenance. In banks, up to 30% of jobs until

2025 can be automated (Technology at Work v2.0, 2016) due to the introduction of Internet banking, big data methods for risk analysis, robot consultants, and blockchain. By 2020, up to 50% of those employed in the extractive industries of the OECD may lose their jobs (Cosbey et al., 2016) due to the use of self-propelled trucks, forklifts, drones, etc. New mines and those with low qualifications are most vulnerable. In Russia, according to estimates of the SuperJob recruiting portal, by 2024 about 20% of those employed will lose their jobs, and the unemployment rate may increase to 20–25% by 2022 (in November 2016 it was about 5.4%).

At the same time, in the UK over the past 140 years (Steward et al., 2015), technologies have created more jobs than they have reduced. In 2001 to 2015 in jobs with a low probability of robotization in the UK, 3.5 million new jobs were created, and only 0.8 million in the most vulnerable professions (From brawn to brains, 2015). The number of librarians, vendors, travel and credit agents, secretaries has decreased, and jobs have been created primarily in the field of STEM. In the United States, employment is increasing in industries with high vulnerability (Berger, Frey, 2016b), and there is an intra-sectoral redistribution of functions from more to less routine.

However, robotization in the 2000s led to a reduction of 9.6 million jobs in the European Union (Gregory et al., 2016), in the same time 8.7 million were created. In the paper (Acemoglu, Restrepo, 2017), data on the introduction of industrial robots in the United States in 1990-2007 were used to show that increase in the number of robots (one per 1000 employees) leads to a decrease in the share of employees (0.18-0.4 percentage points), and wages (0.25-0.5) in local labor markets, taking into account the impact of imports from other countries, reducing the proportion of routine work and introducing ICT. At the same time, estimates of unemployment in the United States do not include the ever-increasing number of disabled, part-time and forced retirees (Jordan, 2016).

Research methods and data

Existing assessments of potential employment automation are reduced to three main approaches: analysis of professional groups, share of routine work tasks and expert surveys. The latter were not used for regional estimates because of their high cost and low verifiability. Other methods require strong assumptions about the compliance of the level of automation of professions and routine tasks in the United States and Russia, as the author is not aware of such calculations for Russia, and their implementation was not part of the research tasks. For preliminary assessments, these methods are applicable.

RLMS-HSE data[1] can be used for estimates by the method (Frey, Osborne, 2017). After comparing classifications from work (Frey, Osborne, 2017) and RLMS-HSE from 18 thousand respondents, the probability of automation was determined for 3325 respondents (Fig. 2). Accordingly, the potential of robotization in Russia can be estimated at 26.5%, which is significantly lower than the estimates for other countries (Table 2), but there are doubts about the representativeness of the results obtained in relation to the structure of professions in Russia. Unfortunately, the sample is not representative for regions, and therefore the data is not applicable for the main task.

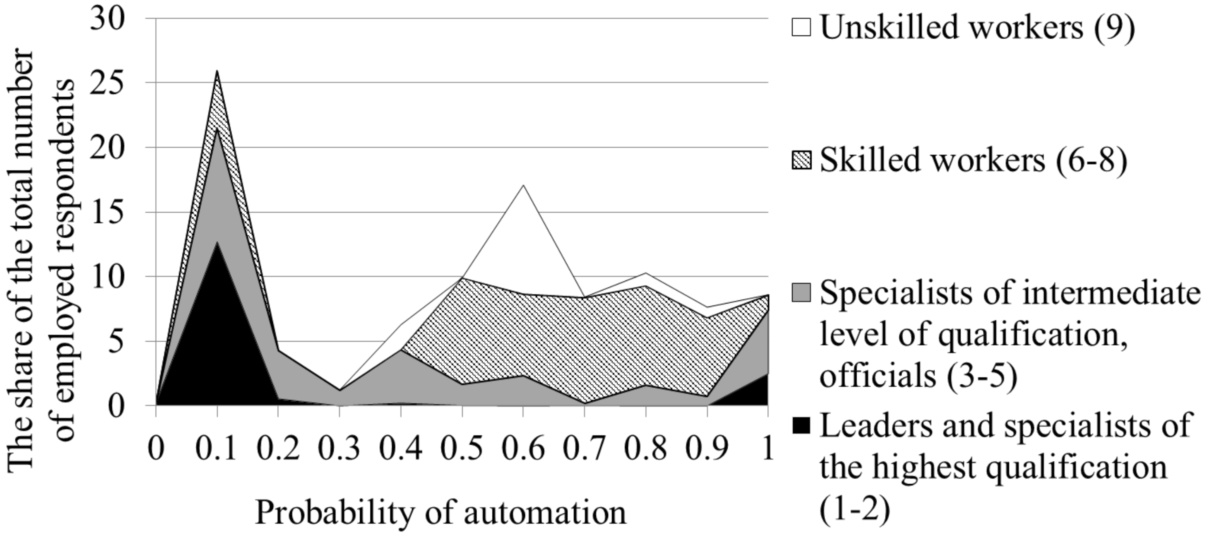

Figure 2 - Distribution of integrated professional groups (in parentheses are their numbers in the classification of RLMS-HSE, that is, ISCO-88) according to the probability of automation

We used the official data of Rosstat (the Russian statistical service) about regions and economic activities. For the basic calculations, the McKinsey Global Institute methodology (Manyika et al., 2017) was applied, which smoothed the shortcomings of the first approach, which does not take into account the variation of occupations according to the routine of tasks.

Table 5 – Assessment of the automation potential for economic activities in Russia

NACE Rew.2	Share of potentially automated workforce, %
Agriculture	58
Mining	51
Manufacturing	60
Utilities	44
Construction	47
Retail trade	53
Wholesale trade	44
Accomodation and food services	73
Transportation and warehousing	45,8

[1] https://www.hse.ru/rlms/spss

Finance and insurance	43
Real estate	40
Information	36
Professionals	35
Professionals	35
Administrative	39
Educational services	27
Health care	36
Other services	44
Arts, entertainment and recreation	41

Source: https://www.fedstat.ru/. Indicator: Average number of employees in all organizations

Automation itself does not lead to an increase in unemployment, but it increases the need to continuously update your knowledge, skills, to be prepared for changes and to maintain creativity in yourself. There is a threat that a part of the population will not be able to adapt to the new conditions, there is a probability of excluding them from economic activity. In fact, it is about the formation of the economic sector, where citizens will not participate in modern processes associated with the creation, development, and diffusion of new ideas, technologies and products. It is proposed to call this sphere 'nescience economy' as opposed to the knowledge economy (Powell, Snellman, 2004). The gap between the exponential growth of automation and the lagging processes of retraining and creating new jobs is possible.

On the second part of our research we tried to estimate the share of nescience economy. Older people, people with lower levels of education and low-paid physical labor are most susceptible to falling into 'nescience economy' (World bank, 2016; Chang, Huynh, 2016; Arntz et al., 2016). In addition, in many Russian regions, a substantial part of the working-age population is employed in the informal sector, some of people live in subsistence farming. It is also important to mention that previously described approach (Manyika et al., 2017) does not take into account an informal sector.

The number of persons (NSE) that can be excluded from the modern economy ('nescience economy') was calculated using the following formulas (the number of the sector in brackets in Figure 3 is given for Russia as a whole in 2015):

$$NSE_{i,t} = AE_{i,t} + AIE_{i,t} + ANE_{i,t} + CUE_{i,t} \quad (4),$$

where i is a region; t is the year; NSE - the number of working age citizens potentially excluded because of automation processes (42.13 million people); AE - the number of formally employed, subject to automation, million people. (I; 24.343); AIE - the number of people employed in the informal sector, subject to automation, million people. (II; 7.433); ANE - the number of not-working citizens (but they do not consider themself unemployed), subject to automation, million people. (III; 6.064); *CUE* - the number of “permanent” unemployed, million people (IV; 4.289).

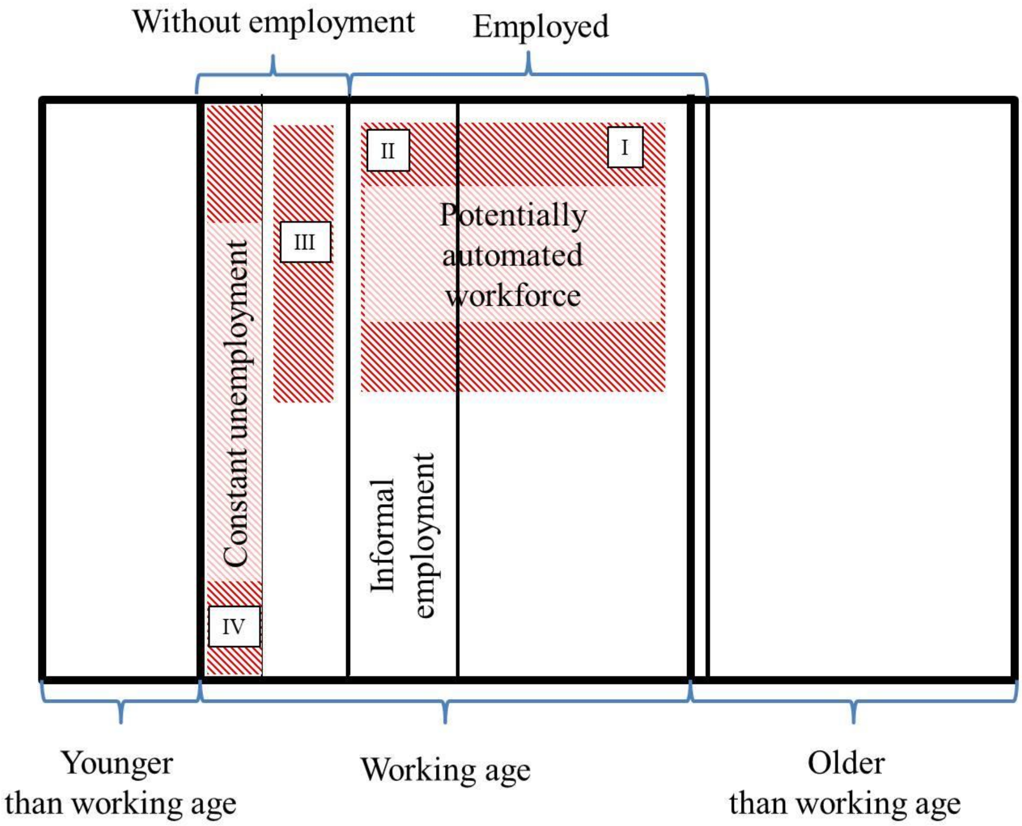

Figure 3 - The structure of population in Russia with potential ‘nescience economy’ (spheres shaded by the background)

At first, we used the share of formally employed (*AUT*) susceptible to automation according to the previously proposed technique [6]

$$AE_{i,t} = (E_{i,t} - (E_{i,t} \times IE_{i,t})) \times AUT_{i,t} \qquad (5),$$

where *E* is the number of employees, million people (68.39 mln persons); *IE* - share of employed in the informal sector, %.

Secondly, based on the sectoral structure of informal employment, the coefficient of its potential automation (*AUT* *) was estimated. Expectedly, its value turned out to be higher than for the formal sector, since the share of trade and other services, where routine labor prevails, is higher. For comparison, the share of automation-prone for the formal sector in Russia in 2015 is 44.78%, for the informal sector it is 53% (52.2% for men, 54% for women; 51.9% for citizens, 54 , 8% - for the villagers).

$$AIE_{i,t} = (E_{i,t} \times IE_{i,t}) \times AUT^{*}{}_{t}, \qquad (6)$$

where *AIE* - the number of people employed in the informal sector, subject to automation, million people.

The number of unemployed citizens who do not consider themselves unemployed (*ANE*) is calculated by excluding from the working population (*WAP*) the employed and "permanent" unemployed (*CUE*) (see explanation below). This category of citizens is very heterogeneous, including students, renters, women housewives, engaged in subsistence farming, etc. Estimates of technological exclusion for them cannot be lower than for informal workers (*AUT* *), since many of them already do not participate in the creation and development of new technologies.

$$ANE_{i,t} = (WAP_{i,t} - E_{i,t} - CUE_{i,t}) \times AUT^{*}{}_{t}\,. \qquad (7)$$

In our calculations, it is methodologically incorrect to use the current number of unemployed, as it is changing, and people may be in the process of retraining. Therefore, the number of "permanent" unemployed (CUE) was calculated on the basis of the minimum (minimum) unemployment rate for each region in 1995-2015 according to the methodology of the International Labor Organization (minUE). It is assumed that minUE will not fall lower in conditions of automation; it can be conditionally considered natural for the region.

$$CUE_{i,t} = \min UE_{i,1995-2015} \times EAP_{i,t}\,, \qquad (8)$$

where EAP - labor force (economically active population), mln people (76,588).

In this case, we are also talking about preliminary estimates, since intersections are possible between the identified groups according to official statistics from Rosstat. For more accurate assessments, it is necessary to conduct a specialized sociological survey, which was not part of the task.

At the last part we proposed an empirical model to assess factors which affect 'nescience economy' share in the Russian regions' workforce. It is important for further policy recommendations for elimination of possible negative effects:

$$dNSE_{i,t} = const + Agglomer_{i,t} + Income_{i,t} + HumCap_{i,t} + EntrInstit_{i,t} + ICT_{i,t} + Control_{i,t} \quad (6),$$

where *dNSE* – share of working age population, which potentially can be excluded from modern economy, %; *const*; *Agglom* – urbanization, %; *Income* – income and retail per capita, rubles; *HumCap – human capital:* share of employees with higher education, %, students per capita, patents per capita; *EntrInstit* – institutions: number of small firms per capita; number of crimes per capita; *ICT* – ICT development: share of firms with web-sites, %; *Control* – control variables.

Results. Potential employment automation

44.78%, or 20.196 million employed in Russia can suffer from automation, which is lower than the original estimate - 50% (Manyika et al., 2017) due to more accurate accounting of the ratio of sub-sectors in the used classifiers. The level is lower or comparable with the majority of developed countries (Table 3). At the same time, only 34% of employees in Russia work in industries that are potentially more than 50% susceptible to automation. A significant part of the population is engaged in less automated sectors: trade, education, services, health care, transport and communications, and public administration (see also Gimpelson, Kapelyushnikov, 2015).

The differences between the regions is more than 10% (Fig. 5): the maximum value is 47.6% in the Leningrad Region; the minimum is 37.1% in the Republic of Tyva, as in the case with countries, that is, in fact, do not exceed the inter-sectoral differences (Table 4).

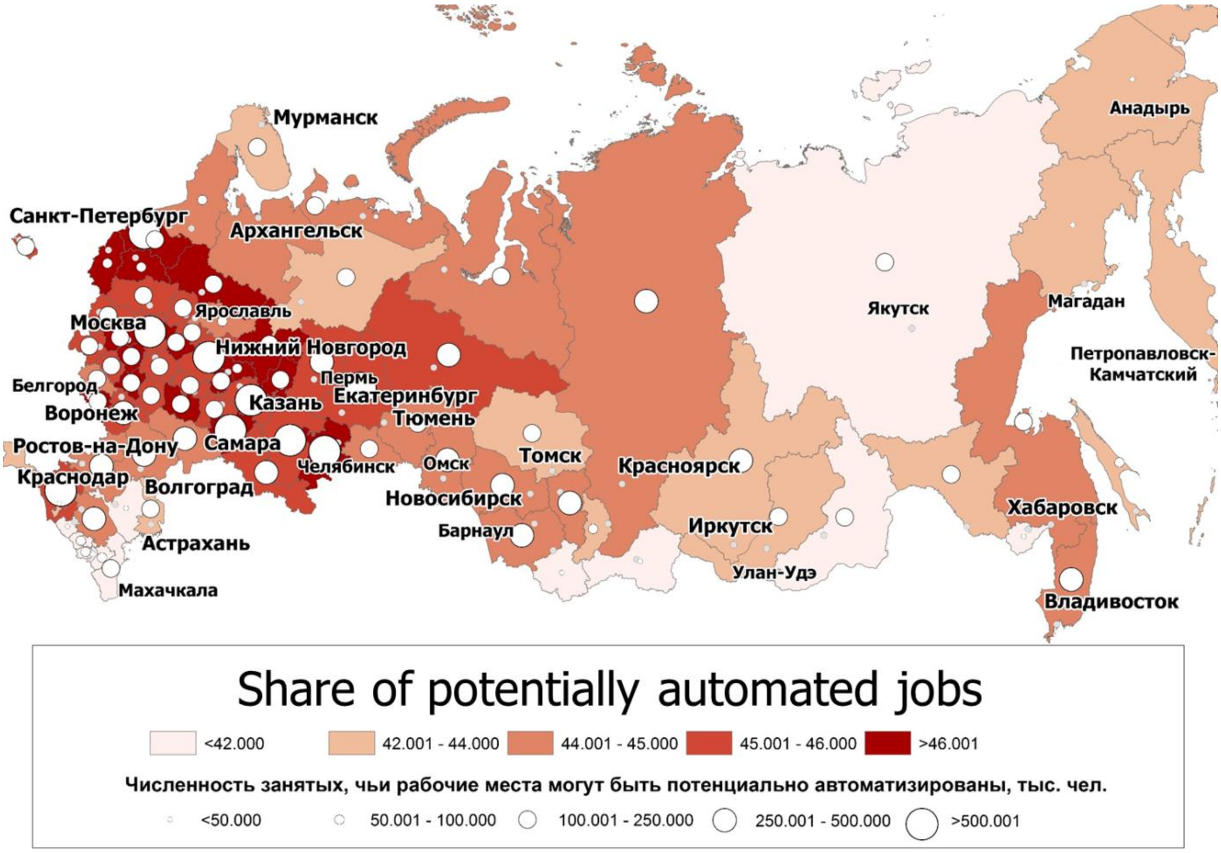

Figure 5 – Share of potentially automated workforce in the Russian regions in 2015

About 30% of the total number of potential technological unemployed is concentrated in six large regions: Moscow (2.01 million people; 43.1%); St. Petersburg (0.91; 44.2); Moscow region (0.94; 45.5), Sverdlovsk (0.7; 46) region; Krasnodar Territory (0.64; 45.1) and the Republic of Tatarstan (0.61; 45.9). An increase in their numbers from 2009 to 2015 was observed in Ingushetia, Chechnya (increase in government employment), St. Petersburg, Novosibirsk, Kaluga, Penza, Tyumen and Belgorod regions (in the manufacturing industry), Nenets and Yamalo-Nenets autonomous districts (in the extractive industries). Table 6 presents average indicators characterizing different groups of regions (Fig. 5).

Table 6 - Average values of characteristics by groups of regions

Group of regions by the share of potentially automated workforce,%	>46	45-46	44-45	42-44	<42

GRP per capita in 2014 prices, taking into account the inter-regional price index, thousand rubles	281	348	628	556	205
The share of manufacturing in GRP,%	27,5	19,8	17,5	9,4	5,4
Average monthly wage (in 2015 prices), rub.	25,7	27,5	33,5	44,4	26,1
The share of employed in the economically active population (EAN),%	89,2	89,9	96,1	91,1	77,9
Percentage of employed citizens with higher education in the population,% (Zemtsov, Barinova, 2016)	9,5	10,5	11,7	12,7	5,9
Unemployment rate on average per year,%	5,08	5,13	6,19	6,34	13,1
Share of employed in state and municipal organizations,	37,7	40	43,3	50	69,9
Share of people employed in the informal sector,%	21,7	21,5	20,4	19,2	38,4
The number of PCT applications for inventions per capita	3,97	4,01	4,56	6,07	2,07
Share of organizations having a website,%	43,9	43	40,7	43,2	34,7
The number of small enterprises per capita	25,5	25,1	29,5	24,5	14,5
Investment Risk Index (RAEX)[2]	0,96	0,96	1,05	1,19	1,55

The high share of the manufacturing industry in the GRP is a factor of higher vulnerability (> 46%), since the use of industrial robots and unmanned technologies is most common in machine building. Regions with a high share of manufacturing, have lower wages and poorer education, which also increases their vulnerability. But the regions with low level of investment risks and medium entrepreneurial activity can smooth out the effects of robotization. The real unemployment rate is inversely proportional to the level of potential automation, which can be explained by political measures to control unemployment (Zubarevich, 2010). In the group with low rates (42-44%), there are regions with a high level of development (Moscow), higher wages and higher shares of employed citizens with higher education, with maximum patent activity. The lowest indicators of potential robotization (<42%) are observed in the least developed regions (the minimum ratio of gross regional product per capita) with the highest share of the public sector in the economy, high unemployment, the lowest employment and high share of informal employment. These are the regions with the least ICT deployment and innovation potential. Thus, the hypothesis of high heterogeneity of potential automation is only partially confirmed, since its variations are lower than the industry average values.

Results. Potential technological exclusion

The diffusion of new technologies in Russia may lag behind in time from developed countries (except Moscow and St. Petersburg), but then it spreads exponentially (Baburin, Zemtsov, 2015). Most regions may not be ready for the increased burden on the social sphere if many people will be excluded from economic activity. In other words, social threats do not come from automation processes per se, although as shown in (Acemoglu, Restrepo, 2017), they are

[2] URL: http://raexpert.ru/ratings/regions/2016/

already being realized, but from the impossibility to adapt and the low mobility of a significant part of the population.

If we use the end-to-end assessment methodology for different years, then, in general, the number of potentially excluded citizens in Russia decreased from 2009 to 2015. (Fig. 6) from 42.3 to 40.1 million people. (by 5.2%), but their share decreased not so significantly: from 50% to 49.3%. There is a slow adaptation of employment, an increase in the share of less susceptible to automation of activities

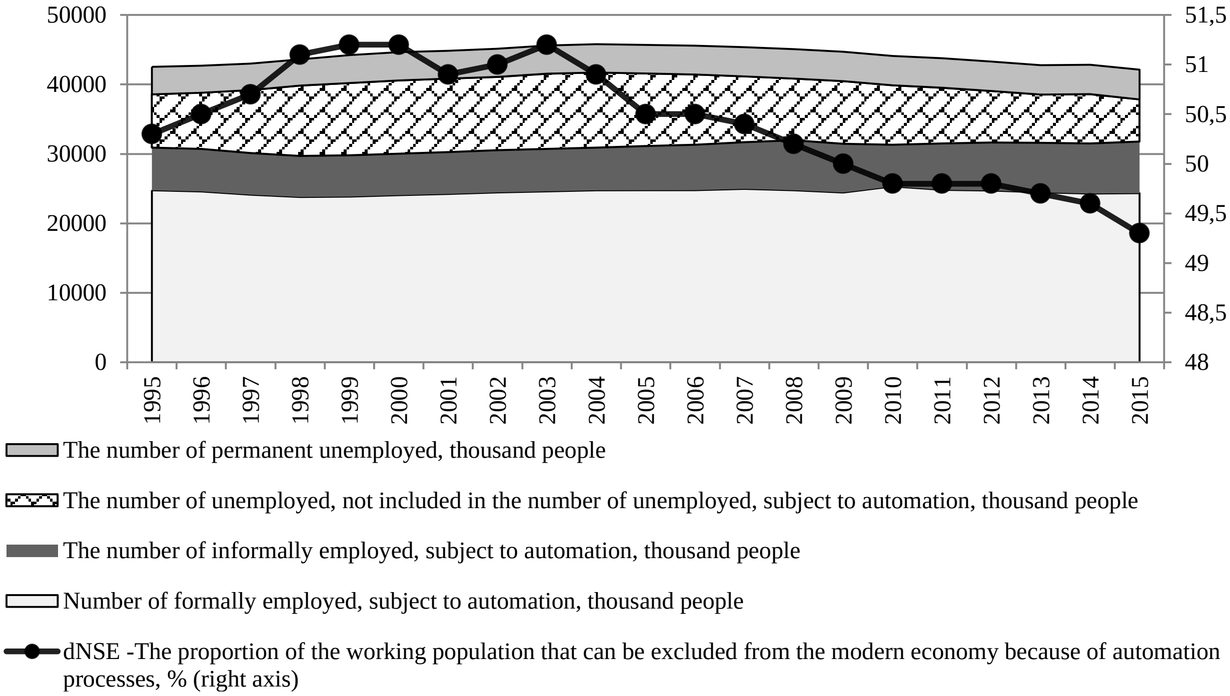

Figure 6 – Dynamics of potentially excluded citizens (‘nescience economy’) in the Russian Federation

The maximum share of potentially excluded citizens (‘nescience economy’) is in the southern republics: Ingushetia (30.4%), Chechnya (23.4), Dagestan (20.9), Kabardino-Balkaria (18.9), Karachay-Cherkessia (18.5), Adygea (18.2), Tyva (18.1), characterized by a low level of general socio-economic development, a high proportion of the informal sector of the economy and rural residents (*Fig. 7*).

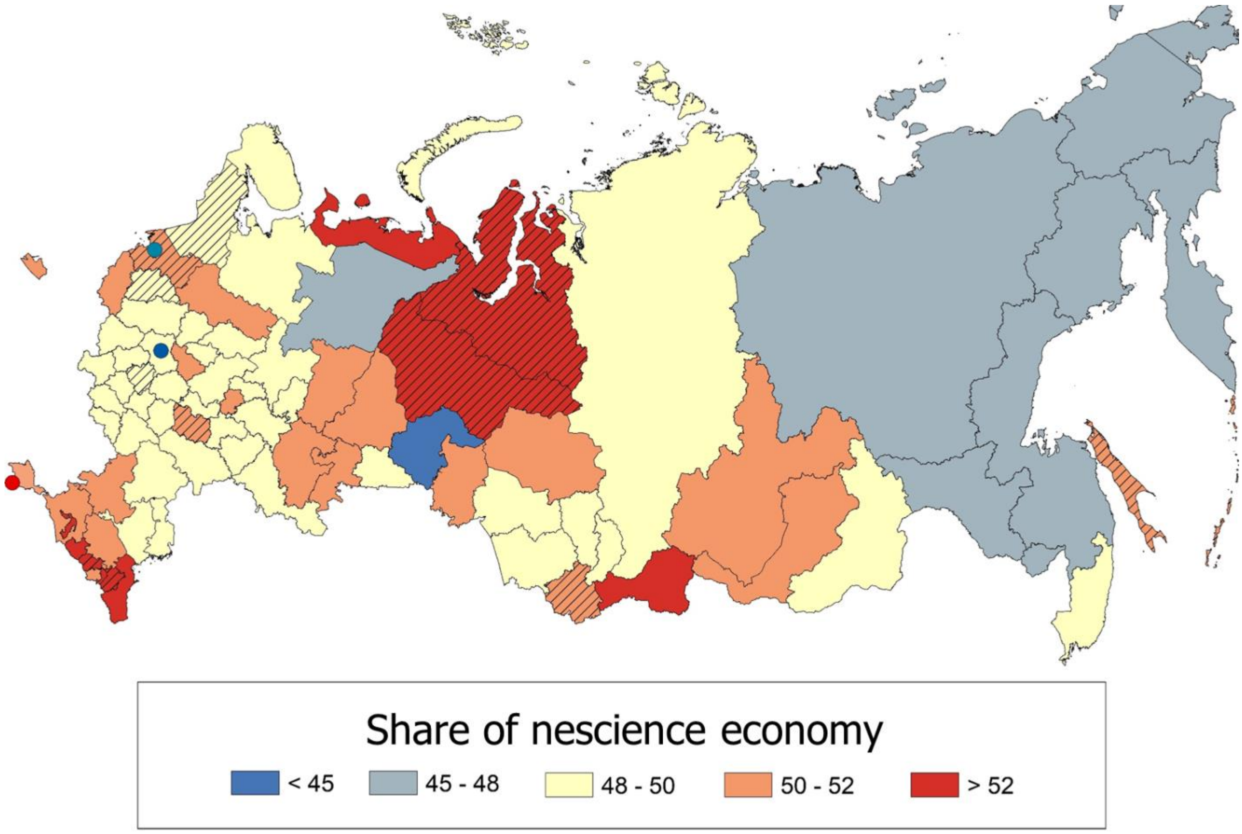

Figure 7 - The working age population who may be excluded from modern economic activities in the Russian regions in 2015

At the last stage, we identified factors (Table 7) that affect the formation of 'nescience economy', and, accordingly, mechanisms for reducing the negative impact of technological exclusion.

Table 7 - Factors affecting the level of 'nescience economy' in the Russian regions

Fixed effects panel model. The dependent variable is the share of potentially excluded from the economy persons ('nescience economy'). 553 observations. 2009-2015 All variables are logarithmic. In brackets - robust standard errors.			
The share of employed citizens with higher education in the population	-0,54 (0,04)***	-0,29 (0,05)***	-0,29 (0,04)***
Gini index	0,9 (0,12)***	0,87 (0,18)***	0,84 (0,11)***
Investment risks index (RAEX)	0,33 (0,07)***	0,16 (0,06)**	0,18 (0,05)***
The number of small firms per capita	-0,19 (0,02)***		
Market potential[3]		-0,49 (0,05)***	-0,52 (0,06)***
The number of mobile subscribers per capita		-0,12 (0,05)**	-0,13 (0,04)***
The share of enterprises with a WEB-site		-0,03 (0,02)*	-0,04 (0,02)**
Constant	5,01 (0,13)***	6,3 (0,47)***	5,88 (0,31)***
Control variable (GRP per capita, thousand rubles)			0,10 (0,04)**
LSDV R2	0,97	0,98	0,98
Within R2	0,64	0,76	0,76

[3] Zemtsov S. P., Baburin V. L. How to assess advantages of economic-geographical position for Russian regions? //R-Economy. – 2018. – T. 2. – №. 3. – C. 385-401.

Schwartz Criterion	-1090	-1288	-1289

It was revealed that an increase in the share of employed citizens with higher education by 1% will lead to a reduction in the share of citizens potentially excluded from economic activity by 0.27-0.54%, and an increase in the share of entrepreneurs by 0.19%, respectively. Reducing social inequality (Gini index) by 1% will lead to a reduction in the level of ‘nescience economy’ by 0.7-0.9%. Reducing investment risks by 1% will lead to a reduction in potential exclusion by 0.15-0.33%. The development of ICT in the regions also contributes to a decrease in ‘nescience economy’ by 0.11-0.17%. Access to large markets in other regions and countries is also important, contributing to employment in the business sector.

Conclusion and recommendations

The analysis of theoretical and empirical works does not give a definite answer to the question about the level of new technologies threats to the social sphere. In the long run, new technologies created more jobs than they destroyed. Despite the significant potential of automation (up to 50% of jobs in the world), the speed of processes is slowed down due to economic (high cost of robots), political (fear of social consequences), legal (ban on the introduction of some technologies) and other restrictions. Therefore, there is a adaptation of the labor market (Smith, Anderson, 2014): new industries, production of new products and services, transition from routine to more complex, responsible and creative tasks. However, work (Acemoglu, Restrepo, 2017) shown the presence of a negative relationship between the introduction of industrial robots in the USA and employment for 1990–2007.

Based on the analysis of empirical works, we can distinguish five main human functions that modern robots are unable (or not yet trained) to perform:

• creativity - research and creation of a new, entrepreneurship;

• STEM (science, technology, engineering, mathematics) - development of robots, software and their maintenance;

• social interaction - personal contact, ability to feel, empathize (social workers, teachers, etc.);

• work in changing conditions (adaptability) - the ability to think ‘outside the box’ and quickly adapt (examples: medics, emergency workers);

• responsibility and management - the ability to bear financial, legal or other responsibility (profession: top management and close in essence);

• mentoring - the transfer of implicit knowledge and the ability to convince (examples: academic leaders, clergy, sports trainers, etc.).

It is necessary to stimulate the development of these areas and competencies, reflect this in strategic documents, include them in educational programs, etc.

Using comparable methods of assessing the level of potential employment automation, it is shown that in Russia this level is lower than in most countries of the world: according to the (Frey, Osborne, 2017) methodology it is about 27.6%, and according to a revised estimate of the McKinsey Global Institute it is about 44 % This is due to the relatively high share of industries in which social and creative intelligence (education, government, finance) are important, with high ICT penetration and the development of relevant activities. In Russia, especially in underdeveloped regions, the share of informal employment is high, for which there are no estimates of potential automation.

High spatial differentiation in the rate of new technologies diffusion (Baburin, Zemtsov, 2013) may in the future lead to the formation of old industrial regions with a long-term high unemployment rate. The share of citizens who could potentially be excluded from economic activity is quite high in the regions and varies greatly: from 14% in the Yamalo-Nenets Autonomous District to 42% in the Republic of Adygea. At the same time, the main problem is that the sources of 'nescience' economic growth in the future are unclear. We are talking about the formation of a group of the population, using pension and social benefits as a source of income, as well as leading a subsistence economy. At the same time, according to our calculations, the share of 'nescience economy' is not related to the share of employed vulnerable to robotization. The absence of such a link may indicate that increased competition in the global economy as a result of increased labor productivity (through automation) may lead to increased unemployment and technological exclusion, regardless of the level and scale of robotization in Russia. In the republics of the South and North Caucasus federal districts, there will be double pressure on the regional budget: there are no conditions for productivity growth and, consequently, an increase in own revenues, but at the same time, the share of excluded people is potentially high, which greatly increases social risks in the future.

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