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Technological unemployment

The risk of automation in Belgium

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I. Introduction

In recent years, economists and policy makers have once again raised the flag of technological unemployment. Based on the later technological change occurring in mobile robotics and machine learning, Frey and Osborne (2013) have estimated the “risk of automation” of occupation, for the next two or three decades, to be at 47 percent of all US employment. Follow-up studies have found similar results for the European employment. While this figure only represents the destruction effect of technological change and has been challenged by significantly lower results (see for example Arntz, Gregory and Zierahn (2016) or Nedelkoska and Quintini (2018)), the “risk of automation” is still a major concern for advanced market economies. That is, even looking at the lowest estimates, it might still concern many workers:

“[Arntz, Gregory and Zierhan, 2016] put this share to 9% in the United States. While this figure is only a fraction of the estimate provided by Frey and Osborne [2013], it translates to approximately 13 million jobs across the United States, based on 2016 employment figures”

(Nedelkoska and Quintini (2018), pp. 6).

In the case of Belgium, the lowest estimate speaks of 7 percent of jobs being at high risk due to computerization (Arntz, Gregory and Zierhan, 2016). Looking at Belgium’s employment figure, this amounts to 331.6 thousand persons being at risk of losing their jobs in 2016. In the case of Nedelkoska and Quintini (2018), who estimates the “risk of automation” for jobs in the OECD countries, they find that around 14% of jobs in Belgium have a high risk of automation (higher than 70%) and 29% have a risk of “significant change” in the job task composition (risk of automation between 50 to 70%). No fresher data being available for Belgium. Therefore, the number of workers at high risk sums up to 663.2 thousand for 2016. The transformation of the organization of labor affects even more workers if including the ones regarded as being at risk of “significant change” in their job’s task composition. The upcoming transformation of the labor market could thus be the largest one in Belgium since the mines shutdown process that occurred after the end of the second world war.

In the context of a forthcoming economic slowdown, concerns over repartition of the wealth and the distribution of growth gains arise more frequently (OECD, 2019). As a matter of fact, while the frequencies and the length of economic crisis seem to have risen over the last decades (Kose and Terrones, 2015), its social effects differ quite a lot. Notably, the growth shares being distributed among the fewer richest persons through the years, as shown in Piketty (2013) or in (Oxfam, 2019). As an example, the overview proposed by Acemoglu and Autor (2011) for the evolution of the real wage income distribution, from the sixties until today in the United States. Aside from college graduate and higher educated workers, who have seen their wage rise over this time period, most workers have seen their real wage reduced since the first petrol shock. The less educated

workers having either lower or equal wage compared to 1963. The automation process plays an important role in this respect, as it has been quoted by numerous authors:

“The mounting evidence that the automation of a range of low-skill and medium-skill occupations has contributed to wage inequality and employment polarization adds to these worries”

(Acemoglu and Restrepo, 2017: pp 1).

As it is well known that technological innovations do not affect workers in the same ways, the observed polarization of the labor market over the last five decades is puzzling. As a matter of fact, as computer capital usually substitutes for routine intensive jobs, employment shares are growing in the less-educated manual routine jobs¹ and in the high-educated non-routine jobs. Thus, amplifying the income disparities before employment. Many recent studies point that way (Autor, 2015, 1; Nedelkoska and Quintini, 2018; Foster and Wilson, 2019). In Belgium, the situation in this regard requires attention. Notably, the problem of youth unemployment is a secular one. The example of Cockx (2013) paper's might be emblematic. Looking at youth mean unemployment over the 2003-2012 decade, he finds its highest level for the EU countries to be in Brussels capital region (35%), with Wallonia (29,6%) placed fourth after Greece and Spain, while the Flemish region is doing better than the European average with “only” 13,5%. In each case, the situation appears to be much worst when considering the socio-economic background of the job seekers.² Already in 2007, the OECD pointed out at the critical situation of Belgium's regions, asking for solution for youth unemployment (Van der Linden, 2007).³

The literature on the risk of automation already numbers many studies for Europe as a whole (Arntz, Gregory and Zierahn, 2016; Nedelkoska and Quintini, 2018), or for other specific countries (Bowles, 2014; Pajarinen and Rouvinen, 2014; Brzeski and Burk, 2015; Foster and Wilson, 2019), and various estimates have been produced for Belgium. Yet no study has considered that Belgium cannot be seen as a unique entity, as its divergence between regions is far too great. As shown in Dejemeppe and Van der Linden (2016), unemployment in the Flemish region over the 1999-2014 period has been at least two times smaller than in Wallonia (three for Brussels capital region), the differences spreading over the years. As all the previous studies that have produced estimates for Belgium relied on PIAAC (Program for the International assessment of Adult Competencies) dataset, it is important to note that this database only covers the Flemish region. The Belgian labor market being somewhat special, even for the OECD countries,

¹ Indeed, as it will be showed later, the computerization of tasks to be performed in non-clearly structured environment are difficult to render effective. The long years of dedication needed for the development of the autonomous car being a good example.

² For freshly out of school young people without additional formation (of the type: high school, university or tertiary college), their expected time as employed in the next three years is less than one year for Wallonia and Brussels capital region (Cockx, 2013).

³ This is consistent with the findings of McGrattan and Rogerson (2004) for the US. As the employment-to-population ratio increased over the period 1950-1990, the number of hours worked per worker decreased. And when this ratio declined afterwards, the hours worked per worker started increasing as well.

is often mistakenly overlooked as a simple small unique market. As I will argue later, this misunderstanding of the Belgian labor market has led to downward biased estimation of the risk of automation. The reason being the differences in the organization of labor in the between industry component as well as the within industry component.

The alarming effects of climate change add to those anxieties. As its direct impacts can now be seen and are heading in the direction of the expert assessment of Meadows and al. (1972). Many have pointed out the impossibilities of combining growth with the reduction of the exploitation of natural resources (Peeters, 2016; Rethinking Economics, 2019). Thus, political actions directed at maintaining climate change under the 2°C degrees increase for 2050 might as well affect economic prospects. In this context of “post-apocalyptic” future scenarios, the significant rise of nationalist political groups in Europe, or the appearance of a “revolutionary” movement like the “Gilets jaunes,” should not be surprising. As growth and added-value can be seen as the consequences of labor (Marx, 2006), and as employment is often considered as the prime source of wealth distribution, an analysis of the labor market and the risk of labor automation seems to be a good starting point to address those societal worries.

This study will therefore focus on technological change and its historical and expected outcome on unemployment, emphasis put on the Belgian case. As explained before, the reason behind this choice can be summarized by Drucker’s quote and the questions that ensued such a statement half a century after:

“The technological changes now occurring will carry the industrial revolution a big step further. They will not make human labor superfluous. On the contrary, they will require tremendous numbers of highly skilled and highly trained men – managers to think through and plan, highly trained technicians and workers to design the new tools, to produce them, to maintain them, to direct them.”

(Drucker, 1954: pp 22).

In particular, the concerns over Keynes’s prophecy of major technological unemployment and the related works of Frey and Osborne (2013) and Brynjolfsson and McAfee (2014).

The structure of the paper will be as follow. In the second section, I will present the three main phases of technological transformation and their impact on the organization of labor and employment. The first point will focus on the first and second industrial revolutions, the mechanization process, and the effects on aggregate employment, skills demand and the adoption of innovations. The second point will be dedicated to the more recent works on what is referred as the skill-biased technological change. In particular, the rise in the demand for skilled workers. In the third section, I will discuss the occupation-biased technological change approach and the concerns over the prospects of massive technological unemployment. I will conclude the second section by confronting those two approaches with the empirics. The third section will be dedicated to exploration on the model developed by Autor, Levy and Murnane (2003). I will then finish with some concluding remarks.

II. Technological transformation: automation and the Belgian labor market

Technological development has always had its pros and cons, anxieties about the impact of the implementation of new technologies on employment being numerous and going a long way throughout history. In 1589 already, Queen Elisabeth I, seeing the stocking frame knitting machine for the first time, displayed her fears about its impact on artisan employment, as quoted by Acemoglu and Robinson (2012). Another example could be the Luddite riots in Great Britain in the early 19th century, where workers attacked the machinery seen as responsible for their job losses. While technological unemployment has been discussed many times by well-known economists in the last three centuries, such as David Ricardo, John Maynard Keynes or Joseph Schumpeter, it has come forth, once again, as a menacing shadow for the future. In particular, Frey and Osborne (2013)'s paper have rose concerns about the future of employment. To gain understanding of the labor market projections and its link with recent technological change, a brief analysis of the long-term trends can be useful.

II.A. The first and second industrial revolution

After centuries of (near) absent efficiency gains, the exceptional productivity growth brought forth by the industrial revolution is an exception of the modern times. Common to all countries, its impacts on populations and nature induced tremendous transformation in labor organization. The starting point being similar for an important part of Europe, the case of Belgium is comparable in many ways to the one of UK. The revolution first reached the agricultural sector, who gradually increased its productivity by means of technological innovations and reorganization of the fields work. The spillover effect inducing changes in the industrial organization. The reasons being the considerable amount of workers "freed" from the agricultural labor and the mechanization process of the industry.

When considering the effects of the industrial revolution on workers and the labor organization, the famous examples of the working time per day, stressed by Marx (2006) and explaining the organization of work in the industry of England, comes to mind. The current law (speaking of the Factory Acts of 1850, still applied at the time) allows until ten hours work per day, six days per week. During the week, a normal day start at six o'clock in the morning and finish at six in the evening. Workers receiving half an hour for their breakfast and one for their lunch, thus working ten and a half hours per day. On Saturday, the factory close earlier so that they only work seven and a half hours. All in all, it is 60 hours per week. Marx process then further by producing quantity of examples of overtime in all types of industry (for child, women and men altogether). In most of the case, the use of machines as the main tool of the production process is given as an excuse for overexerting the labor supply. Working with machine being easier for workers, according to the entrepreneurs. This working day being the norm on the continent as well. For Belgium's industry, Neuville (1981) references similar trend for the workweek in the 19th

century. Another example can be found in Emile Zola (1988)'s description of the work in the mining sector. He finds working day of similar length for France and Belgium.

While these two pictures depict the situation at the end of the 19th century, only few attempts at studying the situation before the industrial revolution have been made. In this respect, the work of Mokyr (1976) on the industrialization in the low countries is to be acknowledged. In particular, after describing the Belgian pre-industrial proto-industry, he also presents the early stages of the labor organization transformation that occurred at the beginning of the 19th century.

In the case of Belgium, the theater of most major European wars until the beginning of the 18th century, the premises of industrial revolution are to be found quite early as well. From 1713 to 1794 – i.e. the Austrian period, while the urban population recovered slowly its previous level of 1700 (before the war of the Spanish succession), the rural population nearly doubled. For Mokyr (1976), the main reasons are to be found in the rise of the agricultural productivity brought forth by enclosures,⁴ drainage and poldering and the introduction of potato (which doubled the nutritional value of a unit of land planted with wheat and other traditional cereals). The other important factor being the growing rural “proto-industry”, consequence of the increasing population, and its output that was mostly exported. Thus, rising earnings to be allocated for food and importation goods. At the time, the rural industry was mostly composed of the linen industry in Flanders, the woolen industry along the Vesdre river in Wallonia and the metallurgical industries in Liège, Namur and Hainault.

The linen “proto-industry” was characterized by small production unit, mostly the household, and amounted up to a quarter of the population in East and west Flanders, and about 250,000 workers for the whole Flanders in the 18th century. Most of them being domestic workers. Representing therefore the biggest sector in Belgium (aside from agriculture) and accounting for around one third of the total industrial exports until 1840.⁵ The tools used in the linen production being mainly owned by the workers or rented cheaply. In 1804, Mokyr (1976) estimates the daily wage to be 0,34 francs for a spinner and 0,68 for a weaver. The population lived in extreme poverty.

Remnant of the middle age industry of Flanders, the woolen industry resettled around Verviers. According to Mokyr (1976), there around 37,000 workers were employed (about 10 percent of the population) and lived in a similar situation as in Flanders. Compared to the linen or the metallurgical industry, entrepreneurs and firms were responsible for an important part of the production.

⁴ The enclosure movement refers to the process of privatization of the common agricultural area (Enclosure Acts). Consequently, wealthy farmers would end up with larger and more complex farms and the number of farmers would drop by the years.

⁵ The enormous majority of the linen proto-industry were also agricultural workers. As agriculture was seasonal, linen work replacing fields work during low season (Mokyr, 1976).

Finally, the metallurgical sector comprised about 30,000 workers in the Liège, Limburg, Hainaut and Namur province. The production was mainly nails, pins and cutlery and the population also suffered from low wages and the truck system.⁶ According to Mokyr (1976), this can be seen as the situation in Belgium at the starting point of the industrial revolution. The transformation that occurred after, sometimes known as the first industrial revolution, are described in appendix 1. Particular emphasis is put on the two main industry of the time: textile and metallurgy.

The following tables come from one of the first reliable labor survey of Belgium and have been put together by Mokyr (1976). They summarize the situation after the earliest wave of the industrial revolution and its effects on employment. As the survey did not cover the rural-domestic workers, it can be regarded as the picture of urban Belgium after 50 years of industrialization. Therefore, it is important to be aware that the numbers of workers in the linen industry (and the other still active proto-industry) should be seriously underestimated as most of them were rural-domestic workers. Nonetheless, even after more than a quarter century of decline, the linen industry remained the largest employer of Belgium with as much as 216,855 workers in 1843 for the Flanders.⁷ Looking at the composition of the Belgian industrial labor force in table 1, and at the evolution in the composition of Belgian exports in table 2, allows a few conclusions:

First, having in mind that the survey only takes into account the urban labor force, the share of employed workers in the textile industry declined strongly. Although the number of employed workers rose for the cotton and woolen industry,⁸ the fall in the linen industry employment offset it. In this regard, mechanization has been labor savings for the textile industry.

Second, even after the introduction of labor saving technologies in the textiles production process, the old fashioned ways of productions remained for a long time. Indeed, as cotton and wool industry employed 7.9 percent of total employment altogether and accounted for 27.2 percent of Belgian exports in 1846. The linen industry employed 18.9⁹ but accounted for only 16.1 percent of exports. The coexistence of the old and new production process being usual in the Belgian industry:

“It is a common characteristic to most of the modern industries in Belgium that they existed side by side with remnants of the traditional manual sector, which resisted modernization for many decades.”

⁶ The truck system was employed in Belgium until the end of the 19th century (suppressed by law on August 16, 1886). Under this system, workers received all (or a part of) their pay in goods or in tokens (only used in the employer shops).

⁷ The difference in numbers between 1843 and the survey of 1846 comes from the domestic workers (Mokyr, 1976).

⁸ For the woolen industry, while the number of worker increased over the 50 years' period, its share in total employment still diminished as the population growth was tremendous.

⁹ This is a minimum. As stated before, as the study does not take into account domestic workers, the number of “employed” in the linen industry should at least be two time higher.

(Mokyr, 1976: pp 78).

	<i>Male</i>	<i>Female</i>	<i>Children under 16</i>	<i>Total Em- ployment</i>	<i>Firms</i>	<i>Total</i>	<i>Percentage of Total</i>
Coal mining	31,742	4,105	10,339	46,186	202	46,388	10.80
Metal	35,598	1,659	5,032	42,289	14,447	56,736	13.21
Quarries, potteries	25,945	1,265	4,555	31,765	8,399	40,164	9.35
Cotton	7,552	3,129	3,999	14,680	393	15,073	3.51
Wool	10,134	4,686	3,333	18,153	768	18,921	4.40
Linen, hemp, lace ^a	18,565	17,413	24,045	60,023	21,133	81,156	18.89
Other textiles	7,694	3,374	3,674	14,742	11,137	25,879	6.02
Glass	2,953	319	687	3,959	530	4,489	1.04
Paper	3,236	924	1,216	5,376	753	6,129	1.43
Foodstuffs	24,742	2,491	2,628	29,861	16,362	46,223	10.76
Leather	10,331	398	2,422	13,151	12,809	25,960	6.04
Wood	18,484	222	2,251	20,957	21,668	42,625	9.92
Others	10,808	688	2,204	13,700	6,150	19,850	4.62
Total	207,784	40,673	66,385	314,842	114,751	429,593	100.00

^aSee text concerning the significance of this row.

Table 1: Composition of the Belgian urban industrial labor force in 1846 (artisans included). Source: *Statistique de la Belgique, Recensement Général 1846, "Industrie"*, pp X-XI (in Mokyr, 1976: pp 80).

	<i>1831-35</i>	<i>1836-40</i>	<i>1841-45</i>	<i>1846-50</i>
Iron (pig and wrought)	0.75	1.34	6.15	10.82
Machines	2.11	4.77	5.93	4.76
Nails	2.58	3.24	3.59	5.71
Armaments	3.37	3.45	3.27	5.15
Total metal	8.81	12.80	18.94	26.44
Linen cloth, lace	41.14	36.86	26.04	16.14
Woolen cloth	11.39	14.72	19.20	17.27
Cotton cloth	9.06	7.16	7.74	9.97
Total principal textiles	61.59	58.74	52.98	43.37
Glass	1.10	3.67	8.41	13.92
Sugar	6.75	15.14	11.69	13.15
Paper	0.23	0.39	0.47	1.08
Others	—	9.26	7.51	2.04
Total industrial	100.00	100.00	100.00	100.00
Industrial exports as a percentage of total exports	58.01	56.94	52.40	46.42

Table 2: The composition of Belgian exports in percentages (1831-50). Source: *Statistique de la Belgique, Tableau Général du Commerce*, 1838 and subsequent issues, passim (in Mokyr, 1976: pp 79).

This phenomenon (still common today) is to be considered when making employment expectations on the impact of new technologies adoption. The social context being an extremely important factor in the implementation of labor saving innovations.

Third, while it is true that employment share has been decreasing in the textile sector, industrial employment as a whole increased substantially after the introduction of mechanization. Looking at the picture exposed in the 1846 survey. The rise in employment that occurred in the newly transformed mining and metallurgical sector (as well as in the glass and sugar sectors) more than compensate the employment loss in the linen industry. In this respect, taking a look at the composition of the Belgian's exports shares, and at the example presented in appendix 1 (for the number of employed person by industry), gives a good insight of the phenomenon.

Four, industrialization have impacted labor organization in many ways, one of them being labor concentration. Column "Firms" in table 1 being an unavoidable prove of that. Aside from the agricultural sector that was already reorganized toward concentration by the enclosure movement, most of the old proto-industry sectors were composed of domestic workers. This was specially the case in the linen and metallurgical industry. Instead, the newly born modern industries are mainly of important size, as appear clearly when looking at the mining, cotton, glass and paper industries. This is also an evidence when considering the flourishing example of gigantic plant like John Cockerill's in the metallurgical sector, or the number and size of active spinning machine and steam engine in the modernized woolen industry.¹⁰

And lastly, the deskilling impact of mechanization on workers and labor demand. In all the modern industry, machines are at the center of the production process. Workers mostly operate them by specializing in one (or sometime a few) task. When in the old time, they used to work at each step of the production process, work is now separated between the different tasks to be provided. Common for all types of industries, be it textile or metallurgy, workers have merely become production tools when they were artisans before. In this regard, the example of the assembly line might be the strongest. Even if its invention is not dated as early as that (more or less at the turn of the 19th century), it is the result of decades of the specialization process of worker tasks that started with mechanization and the industrial revolution.

What followed after the first industrial revolution will only be sketched in the next paragraphs. As most of the technologically induced transformation of the labor organization depicted earlier went on until the mid-20th century, I will just reference the most important trends that were not labeled yet.

First, it is important to note that the phenomenon that ensued the mechanization process of the first half of the 19th century have continued through the 20th century and until the computer-era. In particular, while suffering from a few slowdowns, productivity gains

¹⁰ In Verviers, for example, the output of capital goods for the linen industry was 554 carding machines, 3,062 spinning machines for fine yarn, 1,650 shearing machines, etc. just for 1812 (Mokyr, 1976).

continued even stronger hereafter. The process of the concentration and specialization (deskilling process) of labor continued as well. The example of Henry Ford and the production of the Ford T model being a typical one. Aside from the size of the plant itself, the production process designed by breaking down the production steps in separated task, to be performed on the assembly line, allowed to bring down the time needed for the production of a Ford T from 12 hours to 93 minutes (ThoughtCo, 2019). Therefore, productivity gains acquired through the concentration of labor strengthened the decreasing trend of the old domestic sectors. Nearly disappearing completely since then. The textile industry employment share decline continued as well, being supplanted by the mining and metallurgical sectors. All in all, the domestic industrial sectors faded away as the accrued concentration of work accentuated the deskilling trend of labor demand and supply.

Second, the fall in the length of the workweek. In the US for example, passing from an average of 70 hours worked per week in the marketplace in 1830 to 41 by 2002 (Greenwood and Vandenbroucke, 2005). Most of it was acquired since 1900. In the case of Belgium, a similar trend can be observed until the mid-1970s where the number of hours worked per worker continued to fall in the case of Belgium, when it remained nearly constant for the US (Biatour and Kegels, 2015). Since the early nineties, it stagnated for Belgium as well. The difference with the US accounting for more than 140 hours worked per worker for 2014.

Third, the rise of the real wage, out of which the most part occurred since the end of the first world war, who rose by nine time since mid-18th century. While real wage has been rising secularly since its level has been recorded (Piketty, 2013; Autor, 2015: 1) the trend has been reversed since the middle of the seventies and the first petroleum choc (Greenwood and Vandenbroucke, 2005). Since then, it is slightly falling.

Lastly, the rise in the participation of women to the labor market, which accounted for a huge part in the decline of hours worked per worker. As described in Greenwood, Seshadri and Yorukoglu (2005) the revolution bring about by the adoption of new goods for home production, like the vacuum cleaner or the washing machine, or time saving equipment, like frozen foods, has allowed for a rising share of women participation to the labor market. The portion of married women taking part in the labor marked rising from less than 10 percent in 1900 to more than 60 percent in 2000 (Greenwood and Vandenbroucke, 2005). All those changes being the consequences of technological progress leading workers away from work (even calling these technologies “engines of liberation”). This have been challenged by the estimates of home production time found by Ramey (2009), showing no decrease in the total time spent at home production (aggregated over the whole population).

In a sense, the drop in the workweek length and the reduction of dedicated time to home production referenced by Greenwood and Vandendroucke (2005) could be seen as what Keynes speculated to be forthcoming: the abundance of leisure time, or massive

technological unemployment.¹¹ This point of view has been challenged by the real business cycle theories. For example, Prescott (1986) assessed the stagnation over the decades of leisure time while real wage increased gradually. More recently, the work of Ramey and Francis (2009) presents interesting data on the subject. By building time allocation measure incorporating human capital accumulation (schooling) and time spend in home production, they present data on the US population allocation of time through the 20th century. Their results are quite puzzling when compared to previous studies:

“The new measures reveal a number of interesting twentieth century trends. First, hours worked per member of the working age population have declined much less than hours worked per worker. Although hours per worker declined by almost 16 hours per week during the last century, hours per member of the working-age population have declined by between five and six hours per week. Second, all of the decline in hours worked per capita has been concentrated among the young, ages 14-24, and the old, ages 55 and up. Prime-age individuals between the ages of 25 and 54 are working the same number of hours now as in 1900 because the rise in female hours in this age group has offset the decline in male hours. Third, the decline in hours worked among the young did not translate into a rise in leisure. Instead, almost all of the decline in work hours was reflected in a rise in school hours in this age group.”

(Ramey and Francis, 2009: pp 190-191).

This could be considered as contradictory to the idea that industrialization induced a deskilling process in the labor supply and demand. But it is not the case. Indeed, mandatory schooling was not yet the reference in the 19th century.¹² But, even more than that maybe, the skills needed by the industrial sector changed through time. Before mechanization, most of the workers spent an important part of their time as apprentice of a master. The modern production process having no need for this type of qualification as the introduction of machine typically substituted for an important range of skilled labor. In the modern textile industry that appeared in the early 19th century, for example, workers mostly operated machines. Therefore, focusing their skills on one or two actions only. For the 20th century, the rise of the educated workers being able to read was of importance to the industrial sector as it began easier to convey orders, for example. At the same time, most of the workers were still specialized in so few different types of action that the idea of “alienation” of the worker to made its appearance (Marx, 1996, 2006; Weil, 1951).

¹¹ Other authors going even further by advocating “the right to be lazy” for every human (Lafargue, 1880).

¹² An example of the importance of child labor in Belgium can be found in the column “children under 16” of table 1.

II.B. The computer revolution and the skill model

In 2003, Autor, Levy and Murnane, with their study on “the skill content of recent technological change”, tried to explain the correlation between the increasing share of high-educated workers within industries and the adoption of computers. Their theory, known as the Skill-Biased Technological Change (SBTC) approach, presents striking results of a bias towards routine tasks computerization. Their paper provides an empirical analysis of the task input, from 1960 to 1998, in the United States. The model relies on the postulates that:

“Computer capital substitutes for workers in performing cognitive and manual tasks that can be accomplished by following explicit rules – i.e. routine tasks – and complements workers in performing non-routine problem-solving and complex communications tasks”

(Autor, Levy and Murnane, 2003: pp. 1279).

As the price of computer capital decreases over the years, the model predicts that routine labor intensive industries in the 60’s should have larger computer capital investment than others. Therefore, the demand for humanly provided routine task input should drop, being substituted by computer capital, and demand for non-routine task should rise, being complemented by it. The intuition behind the analysis is further supported by the evidence found in the data from the Dictionary of Occupational Titles (DOT),¹³ Census and Current Population Survey (CPS). According to the authors, this database has the advantage to account for the transformation in the content of task input within industries, as it measures the tasks performed rather than the education of workers. Particularly, emphasis can be put on the pervasiveness of the task shifts away from routine labor input and toward non-routine labor input for all educational level. This being an improvement compared to previous studies.

To construct their model, Autor, Levy and Murnane (2003) first identify the tasks that can be performed by computers. That is, repetitive tasks that can be translated into programmed rules – i.e. routine tasks – are performed faster and more accurately than by workers. Polyani’s paradox¹⁴ setting the boundaries of computerization by excluding non-routine tasks from it. As will further be shown in the paper, this fundamental assumption will be challenged only ten years later by Frey and Osborne (2013). Computer capacity having outrun their growth expectations with the emergence of new learning process.¹⁵ Which allows computer capital to go further than just performing repetitive tasks determined by programmed rules (instructions that designate which actions to perform in

¹³ DOT provides objective and subjective detailed information on occupation, in order to classify and place workers and work seekers along dimensions such as required aptitudes, training times, skills, etc. Starting in 1939, it covers data until the nineties, its successor is the O*NET database.

¹⁴ Stating that “we know more than we can tell”, Polyani (1966, pp 4 as quoted by Autor, Levy and Murnane, 2003) express the idea that there is knowledge that cannot be expressed by rules, as it is usually the case with arts or social interaction.

¹⁵ This have been made possible through the availability of bigger and bigger data sets, known as big data.

order to achieve the chosen results). The renewed interest over technological change and its impact on the labor market, as stated in Autor, Levy and Murnane's paper (or in the related literature), can be summarized as follow: while in the pre-computer era the adoption of new technology spurred out routine input provided by humans. It can now be automated through computerization instead. This transformation in the structure of the labor market occurring faster as the real price of computer technology fell down quite drastically over the years. Therefore, ensuing an economy wide reallocation of tasks.

To assess the extent of the shift in the skill content, Autor, Levy and Murnane (2003) rely on data from the US labor's department DOT, the Integrated Public Micro Samples (IPUMS)¹⁶ as well as the CPS Merged Outgoing Rotation Group (MORG).¹⁷ Using full-time equivalent hours, the authors examine the employment occupational distribution change over time (called the "extensive" margin), and the evolution of the tasks content within occupation (referred as the "intensive" margin). Setting 1960 as the base period distribution of task input, reproducing the pre-computer era, they selected five variables reflecting their task constructs (see appendix 2, table 6 for the complete description of the selected variable).¹⁸ Measured results thus expressing the task input distribution change compared to its initial level.

This choice of variable, being perhaps adequate in 2003, have been challenged less than ten years after the publication of their paper. The reason being explained by the technical advance in the computation power and the means to process data. While the chosen variables were accurate to express the extend of computerization of routine task at the time, computer "routinization" has spread to many other tasks and occupations since then. Even if their model differs, Frey and Osborne (2013) have shown that other variables¹⁹ might be more effective (and/or more available) to express the risk of automation of routines tasks today. This view was also shared by Nedelkoska and Quintini (2018) who slightly modified some of them to compare the explaining power of the two approach.

Turning to the results. On the aggregate, as expected computer capital demand is higher in routine task intensive industries. Either looking at its adoption or its on-the-job use. The share of labor force employed in non-routine tasks occupations, except from manual, has increased faster in the computer era (1970 and onwards). Whereas routine tasks occupations have declined substantially, while rising in the pre-computer era. Panel A of

¹⁶ IPUMS provides census and survey data from around the world. They produce harmonized variable codes and documentation to be consistent across datasets. The purpose being comparative research, merging information across data types at an individual level (<https://ipums.org/about/what-is-ipums>).

¹⁷ "Extracts from the Current Population Surveys monthly cover 1979 through the most recently completed calendar year. Fifty or more variables each month are selected for continuity across years." (<https://www.nber.org/data/morg.html>).

¹⁸ Direction, control, and planning of activities (DCP) and a measure of quantitative reasoning (GED-MATH) for non-routine cognitive tasks; adaptability to situation requiring set limits (STS) for routine cognitive; finger dexterity (FINGDEX) for routine manual; and the ability to move with coordination (EYEHAND) for non-routine manual.

¹⁹ Using the O*NET database, successor of the DOT. For further explanation and complete description of the variables, see point II.C.

table 3 presents the summarized results by tasks on aggregate and by gender. While the changes are pervasive along all dimensions, the Bell-shaped curve for the routine tasks inputs appears more pronounced for females. This being even clearer when looking at non-routine analytic and non-routine interactive tasks inputs. Autor, Levy and Murnane's (2003) explanation is to be found in the rapidly increasing share of women participation in the labor market. Their stock of job tasks being impacted faster by the demand shift than men's.

A. Weighted means of economywide task input by decade (percentiles of 1960 task distribution)															
	1. Nonroutine analytic			2. Nonroutine interactive			3. Routine cognitive			4. Routine manual			5. Nonroutine manual		
	All	Male	Fem	All	Male	Fem	All	Male	Fem	All	Male	Fem	All	Male	Fem
1960 (Census)	50.0	54.6	37.0	50.0	58.4	26.4	50.0	48.6	53.8	50.0	43.2	69.2	50.0	56.5	31.6
1970 (Census)	52.5	57.5	41.5	51.1	61.7	27.5	52.2	49.8	57.5	54.0	44.9	74.4	46.9	54.1	30.8
1970 (Census)	51.9	56.4	41.8	50.7	60.8	28.1	53.1	50.8	58.2	53.5	44.7	73.3	46.2	53.2	30.7
1980 (Census)	54.9	58.2	49.2	55.4	63.3	41.8	52.9	50.0	58.0	55.1	44.6	73.3	44.0	53.2	28.1
1980 (CPS)	53.2	56.6	47.9	53.3	61.4	40.4	51.8	50.0	54.8	53.8	43.3	70.4	44.4	55.0	27.5
1990 (CPS)	56.2	57.4	54.6	58.6	62.7	53.0	48.3	48.1	48.6	52.3	42.8	65.5	41.8	53.1	26.3
1998 (CPS)	58.7	59.3	58.0	62.2	63.9	59.9	44.4	46.6	41.6	49.2	41.5	59.3	41.3	52.6	26.5

B. Decomposition of task shifts into between and within industry components for combined genders (10 × annual changes in mean task percentile)															
	Total	Btwn	Wthn	Total	Btwn	Wthn	Total	Btwn	Wthn	Total	Btwn	Wthn	Total	Btwn	Wthn
1960–1970	2.57	1.74	0.83	1.15	−0.34	1.49	2.20	1.14	1.06	4.01	2.39	1.62	−3.03	−2.28	−0.74
1970–1980	3.02	1.54	1.48	4.68	0.26	4.42	−0.14	0.33	−0.47	1.63	0.79	0.84	−2.25	−1.00	−1.25
1980–1990	2.97	0.92	2.05	5.31	0.52	4.79	−3.48	−1.42	−2.07	−1.47	−0.16	−1.31	−2.58	−1.27	−1.31
1990–1998	3.12	0.67	2.45	4.48	0.54	3.94	−4.88	−1.31	−3.57	−3.88	−0.38	−3.50	−0.63	−0.31	−0.31

Table 3: Weighted means of task input and the decomposition into between and within industry components, by decade. Source: Autor, Levy and Murnane (2003, pp 1298).

At first sight this can look like the right answer, but it might not add-up with the empirics. In particular, one could find puzzling that in a similar situation regarding their participation rate, young workers seem to be more exposed to the risk of automation (Autor 2015, Nedelkoska and Quintini 2018). Another explanation can be found in Ramey and Francis (2009). Their study, focusing on the change in leisure time in the United States over the 20th century, also covers the amount of time devoted to schooling. For young people aged 18 to 24 years old, males average weekly hours²⁰ of school time rose from 6.6 in the sixties to 6.8 in 2005, while women's skyrocketed from 3.6 to 9.3 over the same period. Women's school time having exceeded men's by 1980. Autor (2015) also references for the same period that the share of hours worked by women with fewer than ten years of experience have increased significantly for college graduates, while remaining stable for men. Therefore, whereas one of the reasons for the shift to be more noticeable for women

²⁰ The data have been averaged over the entire year and are consistent with Goldin (2006) findings.

than men could be found in the participation rate, this might not be the main one. Another important candidate being the rise in time devoted to schooling.

This reason has also met a few critics and concurrent approaches have emerged since then. Notably, the one proposed by Sachs, Benzell and LaGarda (2015) who analyses the diminished demand for young laborers in a multigenerational economic environment. The young generations suffer more from technological change because the fruits of it are consumed by the old. Young people thus facing stronger credit constraint reducing their human capital accumulation and diminishing the demand for their labor. This explanation is also a good candidate in the case of Belgium, the legislation being particularly favorable towards older people.²¹

Nevertheless, the rising share of non-routine versus routine tasks labor is consistent with a number of follow-up studies. Notably Goos and Manning (2003), Goos, Manning and Salomons (2009, 2014) or Autor and Dorn (2013) who studied the polarization of the labor market in the United States and in Europe. Job polarization can be summarized by the description made by Autor (2015):

“Because jobs that are intensive in either abstract or manual tasks are generally found at opposite ends of the occupational skill spectrum – in professional, managerial, and technical occupations on the one hand, and in service and laborer occupations on the other – this reasoning implies that computerization of routine job tasks may lead to the simultaneous growth of high-education, high-wage jobs at one end and low-education, low-wage jobs at the other end, both at the expense of middle-wage, middle education jobs. A phenomenon [...] called job polarization.”

(Autor, 2015: pp 12).

Other types of studies have also produced similar results. Looking at the impact of the adoption of industrial robots, Acemoglu and Restrepo (2017) showed that routine labor intensive industries were faster and more prone to adopt new industrial robots than non-routine labor intensive industries. This clearly shows when looking at the data on the distribution share of industrial robot per economic sector. With only four industrial sectors totaling 76 percent of the robots in 2007 (automotive, electronics, metal and plastic and chemicals).

Table 3 panel B also presents the within and between industry decomposition, with the within component explaining most of the task input shift in every ensuing decade after the pre-computer era. But are those tasks shifts explained by the adoption of computer capital? Autor, Levy and Murnane (2003), looking at the relationship between computer adoption and the task input change at the within industry level, provide large and statistically significant positive estimates for non-routine tasks inputs (and similar negative

²¹ Nedelkoska and Quintini (2018) have shown that the most exposed population to technological change was either young or old worker. The case of Belgium being somewhat of an exception with younger workers being more exposed than anywhere else while older workers being the less exposed of Europe.

ones for routine tasks inputs). The magnitude of the estimates growing in each subsequent decade, while being non-significant before the computer era, thus clearly in line with the model's expectations. Furthermore, relying on the dataset National Income and Product Accounts (NIPA)²² allows for deeper insight into industries investment. Comparing between industrial investments, they show that industries that allow a relatively greater share of their investments to technology are responsible for the major part of the shift away from routine tasks and towards non-routine tasks.

To assess their claim that the tasks shift favoring educated labor is a consequence of technological change, Autor, Levy and Murnane (2003) look at the changes within education groups and within occupations. First, looking at the occupational composition (extensive margin), they find that the computer capital level is predictive of the shifts for all educational groups, particularly for the middle of the educational distribution. But their results are not significant. They also find the shift in task content to be mainly explained by the within educational group components. They follow up by analyzing the change in the occupations themselves. That is, most of the occupation description provided by the U.S. labor department evolved through the decades.²³ This time the results are all significant and of the right signs, but unexpectedly intra-occupational changes seems insensitive to the educational distribution of its employees.

As their analytic method focuses on the change of tasks within educational groups, it measures how strongly members of a particular group are affected by technological change. That is, how important is the technologically induced reallocation of tasks in that group. The reason the most affected groups are the ones in the middle of the educational distribution can be described as follow: more educated workers are expected to already be employed in non-routine intensive tasks and should therefore be less affected by computerization; less educated workers are expected to be employed in routine intensive tasks but may not have the human capital needed to reallocate it towards non-routine tasks. Hence, the consequences for this last category of person is quite dramatic.²⁴ A

²² The NIPA provides data on capital stocks accumulation for a list of major industries in the U.S. In particular, it presents useful measures of computer capital investment (in hard and software).

²³ An example could be the description of the job of secretary, from labor's Occupation Outlook Handbook, as presented in Autor, Levy and Murnane (2003). In 1976 the description says: "Secretaries relieve their employers of routine duties so they can work on more important matters. Although most secretaries type, take shorthand, and deal with callers, the time spent on these duties varies in different types of organization" (U.S. Department of Labor 1976, pp 94). Later, its description changed to: "As technology continues to expand in offices across the Nation, the role of the secretary has greatly evolved. Office automation and organizational restructuring have led secretaries to assume a wide range of new responsibilities once reserved for managerial and professional staff. Many secretaries now provide training and orientation to new staff, conduct research on the internet, and learn to operate new office technologies" (U.S. Department of Labor 2000, pp 324). Since then, the number of software or their relative importance in the job of secretary have never ceased to grow. The required knowledge for what used to be mostly a routine task intensive job is nowhere close to what it was less than forty years ago. The majority of the required skills being now centered around non-routine tasks.

²⁴ This is in itself a puzzling point of the model developed by Autor, Levy and Murnane (2003): by only looking at the shift in demand and supplied tasks, their model is not well suited to account for the risk faced

decrease in the price of computer capital reducing their nominal wage by the exact same amount (by assumption), less-educated workers real wage will shrink as long as the effect on goods price does not compensate the drop in nominal wage (which is something totally unexpected to happen).²⁵

One of the major concern over new technological development and the need for more educated workers is the recent polarization of the labor market that started since the beginning of the computer era. As have argued numerous authors,²⁶ the rising evidences that automation of medium and low-skill occupations has accentuated employment polarization and wage inequality play a huge part in the worries about massive technological unemployment. As an example, the overview proposed by Acemoglu and Autor (2011) for the evolution of the real wage income distribution, from the sixties until today in the United States. Aside from college graduate and higher educated workers, who have seen their wage rise over this time period, most workers have seen their real wage reduced since the first petrol shock. The less educated workers having either lower or equal wage compared to 1963.

All in all, the task model they developed explains from 25 to 65 percent of the relative demand growth for college employment in each decade following 1970, accelerating through the years. A huge part, almost 40 percent of it, being the consequence of the what the authors call the “shifts in task composition within nominally unchanging occupations” (pp 1321). The fundamental assumptions from the authors seem rather on mark. With the falling computer price, labor routine tasks are being substituted for, while tasks requiring creativity, adaptability or social intelligence are being complemented. Therefore, inducing the well referenced shift of demand towards more educated workers observed since the beginning of the computer era. This phenomenon, occurring faster in routine labor intensive industries, is at the center of recent studies that looks at the future of employment. Being somewhat one of the first to clarify, in economic terms, what are the characteristic of the new industrial revolution of “computer capital induced technological change”, a thorough insight appeared to be needed before proceeding further with this analysis.

by the population. The workers facing the higher risk of seeing their situation deteriorated (for example by losing their jobs to automation) does not appear clearly in the statistical analysis.

²⁵ See section III for more details on the subject. For productivity gain distribution, see Piketty (2013) and Oxfam (2019).

²⁶ Here is a non-exhaustive list: Goos and Manning (2003), Goos, Manning and Salomons (2009, 2014), Autor (2015; 1 and 2), Mokyr, Vickers and Ziebarth (2015), Arntz, Gregory and Zierahn (2016) Acemoglu and restrepo (2017, 2018 and 2019), or Nedelkoska and Quintini (2018).

II.C. The 21st century, big data and the occupation model

To understand the extent of the transformation induced by computers technologies, it is needed to know what they do and how it impacts employment. While Skill-Biased Technological Change (SBTC) models have been prominent in doing so for the end of the 20th century. Being aimed at:

“[formalizing and testing] a simple theory of how the rapid adoption of computer technology – spurred by precipitous real price declines – changes the tasks performed by workers at their jobs and ultimately the demand for human skills.”

(Autor, Levy and Murnane, 2003: pp 1280).

Other new studies have shown great results in explaining the labor market development characteristics of the 21st century.

Notably, Frey and Osborne presented in 2013 a framework grounded on the extrapolation of what computer will do in the near future. Their point is that the increasing availability of big data²⁷ will reorganize and affect the labor market stronger than ever. These new technology advances, and in particular their effects on machine learning (ML) and mobile robotics (MR), enhancing the risk of automation and computerization. Whereas this is not a new characteristic of technological change, the computerization of routine jobs occurring since a few decades already, this is a first for non-routine jobs. Therefore, the destruction of labor brought by these changes could outrun its creation effect – i.e. new uses for labor – as feared by Keynes in his famous quote on technological unemployment (Keynes, 1933).²⁸

Taking into account the now wider range of tasks at risk of automation, thus reflecting the advances in MR and ML, they part with previous studies by including the susceptibility of non-routine tasks automation. To do that, they build on the task model from Autor, Levy and Murnane (2003) and implement it as to display new and expected technological progress and their computerization effect. By adopting this stance, they produce a measure of the potential destruction component of new technical advance. They present the measure of “automatability” for each referenced types of occupation in the US. The accuracy of this measure to assess the extent of job computerization and its expected impact on the labor market have been subject to critics. Notably, Autor (2015, 1) for the US, or Arntz, Gregory and Zierahn (2016) for the EU, argue that even newly available technologies would still require to be recognized as socially “proper” to be adopted.

²⁷ “Large and complex datasets” (Frey and Osborne, 2013: pp 15).

²⁸ The very idea behind their paper is the increased range of tasks able to be (or that will be, in the near future) performed by computer. As developed in Brynjolfsson and McAfee (2011) or McKinsey Global Institute (2018), the scope of what computer can do is growing further and further away from just the previous referenced “routinization” of tasks. Being now called “The second machine age” (Brynjolfsson and McAfee, 2014), autonomous cars, pattern recognition allowing computer to decipher handwriting or health care medical diagnostics provided by computer are particular example of non-routine categorized labor being computerized or at risk of computerization.

Examples of this ordeal are the virulent critics or destruction (of these new technologies) that have always occurred throughout the centuries.²⁹

One of the major differences between the task and the occupation model developed by Frey and Osborne (2013) can be found in its underlying objectives. While the first can be described as downward looking. That is, it tries to ascertain the reason behind the increasing share of high educated workers taking part in the labor market. A feature pervasive for all sectors and industry and occurring since the early seventies. To do that, they focus on the shift away from routine task and toward non-routine task, attributed to technological developments. In their model, individuals and firms adopt a maximizing stance. The causal force of the model thus being the decreasing price of computer capital. The second is considered forward looking. Not only the center of the analysis is here the new technological development, the causal force can be regarded as the possible adoption of those “not yet developed technologies.” Expected that it will impact strongly the labor market in the future. This last type of theory presents the major drawback to be difficult to test against empirical data (or at least that was the case at the time of their publication).

In order to address the question “how susceptible are jobs to computerization?” they develop a methodology to categorize occupations. They then estimate the probability of computerization for each occupation. This allows Frey and Osborne (2013) to examine the expected impact of future technological change on the labor market. One could do so by adopting a “technological capabilities point of view” – i.e. to highlights technical problems yet to be solved by engineers. The analysis relies on the O*NET³⁰ database which allows to account for particular change on the six-digit SOC occupations level for either routine and non-routine tasks computerization. To ascertain the range of technological capabilities, they ask experts to answer the question:

“can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer controlled equipment?”

(Frey and Osborne, 2013: pp 30).

²⁹ One of the most recent examples could be the electric scooter that has been the center of many arguments. Either welcome or banned, applauded or disregarded for environmental purpose, they have been the focus of debates since their first appearance (En Marche, 2019; South-Park season 22: “The Scoots”).

³⁰ The O*NET database is the successor of the Dictionary of Occupational Titles (DOT), depicted earlier in the paper. It presents detailed information on “903 occupations, most of which correspond closely to the Labor Department’s Standard Occupational Classification (SOC)” (Frey and Osborne, 2013: pp 28). The Standard Occupational Classification (SOC) system, developed for the U.S. government, is “a federal statistical standard used by federal agencies to classify workers into occupational categories for the purpose of collecting, calculating, or disseminating data. All workers are classified into one of 867 detailed occupations according to their occupational definition. To facilitate classification, detailed occupations are combined to form 459 broad occupations, 98 minor groups, and 23 major groups. Detailed occupations in the SOC with similar job duties, and in some cases skills, education, and/or training, are grouped together.” Obtained from the Bureau of Labor Statistics website (<https://www.bls.gov/soc/>).

From the answer to this question they identified three engineering bottlenecks tasks characteristics non-susceptible to computerization: “perception and manipulation tasks”, “creative intelligence tasks” and “social intelligence tasks”. This particularly allows them to set the boundaries of non-routine tasks computerization and thus estimate the susceptibility of automation for a range of specific occupations. The experts then subjectively hand-labelled 70 of them as automatable (1) or not (0). Finally, they rely on nine objective O*NET variables to correct the potentials errors from subjectively hand-labelling occupations. And hence develop a probabilistic classification algorithm³¹ to produce “automatability” estimate for the other occupation. Each chosen variables are used as proxy (or indicators) for the identified computerization bottleneck. Table 4 presents the chosen engineering bottlenecks, the associated objective variables from the O*NET database and their description. As I have argued in point II.B, this choice of variable seems to reflect more accurately the extent to which task are at risk of computerization than the one selected by Auto, Levy and Murnane (2003). The main reason being maybe the release year of their respective paper. A ten years’ difference is in no way a small amount of time, regarding computer capacity in the history.

The identified engineering bottlenecks, and their associated objectives attributes, where quite well received by the scientific literature. Despite that, the methodology employed to pinpoint them has suffered critics. For example, Arntz, Gregory and Zierahn (2016) are concerned about the selection of the objective variables. Notably, the fact that they were only identified after defining the engineering bottlenecks. Therefore, taking no part in the hand-labelled selection of the occupations used as the basic material for their probabilistic classification.

³¹ To test their classification model, Frey and Osborne (2013) first apply it to their 70 hand-labelled occupations, and produce vectors representing the mean “automatability” of an occupation. All nine O*NET variables being weighted equally. Hand-labelled occupation being branded as fully “computerisable” are expected to present similar results when looking at the selected variables (Table 4). After this first test drive, they use the model producing the best results for the discriminant function (which can be described as a continuous function of the “automatability” of an occupation) to evaluate the risk of automation for the other 632 occupations.

Computerisation bottleneck	O*NET Variable	O*NET Description
Perception and Manipulation	Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
	Cramped Work Space, Awkward Positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Creative Intelligence	Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
	Fine Arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.
Social Intelligence	Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.
	Negotiation	Bringing others together and trying to reconcile differences.
	Persuasion	Persuading others to change their minds or behavior.
	Assisting and Caring for Others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.

Table 4: The identified bottlenecks to computerization and the indicators variables from O*NET database. Source: Frey and Osborne (2013, pp 31).

This analysis of technological impact on the level of employment presents the major drawback of being confined to its substitution effect. Indeed, looking only at the risk of computerization of an occupation does not take into consideration the labor creation effect behind the adoption of new technologies. Even more important maybe, their model speculates on the advance of technology itself and the potentiality of the computerization bottleneck to be overcome. Therefore, it cannot be used to forecast changes in the labor market occupational composition. Rather, it just focuses on the future potentiality of job automation – i.e. pure technological change itself. Nevertheless, the market outcomes predicted by their model are puzzling. Frey and Osborne's findings, as those of Autor, Levy and Murnane (2003), and Autor and Dorn (2013), or more recently Nedelkoska and Quintini (2018), suggests that new technological developments in ML and MR will have two major impacts. One being negative for employment: it will reduce labor demand for tasks that can be computerized by means of pattern recognition.³² And one being

³² In Frey and Osborne (2013). Pattern recognition refers to new learning means for computer to transcend what Autor, Levy and Murnane (2003) originally called the computer "routinization" of tasks (computerization by means of explicitly codified or programmed rules, usually known as "routinization"). The difference being the process through which the knowledge is learned by the machine: while one is to be represented by rules designed by humans (coded), the other can be considered as the consequence of a particular learning process of trial and error conditioned by the available sets of big data.

favorable for employment: it will augment demand for non-susceptible to computerization tasks. The extent to which a task can be computerized widely differs from one article to the other. Frey and Osborne's estimations are as follow: the total share of US employment being in the high risk automation category is 47 percent. It means that the associated occupations are, or should soon be, automatable (maybe in 10 to 20 years from now). Figure 1 presents the risk of automation by categories, occupations being either at high risk of automation (>70% probability), middle or low (<30% probability). The biggest share of high risk occupation being office and administrative support, services and sales.³³

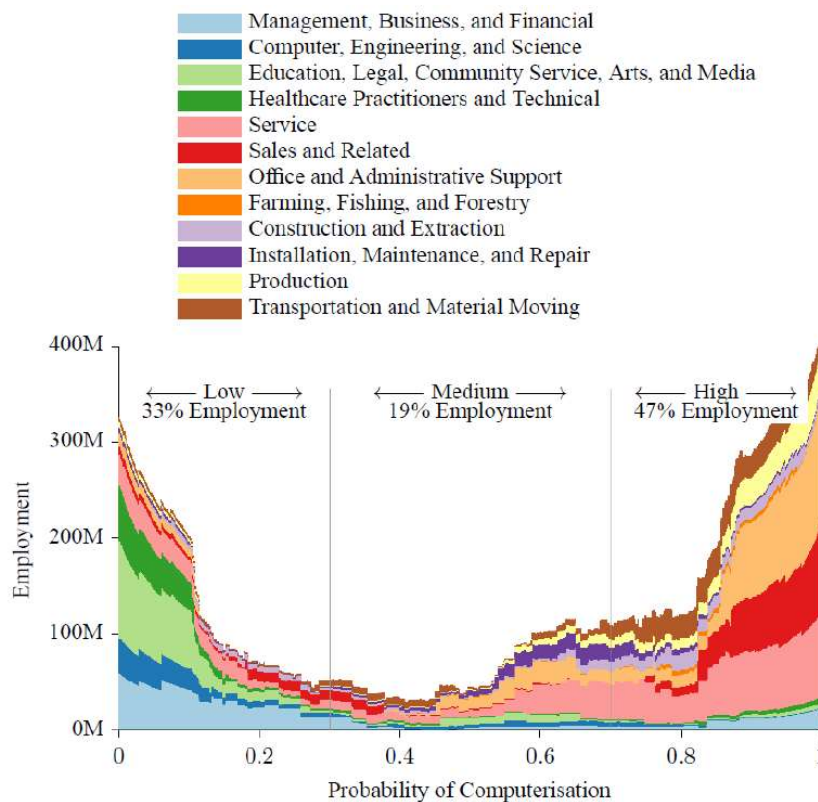


Figure 1: US employment automation risk. Source: Frey and Osborne (2013, pp 37).

A few authors have expressed their concerns over Frey and Osborne's approach choice. Notably, Arntz, Gregory and Zierahn (2016), who were fast to react to the paper, argued that it was rather tasks that were being automated and not the whole occupation itself. Therefore, as most of the occupation listed in the high risk automation category comprise at least some task that will not be fully automatable soon, the risk of automation presented in Frey and Osborne (2013) might be seriously overestimated. Instead of their high two-digit estimate, Arntz, Gregory and Zierahn (2016) present a significantly lower risk of automation while using the same framework. The only change being their assumption of

³³ On the other hand, main low risk occupations include, in order of importance: healthcare practitioners and technical; management, business and financial; education, legal, community service, arts and media; computer, engineering and science.

task automation in place of occupation automation. Moreover, their analysis is built on PIAAC data. Their estimates of the share of workers being at risk varies in between 6 percent for Korea to 12 percent for Austria. For example, US have 9 percent of their workers in the high risk of automation category (compared to 47 in Frey and Osborne's case). Nevertheless, as Nedelkoska and Quintini (2018) have pointed out, this still amount to 13 million jobs for the US only (based on 2016 employment figure). This share has been estimated between 7 percent (Arntz, Gregory and Zierahn, 2016) and 14 percent (Nedelkoska and Quintini, 2018) for Belgium.³⁴

Frey and Osborne's model suggests as well, albeit the labor market polarization trend massively referenced and observed over the last decades (notably: Goos and Manning, 2003; Goos, Manning and Salomons, 2009, 2014; Autor and Dorn, 2013), that future computerization will mostly affect low-wage and low-skill jobs instead of middle-income routine jobs. Thus leading to even more inequalities before wage and wealth. As Autor (2015, 1) have stated, the problem of wealth distribution will remain a major issue in market economies, be it a world of abundance bring about by automation with superfluous human labor or not.³⁵ This view is shared by Piketty (2013) who depicted capital ownership and its recent evolution.

Follow-up studies have also produced high estimates for Europe (Bowles, 2014; Pajarinen and Rouvinen, 2014) and other countries. All relying on the risk of automation per occupation calculated by Frey and Osborne (2013). For example, Brzeski and Burk (2015) find the share of jobs at risk of automation to be 59% for Germany. Those studies share the assumption that the difference in the share of jobs being at risk of automation only comes from the occupational structure of each country.³⁶ In this regard, critics have emerged about the choice of an occupation based approach.³⁷ In particular, to simply translate automation estimates of specific occupations from one country to another also present its cons, as the content of an occupation differs quite importantly by regions. For example, Autor, Levy and Murnane (2003) and Spitz-Oener (2006) have argued that while

³⁴ The results presented for Belgium are to be taken under caution as the data used to produce them only reflect the situation of the Flemish Region. Not only there are huge differences in the occupational structure between regions but also in the tasks structure of the occupation itself. Thus, the estimated share of workers being at risk could be downward biased.

³⁵ "A final point, typically neglected in recent dismal prophesies of machine-human substitution, is that if human labor is indeed rendered superfluous by automation, then our chief economic problem will be one of distribution, not of scarcity. The primary system of income distribution in market economies is rooted in labor scarcity; citizens possess (or acquire) a bundle of valuable "human capital" that, due to its scarcity, generates a flow of income over the career path. If machines were in fact to make human labor superfluous, we would have vast aggregate wealth but a serious challenge in determining who owns it and how to share it. One might presume that with so much wealth at hand, distribution would be relatively straightforward to resolve. But history suggests that this prediction never holds true." Autor, 2015 (1): pp 28.

³⁶ Indeed, using the risk of automation produced by Frey and Osborne (2013) for the US, to express the risk of automation for the same occupation in Europe (or in other country) is similar to saying that, as long as the title of the occupation is identical, the occupations are unchanged (rely on the same organization and tasks, ...). This is not consistent with the observed data.

³⁷ Arntz, Gregory and Zierahn (2016) among others discussed that it was rather tasks that were being automated and not the occupation itself.

the susceptibility of jobs automation does change between occupation, it is instead the within occupation differences that explain most of the tasks shift over the last few decades. Figure 2 in appendix 3 shows the difference across countries in the between and within task variation of occupations. The table shows that, aside from a few countries whom Belgium is a part of, it is mainly the within component that explain the cross-country differences in the level of “automatability.”

Lastly, the Frey and Osborne’s approach display another huge difference with Autor, Levy and Murnane (2003), as one of them discuss the:

“substitution of routine tasks by machines as a result of profit maximizing firms. Hence, whether substitution takes place hinges not only on technological capabilities, but on the relative price of performing tasks by either humans or machine. In contrast, [Frey and Osborne (2013)] only assess the technical capability of substituting a certain task by machines and not its economic feasibility” (Arntz, Gregory and Zierahn, 2016: pp 10).

Thus their approach does not take into consideration either the pace at which it could occur, nor the economic mechanism underlying such a development or its complementarity effects. It is only the destruction effect of technological advance that is accounted for. Another difference in the two theories, as I have already stated before, is that one is Skill-biased (TBTC) – i.e. technological change is aimed at substituting capital for routine tasks performed by workers –, while the other one is Occupation-biased (OBTC) – i.e. it is occupation as a whole that are being substituted by capital. Consequently, the provided estimates for the risk of automation are likely to be upper biased in the case of Frey and Osborne.

II.D. Labor market outcomes and the two models

With the most recent available data to this day, Nedelkoska and Quintini (2018) present a comparative analysis of the skill and occupation-biased approach. First, they use PIAAC data (2012 and 2015) to test how the risk of automation relates to employment shares and wages for OECD countries, they then compare Autor, Levy and Murnane (2003)'s and Frey and Osborne (2013)'s estimates for Germany.

The first question they try to answer is: does a higher risk of automation correspond to a declining share of employment, either industry or occupation-specific? Nedelkoska and Quintini (2018) found a positive correlation between occupation-specific unemployment rates and the risk of automation (while weaker, the relationship holds for industry-specific analysis). In general, more than a third of the variance can be explained. Using data on hours worked instead, workers in the most automatable jobs works on average 8 hours less per week than in least automatable ones. In the case of Belgium, this account for 6 hours.

Turning to the wage level now. As expected, there is a negative relationship between the risk of automation and wages. Over the full sample data, they find that a 10 percentage points higher risk of automation results in a 4,3 percentage points lower hourly wages. Including industry controls does not impact the results, but they differ quite a lot from country to country. In Belgium, a 10 percentage points higher computerization risk corresponds to only 1,9 percent lower hourly earnings.

Finally, they compare labor market outcomes with the estimates of the skill-biased approach of Autor, Levy and Murnane (2003) and the engineering bottlenecks approach of Frey and Osborne (2013). They find similar results for both of them, the two approach being somewhat equally predictive for the labor market outcomes in 2006 and 2012. In each case, higher estimated "automatability" is related to lower hourly wages and hours worked. The difference between the coefficients of the two method being statistically non-significant. The last available PIAAC data being 2012 and 2015 for Europe, depending from countries to countries. Further comparison of the estimates would require the access to data from round 3, who will only be released in November 2019.

The estimates on the risk of automation in Belgium will have to deal with the problem of data availability. The classifications of occupations number around one thousand descriptions, the sample size for Belgium being of only 3,386 respondents in the case of PIAAC.³⁸ Therefore, it is a brake for additional attempt at labor market expectations. Moreover, as the data only covers the Flemish region, inference of the results for the whole country might suffer from it. Notably, as a part of the between component could probably be accounted for, if not by occupation at least by industry, on an aggregated level,³⁹ as most of the difference observed in the risk of automation usually comes from

³⁸ Largest dataset to this date for Belgium.

³⁹ In this case as well, obtaining sufficiently disaggregated data for each region has proven to be difficult.

the within industry component, the result would still lack the insight needed for policy implementation. The new data will be released in November 2019.

Another recent study provided by Acemoglu and Restrepo, in March 2017, try to quantify the equilibrium impact of the increase of industrial robots⁴⁰ on the US labor market. While their study only account for a small part of recent technological change – i.e. merely industrial robot adoption –, their model reflects the impact of competition between human and robots labor for different tasks. Using local labor market data, which they proxy by commuting zones, they develop a measure of the exposure to robots (penetration) that allows them to estimate large negative effects on employment and wages. Their study covers the early nineties to 2007, period where the stock of industrial robots was multiplied by four in Western Europe and the US.⁴¹ The adoption of a new robot per thousand workers would reduce from 0,18-0,34 percentage points employment to population ratio and 0,25-0,5 percent wages. This being the results of a negative displacement effect, moving workers away from their tasks, and a positive productivity effect (or income effect), reducing production costs and thus increasing the demand for labor. Those findings hold when controlling for the impact of offshoring, the decline in routine-jobs triggered by the adoption of software performing information processing tasks, total capital stock, imports and other types of IT capital. The effects of industrial robots on employment and wage (being particularly noticeable in manufacturing industries, routine manual occupations and on the less educated workers) is therefore to be interpreted as the effects of industrial robots and the technological changes triggered by its adoption.

⁴⁰ An industrial robot is “an automatically controlled, reprogrammable, and multipurpose machine,” according to the International Federation of Robotics (IFR, 2014). Hence, they do not need human operator. The authors especially choosing this type of technology that does not need human labor to be operated in order to avoid having to study the complementary effect on employment.

⁴¹ Which correspond to an increase of 1,6 industrial robots for every thousand workers in Western Europe (or one in the US). Most of those existing robots being concentrated in only four industries: automotive (39%), electronics (19%), metal and plastic and chemicals (9% each).

III. Human capital accumulation and the skill model

The model developed by Autor, Levy and Murnane in 2003 is centered on explaining the reason behind the increasing share of high-educated workers. Relying on the falling price of computer capital as the causal force of their model, they show that the decreasing demand for less-educated workers is merely a consequence of computerization bias towards routine tasks. This is explained by the rapid adoption of computer capital, allowed by its dropping price, in routine tasks intensive industry and occupation. The effect on employment being a reduced need for humanly performed routine tasks, more than compensated by the rise in computer capital, and an increased demand for non-routine tasks. Routine and non-routine labor being complements.

III.A. Autor, Levy and Murnane (2003)'s model

To describe the demand for tasks, Autor, Levy and Murnane (2003) rely on two postulates: computer capital (C) substitutes (perfectly) for routine tasks provided by humans (L_R);⁴² non-routine (L_N) and routine tasks are complements. Their model is described by the following equations:

- (1) $Q = (L_R + C)^{1-\beta} L_N^\beta, \beta \in (0,1),$
- (2) $w_R = p_c,$
- (3) $\eta^* = w_R/w_N,$
- (4) $w_R = \partial Q / \partial L_R = (1-\beta)\theta^{-\beta} \quad \text{and} \quad w_N = \partial Q / \partial L_N = \beta\theta^{1-\beta},$
- (5) $\theta = (C + g(\eta^*)) / h(\eta^*).$

Output (Q) is given by the constant returns to scale Cobb-Douglas production function, where the computer capital price (p_c) is the causal force as described above. Workers are endowed with heterogeneous productivity at routine and non-routine tasks and choose to provide either of them (or any convex combination). They supply their endowed (one) unit of labor between routine and non-routine in order to maximize their income as in Roy (1951). Thus, clearing the labor market. (w_R) and (w_N) are the wages per unit of labor supplied. (η_i) represents individual i non-routine relative efficiency.⁴³ Lastly, (θ) expresses the share of routine to non-routine task input in the production process. With $g(\eta^*)$ and $h(\eta^*)$ being the population endowments function. Therefore, the endogenous variables are ($w_R, w_N, \theta, C, \eta$) and varies with the price of computer capital. A decline in p_c leading to a higher demand for routine task, met by a rise in computer capital, and a smaller wage per

⁴² Hence, the price of labor routine task should be smaller than the price of computer capital in the pre-computer era, as it was not adopted yet: $w_R < p_c$ before the computer era. Furthermore, it is assumed that computer capital is supplied (perfectly) elastically.

⁴³ Implicitly, a worker is indifferent between providing either routine or non-routine labor at equilibrium. An individual supplies routine labor if $\eta_i < \eta^*$.

efficiency unit of routine task input. Therefore, a reallocation of labor input towards non-routine tasks occurs.

Finally, they adapt this single industry framework to encompass more industries and goods, with j industries producing q_j goods. Each industry facing a specific non-routine tasks factor share (β_j). And consumers expressing their preference for variety as in Dixit-Stiglitz (1977) utility function. They adjust their model as follow:

$$(1') \quad q_j = r_j^{1-\beta_j} n_j^{\beta_j}, \beta_j \in (0,1),$$

$$(6) \quad U(q_1, \dots, q_j) = (\sum_j q_j^{1-\nu})^{1/(1-\nu)},$$

This allows for the main proposition of the model: facing the same price decline of computer capital, each industry adopts it according to their specific routine factor share. An originally more routine task intensive industry, facing a drop in p_c , would increase its computer capital and its demand for non-routine task more, compared to industries less intensive in routine task. This is also true if you look at it from an occupation point of view. Sectors or occupation that adopt computer capital relatively faster, will have stronger shift from human labor routine to human labor non-routine input.

In their model, individuals are faced with two options concerning their time allocation: to either supply routine task or non-routine task. Each worker supplies one efficiency unit of labor to be allocated between routine and non-routine, or any convex combination of the two. Their choice being dependent on their productivity endowment: $E_i = [r_i, n_i]$ and $0 < r_i, n_i \leq 1 \forall i$; and the wages levels. Their choice thus depends on their comparative advantage.

From the point of view of workers, Autor, Levy and Murnane (2003) framework can be described as follow. Individuals have no problem switching from routine to non-routine tasks, they just have different productivity endowment. Hence workers have a different “optimal reaction time” given by their relative productivity (and the economy wages levels). This optimal time can be described by the statement that the less efficient a worker is at non-routine tasks, the later he will choose to move from one occupation to the other. The only barrier for a worker supplying routine tasks to enter a non-routine intensive task job is therefore its opportunity cost. As a consequence, workers with relatively low efficiency at non-routine versus routine tasks are expected to see their welfare reduced compared to their situation before the fall in computer capital price.⁴⁴ It is only when the wage per efficiency unit of routine task has been sufficiently lowered that they will switch to supply non-routine task. Until that point, each previous drop in the computer capital price will only results in worsening their earnings. Hence, the only drawback for less-educated workers

⁴⁴ Even in the case where all productivity gains are to be distributed among consumers – i.e. workers (which is quite unlikely to happen), in the form of reduced prices. As computer capital typically cannot substitute for every task in the production process, only a part of the products prices will be affected by its adoption. Thus, the general level of price will be diminished less than proportionally for any fall in the wage of routine task.

is that, as they are not as efficient at non-routine tasks, they will see their total wealth reduced.⁴⁵

Their model state that a fall in computer price will ultimately lead to a lower demand and supply of routine intensive human labor, and a higher demand and supply for non-routine intensive labor. This in itself explain the increasing share of individuals taking part in formation and studies. They do it in reaction to the higher demand for qualified workers.⁴⁶ While this is certainly the implied explanation, it is not stressed in the model. The very aim of this model, as expressed by its authors, is to explain the pool of qualified worker growth (or the need for qualification). While the model does present the cause behind the need for qualification, and the process through which workers reallocate their working time, it does not explain the mechanism through which workers acquire the skills to do so. Nor does it allow for a change in the distribution of skills through the population.

III.B. The accumulation of human capital

This simple framework, being especially accurate to explain the shift in the labor demand and labor supply, does not explain how workers adapt their skills. That is, while their model explains the reason behind the re-sorting of workers and skills across industries and jobs, it does not provide insight of the process through which workers “transform” their skills itself. The reason being the heterogeneously given productivity endowment at routine and non-routine task. As it is assumed to be fixed, so that a change in wage would induce a reallocation of labor, there is no space for skill improvement. This might not be a huge issue for middle or high-educated workers who possess the skills to reallocate their efficiency unit of work between routine and non-routine. But, for less-educated workers who are typically not efficient at non-routine tasks, it might not be that easy. The reason being as simple as that they lack the necessary skills to reallocate them proficiently.

As this population is particularly at risk in the computer era, I argue that introducing a path for human capital accumulation in Autor, Levy and Murnane (2003) framework will benefit the analysis of future technological impact to the labor market. The reason being as simple as this: focusing on skills reallocation without taking into account the skills formation process might prove to be somewhat lacking for policy implementation. Notably, this idea might be consistent with the recent recommendations addressed by the European Union to Belgium’s policy makers regarding the challenges caused by new technological

⁴⁵ This is the case as long as their real wage per efficiency unit of work is not reduced through the process of computer capital adoption. As I have previously argued, this is unlikely to happen.

⁴⁶ The traditional economic argument would be stated like this. As the price of computer capital fall (thus routine wage), demand for routine and non-routine labor augment. Computer capital labor share will increase more than proportionally to the fall in its price, demand for routine human labor will decrease while demand for non-routine labor will rise. As a result, non-routine wage increases to attract more workers. New entrants, typically faced with the choice of entering the labor market or to undergo formation, would choose more often than before to go for the studies. Hence, increasing the pool of qualified workers. The last part being implied but does not appear in the model.

developments to youth unemployment, formation and additional training (Van der Linden, 2007; OECD, 2013).

While this structure offers the advantage of displaying the apparatus behind the reallocation of labor from routine to non-routine task, it does not take into account the process behind the “transformation” of skills. The re-sorting of individual skills being impossible in a model where individual productivity endowment is fixed. To adapt the framework of Autor, Levy and Murnane (2003) as to encompass human capital accumulation would therefore require three different adaptations: one concern the allocation of time, another the introduction of human capital accumulation, and lastly to make the model dynamic. What follows can be looked as my reflections on the implementation of their model with human capital accumulation.

The first question thus concerns the allocation of time. In the original model, individuals are faced with two options concerning their time allocation: to either supply routine task or non-routine task. There exist many forms of human capital accumulation, studies or on-the-job formation are typical example. Following Ben-Porath (1967), the easiest way would be to start by excluding on-the-job formation. The idea is that, by only considering the possibility of human capital accumulation through the allocation of time for it, ALM’s framework only need a slight modification. Instead of being faced with two options for their time allocation, individuals are now faced with three options: to supply routine task, non-routine task or formation. Individual being endowed heterogeneous productivity at human capital accumulation. Each worker could still supply one efficiency unit of labor to be allocated between routine, non-routine and study. As before, their choice being dependent on their productivity endowment. An example could be: $E_i = [r_i, n_i, hca_i]$ and $0 < r_i, n_i, hca_i \leq 1 \forall i$.

By doing so, workers could now decide to allocate their unit of labor, or a part of it, to the production of human capital. But this raises another question: how does the accumulation of human capital affects productivity? By assumptions, to rely on ALM structure, the variables expressing the productivity endowment need to be independent. Therefore, capital accumulation cannot be expressed through the individual efficiency at routine or non-routine task. Rather, it could be possible to express the accumulation of human capital by adding a factor that plays a role in the relative efficiency of an individual at non-routine versus routine tasks (and thus in the total amount of labor provided by this individual). Instead of being a function of routine and non-routine productivity endowment only, as in ALM, it could also be a function of the accumulated human capital (α_i). The relative efficiency could thus be written as $\eta_i = \alpha_i (n_i/r_i)$ with $\eta_i \in (0, \infty)$. So that an individual could increase his relative efficiency at non-routine versus routine tasks by investing in human capital (but not his relative efficiency at routine versus non-routine). α_i being the production function of human capital, for example.⁴⁷ Hence, the labor provided by an

⁴⁷ For an example of typical human capital production function see Ben-Porath (1967).

individual could be written as $L_i = [\lambda_i r_i, \alpha_i(1 - \lambda_i)n_i]$, where $0 \leq \lambda_i \leq 1$.⁴⁸ Workers choosing formation and tasks according to their comparative advantage as well.

The main remaining problem being that Autor, Levy and Murnane (2003)'s model is a static one. Any attempt at including a human capital accumulation function would require the model to be made dynamic. Otherwise, individuals would have no reason to choose to supply formation instead of supplying routine or non-routine task labor as they would retire no gains from it. In order to process further in this direction, the need for data on the formation process of human capital are needed. As this is not the case in PIAAC dataset, and as I have no knowledge of other database of the sort, this section is at a standstill.⁴⁹

⁴⁸ Compared to $L_i = [\lambda_i r_i, (1 - \lambda_i)n_i]$, where $0 \leq \lambda_i \leq 1$, in Autor, Levy and Murnane (2003).

⁴⁹ While data on the formation of human capital are available (for example the PISA, Program for International Student Assessment), there is no common database that references the skills per occupation and the formation needed to develop them (or I am not aware of it).

IV. Conclusion and remarks

The question of technological unemployment will remain at the center of attention in the following years. Indeed, the automation process have already reached at many non-routine tasks, and the risk of automation threatens so many workers, last estimates being of 14 percent of jobs at high risk for Belgium. While not as severe as what it could have been, according to Frey and Osborne (2013) for example, as it does not affect workers in the same way it will persist as a major concern. In particular, less-educated workers as well as the young ones being especially at risk, inequalities are thus expected to increase. Policy implementation, and the tools to design it, are more than ever needed in this matter.

As I have argued, as the accumulation of human capital plays an important role in the shift of demand away from routine-task labor and towards non-routine task labor.⁵⁰ To integrate the process of formation in a model would help understand how individuals will react to technological innovations in order to acquire the skills needed to redirect their labor force towards safest occupations.

Further research on the risk of automation in Belgium will have to deal with the problem of data availability. As the different classifications of occupations usually number description of around a few hundreds to more than 1,000 occupations (the O*NET database have 1,100 for example), the sample size for Belgium being of only 3,386 respondents in the case of PIAAC.⁵¹ It is a brake for additional attempt at labor market expectations. Moreover, as the data only covers the Flemish region, inference of the results for the whole country might suffer from it. Notably, as a part of the between component could probably be accounted for, if not by occupation at least by industry, on an aggregated level.⁵² As most of the difference observed in the risk of automation usually comes from the within industry component, the result would still lack the insight needed for policy implementation. The release of the newest data set in November 2019 might be a ray of hope in this respect.

Lastly, it is to be noted that technological unemployment is not a risk in itself. As environmental transition researchers have argued, limiting the use of natural resource should generate a massive amount of jobs. The real question we are faced with might therefore be the purpose of our society and its labor market. Until now, labor was considered as the main wealth redistribution process. Will it still the case or should we see labor in a different way? Reassess it as its original purpose of goods and products creations?

⁵⁰ While some non-routine tasks are now being at risk as well, most of them are still out of reach for a long time (if they ever are).

⁵¹ Largest dataset to this date for Belgium.

⁵² In this case as well, obtaining sufficiently disaggregated data for each region has proven to be difficult.

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Appendix

Appendix 1: the first and second industrial revolution

In this section, I will mostly make use of the work of Joel Mokyr on the industrialisation process of Belgium and the Netherlands (1976). I will not refer to his paper in the next paragraphs. Any other sources will be referenced instead. The lector can thus assume that all information not referenced are coming from Mokyr (1967). Furthermore, while the tables come from various sources, Joel Mokyr is to be acknowledged for the work he has done analysing and putting them together.

With the start of the first industrial revolution, Belgium has seen a few previously near nonexistent industries emerge. These new born industries have flourished through the mechanisation process brought about by technological innovation. One of them is the cotton industry in the Flanders. In 1798, Lievens Bauwens introduced the first mules. A few years later it was the flying shuttle in weaving that made its appearance. Cotton being one of the first industries from the textile sector to undertake massive mechanisation, its history can be summarised by the example of the development of the city of Ghent in the early 19th century. Table 5 present the data covering the labor expansion from 1801 to 1838, as well as the capital and output evidence of the mechanisation process in this line of industry. Just a short look at output levels is enough to assert the importance of the technological innovation process. Employment growth being way smaller than output's.⁵³

	1801-02	1807-08	1810-12	1817	1826	1830	1838
<i>Labor</i>							
Spinners	227	1,838	3,790	n.a.	n.a.	n.a.	} 18,700
Weavers	400	2,000	4,105	n.a.	n.a.	n.a.	
Printers	1,700	1,135	1,350	n.a.	n.a.	n.a.	
<i>Capital</i>							
Spindles	—	78,022	115,000	n.a.	150,000	300,000	283,000
Looms ^a	n.a.	500	3,600	n.a.	n.a.	2,200	2,900
<i>Output</i>							
Yarn spun ^b	55	320	693	374	1,700	2,700	4,600
Cloth ^c	n.a.	n.a.	101	n.a.	410	n.a.	n.a.

^aIncluding power looms

^bIn thousands of kilograms

^cIn thousands of pieces

Table 5: Development of the Cotton Industry in Ghent. Source: Coppejans-Desmedt, *Gentse Textielnijverheid*, pp 508; Van der Wee, "Industriële Revolutie," pp 192; Demoulin, *Guillaume Ier*, pp 329; Briavoinne, *De l'Industrie*, 2: 374ff (in Mokyr, 1976).

⁵³ It is interesting to note that the cotton industry, as the linen one, employed a huge part of its workers from the countryside. The earlier figure for employment being thus downward biased.

Another interesting point for this study on technological unemployment is the origin of the workers that supplied their labor to this new born industry. This is especially the case when considering the size of the population of the city of Ghent in 1938. The workers of the cotton industry accounting for close to 20 percent of it. Indeed, the population size nearly doubled between 1801 and 1843 (while only increasing by 35 percent for Flanders), the bulk of it coming from the immigration of the rural area. An answer can be found by looking at the linen proto-industry. Having experienced a small employment growth of 10 percent over the first four decades of the 19th century and decreasing strongly after, the linen industry employment shares have been reduced since the beginning of the industrial revolution.⁵⁴ Hence, the labor supply needed by the cotton industry might have come from a large part from the linen proto-industry. Therefore, whereas textile remained the most important industrial sector till the late 1850s, the center of production moved from the rural area, mostly performed by domestic workers, to the city and firms.⁵⁵

While the transformation of the textile industry might appear like a clear linear course, it is essential to understand that the old and new production process coexisted for a long period.⁵⁶ One of the main downfall of the Belgium linen industry being the difficulty met by engineers to mechanise the production process, entrepreneurs hence favoring investment in the cotton industry instead. It was rather the shift in labor demand, away from the linen production and towards the cotton industry, that led workers to change their occupation, than technological unemployment arising from productivity gain in the linen industry.⁵⁷

The other side of the main textile production in Belgium is the wool industry. Being much less important in size than the linen or the cotton ones, its production and export rapidly expended with mechanisation. The transition towards the modern production process started just before the end of the 18th century with an English mechanic, William Cockerill, hired to supplied carding machines, cards and spinning machines for yarn in Verviers. The mechanisation process continued later on with the introduction of steam engines. By 1805-1810, output in Verviers had already increased by 50 percent, output production growing from 22,500 pieces to 70,000 pieces between 1780 and 1845. It is interesting to note that in the same time as output production increased by three time, the number of employed workers remained constant at around 7,000. Similar to what has happened for the linen industry, or more recently the example of the introduction of ATM in the 1970s (US) provided by Bessen (2015): as employment in the woolen industry remained quasi-

⁵⁴ Going from around 250,000 workers (for the Flanders) in the 18th century to around 277,759 workers in 1840, the size of the linen industry decreased thereafter. In 1843, only 216,855 workers where employed in the Flanders linen industry.

⁵⁵ The concentration of work and capital was so intense that, already in 1838, three firms owned more than half of the spindles.

⁵⁶ One of the reasons, among others, being the "attachment of the peasants to custom and habit," as quoted by P. Van Griethuizen (Mokyr, 1976: pp 73).

⁵⁷ While it is true that it was not the case in Belgium itself, the introduction of the mechanized flax spinning happening only in the late 1830s (way later than the English who adopted such devise in the earliest years of the 19th century). The competition with mechanically advanced cities in the field, like Leeds and Dundee, being a major blow to the Flemish linen industry. Nonetheless, it remains clear that the increasing returns in the cotton industry, when no similar trends were observed for the linen production, attracted most of the available capital. Therefore, affecting the future growth of the linen proto-industry.

constant while population had increased, its share was reduced. Furthermore, significant mechanisation induced occupation shifts were referenced within the industry.⁵⁸

Other new born sectors, the paper industry, sugar refineries and glass and crystal work share similar development progress as the cotton or the metallurgical capital good industry (who will be described in the next paragraph). Being near non-existent before the introduction of mechanised production process, their growth rate exploded thereafter.⁵⁹ In this regard, the cohabitation between the new and old production process in the paper industry is similar to the continued use of the charcoal furnace for the iron production. In 1846, while steam engines accounted for the biggest part of their power supply, more than half of the firms still employed water and wind mills.

Last but not least, the metallurgical and heavy industries for whom the center of gravity shifted from Luxembourg and Namur, to Liège and Charleroi. This sector in particular would remain the main industrial sector of Belgium till the second world war. It can be divided in three different types of output: the mining sector with extraction itself as its output, the production of cast iron and the weapons and machinery industry (as well as nails, cutlery, ...).

For the refinement of cast iron, technological transformations came first by the development of the new blast furnace, producing up to three times more in the same amount of time by using higher heating process. From 1795 to 1814, production rose by 50 percent. In the 1820s, the introduction of Henry Cort's puddling process followed by the use of coke for smelting (instead of charcoal) induced the exceptional growth that made Wallonia the most industrialised place of the European continent (except from the UK). In this regard, the story of the province of Hainaut and its capital Charleroi is indeed extraordinary. In 1831, the total production of 6,600 tons of cast iron accounted for 7.3 percent of Belgium's. By 1846, it was 53.8 (101,802 tons). And 57.5 (183,910 tons) by 1860. Wrought iron production followed similar trend as well. While the large majority was produced by the newly made coke furnaces, it is surprising to see that the few existing charcoal furnaces were still in use in the late 1840s.⁶⁰ Here again, the impact of new technological development on the old production process was, rather than just displacing the workers from the old to the new furnaces, mostly to attract capital as well as the new labor supply to the more competitive industry. Thus, increasing the labor demand for coke refinement while leaving the demand for charcoal refinement unchanged at first.

Another incredibly dynamic industry in south Belgium was the machinery production as well as the other products using iron as an input. In this respect, the transformations that occurred in the city of Liège industry and its shares of workers between 1800 and 1838 is astonishing. At first, the metal workers of the city only numbered 8,753, with 1,477 in the

⁵⁸ The change in the organization of work in the production process, referenced by Thomassin (in Mokyr, 1976), gives some insight of the transformation that occurred with the introduction of machinery. When the ancient production process employed 297 workers to produce 1,500 pieces of cloth, the new one needed only 109 (in the two-case weaving is excluded, and thus the effect of the adoption of the flying shuttle, to only take into account the introduction of machinery in the woolen industry).

⁵⁹ In sugar refining for example, the stock of steam engines went up from zero in 1828 to 40 in 1838 with the discovery of Howard's heating pans process (1829).

⁶⁰ For example, in 1848 there were 18 coke and 2 charcoal active furnaces in Hainaut. The output of the charcoal furnaces accounting for approximatively 1.67 percent of the total production of 69,887 tons.

production of capital goods for the woolen industry (machinery). Most of the metal workers living in the rural area. In the case of the weapons production, it remained mostly a domestic industry for a long period. The production growing from 2,500 workers in 1800 to 7,538 in 1846, out of which 5,796 were domestic worker from the rural area. In the case of the nail industry, a preeminent part of the metallurgical proto-industry, the introduction of mechanical device at the beginning of the 1830s did a massive blow to employment.⁶¹ The number of domestic workers declining until the end of the 19th century. Total employment in the nail industry numbered 11,000 workers in 1838. Lastly, the capital good production. At the center of Liège metal industry since the early years of the 19th century, John Cockerill's activities who employed (in the whole province) 2,000 workers in 1812 already. It was 4,500 by 1816. The foundry in Seraing alone employing more than 2,000 workers in 1830, being thus the second largest in the world. For the whole Belgium, the stock of steam engines going from around 800 in 1830 to 2,040 in 1850.⁶² Being as small as it was before the start of the industrial revolution, machinery production employment increased by a factor of around 30 in less than 50 years. Thus, being more than doubled every 10 years.

Appendix 2: DOT definitions of task measures in 1977

Variable	DOT definition	Task interpretation	Example tasks from <i>Handbook for Analyzing Jobs</i>
1. GED Math (MATH)	General educational development, mathematics	Measure of nonroutine analytic tasks	Lowest level: Adds and subtracts 2-digit numbers; performs operations with units such as cup, pint, and quart. Midlevel: Computes discount, interest, profit, and loss; inspects flat glass and compiles defect data based on samples to determine variances from acceptable quality limits. Highest level: Conducts and oversees analyses of aerodynamic and thermodynamic systems . . . to determine suitability of design for aircraft and missiles.
2. Direction, Control, Planning (DCP)	Adaptability to accepting responsibility for the direction, control, or planning of an activity	Measure of nonroutine interactive tasks	Plans and designs private residences, office buildings, factories, and other structures; applies principles of accounting to install and maintain operation of general accounting system; conducts prosecution in court proceedings . . . gathers and analyzes evidence, reviews pertinent decisions . . . appears against accused in court of law; commands fishing vessel crew engaged in catching fish and other marine life.
3. Set Limits, Tolerances, or Standards (STS)	Adaptability to situations requiring the precise attainment of set limits, tolerances, or standards	Measure of routine cognitive tasks	Operates a billing machine to transcribe from office records data; calculates degrees, minutes, and second of latitude and longitude, using standard navigation aids; measures dimensions of bottle, using gauges and micrometers to verify that setup of bottle-making conforms to manufacturing specifications; prepares and verifies voter lists from official registration records.
4. Finger Dexterity (FINGDEX)	Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately	Measure of routine manual tasks	Mixes and bakes ingredients according to recipes; sews fasteners and decorative trimmings to articles; feeds tungsten filament wire coils into machine that mounts them to stems in electric light bulbs; operates tabulating machine that processes data from tabulating cards into printed records; packs agricultural produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipment; attaches hands to faces of watches.
5. Eye Hand Foot Coordination (EYEHAND)	Ability to move the hand and foot coordinately with each other in accordance with visual stimuli	Measure of nonroutine manual tasks	Lowest level: Tends machine that crimps eyelets, grommets; next level: attends to beef cattle on stock ranch; drives bus to transport passengers; next level: pilots airplane to transport passengers; prunes and treats ornamental and shade trees; highest level: performs gymnastic feats of skill and balance.

⁶¹ In this respect, the nail industry does look like an exception in Belgium. The introduction of machinery, and its use in the production process of small sized nails, substituted substantially for human labor. While in other sectors the old and new production process coexisted for quite a long time, in the nail industry the old way only subsisted in the production of the bigger sized nails. As the mechanization of their production took longer to be implemented efficiently.

⁶² The stock of engines being already very high in 1830, compared to the other countries (aside from England, that is).

Table 6. Source: US Department of Labor, Manpower Administration, Handbook for Analysing Jobs, Washington, DC, 1972 (in Autor, Levy and Murnane, 2003: pp 1323).

Appendix 3: “Decomposition of cross-country differences in the level of automatability along the occupation dimension.”

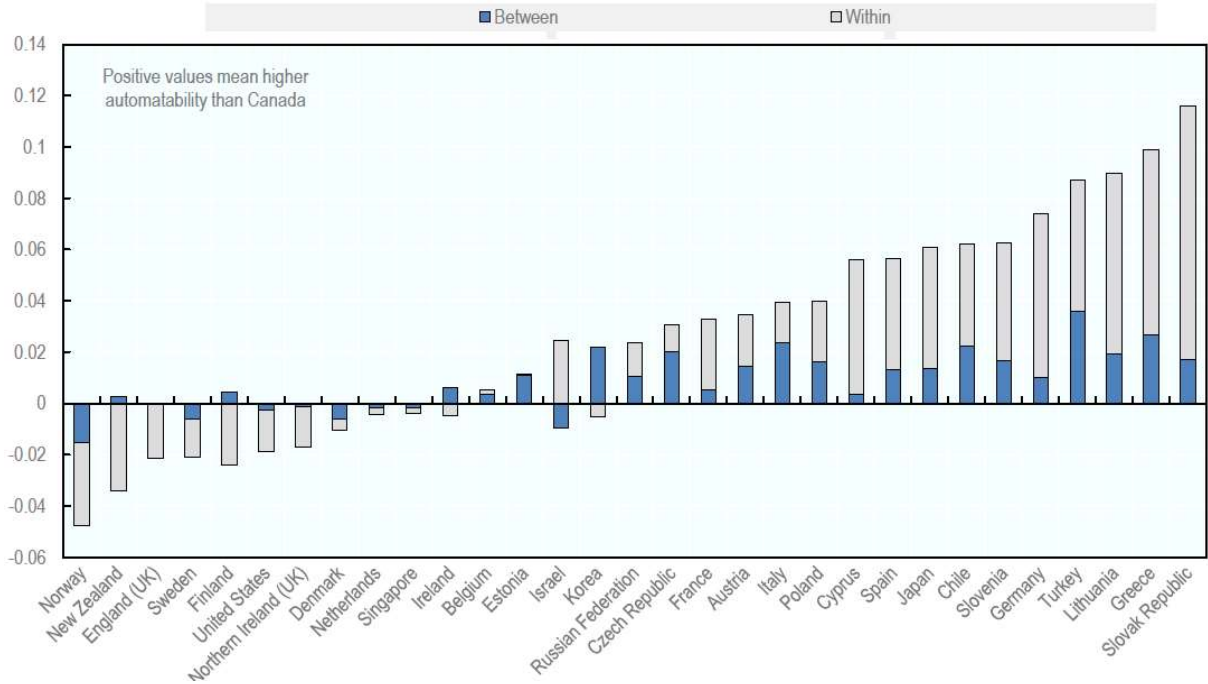


Figure 2. Source: Survey of Adult Skills (PIAAC) 2012, 2015 (in Nedelkoska and Quintini, 2018: pp 61).