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Veröffentlichungsversion / Published Version

Zeitschriftenartikel / journal article

Empfohlene Zitierung / Suggested Citation:

Kapeliushnikov, R. (2019). The phantom of technological unemployment. *Russian Journal of Economics*, 5(1), 88-116.
<https://doi.org/10.32609/r.j.ruje.5.35507>

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The phantom of technological unemployment

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Abstract

Nowadays there are many gloomy prophecies provided by both technologists and economists about the detrimental effects of the so-called Fourth Industrial Revolution on aggregate employment and its composition. These prophecies imply that in the near future we will face Robocalypse—a massive replacement of people by machines alongside an explosion in joblessness. This paper provides theoretical, empirical and historical evidence that the phenomenon of technological unemployment is a phantom. The most general results can be summarized as follows: in the long run, reduction in labor demand under the impact of new technologies is merely a theoretical possibility that has never before been realized in practice; at the level of individual firms, there is a strong positive relationship between innovations and employment growth; at the sectoral level, technological changes cause a multidirectional employment response, since different industries are at different stages of the life cycle; at the macro level, technological progress acts as a positive or neutral, but not a negative factor; a surge in technological unemployment, even in the short-term, seems a remote prospect since in coming decades the pace of technological change is unlikely to be fast enough by historical standards; the impact of new technologies on labor supply may be a more serious problem than their impact on labor demand; technological changes seem to have a much greater effect on the composition of employment than on its level.

Keywords: technological change, labor demand, compensation theory, technological unemployment, computerization, robotics.

JEL classification: E24, J20, J23, J24, O30.

“An unlimited number of jobs are available in a world of scarcity.”
(Alchian and Allen, 1972, p. 827)

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1. Introduction

In recent years, an avalanche of apocalyptic predictions of devastation to employment prospects has struck the public, triggered inevitably by the so-called Fourth Industrial Revolution, connected with the latest technological advances—robotization, digitalization and the creation of artificial intelligence, etc. The bearers of catastrophic forecasts on this issue are politicians, journalists, sociologists, futurologists, engineers, and many others. Although the majority of economists traditionally retain a certain immunity to such prophecies, nevertheless quite a few alarmists currently figure among them. We are told that as a result of the implementation of new technologies, a huge mass of people will remain out of work—machines will finally have triumphed in the race between machines and people (Brynjolfsson and McAfee, 2014); that the world is entering an era of unprecedented high technological unemployment (Frey and Osborne, 2013); that the traditional welfare state is unable to help its victims and therefore it is necessary to impose a tax on robots (proposal of Bill Gates), as well as immediately begin to implement the idea of basic unconditional income (Ford, 2015); that in the coming decades about half of all existing occupations will die out (Frey and Osborne, 2013); that the pace of technological change will be so rapid that workers will simply not physically have time to retrain for new skills and competencies, thus continually expanding the army of the unemployed (Ford, 2015); that it is necessary to be ready for the complete disappearance of a multitude of not only low-skilled, or medium-skilled, but also high-skilled jobs, since new technologies will increasingly take on the performance of intellectual functions that still remain the exclusive domain of human activities (Brynjolfsson and McAfee, 2014); that the main existential problem that mankind will soon face is what to do with ourselves in conditions of enforced idleness when the very concept of “work” is a thing of the past and smart machines will do everything for us (Summers, 2013).

The future state of labor market is depicted in the darkest colors. A well-known American engineer from Carnegie Mellon University Vivek Wadhwa warns: “The reality is that we are facing a jobless future: one in which most of the work done by humans will be done by machines. Robots will drive our cars, manufacture our goods, and do our chores, but there won't be much work for human beings.” Bill Gates agrees with him: new technologies “will reduce demand for jobs, particularly at the lower end of skill set”. Futurist Martin Ford, who published a book in 2015 under the revealing title “Rise of the robots: Technology and the threat of a jobless future” (Ford, 2015), says that in the past, “machines have always been tools that have been used by people”, but now they are “becoming a replacement or a substitute for more and more workers.” In connection with this prospect, former US President Barack Obama expressed serious concern that today a significant part of American business “learned to become much more efficient with a lot fewer workers” (all cited from Bailey, 2017). Well-known Israeli historian Yuval Noah Harari predicts that by 2050, the creation of artificial intelligence will lead to the emergence of a massive new non-working class—“useless class”, which will not only be unemployed, but which will not be able to be employed (Harari, 2017). In general, in the labor market, according to the witty expression of Autor and Salomons (2017), humankind will soon be waiting for “Robocalypse”.

The picture of the world emerging from such statements appears as a bizarre mixture of excessive optimism and excessive pessimism: over-optimism in terms of the prospects for modern technological change, and over-pessimism in terms of the ability of the economy (in particular, the labor market) to adjust to its upcoming breakthrough achievements.

Immediately, we note one oddity. Conversations about the Fourth Industrial Revolution began when its fruits—at least, so far—were not visible in general. The situation with the First (steam engines), the Second (electricity and internal combustion engines) and the Third (computers) industrial revolutions was different: first, they sharply accelerated the growth of labor productivity and radically transformed living conditions and only some time later, retrospectively, were they recognized as a “revolution”. Now, we are not seeing a sharp acceleration in the dynamics of labor productivity (rather, the situation is exactly the opposite) or signs of a cardinal breakdown in people’s usual way of life. In essence, the subject matter under discussion is not so much the real, but rather the expected state of affairs, and no one can be sure whether it will really occur. In this sense, it is characteristic that many researchers regard the technological achievements taking place today not as manifestations of the Fourth Industrial Revolution, which has already come, but only as the “tail” end of the Third Industrial Revolution—with its distant, and weakened, consequences still manifesting themselves (Gordon, 2016).

As for the idea of “technological unemployment” itself, it is far from new and has a near two-hundred year history, although this term itself was introduced into the scientific lexicon by J. M. Keynes not long ago—only in the 1930s.¹ There have been several waves of technological alarmism, during which fears associated with the crowding out of people by machines acquired the character of severe phobias. The first, dating back to the beginning of the 19th century, related to the experience of industrialization in Great Britain; the second, dating back to the 1960s, was provoked by fears of automation (the main propagandist of the idea of technological unemployment was Wassily Leontief²); the third, which arose at the turn of the 1980–1990s, was a reflection of the computer revolution (Rifkin, 1995). In all these episodes, predictions of a future characterized by mass joblessness collapsed over and over again and soon the threat of technological unemployment was safely forgotten. Therefore, it is unsurprising that among the experts in economic history and the history of economic thought, this idea itself has long enjoyed a deservedly bad reputation. However, now, we are told, everything will be different because the nature of modern technological change is fundamentally different from before, so this time the surge in technological unemployment cannot be avoided.

When analyzing the possible impact of technological progress on employment, two aspects of the problem should be clearly distinguished—*long-term* and *short-term*. In the first case, we are talking about a *permanent* reduction in the demand for labor under the influence of new technologies, in the second—a *temporary* increase in unemployment due to the increased discrepancy between the struc-

¹ “We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come—namely, *technological unemployment*” (Keynes, 1931).

² Back in the early 1950s he wrote: “Labor will become less and less important... More and more workers will be replaced by machines. I do not see that the new industries can employ everybody who wants a job.” (Leontief, 1952; cited from: <https://medium.com/swlh/will-artificial-intelligence-take-your-job-e708b40caf19>).

ture of labor demand and the structure of labor supply (meaning that when the transition period associated with adaptation to new conditions is over, unemployment will return to the “normal” level). The long-term and short-term effects of technological change need not be the same. In the following discussion, we will consider both.

2. Theoretical aspects

Over the long years of studying the problem of technological unemployment by several generations of economists, economics has accumulated many theoretical arguments, empirical facts and historical evidence to assess whether the predictions of today’s techno-alarmists are justified and whether in the near future we should expect complete, or at least partial, but nevertheless large-scale, crowding out of employees.

According to the results of the analysis, which stretched for almost two centuries, in order to denote a logical error, which many easily fall into when discussing this problem, economic theory even developed a special term—the lump of labor fallacy (misconception implying a fixed volume of labor). We are talking about conclusions by type: “if labor productivity as a result of the introduction of new technologies increased by X percent, then the demand for labor will also decrease by X percent.” This syllogism is false, since it is based on the assumption that the volume of output is fixed and does not take into account the actions of various macroeconomic feedback mechanisms. In fact, while increasing labor productivity, output does not remain unchanged: its growth entails an increase in incomes of either entrepreneurs who have introduced innovations, or workers who begin to use more advanced equipment, or consumers who receive access to cheaper goods, and most often, of all at a time. Increased incomes are translating into higher consumer and investment demand, and it cannot be satisfied without attracting additional workers. As a consequence, the relationship between the dynamics of labor productivity and the dynamics of demand for labor appears to be extremely complex and not unidirectional. Due to indirect macroeconomic effects, it may well turn out to be not negative, but, rather, positive. In other words, both in theory and in practice, a situation is quite probable when the introduction of new technologies will not *reduce*, but *increase* the number of jobs in the economy. However, from the statements of current techno-alarmists, it is clearly seen that most of them (unless they are professional economists) in principle are unaware of the existence of such indirect links and still continue to use “frontal” arguments, the failure of which has been convincingly revealed by economic theory almost two hundred years ago at the beginning of the 19th century.

Indeed, the main theoretical ideas concerning technological unemployment as a long-term phenomenon were also expressed by classical economists (Vivarelli, 2007). Subsequent generations of economists were more likely to clarify, refine and formalize the ideas put forward by them, rather than deepening or revising them. For the most part, the conclusions drawn within the framework of the classical school remain valid.

David Ricardo started the discussion of this issue among classical economists when he included a new chapter “On Machinery” (Ricardo, 2001) in the third edition of his “Principles of political economy”. In it, Ricardo abandoned his previous position, which coincided with the position of Adam Smith, that ultimately

the introduction of machines is always beneficial for the working classes. Now he argued that replacing people with machines can be extremely harmful and that the views of ordinary workers on this issue are not based on prejudice, as one might think, but correspond to the general principles of economics.³

Ricardo's conclusion that the introduction of machines would result in a reduction in the demand for labor in the long term caused a detailed response from other classical economists—J. S. Mill, J.-B. Say, J. McCulloch, N. Senior.⁴ In the course of this discussion, a number of macroeconomic mechanisms were identified that can neutralize the initial labor-saving effect of new technologies. In “Capital”, Marx (1960, ch. 13) ironically dubbed these anti-Ricardian arguments “compensation theory” and under this name they entered the history of economic thought.

The first, most fundamental, compensation mechanism is related to the fact that under perfect competition, the growth of labor productivity will lead to a proportional reduction in prices for goods, which in turn will stimulate additional demand for them (it is believed that the first to pay attention to this compensation channel was a contemporary of Smith J. Stewart).⁵ Moreover, consumers can begin to increase demand both directly (for goods produced in the sector in which technological innovations were introduced) and indirectly (for goods produced in other sectors). To meet this additional demand, firms will have to increase output, for which they will need more labor. And if it turns out that the price elasticity of demand for goods produced in the sector that started technological re-equipment is quite high, then employment in it will not only decrease, but even increase—and this is without taking into account the effect of reduced prices on demand for goods produced in other sectors.⁶

The second—“investment”—mechanism, is connected to the fact that productivity growth means an increase in the profitability and competitiveness of innovation firms. In response, they will begin to increase investment, which will automatically entail the creation of new additional jobs. The first to describe the operation of this compensation mechanism was Ricardo himself; later, its importance was emphasized by A. Marshall, J. Hicks and many other authors.

The third mechanism was identified by Wicksell (1961). The point is that the initial labor-saving effect of new technologies can be compensated within the framework of the labor market itself: increased unemployment will place downward pressure on wages, and a reduced price of labor will stimulate an

³ At the same time, Ricardo made the reservation that a reduction in employment under the influence of new technologies can take place only when their introduction is accompanied by a *decrease in national income* (Samuelson, 1989). But the situation whereby technological change will cause a fall in GDP is so rare that it can be considered almost unbelievable. From this point of view, the Ricardian approach appears rather as a theoretical curiosity than as an attempt to comprehend economic reality.

⁴ In the “History of Economic Analysis”, Schumpeter (2006, p. 653) commented on Ricardo's position: “...he never clearly realized that the *essential* fact about capitalist ‘machinery’ is that it does what, quantitatively and qualitatively, could not be done at all without it or, to put it differently, that it ‘replaces’ workmen who have never been born.”

⁵ Under the conditions of imperfect competition, the compensating effect will be achieved not so much by lowering prices for consumers, but rather by increasing the incomes of entrepreneurs and workers (see below).

⁶ T. Malthus' and S. Sismondi's idea (see Vivarelli, 2007) that the initial fall in employment under the impact of new technologies will be accompanied not by growth, but by a reduction in aggregate demand (since some workers will lose income) can hardly recognize an effective counter-argument, since the effect they have noted is transient and can cause an increase in unemployment only in the short-run.

increase in demand for it. A reverse rollback from more labor-saving to more labor-intensive technologies will begin, with the result that losses in employment will not be so significant. Moreover, the low wages caused by oversupply of labor will weaken incentives not only for using, but also for developing, new labor-saving technologies.

The fourth mechanism, to a certain extent opposite to the previous one, is based on the assumption of wage growth, when, as a result of technological innovations, more advanced equipment is at the disposal of workers. Indeed, replacing people with machines means increasing the capital-labor ratio, and this, according to the neoclassical growth theory, should increase marginal labor productivity. Correspondingly, the wages of employees who have retained employment should also increase, and since their increased incomes will be translated into additional demand for goods and services, additional jobs will be created to satisfy it.

All the market compensation mechanisms discussed above describe the possible consequences of process innovations, that is, changes in production methods. But classical economists have not ignored the possible consequences of product innovation, connected with the introduction of new types of goods and services to the market (although, of course, no such terminology existed at that time). They believed that such innovations, by definition, are labor-intensive and, accordingly, should be accompanied by an increase rather than a reduction in the total number of jobs, which even Marx (1960) did not deny. The “friendly” nature of product innovations (such as the emergence of cars or computers) is emphasized by all modern authors.⁷ However, the differences between the two types of innovations should not be exaggerated. So, a new, more productive equipment is a product innovation for firms that produce it, but a process innovation for firms that use it.

As we see, in the way as economic theory portrays it, the relationship between technological change and employment appears to be extremely complex and ambiguous. The combined effect of various market mechanisms can compensate for the initial labor-saving effect of new technologies, either partially or completely, or even overcompensate for it, so that compared with the initial situation, the total number of jobs in the economy will not only decrease, but increase. Based on purely theoretical considerations, one cannot a priori say which of these scenarios will be implemented in a particular case: in fact, this is an empirical question. The net (“pure”) effect of technological changes in terms of their impact on employment dynamics will depend on the ratio between product and process innovations, as well as on the balance between various compensation mechanisms. But even in the conditions of only partial compensation, it is safe to say that, taking into account the various indirect effects, the reduction in employment will in any case turn out to be much less than is assumed by naive arguments like “if labor productivity has increased by X percent, then, the demand for labor must fall by the same X percent”.

If we turn from theory to the facts of economic history for various countries, it becomes obvious from them that periods of accelerated growth in labor produc-

⁷ However, the increase in employment generated by product innovations in technologically advanced industries may be offset by the loss of jobs in the “traditional” industries, whose products may start to fade due to the appearance of new types of goods on the market.

tivity almost always turned out to be simultaneous with sharply increased demand for labor. (As an illustration, we refer to the recent experience of the Russian economy: in 2000s, high growth rates of labor productivity were accompanied by a significant increase in employment.) As noted by Mokyr et al. (2015), the possibility of permanent reduction in the total number of jobs under the influence of new technologies never became a reality. Given this, we at least should not take on faith the disastrous predictions of the current techno-alarmists.

3. Empirical evidence

A huge amount of empirical research is devoted to the impact of innovations on employment. Such an analysis can be conducted at several levels—micro (individual firms), meso (sectors or regions) and macro (the whole economies). For many reasons, analysis at different levels can produce divergent results.

One of the key problems arising in this context is measurement. How can we quantify the pace of technological change? In the literature, a variety of indicators are used as a proxy for measuring the pace of technological change—expenditures on research and development, investments in new equipment, number of patents, activity in the use of ICT and many others; recent work is increasingly using such a new important indicator as the level of robotization. Obviously, when using different metrics, the results of the analysis will not necessarily coincide.

What does the available empirical evidence say?

Almost all studies at micro-level point to the strong positive effect of technological change on employment.⁸ In the paper by Blanchflower and Burgess (1998) it was shown that in the late 1980s the introduction of new technologies ensured an annual increase in employment for innovation firms by 1.5% in Australia and by 2.5% in the UK. A similar result was obtained on the data for Great Britain in 1976–1982 (Van Reenen, 1997). A positive relationship between the introduction of new technologies and employment dynamics for British firms was also observed for the later period 1998–2011 (Cortés and Salvatori, 2015). A study of a large sample of American manufacturing firms that spanned a forty-year period from 1963 to 2002 demonstrated that the higher their patent activity, the greater the rate of job creation (Coad and Rao, 2011). A similar conclusion that innovators had higher employment growth than non-innovators was obtained on panel data for the manufacturing industry of West Germany for 1980–1992 (Smolny, 2002). In France (1986–1990), innovative firms also showed much more activity in creating jobs than non-innovative ones (Greenan and Guellec, 2000). Surprisingly enough, this work also implies that process innovations have a stronger positive effect on employment than product ones. The same counter-intuitive result was obtained for manufacturing companies in Germany (1982–2002): both process and product innovations stimulated the creation of new jobs, but the effect of the former exceeded the effect of the latter (Lachenmaier and Rottmann, 2011). A positive but not over-strong link between intra-firm innovations and employment was also found for Italy (1992–1997) (Piva and Vivarelli, 2005). According

⁸ If more efficient firms increase jobs, while less efficient ones lose them, then this leads to an increase in the overall level of labor productivity in the economy. Such a restructuring of employment is one of the most important sources of economic growth.

to the results of another study, also on Italy, about half of the increase in employment in the manufacturing industry of this country during the period 1995–2003 was driven by product innovations, while the effect of process innovations was neutral (Hall et al., 2008). Similarly, in the economy of Taiwan (1999–2003), product innovations were accompanied by an increase in the number of people employed in all branches of manufacturing industry, whereas process innovations had similar effects only in high-tech ones (Yang and Lin, 2008). Analysis of industrial firms in Israel for 1982–1993 also indicated that while high-tech firms increased employment, others lost jobs (Regev, 1998). In one of the newest studies on Spain (2002–2009), it was demonstrated that more innovative, smaller and younger firms increase employment more quickly, and their advance relative to non-innovative firms is persistent over time (Ciriaci et al., 2016). However, in another work, also on the Spanish manufacturing industry (2002–2013), no significant relationship between innovations and employment was identified (Pellegrino et al., 2017). The zero effect of R&D expenditure in terms of the intensity of job creation was found for manufacturing firms in Norway for the period 1982–1992 (Klette, Førre, 1998).

A number of micro-level studies have been based on cross-country data. The study on four European countries (Great Britain, Germany, Spain and France, 1998–2000) showed that in the manufacturing industry of these countries product innovations were associated with a significant increase in employment at the firm level, while process innovations were associated with weak decline in it. By contrast, in services the former provided only a small increase in employment, but the latter did not affect it either positively or negatively (Harrison et al., 2014). Another cross-country study (1998–2008) showed that R&D expenditures are positively and significantly related to employment dynamics in the service industries and high-tech manufacturing industries, but negatively in traditional manufacturing industries (Bogliacino et al., 2012). At the same time, analysis using the European survey of the manufacturing industry for 2009 for seven European countries did not reveal any significant correlation between the activity of firms in the use of robots and the dynamics of employment (Jäger et al., 2015).

In general, research at the micro level allows us to conclude that there is a strong positive effect of technological change on employment, especially in the service industries and high-tech manufacturing industries; at the same time, robotization may not be as positive for the dynamics of employment as many other types of modern technological innovations.

However, analysis at the level of individual firms has serious limitations. First, it rarely turns out to be able to effectively solve the problem of causality: it is possible that innovative firms do create jobs more actively, but it is also possible that more successful and therefore more rapidly growing firms will be more likely to introduce innovations. Secondly, such an analysis can significantly overestimate the positive effect of technological changes in terms of employment dynamics if innovative firms manage to increase their market share at the expense of non-innovative firms, which, therefore, have to curtail employment. Thirdly, it is not able to take into account the indirect effects of compensatory market mechanisms operating at the level of entire sectors or the entire economy.

Partially, these limitations are overcome in the analysis at the sectoral level. With its use, the variance in estimates is much larger due to the idiosyncratic situ-

ation in different industries. Some studies using meso-data conclude that modern technologies exhibit “hostility” toward employment.

Thus, using the example of 21 manufacturing industries in five European countries (1989–1993), it was demonstrated that job losses were higher in sectors characterized by higher innovation activity (Pianta, 2000). This result was confirmed at a later date (1994–1999) for 10 manufacturing industries in eight European countries (Antonucci and Pianta, 2002). In a study on Spain, it was found that the period from the mid-1980s to the end of the 1990s was characterized by a sharp decline in the share of employment in high-tech sectors (Sacristán Díaz and Quirós Tomás, 2002). A similar trend was recorded for individual manufacturing industries in the work cited above for Norway (Klette and Førre, 1998). For Italian manufacturing industries (Vivarelli et al., 1996), a negative relationship was found between productivity growth rates and employment growth rates (although product innovations had a positive effect, they were neutralized by a negative effect of process innovations). According to Clark (1987), in the manufacturing sectors of the UK, the “creative” effect of new technologies appeared until about the mid-1960s, after which it became “destructive”.

At the same time, in the already mentioned study on France, which covered 18 branches of the manufacturing industry of this country, it was shown that in more innovative industries jobs were created at a higher rate than in less innovative ones. Moreover, unlike the results obtained in the analysis at the firm level, the effect of product innovations was stronger than that of process innovations (Greenan and Guellec, 2000). The research on the service sector in Italy (1993–1995) concluded that innovation had a positive effect on employment dynamics in innovative and intellectual-intensive fields of this sector, but a negative one in its “traditional” parts, such as finance, trade and transport (Evangelista and Savona, 2002). For Germany (1999–2005) it was found that the increase in the number of patents is positively associated with the subsequent growth in employment in high-tech manufacturing industries (such as electrical equipment, electronic, optical, and medical equipment) (Buerger et al., 2012). Considering together both manufacturing and services for five European countries for 1994–2004, the authors of the study (Bogliacino and Pianta, 2010) identified a strong positive effect on the employment of product innovations. Similarly, an analysis of 25 manufacturing and service industries in fifteen European countries for 1996–2005 showed that the growth in R&D spending had a strong positive effect on the rate of job creation, especially in high-tech industries (Bogliacino and Vivarelli, 2012). In a recent paper (Piva and Vivarelli, 2017) on 11 European countries (1998–2011), which also analyzed both manufacturing and services, it was found that the growth of R&D expenditure in general has a positive effect on employment. However, this is observed almost exclusively in high- and medium-tech industries, while in low-tech industries it results in the loss of jobs. In a recent paper, the results of an interesting “natural” experiment carried out in the UK were analyzed during 2000–2004 when small businesses were given a 100 percent tax credit for funds invested in ICT (Gaggl and Wright, 2014). According to estimates, the intensification of investments in ICT has provided an increase in the number of hours worked in the small firms, which were entitled to such a discount, by 0.7%. But at the same time, employment increased only in trade and finance and practically did not change in all other sectors, including manufacturing. An important study on panel data for 14 indus-

tries of 17 countries for the period 1993–2007 was performed recently by Graetz and Michaels (2015). They demonstrated that, at the sectoral level, the use of robots dramatically increases the growth rate of value added (moving from the lower to the upper decile in terms of robotization intensity provides additional 0.37 p.p. of value added annual growth), as well as the growth rates of labor productivity and wages, but it does not adversely affect the number of hours worked.

Important results were obtained in a recent paper by Bessen (2017). He showed that within the same sectors the relationship between dynamics in labor productivity and dynamics in employment does not remain unchanged over time: if at the early stages of industry's life-cycle it is positive (the introduction of new technologies leads to an increase in the number of jobs), then at later stages it becomes negative. Thus, in the USA, the number of production workers engaged in the manufacture of cotton fabrics was 20,000 people in 1820, increasing to 450,000 in 1930 (peak) before returning to the initial level of 20,000 currently. In the steel industry, it was 10,000 people in 1870, reaching 550,000 in 1960 (peak) and falling to 100,000 currently. The figures were similar for the automotive industry: 20,000 people in 1910, 800,000 in 1970 (peak) and 600,000 at the present time. At the same time, in the first of these industries, throughout the entire period of its existence, the annual growth rate of labor productivity was 2.9%, in the second—2.4%, in the third—1.4%. Why, despite the steady growth in labor productivity, did employment first grow rapidly and then quickly decline?

Bessen (2017) connects this with the fact that the price elasticity of demand can vary greatly over time. When a new product appears on the market, it is much higher than one, since only a few, the most affluent consumers, can afford to buy it at a high price; then, as prices fall, the circle of its consumers becomes wider and wider; finally, when its price drops so much that it becomes accessible to almost everyone, the saturation point is reached and the price elasticity of demand drops to a level significantly lower than one. From this moment onwards the influence of technological changes on employment (within this sector) turns negative from positive. Moreover, in the ascending phase, while the price elasticity of demand significantly exceeds one, the *faster* productivity increases, the *faster* increase in employment is observed. This in particular explains, according to Bessen (2017), why the effect of ICT on employment by individual sectors was so different. Thus, according to his estimates, in the USA, a 1% increase in computerization was accompanied by a 3% contraction in employment in manufacturing, but led to its expansion by 1% in sectors unrelated to the manufacturing industry. Concerning future trends in the American economy, he anticipates that the reduction in employment under the influence of technological change in manufacturing will be over-compensated by its rapid growth in services.

The most general conclusion that can be drawn from research at the meso level is that in various sectors the demand for labor responds unequally to the introduction of new technologies: as a rule, its response is positive in services, as well as in “young”, high-tech manufacturing industries, but negative in its “mature” low-tech industries. However, analysis at the sectoral level has many limitations similar to that at the firm level. Nor can it take into account the effects of various compensating mechanisms at the macro level, and, therefore, is unable to answer the question regarding the overall effect of technological changes in terms of employment dynamics.

Therefore, research based on aggregated data is of great importance. In particular, it allows to evaluate the comparative effectiveness of alternative compensatory market mechanisms. For this, various methodological approaches can be used (Vivarelli, 2007).

In early work, simulations based on input-output tables were used as the main analytical tool. So, from a series of simulations performed for the US economy of the mid-1980s, it followed that employment in it would grow under any possible rates of technological change, although in scenarios with higher rates its growth should be slower (Leontief and Duchin, 1986). The forecast of employment dynamics in the British economy as of the beginning of the 1990s showed that the compensating mechanisms operating in it are strong enough to completely neutralize the initial labor-saving effect of new technologies. At the same time, the most effective was the compensation channel associated with price cuts, which, according to calculations, accounted for more than half of all compensated jobs (Whitley and Wilson, 1982). However, later estimates by the same authors for 1985–1995 already assumed that compensation would be only partial (Whitley and Wilson, 1987). A similar conclusion about incomplete compensation of job losses due to the spread of ICT was also obtained for West Germany (Kalmbach and Kurz, 1990).

Another research direction was associated with attempts to directly assess the elasticity of employment by economic growth rates. The research for several OECD countries that covered the years 1960–1993 showed that the correlation between the rates of change in employment and in GDP is positive, and it remained so even in the first half of the 1990s—in the period that is commonly described as “economic growth without creating jobs” (Boltho and Glyn, 1995). However, the negative elasticity of employment depending on the rate of economic growth was found for four of the seven developed countries (1960–1997) analyzed in Piacentini and Pini (2000). Moreover, in all seven countries there was a negative elasticity in manufacturing, but a positive one in services. However, in Padalino and Vivarelli (1997), different results were obtained for the same seven developed countries in 1960–1994. In the long-term, the negative impact of economic growth on employment dynamics was not revealed, and in the short-term there was a strong positive relationship between them.

The relationship between employment dynamics and productivity dynamics is analyzed in detail in a sample of 19 developed countries for the years 1970–2007 in a recent paper by Autor and Salomons (2017). The general conclusion from it is unambiguous: new technologies do not threaten employment, but favor it. According to the authors, an increase in labor productivity by 10 p.p. was accompanied by an increase in the total number of people employed in the economy by an average of 2 p.p. At the same time, productivity growth by 10 p.p. *within* a particular sector led to a fall in employment in it by about 2.5 p.p. However, the direct (intrasectoral) negative effects were over-compensated by stronger indirect (intersectoral) positive effects. First, productivity growth in each particular sector stimulated the creation of additional jobs in other sectors. Secondly, by contributing to an increase in the volume of final consumption, it increased the demand for labor in the whole economy as well. At the same time, the net positive effect turns out to be significantly greater if the indicators of total factor productivity, and not labor productivity, are used in the evaluation. The strongest indirect effect on em-

ployment for other sectors was provided by productivity growth in services. This gives us good reason to believe that in the case of active crowding out of people by robots, the number of people employed in *the whole economy* will not shrink, as many expect, but grow. Another important conclusion is that new technologies cannot be considered the main driver of changes in employment: the key factor here is population dynamics. But this modest depiction of the role of technological change does not fit well into the picture of the coming “robocalypse” (Autor and Salomons, 2017).

But perhaps the most interesting studies at the macro level present an attempt to assess the effectiveness of various compensatory mechanisms in the framework of general or partial equilibrium models. As it was shown for the USA (Sinclair, 1981), the initial loss in employment due to the introduction of new technologies will be overcompensated (that is, the net increase in employment will be positive) if the coefficients of price elasticity of demand and elasticity of substitution between production factors are quite high. In the case of the American economy, the maximum compensation was provided by the mechanism associated with reduction of wages, whereas no evidence was obtained for the mechanism associated with price reduction. Comparative analysis of the economies of the United States and Italy for 1966–1986 showed that if the former was more focused on “product”, the latter was on “process” innovations (Vivarelli, 1995). Accordingly, in the former, technological change was accompanied by an increase in the number of jobs, while in the latter — by reducing them. At the same time, in both countries the most effective mechanism turned out to be the one associated with the price reduction. In a methodologically similar paper using data for the USA, Italy, France and Japan for 1965–1993, it was concluded that most effective in these countries were two compensating mechanisms — decreasing prices and increasing incomes (Simonetti et al., 2000). At the same time, the mechanism through reduction of wages was observed to be effective only in the case of a more flexible American labor market. A strong positive effect due to product innovations was also only recorded in the United States. The negative effect of process innovations for employment dynamics was found in the study analyzing the experience of nine developed countries in 1960–1990 (Pini, 1996). But at the same time it emphasizes the importance of a compensating mechanism associated with the expansion of exports as a result of the introduction of such innovations.

In Layard and Nickell (1985), at a theoretical level, it was shown that the key parameter should be elasticity of the demand for labor with regard to ratio between real wages and labor productivity. When it is high enough, the initial labor-saving effect of new technologies will be fully compensated. According to the authors, in the case of Great Britain its value was 0.9, which excluded any negative impact of technological change on employment. Another UK study focused on a compensating mechanism related to price reduction (Nickell and Kong, 1989). In seven of the nine sectors of the country analyzed by the authors, the price elasticity of demand was high enough so that across the whole economy, between technological change and employment, there was a steady positive relationship.

Despite discrepancies in existing empirical estimates, it is impossible not to notice that most studies at the aggregate level still tend to conclude that technological change is a factor that favors rather than hinders employment growth. At

the same time, they show that much here depends on the degree of flexibility of the labor market, on price elasticity of demand (both for goods and labor), on the elasticity of substitution between production factors, etc. (Piva and Vivarelli, 2017). From a methodological point of view, the main disadvantage of macro-research is that in any country the trajectory of change in employment is determined by many structural, institutional and social factors, which are often impossible to control. Consequently, attempts to isolate the “pure” effect of technological change at the level of the entire economy run up against formidable obstacles.

Most recently, analyses have emerged whereby regions, rather than firms, sectors or national economies, are the objects of observation. Probably the most resonant of them is the study by Acemoglu and Restrepo (2017) devoted to the effect of robotization on employment at the level of local labor markets (commuting zones) in the United States for 1990–2007. According to their econometric analysis, the installation of each additional industrial robot displaces from production between 3 (minimum estimate) to 6 (maximum estimate) workers. In an equivalent formulation, one additional robot per thousand workers reduces the level of employment in the economy (employment-population ratio) by 0.18–0.34 p.p. Cumulative losses as a result of robotization for the entire period under review amounted, according to their calculations, from 360,000 to 670,000 people, and employment in manufacturing suffered most.

Note that even if we take these estimates at face value, quantitatively, the effect of robotization on employment in the United States turns out to be barely noticeable—a decrease by 0.2–0.3% over an almost twenty-year period. Suffice it to say that only the annual labor turnover in the American labor market (the sum of hiring and firing) exceeds 120 million. Moreover, according to the calculations of Acemoglu and Restrepo (2017), when assessing the joint impact on the employment of robotization *and* computerization, the net effect of new technologies from the negative becomes positive. It is also not entirely clear to what extent it was possible to take into account, in their analysis, the influence of compensating market mechanisms operating at the level of the entire economy rather than at the level of local territorial zones. In addition, as already noted, in other papers devoted to the same problem, robotization is evaluated as a factor neutral from the point of view of the dynamics in employment (Jäger et al., 2015; Graetz and Michaels, 2015).⁹

Finally, all studies that also use regional data paint a different picture from Acemoglu and Restrepo (2017). So, in the paper by Autor et al. (2015), in which local labor markets in the USA (722 zones) were also used as units of analysis and which covered the same period of 1990–2007, no negative impact of new technologies on total employment was found. Analysis of local labor markets in West Germany (402 zones) in 2001–2012 showed that in the regions with a high concentration of industries characterized by elastic demand for their products with regard to labor productivity growth, the employment level increased, while regions with a high concentration of industries with inelastic demand lost the jobs (Blien and Ludewig, 2017).

In Gregory et al. (2016), based on the data for 238 regions of twenty-seven European countries in 1999–2010, three main channels were identified for the pos-

⁹ If robotization mostly affects the “old” traditional sectors with low elasticity of demand, then it is natural to expect that it will be accompanied by a reduction in employment.

sible impact of technological change on employment: 1) substitution effect associated with crowding out workers with machines; 2) effect associated with an increase in demand for products due to lower prices; 3) spill-over effect due to the fact that the increased demand may go beyond the boundaries of regions, in which new technologies are being introduced, and flow into other regions. According to the estimates, for the entire period under consideration, the cumulative losses due to the first mechanism amounted to (for all regions in total) 9.6 million jobs, while the cumulative increase due to the second mechanism was 8.7 million and due to the third 12.4 million jobs. The net gain due to technological change was 11.6 million. This calculation was based on the assumption that all additional non-labor income derived from increased production efficiency is spent on the purchase of goods and services in neighboring regions (spill-over effect). As an alternative, a scenario was considered in which all additional non-labor income “left” the system (that is, was spent outside of Europe). But, even in this extreme case, the total net gain in employment still reached almost 2 million jobs (Gregory et al., 2016).

4. Technological progress and the labor market adjustment

Technological change can become the source of a rise in unemployment not only when it reduces the demand for labor, but also when it complicates and slows down the process of matching workers with jobs. The fact is that under its influence not only the *level* of labor demand can change, but also its *structure*. To overcome the discrepancies that have arisen between the composition of labor demand and composition of labor supply, reallocation of labor turns out to be necessary—occupational, territorial and interfirm etc. Some occupations become obsolete, others appear; new technologies put higher requirements on workers’ education and skills; the workforce has to move from regions where the need for it falls to regions where the need is greater; non-innovative firms start dismissals (or they close altogether), while innovative ones open new vacancies, so jobs start to flow from the first to the second. In fact, this is exactly what J. Schumpeter called the process of “creative destruction”.

Naturally, with sharp technological changes, adaptation to them can stretch for a long time and take extremely painful forms. Retraining, learning new trades, raising the level of education, moving to another locality, even changing the place of work, all this takes time and involves considerable costs. In this sense, there is no doubt that technological unemployment as a short-term phenomenon is quite real and, moreover, is always more or less present in modern labor markets. The meaningful question is whether it goes beyond the limits of “normal” frictional unemployment and, if so, how strongly, and whether it resolves over time and, if so, how quickly. For example, Feldmann (2013) showed using data from twenty-one developed countries for 1985–2009 that technological innovations do cause a temporary increase in unemployment during the first three years after the start of their implementation, but then it returns to its original, lower level. It is important to note that such a short-term increase in unemployment can be observed even when in the long term technological change serves as a catalyst for the growth in demand for labor.

There are many factors acting in different directions. Nevertheless, in the general case, it can be expected that the increase in unemployment will be the more

significant and longer in the following hypothetical contexts: (a) the larger the required reallocation of labor, that is, the faster, deeper and broader the technological changes that give it a boost; (b) the wider the gap between the requirements imposed by the old and new technologies to the quality of the human capital of workers; (c) the higher the inflexibility of labor markets, which impedes the process of reallocation and slows down its pace.

Moreover, if we are not talking about a one-time shock, but about a constantly reproducing situation, when the rate of technological change persistently exceeds the rate of adaptation to them by firms and workers, then technological unemployment can be observed not only in the short term, but also in the long term. In other words, under certain conditions, technological change can become a cause for increasing the “natural” (equilibrium) rate of unemployment.

For instance, it can increase the propensity of firms to impose layoffs and weaken their propensity to open vacancies (Aghion and Howitt, 1994). One of the main consequences of changes in technology is the obsolescence of knowledge and skills accumulated by employees. On the one hand, this should encourage firms to get rid of their existing employees with morally obsolete human capital, and, on the other, to hire new employees less actively, because with frequent technological changes, the expected duration of the match between workers and jobs will be shorter (the reason is still the accelerated depreciation of workers’ knowledge and skills). On the other hand, since technological change contributes to the growth of labor productivity, the return on each additionally created job will be higher, and this should stimulate firms, on the contrary, to more actively open vacancies. In a situation where the latter effect is weaker than the first, the introduction of new technologies will lead to an increase in the “natural” rate of unemployment.¹⁰

However, this result cannot be considered predetermined. Technological change can take various forms: sometimes it requires the elimination of existing jobs, but sometimes everything boils down to their renovation (Mortensen and Pissarides, 1998). In the latter case, workers adapt to the requirements of new technologies, updating and replenishing their knowledge and skills, but remaining in their previous jobs. And if technological change in the form of creating/destroying jobs really can increase the “natural” rate of unemployment in the form of their renovation it should, on the contrary, contribute to its reduction.

How often are these episodes of ultra-high short-term technological unemployment? Economic history shows that it is extremely difficult to find examples when the acceleration of technological progress would lead to a sharp jump in general unemployment. At the beginning of the 20th century, the appearance of automobiles did not cause mass unemployment among cab drivers, blacksmiths and saddlers; at the end of the same century, the advent of computers did not cause mass unemployment among typists. This means that most often the speed of technological changes and the speed of adjustment to them are comparable. In previous periods, the introduction of new technologies, as a rule, did not have an explosive character, stretching for a more or less long period, sufficient for firms and workers to adapt to the changed conditions. Thanks to this, it was usually

¹⁰ At the same time, new technologies can also reduce the time, and increase the efficiency, of the search on the labor market. In this sense, there is reason to believe that the emergence of ICT should have contributed, on the contrary, to a *decrease* in the “natural” rate of unemployment.

possible to avoid any sharp jumps in unemployment due to technological factors. (For example, in the USA, where, as we mentioned, the labor turnover exceeds 120 million a year, in order to significantly affect the overall unemployment rate, a one-time inflow into it caused by the introduction of new technologies would have to be at least 0.5–1 million people.)

Nevertheless, some authors tend to associate current problems in the labor markets of developed countries with technological factors. Thus, more recently, Brynjolfsson and McAfee (2011) offered a purely technological explanation for the persistently high level of unemployment in the US economy for several years after the end of the Great Recession. However, now that unemployment in the US has fallen significantly below the 5% mark, it has become obvious that new technologies were not a contributing factor at all.

But do we still expect a rapid surge in technological unemployment in the near future, as techno-alarmists predict? On closer examination, such a development of events seems highly unlikely, for several reasons.

First, as the empirical analysis shows, modern technological change is focused not so much on the elimination of jobs, but rather on their renovation. Thus, computerization has contributed to the large-scale replacement of people by machines in the process of performing routine production operations (for more on this, see the next section). But, as calculated on the data for Germany for 1979–1999 by Spitz-Oner (2006), this was 99% due to a reduction in routine operations performed by employees within existing occupations (that is, without dying out!) and only by 1% due to the elimination of occupations that were entirely routine. But this form of technological change, as already noted, is more likely to be associated with the expansion of employment than with its contraction.

Secondly, many alarmist forecasts are based on the simplified division of all employees into two groups—low- and high-skilled. And if we assume that new technologies reduce the demand for the former, but increase the demand for the latter, then it is easy to come to the conclusion that large-scale technological unemployment is inevitable because, for obvious reasons, low-skilled workers forced out by machines are not qualified to perform high-skilled jobs. However, the division of all employees into two polar groups is just a conventional device to simplify the analysis. In reality, there is a huge variety of gradations depending on the quality of jobs. Nothing is impossible in that, under certain conditions, workers who were at the bottom of the occupational hierarchy could go up one step; the workers who occupied this step earlier also climbed one step and so on up to the very top. The possibility of such a “chain” substitution between various groups of workers dramatically reduces the risk of a sudden surge in technological unemployment.

Thirdly, the advancement of new technologies may encounter not only engineering, but also legal, social and ethical obstacles, which reduce the speed of their spread. For example, a massive transition to driverless cars is impossible without a radical revision of the legislation on liability in case of an accident, but such a revision may take many years.¹¹ When the process of diffusion of

¹¹ For example, according to the forecast of BCG (2015), by 2035 the share of driverless cars in the total US fleet will not exceed 10%. This is a very modest pace, obviously not foreshadowing any explosive growth of technological unemployment in the American labor market.

Table

Average annual growth rates of GDP and total factor productivity (TFP) in developed countries, 1890–2015 (%).

	1890–1913	1913–1950	1950–1975	1975–1995	1995–2005	2005–2015
USA						
GDP	3.8	3.3	3.5	3.2	3.4	1.4
TFP	1.3	2.5	1.8	1.1	1.8	0.6
Great Britain						
GDP	1.7	1.3	2.9	2.4	3.0	1.0
TFP	0.5	1.2	1.8	1.8	1.6	-0.1
Eurozone						
GDP	2.4	1.0	5.1	2.5	2.0	0.6
TFP	1.4	1.2	3.6	1.8	0.7	0.2
Japan						
GDP	2.5	2.2	8.2	3.7	1.1	0.5
TFP	0.5	0.7	4.4	1.7	0.9	0.4

Source: Bergeaud et al. (2017).

technological innovations turns out to be quite gradual, the adjustment to it in the labor market can successfully proceed without generating high technological unemployment even in the short term.

But perhaps the most important thing is that so far (contrary to the predictions of techno-alarmists) nothing indicates a sharp acceleration of technological change that awaits us in the near future. As Table shows, the last decade can be considered one of the worst periods in the economic history of developed countries. During these years, they had the lowest growth rates since the beginning of the 20th century, not only of GDP, but also of total factor productivity, which can be considered evidence of a slowdown in technological change. Of course, one can argue that such disappointing figures are nothing more than the result of the negative impact of the Great Recession of 2008–2009. However, upon closer inspection, this reference to the Great Recession is hardly convincing.

First, the long-term slowdown in productivity growth began in developed countries several years before the Great Recession (in the US since 2005) (Gordon, 2016). Secondly, even after adjusting for its consequences, the growth rates of TFP for developed countries in 2005–2015 still remain lower than in earlier periods (Fernald, 2015). Third, it is quite natural that recessions negatively affect GDP growth rates, but it is not so easy to understand why they should also negatively impact the pace of technological change. For example, in the United States, the decade of the Great Depression (the 1930s) is considered the most “innovative” period in the country’s history (Field, 2003).

Today, most researchers agree that the sharp deterioration in GDP and productivity dynamics in developed countries is not a short-term episode; that since the mid-2000s they all moved to a lower long-term growth path; finally, that in the first place this was due to the slowdown in the rate of TFP, that is, rate of technological change. Of the American economists, only Brinjolfsson and McAffie (2011), who are among the convinced techno-optimists, continue to insist that in the near future the annual growth rates of TFE in the US will accelerate to 2%. However, since they first made this forecast, several years have passed, but there is still no sign of the promised acceleration. All other authoritative researchers

of economic growth in the United States (D. Jorgenson, R. Gordon, J. Fernald and many others), on the contrary, expect a serious slowdown in the growth rates of TFP to 0.5–1%. According to their estimates, in the best case, the American economy will have to return to the indicators observed in the “stagnant” twentieth century years of 1972–1995.¹²

But if this was the case, then for this reason alone it makes no sense to expect any surge in technological unemployment any time soon. If the pace of technological change, as follows from most forecasts, will be even lower than the historical “norm”, then it will be no more difficult to adapt to them, but easier than before. In light of this, even a short-term spate in technological unemployment in the coming years seems unlikely.

Of course, technological progress is hardly a predictable process, being rather fraught with many surprises, so the situation can revert very quickly. Perhaps, already somewhere on the way there are new breakthrough technologies that will once again transform the world. But, so far, available data paint a completely different picture: it seems that the world economy has a long period of — not too fast by historical standards — technological change and, as a result, rather sluggish productivity growth.

At the same time, in discussions about technological unemployment, it is often forgotten that new technologies can influence not only labor demand, but also labor supply. And if effects on the demand side are largely an area of guesswork and assumptions, effects on the supply side are already a reality.

Traditionally, in addition to monetary losses, the unemployed carried no less significant non-monetary (psychological) costs, falling into idleness and social exclusion. However, thanks to computers and the Internet, such costs have rather diminished: now the non-employed have something to do (say, spending time playing video games) and have someone to communicate with (through social networks). And to the extent that the value of leisure has increased, the incentives to seek and obtain paid employment in the market should have weakened. In other words, the unforeseen result of the diffusion of new technologies could be a decrease in the employment rate, and especially so among young people.

Indeed, Auguiar et al. (2017) showed that in the USA, labor supply curves for all demographic groups shifted downward under the influence of ICT, but most strongly — for young men (21–30 years old) with low education (who did not attend college). For the years 2000–2015 their employment rate fell by 10 p.p. — from 82% to 72% and at the same time, the share of those who did not work at least for one hour during the whole previous year increased sharply — from 10% to 22%. As for the average length of time worked per person, they have decreased by 300 (!) hours per year. The balance of time has shifted as follows: time devoted to work in the market decreased by 3.5, and devoted to work in the home, by almost 2 hours a week; study time increased by 1, and leisure time increased by more than 4 hours a week. More interesting is that young men

¹² In a later work, Brynjolfsson was forced to admit that the technologies of the new generation do not have a significant impact on the dynamics in productivity, which explains the sharp slowdown in economic growth in developed countries. Now he warns that in order for their positive effect to manifest, it will take time (perhaps a long period). First, the proliferation of such technologies must reach a certain critical level. Secondly, investment in complementary factors is necessary. Thus, what we are seeing now is just a transitional period on the eve of the future “spurt” of productivity (Brynjolfsson et al., 2017).

with low educational attainment began spending 6.5 hours more at the computer over the week, including on video games—5 hours more than before. According to the econometric estimates of the authors, from a quarter to half of the total reduction in the hours worked by this group can be attributed to switching to “computerized” forms of leisure. In other words, the expansion of access to new “leisure” technologies has led to young, poorly educated American men working 75–150 hours less over the year. Similar trends, albeit in a more relaxed form, are also observed for other demographic groups (Auguiar et al., 2017).¹³

In this sense, there are grounds for asserting that today the serious challenge for economic and social policy is not so much the impact of new technologies on labor demand, as their impact on labor supply.

5. Technological change and occupations

In the past two decades, a large number of studies have appeared in which the topic “technological change/labor demand” began to be viewed from a fundamentally new angle, namely, through the prism of changes in the occupational composition of employment. The nature of modern technological change is conceptualized on the basis of how it affects the demand for certain groups of labor, for certain occupations. “Occupation” means a limited set of tasks (work functions), the fulfillment of which in the course of the production process is imputed to the worker.

Technological change inevitably leads to shifts in the economy, which in the case of the labor market are expressed in the reconfiguration of the job structure. Jobs are heterogeneous in their characteristics: some suggest high, others—low qualification of workers; some are associated with high, others—with low pay; some have attractive, others unattractive working conditions. The nature of technological change can be defined by understanding how under its impact the job structure changes—from “good” to “bad” jobs (as Smith and Marx thought), from “bad” to “good” ones or something else. Naturally, in different historical periods the nature of the impact of technological change on the job structure might be different.

Early research that emerged in the early 1990s focused on how the computer revolution and the spread of information technologies changed demand for different skills. In the simplest variant, two groups of employees were distinguished—low-skilled (without higher education) and high-skilled (with higher education). Experience shows that modern computer technologies are closely related to the process of accumulating human capital, since their introduction and use requires skilled workers with high formal education (Katz and Murphy, 1992). It can be said that ICTs are complementary to highly skilled labor, but substitutes for unskilled labor. This type of technological change is called “skill-biased technological change” (SBTC). SBTC suggests a persistent increase in demand for skilled labor and a decrease for unskilled labor. Its consequences will be: improvement of the job structure (instead of “bad” jobs, “good” will be created); increasing labor productivity and wages, both for low- and high-skilled

¹³ New technologies associated with the Second Industrial Revolution had the opposite effect: they significantly facilitated household work and promoted mass entry into the labor market for women, i.e. provided a huge increase in labor supply.

workers; the increase in the wage gap between these groups (in other words, the growth of the “premium” for higher education); deepening income inequality.

Indeed, as shown by the very first work, where the concept of the SBTC was put forward, in the United States during the 1970–1980s the number of high-skilled workers grew at a rate of 3% per year, while the relative quantity and relative wages of low-skilled workers steadily declined (Katz and Murphy, 1992). Later, a similar result was also obtained for several OECD countries with the proviso that the reduction in the relative wages of low-skilled workers was observed only in Anglo-Saxon countries, but not in continental Europe (Machin and Van Reenen, 1998). Most likely, this was due to differences in their labor market institutions. At the same time, the greatest shift in favor of a high-skilled workforce was noted in firms and sectors most affected by computerization (Autor et al., 1998; Machin, 1996).

However, the range of occupational duties can vary greatly even among workers belonging to the same qualification group. This circumstance was not taken into account in the SBTC conception, but became the starting point for an alternative conception of “routine-biased technological change” (RBTC) (Autor et al., 2003). Supporters of the RBTC idea suggested a more partitioned classification of jobs depending on what tasks should be performed by workers belonging to a particular occupation: physical or intellectual, routine or creative. Accordingly, three integrated clusters of occupations were singled out—non-routine physical ones; non-routine cognitive; routine (regardless of whether it is a matter of routine physical or routine cognitive activity).

The routine occupations imply work operations, characterized by a pre-assigned, monotonous, repetitive nature. On the one hand, such operations require following a strictly defined protocol, so that they are easily codified and programmed using modern ICT. On the other hand, routine work is most characteristic for occupations located on the middle layers of the skill ladder (bank tellers, office clerks, accountants, etc.). At the same time, many occupations that do not require specialized qualifications (waiters, nurses, etc.) are difficult to computerize, because quick reactions, the ability to cultivate personal contacts with customers, etc. are necessary. Occupations that are at the top of the skill ladder (managers, specialists, etc.) are even less amenable to codification and programming since they require the ability to solve complex problems as well as intuition, creativity and gift of persuasion, etc. As a result, modern technologies act as complementary with respect to high-skilled and as neutral with respect to low-skilled labor, but as substitutes with respect to medium-skilled labor.

Three main predictions stem from the RBTC conception. First, in the general array of tasks solved by workers, we should expect a shift from routine operations (both physical and intellectual) to non-routine ones, since the former are increasingly taking over from machines. Empirical evidence of a declining significance of routine tasks was obtained for Anglo-Saxon countries, countries of continental Europe and Japan (Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2009; Ikenega and Kambayashi, 2010). Second: the RBTC implies a polarization of the job structure. In the middle of the occupational hierarchy, there will be a laydown, while employment growth will occur at the poles, in which the “worst” (least paid) and the “best” (most paid) jobs will concentrate. Similar changes were traced for many developed countries (Autor et al., 2006;

Goos and Manning, 2007; Goos et al., 2009; Ikenega and Kambayashi, 2010; Oesch and Rodríguez Menés, 2011). According to available estimates, in 1993–2006 in Western European countries, the share of medium-skilled occupations decreased by 8 p.p. (Goos et al., 2009). At the same time, the fastest growth in the share of holders of “bad” jobs was observed in countries with more flexible labor markets, such as the UK.¹⁴ Third, the RBTC should also be accompanied by a polarization of wage structure. In other words, wage growth at the edges of the job distribution should be ahead of its growth in the middle of the occupational ladder. This is quite a logical result, because reducing the demand for workers with average qualifications, according to the RBTC, should lead to a relative decrease in their earnings. True, such an outcome cannot be considered absolutely predetermined. Thus, new technologies may be complementary to medium-skilled workers who retain employment and may see a boost in their wages (Autor, 2013). In addition, workers who are ousted from medium-skilled jobs can be distributed in very different proportions between the “bad” (low-paid) and the “good” (highly-paid) segments of employment; in case of their active migration to “good” jobs, the average wage may even increase for them (Acemoglu and Autor, 2011). Nevertheless, the trend towards polarization of the wage structure has also been confirmed for the labor markets of many countries (Autor and Dorn, 2013; Firpo et al., 2011; Atkinson, 2008; Dustmann et al., 2009). Currently the conception of RBTC is “mainstream” and is accepted by most economists who study the relationship between technological change and changes in the structure of employment.¹⁵

Here, however, it is worth noting that different technologies may not equally affect different groups of routine occupations. For example, in contrast to computerization which for the most part contributes to the extinction of routine *intellectual* forms of work (such as office workers), robotization contributes to the extinction of routine *physical* forms of work (such as machine operators). Accordingly, the changes they generate in the job structure will not necessarily coincide. Thus, in a number of studies, it is argued that robotization, unlike computerization, leads to a decrease in demand for low-skilled, and an increase in demand, for high-skilled labor, but without a drop in demand for workers of medium qualification, as suggested by the canonical version of the RBTC conception (Graetz and Michaels, 2015). In other words, from robotization we should expect an improvement (upgrading) rather than polarization of the job structure.

As can be seen from this brief review, economists have long been interested almost exclusively in how technological progress is associated with changes in the occupational *composition* of employment. It is only recently that they have addressed the equally important question of how changes can affect the *general level of employment*.

Of this new series of works, the study of two British economists K. Frey and M. Osborne, who presented a forecast of changes in the occupation composition

¹⁴ For an analysis of this problem on Russian data, see Gimpelson and Kapeliushnikov (2015).

¹⁵ At the same time, some authors strongly criticize it. In particular, they note the ambiguity and vagueness of the criteria for the selection of routine and non-routine occupations (Pfeiffer and Suphan, 2015). According to critics, the conception of RBTC is based on a logical vicious circle: first, the definition of routine jobs is given as jobs that are easiest to automate; then it is demonstrated that it is such jobs that most often undergo automation!

of the American workforce, attracted the greatest attention (Frey and Osborne, 2013). Their overall conclusion looks more than pessimistic: according to Frey and Osbourne (2013), in the next ten to twenty years, a myriad of various occupations will be at high risk of full automation, which now account for a total of almost half (47%) of all employed in the USA. Using the methodology they proposed, other researchers obtained no less terrifying numbers: 35% for Finland (Pajarinen and Rouvinen, 2014), 59% for Germany (Brzeski and Burk, 2015), 45–60% for European Union countries (Bowles, 2014). McKinsey's recent prognosis for the US almost coincided with Frey and Osborne's of 45% (Chui et al., 2015). Experts from Price-Waterhouse-Cooper were more moderate: according to their forecast estimates, presented in 2017, by the early 2030s in the US, under the influence of automation, occupations that are expected to disappear embrace “only” 38% of the total employed (Bailey, 2017). Finally, according to the World Bank, in the OECD countries, over the next two decades, as a result of automation, 57% of all existing jobs will be eliminated (World Bank, 2016).

These quantitative indicators are so colossal that they could not but cause a shock to politicians and the general public. Therefore, it probably makes sense to clarify the methodology by which they were obtained.

Frey and Osborne (2013) believe that the modern world has entered a period of unprecedented high technological unemployment. Under the influence of technological changes, the knowledge and skills available to workers will become obsolete at such a rate that neither their retraining, nor improving their educational attainment, will be able to remedy this. They believe that automation will start to force out people not only from routine, but also from non-routine activities, be it cars' drivers or paralegals. Technological unemployment does not threaten only those occupations where automation encounters engineering “bottlenecks”, since the tasks performed in such occupations cannot yet be expressed in the language of codified rules.

Frey and Osborne (2013) distinguish three forms of human actions that are difficult to automate: these are perception and manipulation; creativity; social intelligence. In the occupations where such actions still perform a large role, human labor will still maintain comparative advantages over machine labor (for example, creating new ideas and artifacts, negotiating and caring for others will continue, in the foreseeable future, to be the lot of the people themselves). With this approach, the array of routine (more precisely, potentially automated) types of labor turns out to be much larger than follows from the canonical RBTC conception.

In their calculations, Frey and Osborne (2013) used data on 702 occupational groups from the O*NET Dictionary (edition of 2010) developed and published by the US Department of Labor. (Earlier editions of this handbook were published under the title “Dictionary of occupational titles”.) They selected 70 occupations from this array and presented their descriptions (without specifying their titles) to the participants of a seminar at the Faculty of Engineering Sciences at Oxford University asking them to assess the risk of fully automating such activities over the next one or two decades. The expert assessments obtained using special statistical procedures were extrapolated onto the remaining 632 occupations. Then, using factual data on distribution of the employed by occupations in the United States, the authors divided all workers into three groups depending on the risk of automation of the occupations to which they belong. A probability of up to 30%

was considered as low, a probability from 30% to 70% as medium, and a probability of over 70% as high risk. The first group included 33% of all employed currently in the United States, the second 19% and the third 47%. In other words, according to Frey and Osborne (2013), the occupations, which about half of all Americans work at today, should disappear very soon! Their analysis also showed that, contrary to the RBTC predictions of job polarization, low-skilled workers are exposed to the maximum risk of automation, rather than medium-skilled ones.

However, the quantitative estimates of Frey and Osborne, as well as all those who used their methodology, look quite surreal. As Bessen (2016) remarked, in the few years that have passed since their prediction, out of 37 professions for which they predicted an early demise (accountants, auditors, bank lending officers, couriers, messengers), not one has become automated. He also calculated that out of almost 300 professions that existed in the USA in 1950, by 2010, due to automation, only one had disappeared! These were elevator operators, whose need for services has disappeared after the lift cabins began to be equipped with automatic doors.

Here are some more examples of this kind. The emerging ATM techno-alarmists made predictions about the complete disappearance of the labor market for bank tellers. But in reality, their number (in full-time equivalent) has increased in the United States from 400,000 in 1990 to 450,000 at present—and this is against the background of an increase in the number of ATMs from 100,000 to 425,000 (Bessen, 2016). After equipping cash machines with reading devices, it would seem that the occupation of cashiers would have died off. But their number increased from 2 million to 3.2 million people. Finally, the number of paralegals—Frey and Osborne (2013), as we mentioned, foresee the imminent disappearance of this occupation—has increased in the United States from 85,000 to 280,000 (Bailey, 2017). (It is interesting that all these are medium-skilled occupations, which, according to the conception of RBTC, should be actively supplanted by machines.)

At the methodological level, the main flaw in Frey and Osborne's calculations was revealed by Arntz et al. (2016). It emphasizes that almost all known occupations are extremely heterogeneous and are a set of diverse—both routine and non-routine—functions. Therefore, in the overwhelming majority of cases, not an occupation as a whole is subject to automation, but only some of the functions (tasks) imputed to them. (See the above reference to Spitz-Oener, 2006.) As a result, automation more often leads not to the death of entire occupations, but to changes in the structure of tasks solved within their framework: the amount of time spent on routine operations by workers is reduced, while time spent on non-routine operations is increasing. However, the Frey and Osborne methodology does not take this into account.

As Arntz et al. (2016) showed, when moving from analysis at the level of entire occupations to analysis at the level of individual tasks, the proportion of jobs with a high risk of being exposed to full automation in the next 10–20 years decreases to 9% (average score for 21 developed countries). For individual countries, this figure varies from 7% for South Korea to 12% for Austria.¹⁶ In the case of the United States, it is also 9%, which represents a stark contrast with 47% sug-

¹⁶ A similar result was obtained in a recent survey of German workers. Only 12% considered it probable that in the next ten years they could be replaced by machines (Arnold et al., 2016).

gested by Frey and Osborne (2013). The reason for such much lower estimates is simple: almost all existing occupations imply, to varying degrees, the forms of human actions (such as personal communication with other people), which Frey and Osborne themselves qualify as insurmountable engineering “bottlenecks” in the way of automation. But if this is so, then the potential for automating entire occupations (as opposed to automating individual tasks) is far from being as great as they suggest.

Explaining the reasons for the observed cross-country variation, Arntz et al. (2016) refer to several factors. First, a lower risk of reduced employment when introducing new technologies is observed in countries with more educated labor. (Following Frey and Osborne, they also note that low-skilled workers, rather than medium-skilled workers, are at maximum risk of automation.) Secondly, a lot depends on the principles of work organization in various countries. Where the organization of work is based on the principles of team work and close personal interaction with other workers, the possibilities for automation also turn out to be narrower. Thirdly, it is important how far this or that country has advanced along the path of technological progress. Since unused potential for automation is greater in technologically more backward countries, the scale of the upcoming substitution of people by machines also turns out to be greater in them—simply because in technologically more advanced countries such a substitution has mostly occurred earlier.

But even their own assessments are considered by Arntz et al. (2016) to be greatly overestimated. First, their analysis is based on the same subjective expert data (with three engineering “bottlenecks” identified) as Frey and Osborne’s analysis. But experience shows that experts tend to greatly exaggerate the speed of propagation of new technologies. Secondly, both the Frey and Osborne (2013) estimates and those of Arntz et al. (2016) speak only about the technical feasibility of automation in various areas, but not about its economic rationale. Depending on what are the relative prices of factors of production, it may be unprofitable for firms to introduce certain innovations if they cannot recoup the costs associated with them. Thirdly, workers in obsolete occupations do not necessarily have to be “squeezed out” into unemployment: many of them can successfully adapt to changing conditions, switching from performing one task to performing others and mastering skills and abilities that are complementary to new technologies. Fourth, as already noted, the transition to new technologies can go with a significant lag after their appearance due to various obstacles—economic, legal, and ethical—arising in their way. Their implementation can be hampered by the lack of qualified personnel capable of working with new equipment; legal constraints can also be a serious obstacle (see the discussion in the previous section about the situation regarding driverless cars); there can be strong ethical preferences in society in favor of performing certain types of work by people, not machines (as, say, in the case of caring for the sick and elderly). All this should slow down the pace of transition to new technologies and accordingly make adaptation to them less painful. Finally, neither Frey and Osborne (2013), nor Arntz et al. (2016) take into account the effect of macroeconomic compensating mechanisms. However, as we have seen, technological change leads not only to the elimination of the “old” jobs, but also to the active creation of “new” ones and the latter effect may significantly outweigh the first.

6. Conclusion

The most general results of our analysis can be summarized as follows: in the long run, the reduction in the labor demand under the impact of new technologies is merely a pure theoretical possibility that has never before been realized in practice; at the level of individual firms, there is a strong positive relationship between technological innovations and employment growth; at the sectoral level, technological changes cause a multidirectional employment response, since different industries are at different stages of the life cycle; at the macro level, technological progress acts as a positive or neutral, but not a negative factor; the question of the impact of robotization on employment still remains open, different researchers come to different conclusions; a surge in technological unemployment, even in the short-term, seems highly unlikely, since in the coming decades the pace of technological change will not be sufficiently high by historical standards; the impact of new technologies on labor supply may be a more serious problem than their impact on labor demand; technological changes have a much stronger effect on the composition of employment than on its level; as for occupations, current technological progress is associated not so much with changes in their nomenclature, but with changes to their internal content, namely, with the crowding out of routine tasks by non-routine ones within existing occupations.

As for predictions of technological unemployment, these arguments can hardly be taken seriously because they ignore the fundamental fact that humanity lives, and will inevitably continue to live, in conditions of scarcity. But, as Alchian and Allen (1972) noted, in a world of scarcity there will always be available an unlimited number of (potential) jobs (see their statement, which served as an epigraph to the article). In such a world, many desires of people remain unsatisfied, because attempts to satisfy them would be too expensive, in other words, they would require an excessively large volume of resources. By increasing productivity, technological advancement frees up resources, thereby creating opportunities for satisfying needs, to do that before people just physically could not afford. But the unsatisfied desire of one person is a potential job for another person (Boudreaux, 2017). And this means that as long as some needs of people remain unsatisfied, there will be no shortage of jobs as well. Total replacement of people with machines is only possible in the situation of complete saturation of all human needs, that is, in an imaginary world in which the problem of scarcity would cease to exist (Nordhaus, 2015). But, as one could say paraphrasing Smith (2007, book 1, ch. 11, part 2), if the desire of food is limited in every man by the narrow capacity of the human stomach, the desire of diversity seems to have no limit or certain boundary...

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