

4 On the Employment Consequences of Automation and Offshoring

A Labor Market Sorting View

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1 Introduction

Automation and offshoring are two of the most debated global developments with potentially disruptive effects on the labour market and momentous implications for workers' employment opportunities and wages. Understanding their effects, their relative importance and their possible interactions is, therefore, of preminent relevance and, as such, has attracted a lot of research.¹

The existing literature highlights that, from a country's point of view, automation and offshoring may affect employment opportunities and wages in two main ways. On the one hand, automating or offshoring some tasks implies that these tasks are not performed by the country's workers any longer so that the demand for their services falls. This is the negative "substitution effect", which may cause employment and wages to fall. On the other hand, reallocating tasks from the country's workers to automated systems or foreign workers may promote production efficiency, which in turn expands production activities with a beneficial impact on employment opportunities and wages. This is the positive "productivity effect", which may cause employment and wages to rise.

In the case of automation, most studies stress capital-labour substitution.² This is of primary importance and particularly relevant for automation related to the adoption of robots and machines in production. It may affect different workers differently. With "skill-biased technological change" (SBTC), new technology complements workers with high skills. With "routine-biased technological change" (RBTC), new technology crowds out workers from traditional routine tasks while creating additional jobs involving new complex tasks (see e.g. Acemoglu and Restrepo, 2018b, for a detailed discussion).

Differently from these studies, the present paper investigates the possible existence of an additional negative effect of automation on workers' employment opportunities and wages. This effect is related to what has been called the "paradox of automation" (Bainbridge, 1983). The idea is that, as automation intensifies, the efficient completion of related tasks increasingly requires human operators with specialized knowledge of automated systems involving specific

algorithms, software and machines. Hence, according to the paradox, the more advanced an automated system is, the more crucial the contribution of the specialized human operator may end up being.³ The associated growing demand for specialized knowledge is conducive to a form of workers' specialization that increasingly matters above and beyond what would be needed by the vertical skill content of tasks or their degree of routineness. In this respect, by fostering tasks' horizontal knowledge differentiation, automation also demands workers' horizontal skill differentiation. We call this "core-biased technological change" (CBTC), whereby new technology requires workers with specialized knowledge ("core competencies") independently of them being high or low skilled, or their tasks being more or less routine intensive.

Our investigation of the possible consequences of CBTC for the labor market emphasizes the challenges workers and firms face in matching the formers' horizontally differentiated skills with the latters' horizontally differentiated tasks in the presence of search frictions and rising match assortativity due to automation (see Shimer and Smith, 2000). In a perfectly competitive labor market, more assortativity would increase the surplus of all equilibrium matches as these take place only between "ideal" partners, that is, between workers and firms with perfectly matched skills and tasks. In contrast, with search costs not all matches necessarily involve ideal partners as some firms or workers may find it optimal to accept less-than-ideal counterparts ("mismatch") in order to avoid incurring the opportunity cost of additional search. When the "paradox of automation" is at work, as automation proceeds the surplus of ideal matches increases relative to that of less-than-ideal matches, amplifying the losses from mismatch and making both firms and workers more selective in choosing their partners. As selectivity increases, firms and workers become more willing to spend time searching for better matches. As a result, unemployment duration rises, mismatch falls and specialized knowledge concentrates more on the tasks specifically requiring it.

One could argue that a similar mechanism may be relevant also for offshoring if interpreted as another form of technological change.⁴ For example, the more sophisticated a country's global value chains are, the more crucial may be the contribution of specialized knowledge by the country's workers.⁵ Management studies emphasize what they call "offshoring management capability" (Mihalache and Mihalache, 2020). According to Mukherjee, Gaur and Datta (2013), coordination capabilities (e.g. those leveraging IT coordination applications for enterprise resource planning or customer-relationship management software) are important for creating value through offshoring because geographically dispersed knowledge needs to be transferred and integrated. Manning, Massini and Lewin (2008) argue that, to use science and engineering talent at globally dispersed locations, firms need capabilities such as recruiting, developing, and retaining talent, coordinating globally dispersed innovation activities, and collaborating with external partners. Mukherjee et al. (2019) stress the role of contract negotiation skills, the ability to monitor and evaluate the performance of suppliers, or the knowledge of alternative supplier arrangements and their cost structure.

Whether the “paradox of automation” is of any practical relevance, and whether something similar applies also to offshoring is, first of all, an empirical issue. We look for traces of the paradox at the sector-occupation level.⁶ We focus on 92 occupations at the 3-digit ISCO-88 level and 16 (out of 21) sectors according to the NACE Rev.2 classification. To make sure that our results are not driven by specific countries or institutional contexts, our dataset covers 13 European countries in the period 1995–2010. We analyze the impact of automation and offshoring on “selectivity” as measured by skill concentration, unemployment duration and educational mismatch. To this end, our dataset combines data on employment from the European Labour Force Survey (EU-LFS) with occupation-level measures of “automatability” as in Acemoglu and Autor (2011) and “offshorability” as in Blinder and Krueger (2013). We find that over the period of observation, sectors with higher initial automatability experienced a differential increase in selectivity. By contrast, we find that sectors with higher initial offshorability experienced a differential decrease in selectivity.

We argue that these findings are consistent with the “paradox of automation” and CBTC in the case of automation, while they are inconsistent with something similar happening in the case of offshoring. We spell out our argument through a growth model that, beyond productivity and substitution effects, features search frictions in the labor market and two-sided heterogeneity of horizontally differentiated skills and tasks. Workers and firms in our model are risk-neutral and maximize lifetime discounted utility in continuous time. They meet through a random matching process governed by a canonical constant return to scale function based on one-to-one relations with congestion externalities for each task (see Mortensen and Pissarides, 1994). For analytical transparency, workers’ skills and firms’ tasks are assumed to be uniformly and symmetrically distributed around a circle describing the space of their heterogeneous characteristics. Due to search frictions, workers and firms do not match perfectly, but instead search and optimally accept less-than-ideal matches in an interval around their ideal ones. “Mismatch” is measured by the distance between matched skills and tasks along the circle and negatively affects match surplus. We use a numerical implementation based on specific functional forms to show that the empirical patterns we have uncovered in the data can be reproduced by our model as long as match surplus is assumed to be: (i) log-submodular in mismatch and automation, so that matches at shorter distance have a comparative advantage in exploiting automation; (ii) log-supermodular in mismatch and offshoring, so that matches at longer distance have a comparative advantage in exploiting offshoring; (iii) log-supermodular in automation and offshoring so that, for given mismatch, the impact of more automation on match surplus is amplified when there is more offshoring. When these conditions are met, the model predicts that more selectivity is associated with less employment as firms and workers are willing to search longer for the ideal counterpart. It therefore implies that automation and offshoring have opposite effects on employment due to their opposite effects on selectivity. While automation reduces employment by raising selectivity,

offshoring increases employment by reducing selectivity. The model also predicts that more selectivity is associated with more wage inequality between ideal and less-than-ideal matches as the surplus of the former increases relative to the surplus of the latter.

The rest of the chapter is organized as follows. Section 2 offers some anecdotal examples of the “paradox of automation” and discusses survey evidence on specialization trends in occupations. Section 3 introduces the dataset and describes the empirical analysis. Section 4 presents the model, discusses the conditions on assortativity needed to make it consistent with the empirical findings of Section 3, and studies its implications for employment and wage inequality under those conditions. Section 5 concludes.

2 Ironies of Automation and Skill Specialization

The notion of “core-biased technological change” (CBTC) emphasizes the positive impact that new technologies may have on the horizontal assortativity of skills and tasks. This notion speaks to what was termed the “paradox of automation” around forty years ago by cognitive psychologist Lisanne Bainbridge in a still influential paper titled *Ironies of Automation* (Bainbridge, 1983). Bainbridge’s idea is that, as automation intensifies, the efficient completion by humans of tasks related to the automated systems increasingly requires workers with specialized knowledge of the specific systems. As a result, automation raises the assortativity between workers’ specialized skills and firms’ specific tasks.

In her paper, Bainbridge notes that the classic aim of automation is to replace human manual control, planning and problem solving by automatic devices and computers. Yet, this may have ironic implications:

[T]he more advanced a control system is, so the more crucial may be the contribution of the human operator [as] the designer who tries to eliminate the operator still leaves the operator to do the tasks which the designer cannot think how to automate. [In this respect, there] are two general categories of task left for an operator in an automated system. He may be expected to monitor that the automatic system is operating correctly, and if it is not he may be expected to call a more experienced operator or to take over himself. To take over and stabilize the process requires manual control skills, to diagnose the fault as a basis for shut down or recovery requires cognitive skills.

When called to intervene, a more experienced operator may in turn face similar challenges, only at a higher level. In any case, relevant experience requires “special training”. A traditional example is the flight deck (Malquist and Rapport, 2021):

More automation should mean more training. Today’s highly automated planes create surprises pilots aren’t familiar with. The humans in the

cockpit need to be better prepared for the machine’s quirks. [...] Modern jet aircraft developed using classic methods lead to scenarios that wait for the right combination of events. Unlike legacy aircraft built using only basic electrical and mechanical components, the automation in these modern jets uses a complex series of situations to “decide” how to perform. [...] In the case of the [Boeing] MAX crashes, pilots found themselves in confusing situations, i.e., the automation worked perfectly, just not as expected. [...] Although these challenges can often be “designed out”, pilots can’t wait for planes that are better-designed. They need to be trained now to understand that an aircraft’s response depends on the computer “process model”.

The training needed can be extremely specific in terms of “core competencies” (Aviation Voice, 2008):

[Boeing and Airbus] have very different philosophies about their aircraft. [...] Boeing has a traditional control wheel, whereas Airbus has a highly automated system and a side stick. According to Airbus, the absence of the larger yoke ensures much more comfortable flying. It also allows operating the array of computers easier with more space and one free hand. The competitor states that the yoke is an essential tool to handle emergencies. It does not prevent a pilot from overriding the autopilot if necessary and allows for better coordination between the pilot and co-pilot.

Training in aviation is so specific that generally pilots must be “type-rated”, that is, they must be certified with additional training beyond the scope of the initial license and aircraft class training, tailored to the aircraft type they are asked to fly (Aviation Voice, 2008):

Pilots type-rated on both Airbus A320 and Boeing 737 say that it took a while for them to get used to a fundamentally different way to operate an aircraft.

The general point is that, if an automated system has an error, the system will multiply the error until the error is fixed or the system is shut down. Fixing the error or shutting down may require system-specific experience. Both fixing the error or shutting down may require that a human takes control who knows immediately and exactly what to do. As the knowledge required is very specific, the human holding it is not readily replaced with another human without appropriate system-specific experience. While the need of all this may be tragically self-evident in the case of a flying aircraft, it may be very important also in other less dramatic situations (Kaufmann, 2012):

Imagine a fully automated production line that makes computer processors that sell for \$200. All the human operators have to do is to push a button,

and the production system starts cranking out 2,400 finished products per minute. [...] Imagine that a drill used to bore holes in the silicon wafer becomes misaligned, and starts drilling microscopic holes through the middle of the processor core. Every second the system keeps working, 40 chips are ruined. Assume each processor costs \$20 in material costs—that means the factory start losing \$800 every second the error isn't found. Every minute the system keeps running, the company loses \$48,000 in raw materials. And that's just the direct cost—if you take into account that each processor would sell for \$200, the company is losing \$528,000 a minute: \$48,000 in direct costs and \$480,000 in opportunity cost. [...] When an error happens, operators need to get involved quickly and flawlessly—otherwise, the automated system will amplify the effects of the error until it is fixed.

Having difficulty “finding the right skills or talent” or “filling jobs” is often quoted as one of the main issues raised by employers. For example, the 2018 Talent Shortage Survey by Manpower Group (2018) highlights how talent shortage has been increasing over time, leaving a growing number of jobs unfilled all around the world.⁷ The shortage is strongly linked to technology, but does not necessarily depend on a dearth of workers with higher education (Manpower Group, 2018, p.6):

Most of the top ten in-demand roles today require post-secondary training and not always a full university degree.[...] In the digital age, employment will not always require a college degree, but will rely heavily on continual skills development as even the most traditional roles are augmented with new technology.

A wide range of jobs with different education and routine contents are affected across sectors. Higher than average recruitment bottlenecks tend to be reported in manufacturing, ICT and health care for jobs such as skilled trades workers, machine operators, sales representatives, engineers, technicians, ICT professionals, workers in marketing posts, drivers and office support staff (Cedefop Eurofound, 2018).⁸ A concern for both firms and workers is that retraining from a known to a different machine can be a costly time-consuming process, making them cautious about potential mismatch. This is consistent with evidence collected by Bartel, Ichniowski and Shaw (2007) and Koren, Csillag and Köllö (2020), according to which workers assigned to new machines or IT-enhanced capital equipment are required to have “better” technical and problem-solving skills. These are likely to be horizontally differentiated and acquired mostly through experience as highlighted by Dauth et al. (2019).⁹ Black, Hasan and Koning (2020) report survey evidence that the changing demand of skills has affected how firms search for new hires, in particular through increased firm-driven search for skilled workers.

3 Empirical Evidence from Occupational Data

In this section, we look for evidence consistent with CBTC in occupational data. In particular, we are interested in assessing whether and how more automation and offshoring may lead to higher match selectivity, which we measure in terms of longer unemployment duration, less mismatch, and more concentration of specialized knowledge in specific tasks. While matched employer-employee data with detailed information in skills and tasks would arguably be the most natural setup for our investigation, occupational data have the advantage of being available for several countries in a harmonized way, thus allowing us to control for country-specific aspects.

3.1 Data and Variables

For our investigation we use occupational data on European countries extracted from the *European Labour Force Survey* (hereafter EULFS). To include the maximum number of available countries and keep a consistent classification of occupations, we restrict our analysis to the years 1995–2010. This leads to a sample of 13 countries with various labor market institutions and economic situations. The countries are: Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and the United Kingdom.

We focus on 92 occupations at the 3-digit ISCO-88 level and 16 sectors according to the NACE Rev.2 classification. To ensure the stability of the sector definition across years, we group these 16 sectors into 11 sectors.¹⁰ We aggregate worker-level observations into country \times sector \times occupation \times year cells. For each country, sector and occupation we have information on employment, number of employees, number of hours worked and number of unemployed workers (see Appendix A for more details on the data).

We exploit long-differences between 1995 and 2010 assuming that automation and offshoring shocks materialize between these two dates as documented in other studies.¹¹ Henceforth, the long-difference of any variable \mathcal{Y} between 1995 and 2010 will be simply denoted $\Delta\mathcal{Y}$.

3.1.1 Measuring Automation and Offshorability

The EULFS is merged with data on occupations' exposure to automation ("automatability") and to offshoring ("offshorability"). We use these variables to infer actual automation and offshoring in the subsequent years, which we do not observe. The underlying idea is that automation and offshoring are two general long-run trends whose effects can be assessed in terms of the differential exposure of different occupations to them.

To measure the "automatability" of an occupation we use its *Routine Task Intensity* index (RTI) as computed by Acemoglu and Autor (2011), which has been widely used in previous studies (see among many other Autor, Levy and

Murnane, 2003; Autor and Dorn, 2013; Goos, Manning and Salomons, 2014).¹² The RTI builds on information about the task content of occupations available from the Occupational Information Network (ONET). We use a crosswalk to go from the SOC 2000 classification used in ONET to the 4-digit ISCO-88 classification before aggregating to the 3-digit ISCO-88 classification (see Appendix A for additional details). Comparing our RTI measure with an alternative measure of automatibility constructed by Frey and Osborne (2013) reveals a large positive correlation between them with only few exceptions for specific occupations.¹³

To measure the “offshorability” of an occupation we adopt the index developed by Blinder and Krueger (2013) (hereafter BK). This index builds on questionnaires as well as qualitative observations, and it is constructed by professional coders based on an occupational classification of workers. Offshorability is then reported on a 4-step qualitative scale from *Highly Non-Offshorable* (1) to *Highly Offshorable* (4).¹⁴ A different measure is provided by Acemoglu and Autor (2011), who instead build a quantitative index based on aggregating several ONET indicators. While correlations between these different measures are mostly positive (see Appendix A for additional details), we use the BK index as our benchmark measure of offshorability as Goos, Manning, Salomons (2014) find that this index is more reliable when compared with actual offshoring measures.¹⁵

While both automation and offshoring may displace workers, it is important to note that they are conceptually quite different. The likelihood of automation is linked to the routineness of a task, hence to the possibility that the task can be performed algorithmically by a computer or a robot. By contrast, offshorability à la Blinder and Krueger (2013) refers to the ability to perform one’s work duties, for the same employer and customers, in a foreign country, even though the supply of the good or the service is still based in the home country. Accordingly, while the correlation between our measures of automatibility and offshorability is positive, there are important exceptions across occupations (see column 4 and 5 in Table 4.1 and Appendix A for a full picture).

3.1.2 Measuring Selectivity

We proxy “selectivity” in terms of unemployment duration, mismatch and concentration of specialized knowledge in specific tasks. We capture the last by the concentration of occupations’ employment across sectors. In the wake of Costinot and Vogel (2010) the underlying idea is that, while a sector may cover a rich menu of occupations, these include a submenu of “core” occupations that are disproportionately concentrated in the sector. While the change in concentration is likely determined by many concurrent factors, more concentration triggered by higher automatibility or offshorability would still be consistent with the channel of selectivity we are looking for. Specifically, let $\mathcal{O} = \{o_1, \dots, o_{92}\}$ be the set of occupations, $\mathcal{K} = \{k_1, \dots, k_{11}\}$ be the set of sectors and $\mathcal{I} = \{i_1, \dots, i_{13}\}$ be the

set of countries in our sample. Consider occupation $o \in \mathcal{O}$ in sector $k \in \mathcal{K}$ of country $i \in \mathcal{I}$ with employment denoted by L_{oki} . Our measure of occupation o 's employment concentration across sectors $k \in \mathcal{K}$ in country i is given by the Herfindhal index

$$SSO_{oi} = \sum_{k \in \mathcal{K}} \left(\frac{L_{oki}}{\sum_{k \in \mathcal{K}} L_{oki}} \right)^2, \quad (1)$$

where SSO is a mnemonic for ‘‘sectoral selectivity of occupation’’. Two remarks on eq. (1) are in order. First, as each occupation is not present in every sector, a key feature of SSO is that it is not standardized to account for the number of sectors used in the estimation. To understand this point, assume, for instance, that an occupation is equally observed in five different sectors in 1995, but disappears from one of the sectors in 2010 with previous employment from this sector evenly reallocated to the other four sectors. The distribution of the occupation’s employment across sectors is, therefore, uniform both in 1995 and in 2010. A standardized Herfindahl index would be equal to zero in both cases, implying that no change in selectivity would be detected between 1995 and 2010 for this occupation. Second, high SSO implies that few sectors account for a large share of the occupation’s employment. Therefore, an increase in SSO corresponds to an increase in concentration and thus more selectivity.

Our second measure of selectivity is based on the consideration that, if either automation or offshoring make specialized skills more salient, then firms may be willing to search longer for the right worker. We use unemployment duration as a proxy for workers’ and firms’ willingness to wait. This is computed at the occupation level by associating unemployed workers to their last occupation. Given the small number of observations in any given cell, we use occupations defined by the 2-digit ISCO classification. Moreover, when using this selectivity measure, we have to exclude France and the Netherlands from the sample due to data availability constraints.

Finally, our third measure of selectivity is based on the consideration that, if either automation or offshoring make specialized skills more salient, then the mismatch between workers’ skills and firms’ tasks should decrease. Therefore we use educational mismatch as a proxy for the extent to which workers’ skills in given occupations are aligned with the occupations’ task content. We consider both over-education and under-education by comparing each worker’s years of education with those of her or his peers in a given occupation, sector and country at the time of observation. A worker is considered as over-educated when the worker’s educational level is above the average of the worker’s 10-year cohort by more than 2 standard deviations; vice versa, a worker is considered as under-educated when the worker’s educational level is below the average of her or his 10-year cohort by more than 2 standard deviations (see e.g. Hartog, 2000, for a similar definition). Also in this case, given the small

number of observations in any given cell, we use occupations defined by the 2-digit ISCO classification. However, poor data availability for educational variables restricts our analysis to the years from 1998 to 2010. We then gauge changes in selectivity from changes in the shares of over- and under-educated workers in each occupation \times industry \times country cell. The underlying idea is that, if automation or offshoring makes firms more selective, we may observe a fall in under-education and possibly a rise in over-education among matched workers in more exposed sectors.

3.2 Descriptive Statistics

Table 4.1 presents descriptive statistics on the occupational characteristics aggregated at the 2-digit level for clarity. Occupations are ranked from the least to the most “automatable” (i.e. routine-intensive). Column 1 displays the percentage point change in the share of hours worked between 1995 and 2010. Overall, the change is smaller (or negative) for occupations that are more “automatable”. Among the ten most automatable occupations only *Customer Service Clerks* (42) and *Sales and Services Elementary* (91) do not exhibit a fall in the share of hours worked. On the contrary, the share of hours worked in occupations with a low routine content systematically increases. This illustrates the impact of routine-biased technological change on employment trends. Column 2 reports the change in unemployment. The ranking is less clear but the majority of low-RTI occupations experienced a decrease or stability in their unemployment rate.

3.3 Automation, Offshoring and Employment

Figure 4.1 looks at the direct effects of automatability on employment and its interplay with offshorability. We collapse observations to the occupation level and divide the 92 occupations into two groups according to median offshorability.¹⁶

Overall (dashed line), occupations with a low share of automatable tasks in 1995 experience an increase in total hours worked in subsequent years. Vice versa, occupations with a high share of automatable tasks in 1995 experience a decrease in total hours worked in subsequent years.

When considering the interaction with offshorability, a more nuanced pattern emerges. While the negative relationship between automatability and employment is confirmed for highly offshorable occupations (solid black line), the observed change in hours worked in occupations with low offshorability (solid grey line) is unrelated to the automatability of their tasks.¹⁷

3.4 Automation, Offshoring and Selectivity

To assess whether selectivity has any role to play in explaining the relative decrease in hours worked in occupations more exposed to automation and

Table 4.1 Descriptive Statistics: Occupations

| <i>Occupations ranked by Automation Probability</i> | Δ Share of Hours (1) | Δ Unemployment Rate (2) | Routine Task Intensity (3) | Offshorability (BK) (4) | Rank Offshorability (5) |
|--|--------------------------------|-----------------------------------|-------------------------------|----------------------------|----------------------------|
| Corporate managers (12) | 0.10 | -0.03 | -1.83 | -0.19 | 10 |
| Other professionals (24) | 0.43 | 0.18 | -1.71 | 0.09 | 11 |
| General managers (13) | 0.20 | 0.08 | -1.60 | -0.59 | 8 |
| Physical, mathematical, and engineering professionals (21) | 0.40 | -0.45 | -1.33 | 0.96 | 17 |
| Life science and health professionals (22) | 0.02 | -0.46 | -1.23 | -0.87 | 6 |
| Life science and health associate professionals (32) | 0.63 | -0.01 | -0.87 | -0.83 | 7 |
| Other associate professionals (34) | 0.39 | 0.28 | -0.78 | 0.48 | 13 |
| Physical and engineering science associate professionals (31) | 0.12 | 0.01 | -0.05 | 0.61 | 15 |
| Personal and protective service workers (51) | 0.74 | 0.48 | 0.17 | -0.94 | 4 |
| Models, salespersons and demonstrators (52) | -0.57 | 0.30 | 0.21 | -0.95 | 1 |
| Office clerks (41) | -0.26 | -0.33 | 0.27 | 1.56 | 19 |
| Extraction and building trades workers (71) | -0.43 | 0.30 | 0.32 | -0.95 | 3 |
| Metal, machinery and related trade workers (72) | -0.66 | -0.07 | 0.39 | -0.56 | 9 |
| Customer services clerks (42) | 0.02 | 0.60 | 0.68 | 0.56 | 14 |
| Sales and services elementary occupations (91) | 0.46 | 0.32 | 0.95 | -0.91 | 5 |
| Laborers in mining, construction, manufacturing and transport (93) | -0.10 | 0.08 | 1.02 | 0.43 | 12 |
| Precision, handicraft, printing and related trades workers (73) | -0.43 | -0.63 | 1.03 | 1.86 | 20 |
| Drivers and mobile-plant operators (83) | -0.07 | 0.17 | 1.19 | -0.95 | 2 |
| Stationary-plant and related operators (81) | -0.22 | -0.01 | 1.19 | 2.31 | 21 |
| Other craft and related trade workers (74) | -1.52 | -0.11 | 1.46 | 1.02 | 18 |
| Machine operators and assemblers (82) | -1.31 | 0.03 | 1.48 | 0.93 | 16 |

Occupations are ranked from least to most routine-intensive. Δ Share of Hours and Δ Unemployment Rate is the change in hours worked and the unemployment rate between 1995 and 2010 respectively. Data is from the EULFS. Routine Task Intensity is taken from Acemoglu and Autor (2011) and Offshorability from Blinder and Krueger (2013). Both are standardized to have a mean of 0 and a standard deviation of 1.

offshoring documented in Figure 4.1, we estimate the following equation:

$$\Delta Y_{oki} = \beta_1 RTI_o + \beta_2 Offshor_o + \beta_3 RTI_o \times Offshor_o + Z'_{oki} C + \mu_{oi} + \epsilon_{oki}. \quad (2)$$

On the left hand side, the dependent variable ΔY_{oki} corresponds to the long-term change in selectivity as captured by our three measures. For SSO and unemployment duration, ΔY_{oki} is the difference between 1995 and 2010, while for under-education or over-education, ΔY_{oki} is the difference between 1998 and 2010. This is due to the limited availability of educational data before 1998 as already mentioned. As SSO measures the concentration of occupation o across sectors k , the sample is aggregated at the occupation×country level. On the right hand side of (2), the explanatory variables RTI_o and $Offshor_o$ are the indices of automatability and offshorability respectively, while Z_{oi} is a set of control variables including the initial values of selectivity and of the employment share of the cell. We also include occupation×country fixed effects (μ_{oi}) except when the dependent variable is SSO, in which case we include country fixed effects (μ_i). As the indices of automatability and offshorability are standardized to have a mean of 0 and a standard deviation of 1, β_1 can be interpreted as the

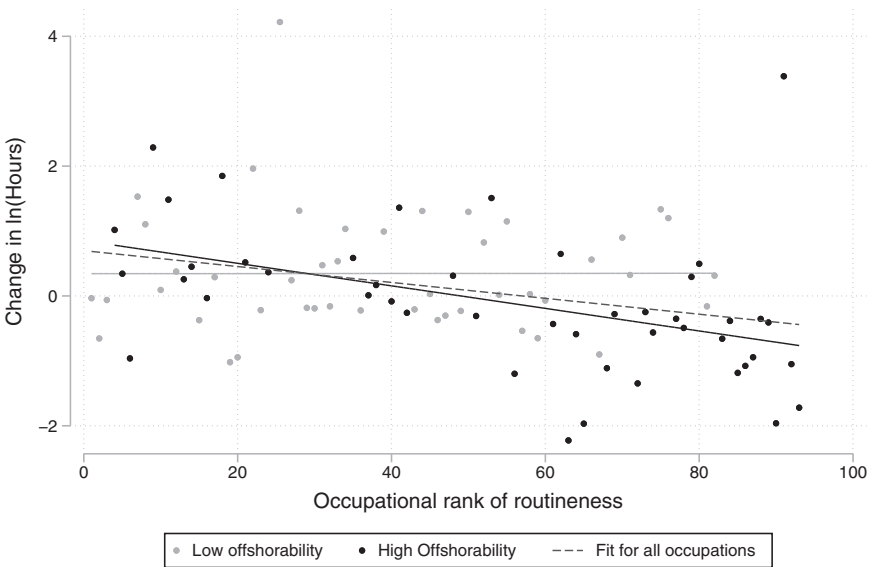


Figure 4.1 The Impact of Routineness and Offshorability on Labour Hours

Notes: Figure 4.1 plots the change in hours worked from 1995 to 2010 against the occupational rank of routineness. Data on employment is aggregated at the occupation level. Routineness of the occupation is taken from Acemoglu and Autor (2011) and data on offshorability comes from Blinder and Krueger (2013). Occupations belong to the low or high offshorability sample if they are below or above the median offshorability. Occupations with below- (above-) median offshorability are displayed in grey dots (black dots) with the corresponding linear sample fit plotted as the solid grey (black) line. The overall sample fit is plotted as a dashed line.

effect of automatability when offshorability is equal to its average value. Analogously, β_2 can be interpreted as the effect of offshorability when automatability is equal to its average value. Moreover, the effect of automatability when offshorability is one standard deviation larger than the average is given by $\beta_1 + \beta_3$. This is also the effect of offshorability when automatability is one standard deviation larger than the average. Unless specified otherwise, we comment on the effect of a variable when the other is at its average value.

The corresponding estimates are reported in Table 4.2. In this table, column 1 reports the results for SSO. It shows that occupations with higher initial automatability become more selective along the period when offshorability is at its average value. The coefficient is, however, imprecisely estimated and its p -value is slightly above the conventional levels of statistical significance. The effect of offshoring when automatability is at its average value is, instead, precisely estimated and negative. Automation and offshoring have thus opposite effects on the concentration of occupations across sectors. Though the trend of increasing concentration may be driven by other factors, the pattern is in line with an increase in selectivity for occupations more exposed to automation and a decrease in selectivity for occupations more exposed to offshoring. Moreover, as the interaction term between RTI_o and $Offshor_o$ is positive and significant, the increase in concentration for occupations more exposed to automation is more pronounced for those that are also more exposed to offshoring. For instance, when offshorability is larger than its average value by one standard deviation, the effect of automatability on SSO is almost twice as large and significantly different from 0 ($\beta_1 + \beta_3 = 0.16$ with p -value = 0.016). Column 2 reports the results for unemployment duration. We observe that the occupations more exposed to automation experience a larger increase in unemployment duration when offshorability is at its average value. This effect is reinforced for occupations that have higher degrees of offshorability. On the contrary, the effect of offshorability on unemployment duration is negative and imprecisely estimated. This effect becomes more negative as RTI decreases (i.e. as automatability decreases). Finally, columns 3 and 4 report the results for educational mismatch, looking at the shares of under- and over-educated workers separately. Column 4 shows that under-education falls in more automatable occupations and increases in more offshorable occupations. The interaction between automation and offshoring is negative, in line with the results in columns 1 and 2. By contrast, in column 3 over-education reacts in the opposite direction.

Overall, this empirical investigation reveals empirical patterns in line with increased selectivity in occupations exposed to automation and decreased selectivity in occupations exposed to offshoring. In particular, the patterns observed for automation are in line with the automation paradox, first highlighted by Bainbridge (1983) and discussed in Section 2. The empirical investigation also reveals that the interaction with offshorability generally reinforces the selectivity induced by automatability.¹⁸

Table 4.2 Selectivity, Automation and Offshoring.

| | (1) $\Delta \ln(SSO)$ | (2) $\Delta \ln(Unemp. \ duration)$ | (3) $\Delta Under \ ed. \ %$ | (4) $\Delta Over \ ed. \ %$ |
|-----------------------|--------------------------|--|---------------------------------|--------------------------------|
| RTI | 0.0802 (0.0506) | 0.0413* (0.0244) | -0.00439*** (0.000685) | 0.00336*** (0.000756) |
| Offshor. | -0.123** (0.0525) | -0.0300 (0.0328) | 0.00274*** (0.000836) | -0.00207** (0.000923) |
| RTI \times Offshor. | 0.0792* (0.0473) | 0.0558* (0.0332) | -0.00236*** (0.000729) | -0.00107 (0.000753) |
| Observations | 1,063 | 905 | 1,915 | 1,915 |
| R-squared | 0.148 | 0.189 | 0.172 | 0.246 |
| Fixed effects | Country | Country-Industry | Country-Industry | Country-Industry |

The table reports coefficients of estimating (2). The dependent variable is our proxy for selectivity. $\Delta \ln(SSO)$ is the log change of the Sectoral Selectivity of an Occupation calculated as the Herfindahl index of occupational employment shares across industries in a country. In Column 1, the dataset is aggregated at the country \times occupation level. It is aggregated at the country \times sector \times occupation level in columns 2 to 4. *RTI* is routine-task intensity as in Acemoglu and Autor (2011) and *Offshor.* measures the offshorability of an occupation as in Blinder and Krueger (2013). Standard errors in parentheses are clustered at the occupation level in column 1 and at the country \times occupation level in columns 2 to 4. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4 A Search Model with Core-Biased Technological Change

In this section we rationalize the empirical findings of the previous section in terms of a simple labor-market sorting model that explains how automation and offshoring can affect match selectivity and employment as observed in the data.

Following Becker (1973) and Shimer and Smith (2000), the model relies on two key elements. The first is assortativity between firms' tasks and workers' skills required to perform those tasks, which implies that there exist "ideal" pairings of skill and tasks producing maximum match surplus.¹⁹ The second element is search frictions, which implies that, as the ideal pairings cannot be immediately located, firms and workers sort according to acceptance regions around their ideal matches. The smaller the acceptance regions, the more selective workers and firms are. More selectivity implies less mismatch between tasks and skills, and more concentration of specialized knowledge in specific tasks. It also implies longer unemployment duration as workers and firms are more willing to forego less-than-ideal matches and wait for alternative future matches closer to the ideal ones. The degree of selectivity depends on the differential surplus of ideal matches with respect to less-than-ideal ones. In particular, anything that increases the differential surplus raises selectivity. Vice versa, anything that decreases the differential surplus reduces selectivity.

We show that calibrating the way automation and offshoring affect match surplus allows the model to replicate the empirical patterns highlighted in the previous section. Specifically, increased selectivity in occupations exposed to automation and decreased selectivity in occupations exposed to offshoring require the differential surplus of ideal matches with respect to less-than-ideal ones to be raised by automation and reduced by offshoring. Moreover, the observation that the interaction with offshorability generally reinforces the effect of automatibility requires the positive impact of automation on the differential surplus to be enhanced by offshoring. As we will see, these requirements discipline the assortativity properties of the production process.

4.1 *Matching, Search and Heterogeneity*

There are two types of heterogeneous agents: workers and firms. Time is continuous, and in each moment the timing of events is as follows. Firms with heterogeneous tasks decide whether or not to enter the labor market and randomly meet one-to-one with workers with heterogeneous skills. After observing their respective tasks or skills, each firm and the worker it has met decide whether to match or not. If they decide to match, they bargain on the wage as a fraction of the match surplus according to the Nash protocol. The steady state pure strategy of each firm or worker is to decide which workers or firms to match with, taking the strategies of all other firms and workers as given.

All agents are risk-neutral, infinitely lived and maximize the present value of their future income streams, discounted by the common discount factor ρ .

Income streams are determined by the match surplus generated by firms and workers through production. Horizontal differentiation in workers' skills and firms' tasks is introduced in terms of different addresses along a characteristics' space represented by a unit circle. Along the unit circle, there is an exogenous measure of domestic workers $L > 0$ with skills indexed $x \in [0, 1]$ clockwise from noon ("skill address"). The distribution of skills across addresses is determined by a uniform p.d.f. $g_w(x)$. Given unit support, there are thus L workers at each address. Likewise, there is a measure of firms with tasks indexed $y \in [0, 1]$ clockwise from noon ("task address"). While the measure of workers L is exogenously given, the measure of firms is endogenously determined by free entry and exit. The distribution of tasks is also governed by a uniform p.d.f. $g_f(y)$. Uniformity is assumed for simplicity as it will lead to the same equilibrium outcome for all addresses.

When a worker with address x and a firm with address y are matched, they produce joint surplus $s(x, y, A, \Omega)$. This surplus depends on the degree of automation A , the extent of offshoring Ω and the distance between the addresses of skill x and task y :

$$d(x, y) = \min [x - y + 1, y - x] \tag{3}$$

where the min function selects the shorter arc distance of clockwise and counter-clockwise travels between x and y along the unit circle. An "ideal" match happens for $x = y$ and thus implies $d(x, y) = 0$. We will focus on the symmetric pure strategy steady state with the acceptance region given by the interval $[-d^*, d^*]$ centered around the ideal match $d = 0$ for all $x \in [0, 1]$ and $y \in [0, 1]$. Accordingly, we will leave the dependence of d on x and y implicit, and simply use $s(d, A, \Omega)$ to denote the match surplus at distance d with degree of automation A and extent of offshoring Ω . As the acceptance interval has measure $2d^*$, we will use $1/d^*$ as the model's index of "selectivity".

All agents know their own type and the types of all potential partners they meet. However, due to search frictions, domestic firms and workers are not necessarily all paired in a productive match.²⁰ Firms can be either producing (P) or vacant (V). Workers can be either employed (E), or unemployed (U). By definition, the sum of employed and unemployed workers equals the labour force, $E + U = L$, and we set $L = 1$ by choice of units. Hence, $E + U = 1$ holds both in the aggregate and for each address.

Only vacant firms and unemployed workers engage in search. Meeting rates are set according to a standard random search setup featuring Poisson distributed meeting intervals. We adopt a linear matching technology described by a homogeneous-of-degree-one Cobb-Douglas matching function $M(U, V) = \vartheta U^\xi V^{1-\xi}$, where ϑ is matching efficiency, U is unemployment, V are vacancies and $\xi \in (0, 1)$ is the elasticity of new matches to unemployment.²¹ In this setup the Poisson arrival rate can be derived as a function of aggregate labor market tightness V/U . We can then define $q_v = M(U, V)/V = \vartheta(U/V)^\xi$ as the rate at which vacant firms meet unemployed workers and $q_u = M(U, V)/U = \vartheta(V/U)^{1-\xi}$ as the

rate at which unemployed workers meet vacancies. Matches can be destroyed by separation shocks, which we assume to happen with per-period probability $\delta \in (0, 1)$.

Firms face a cost $c > 0$ of maintaining a job either filled or vacant paid in units of the final good. Match surplus is shared according to the Nash bargaining solution with worker bargaining weight $\alpha \in (0, 1)$. We impose zero outside options for both workers and firms by normalizing the unemployed workers' and vacant firms' income to 0.²²

The equilibrium of the model is determined as follows. To avoid cluttering the notation, we leave the dependence of variables on automation and offshoring implicit for now. A worker's discounted value of being employed $v_e(d)$ equals the current wage plus the option value of the potential future loss from unemployment:

$$\rho v_e(d) = w(d) - \delta(v_e(d) - v_u). \quad (4)$$

Given that unemployed workers' income is normalized to 0, a worker's discounted value of being unemployed v_u equals the option value of the potential future gain from employment:

$$\rho v_u = 2q_u \int_0^{d^*} (v_e(z) - v_u) dz, \quad (5)$$

which takes into account that an unemployed worker meets a vacancy at endogenous rate q_u and converts the meeting into a job if the worker's type falls in the acceptance interval of measure $2d^*$ centered at $d = 0$. The discounted value of a filled vacancy $v_p(d)$ equals what is left of the match surplus after the wage $w(d)$ and the maintenance cost c have been paid plus the option value of the potential future loss from exogenous separation at rate δ :

$$\rho v_p(d) = (s(d) - w(d) - c) - \delta(v_p(d) - v_v) \quad (6)$$

The value of an unfilled vacancy v_v satisfies

$$\rho v_v = -c + 2q_v \int_0^{d^*} (v_p(z) - v_v) dz, \quad (7)$$

where the right-hand side corresponds to the option value of filling the vacancy at endogenous rate q_v in the future net of the maintenance cost c .

The set of equilibrium conditions is then completed by the Nash bargaining rule

$$(1 - \alpha)(v_e(d) - v_u) = \alpha(v_p(d) - v_v) \quad (8)$$

together with the free entry condition for the value of a vacancy ($v_v = 0$), the zero cutoff value condition for a filled vacancy associated with maximum mismatch d^*

($v_p(d^*) = 0$), and the steady state flow condition for employment

$$q_u = \frac{\delta E}{2d^*(1 - E)}. \quad (9)$$

The last condition requires job destruction δE to be exactly offset by job creation $2q_u d^*(1 - E)$ as an unemployed worker meets a vacancy at rate q_u and matches with the corresponding firm at a rate given by the ratio between the measures of the acceptance interval (equal to $2d^*$) and of the characteristic space (equal to 1).

Using the free entry and zero cutoff conditions, the set of equilibrium conditions can be reduced to a system of the two equations,

$$(1 - \alpha) \frac{2\mathfrak{G}^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}}{\delta + \rho + 2(1 - \alpha)\mathfrak{G}^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u} \int_0^{d^*} s(z) dz = c \quad (10)$$

and

$$(1 - \alpha) \frac{\delta + \rho + 2\mathfrak{G}^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}}}{\delta + \rho + 2(1 - \alpha)\mathfrak{G}^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u} s(d^*) = c, \quad (11)$$

in employment E and maximum mismatch d^* with match surplus $s(d)$ and meeting rate q_u given by (9).²³ Solving this system gives the equilibrium values of E and d^* , which can then be used to evaluate the equilibrium wage of domestic workers as follows:

$$w(d) = \frac{\alpha(\delta + \rho + 2q_u)}{\delta + \rho + 2(1 - \alpha)\mathfrak{G}^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u} s(d). \quad (12)$$

4.2 Automation, Offshoring and Assortativity

Having laid out the search model with two-sided heterogeneity, we can now discuss how assortativity should be affected by automation and offshoring for the model's predictions to be consistent with the empirical patterns discussed in Section 2 and highlighted in Section 3. To this aim we make the dependence of match surplus $s(d)$ on automation and offshoring explicit by rewriting it as $s(d, A, \Omega)$.

There are three requirements that the model's predictions should fulfill in order to be in line with the empirical patterns. First, the differential surplus of ideal matches with respect to less-than-ideal ones should be increased by automation. Second, the differential surplus should be decreased by offshoring. Third and last, the positive impact of automation on the differential surplus should be reinforced by offshoring.

The first requirement is fulfilled by the model's predictions if match surplus $s(d, A, \Omega)$ is log-submodular in d and A . Analogously, the second requirement

is fulfilled if match surplus $s(d, A, \Omega)$ is log-supermodular in d and Ω . In words, better matches (i.e. matches at smaller distance d) have a comparative advantage in exploiting automation, whereas worse matches (i.e. matches at longer distance d) have a comparative advantage in exploiting offshoring. The third and last requirement is met if match surplus $s(d, A, \Omega)$ is log-supermodular in A and Ω . In words, matches with a higher degree of automation have a comparative advantage in exploiting offshoring, and vice versa matches with a larger extent of offshoring have a comparative advantage in exploiting automation. Note that log-submodularity in A and d implies that, as automation proceeds (larger A), workers and firms attribute increasingly higher value to ideal matches relative to less-than-ideal ones. This is what we call “core-biased technological change” (CBTC).

We show that these assumptions on log-modularity allow the model to reproduce the observed empirical patterns through a numerical implementation based on a specific microfounded functional form for match surplus $s(d, A, \Omega)$.

4.3 A Simple Numerical Example

Assume that production by matched worker x and firm y takes place according to a constant return to scale Cobb-Douglas production function employing capital and labor as inputs with total factor productivity $B > 0$ and capital share $\beta \in (0, 1)$. Output is sold in a perfectly competitive product market at a given price normalized to unity. The worker’s productivity is determined by match distance $d(x, y)$, the degree of automation A and the extent of offshoring Ω . Leaving again the dependence of d on x and y implicit, we use $L(d, A, \Omega)$ to denote such productivity, which corresponds also to the worker’s efficiency units of labor as the worker is assumed to supply one unit of labor inelastically. The corresponding capital services can be rented in a perfectly competitive capital market at rental rate $\rho > 0$. Match surplus is then obtained by subtracting capital services from production. Given perfect competition, capital services are related to $L(d, A, \Omega)$ by the firm’s profit maximizing condition that the value of the marginal productivity of capital equals its rental rate. As a result, match surplus evaluates to:

$$s(d, A, \Omega) = \Phi B^{\frac{1}{1-\beta}} L(d, A, \Omega), \quad (13)$$

with bundling parameter $\Phi \equiv (1 - \beta)(\beta/\rho)^{\frac{\beta}{1-\beta}}$.

Each task consists of subtasks that are differentiated over a two-dimensional continuum in terms of their “automatability” and “offshorability”, inversely measured by indices $a \in [0, 1]$ and $\omega \in [0, 1]$ respectively. The two-dimensional representation captures the fact that automatability and offshorability are conceptually and empirically quite different as highlighted in Section 3.1.1. The worker’s productivity in performing a subtask with automatability a and

offshorability ω is given by:

$$l(d, a, \omega) = Fa\omega - \frac{1}{2}(\gamma_a a + \gamma_\omega \omega)d, \quad (14)$$

with $F > 0$. According to (14), in the absence of mismatch ($d = 0$), the worker is more productive in subtasks with low automatability (large a) and low offshorability (large ω). Crucially, in the presence of mismatch ($d > 0$), for given d , automatability and offshorability affect the mismatch penalty $\gamma_a a + \gamma_\omega \omega$, where γ_a and γ_ω are fixed parameters whose signs will play a crucial role in what follows.

The firm first decides which subtasks to automate or offshore; it then looks for a worker whom to assign the remaining tasks to. Given (14), the firm has a stronger incentive to automate subtasks with low a and to offshore subtasks with low ω . Hence, if there are costs of automation and offshoring and these are an increasing function of the measure (“number”) of subtasks that are automated and offshored, there will exist thresholds of automatability $A \in [0, 1]$ and offshoring $\Omega \in [0, 1]$ such that subtasks (a, ω) with $a \in [0, A]$ are automated, subtasks with $\omega \in [0, \Omega]$ are offshored, and subtasks with $a \in [0, A]$ and $\omega \in [0, \Omega]$ are both automated and offshored. For the remaining tasks with $a \in [A, 1]$ and $\omega \in [\Omega, 1]$ the firm searches for a worker.²⁴

The productivity of a matched worker with skill at distance d from the firm’s task can then be evaluated by integrating (14) with respect to a and ω with $a \in [A, 1]$ and $\omega \in [\Omega, 1]$ to obtain:

$$L(d, A, \Omega) = (1 - A)(1 - \Omega) \left\{ \frac{1}{4}F(1 + A)(1 + \Omega) - \frac{1}{4}[\gamma_a(1 + A) + \gamma_\omega(1 + \Omega)]d \right\}, \quad (15)$$

where the term $(1 - A)(1 - \Omega)$ outside the curly brackets is the measure (“number”) of subtasks performed by the worker as they are neither automated nor offshored (“extensive margin”), while the term inside the curly brackets is the worker’s average productivity across these subtasks (“intensive margin”). When more subtasks are automated (larger A) or offshored (large Ω), there are three effects on the matched worker’s productivity (15). First, the extensive margin shrinks as the worker is assigned fewer subtasks. This is the “substitution effect”. Second, the productivity of the ideal match ($d = 0$) increases as the matched worker can specialize in subtasks with higher a or higher ω in which the worker is more productive. This is the “productivity effect”. Third, the productivity of less-than-ideal matches ($d > 0$) increases or decreases relative to the ideal match ($d = 0$) depending on the signs of γ_a and γ_ω . This is the “mismatch penalty effect”.

The sign of the mismatch penalty effect is determined by the assumptions on the log-modularity of labor productivity $L(d, A, \Omega)$ and thus of match surplus $s(d, A, \Omega)$, given that by (13) the latter inherits the log-modularity properties of the former. In particular, $L(d, A, \Omega)$ —and thus $s(d, A, \Omega)$ —is log-submodular in A and d if and only if, for all $d' > d$ and $A' > A$, we have

$s(d', A')/s(d, A') < s(d', A)/s(d, A)$, which is the case for $\gamma_\omega < 0$. Analogously, $L(d, A, \Omega)$ —and thus $s(d, A, \Omega)$ —is log-supermodular in Ω and d if and only if, for all $d' > d$ and $\Omega' > \Omega$, we have $s(d', \Omega')/s(d, \Omega') > s(d', \Omega)/s(d, \Omega)$, which is the case for $\gamma_a > 0$. Moreover, for $\gamma_\omega < 0$ and $\gamma_a > 0$, $L(d, A, \Omega)$ —and thus $s(d, A, \Omega)$ —is also log-supermodular in A and Ω .

Figures 4.2, 4.3 and 4.4 provide graphical representations of the effects of automation and offshoring on the theoretical correlates of our three measures of selectivity. Parameter values are drawn from the literature except for those of the mismatch penalty parameters and productivity of the optimal match, which we treat as free parameters chosen in order to deliver empirically relevant equilibrium rates of unemployment between around 2% and 7%.²⁵ The concentration of occupations' employment across sectors is proxied in the model by the Herfindahl index of concentration of skills's employment (in efficiency units) across tasks in the acceptance interval:

$$H = \frac{1}{2} \frac{\int_0^{d^*} [L(z, A, \Omega)]^2 dz}{\left[\int_0^{d^*} L(z, A, \Omega) dz \right]^2}.$$

Unemployment duration is computed as the inverse of the rate q_u at which unemployed workers meet vacancies. Mismatch is measured by the length d^* of (half) the acceptance interval. Figures 4.2, 4.3 and 4.4 then show that, for the chosen parameter values, selectivity is an increasing function of automation (left panels) and a decreasing function of offshoring (right panels), no matter whether we measure selectivity in terms of employment concentration,

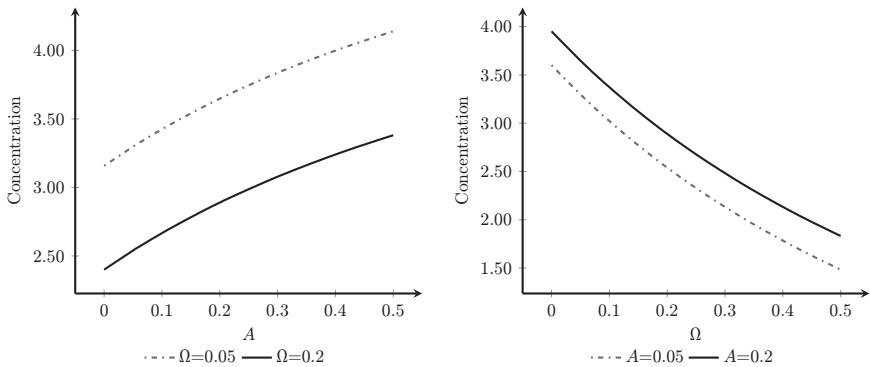


Figure 4.2 Employment Concentration. This figure plots simulated employment concentration over a range of automation A on the x-axis for $\Omega = 0.05$ (dashed) and $\Omega = 0.2$ (solid) in the left panel and over a range of offshoring Ω on the x-axis for $A = 0.05$ (dashed) and $A = 0.2$ (solid) in the right panel. Simulations are based on the system of equations (10)–(11) and parameters as specified in Table 4.C1.

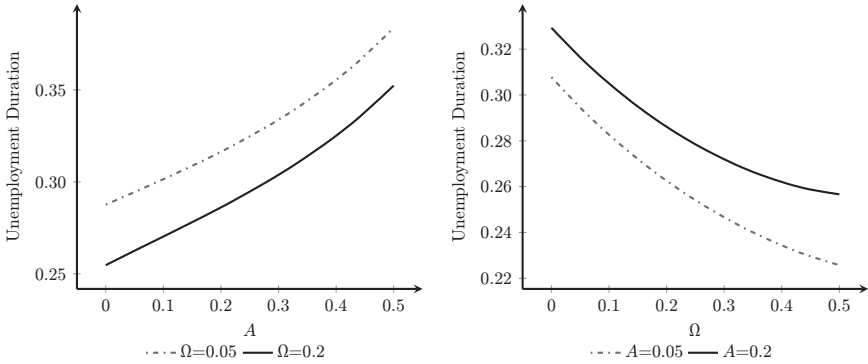


Figure 4.3 Unemployment Duration. This figure plots simulated unemployment duration over a range of automation A on the x-axis for $\Omega = 0.05$ (dashed) and $\Omega = 0.2$ (solid) in the left panel and over a range of offshoring on the x-axis for $A = 0.05$ (dashed) and $A = 0.2$ (solid) in the right panel. Simulations are based on the system of equations (10)–(11) and parameters as specified in Table 4.C1.

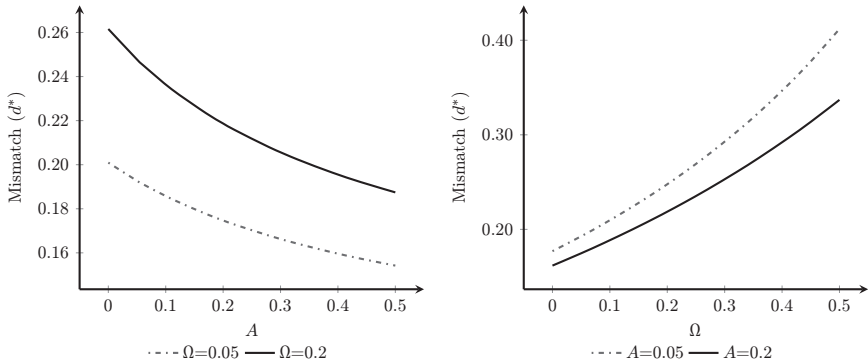


Figure 4.4 Mismatch. This figure plots simulated mismatch d^* over a range of automation A on the x-axis for $\Omega = 0.05$ (dashed) and $\Omega = 0.2$ (solid) in the left panel and over a range of offshoring Ω on the x-axis for $A = 0.05$ (dashed) and $A = 0.2$ (solid) in the right panel. Simulations are based on the system of equations (10)–(11) and parameters as specified in Table 4.C1.

unemployment duration and mismatch. They confirm that our model is able to qualitatively reproduce the empirical patterns we uncovered in the data.²⁶

The parametrized model can then be used to investigate how automation and offshoring may affect workers' employment opportunities and wages, which we do not observe in the data. The results of this investigation, corresponding to the effects on selectivity reported in the previous figures, are shown in Figure 4.5 for employment and Figure 4.6 for wages. Figure 4.5 shows that, for the

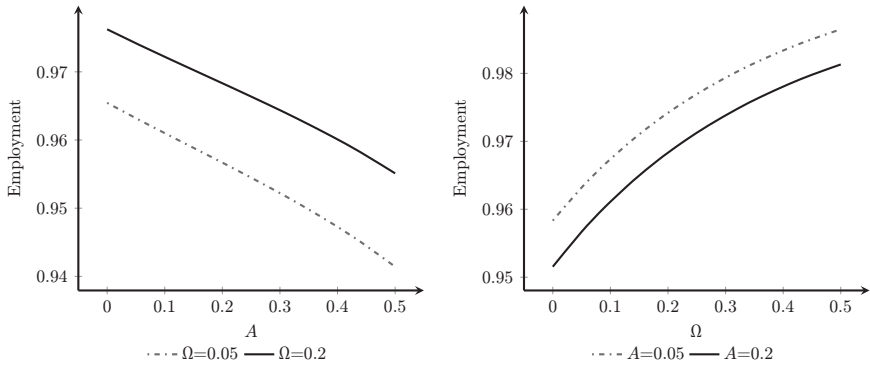


Figure 4.5 Employment. This figure plots simulated employment rates over a range of automation A on the x-axis for $\Omega = 0.05$ (dashed) and $\Omega = 0.2$ (solid) in the left panel and over a range of offshoring Ω on the x-axis for $A = 0.05$ (dashed) and $A = 0.2$ (solid) in the right panel. Simulations are based on the system of equations (10)–(11) and parameters as specified in Table 4.C1.

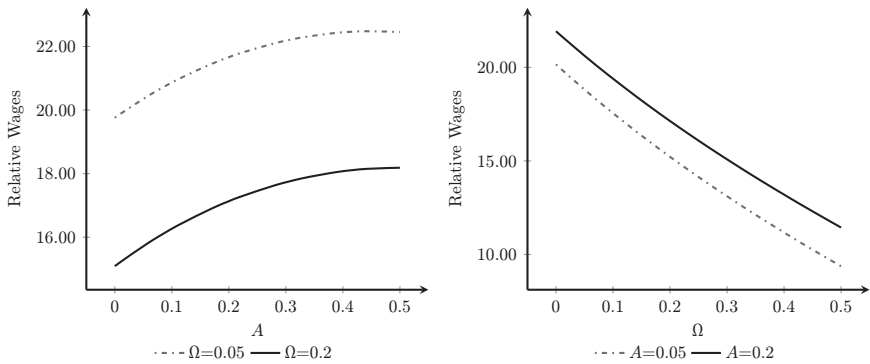


Figure 4.6 Relative Wages of Best vs. Worst Match. This figure plots of the wages of the best possible match ($d = 0$) relative to the worst possible match ($d = d^*$) over a range of automation A on the x-axis for $\Omega = 0.05$ (dashed) and $\Omega = 0.2$ (solid) in the left panel and over a range of offshoring Ω on the x-axis for $A = 0.05$ (dashed) and $A = 0.2$ (solid) in the right panel. Simulations are based on the system of equations (10)–(11) with wages computed as in (12) and parameters as specified in Table 4.C1.

chosen parameter values, equilibrium employment E is a decreasing function of automation A (left panel) and an increasing function of offshoring (right panel). As for interactions, the figure reveals that employment is log-supermodular in automation and offshoring: the negative impact of automation on employment

is stronger when there is more offshoring.²⁷ Figure 4.6 shows that automation increases wage inequality between the best ($d = 0$) and worst ($d = d^*$) matches, especially when there is more offshoring.²⁸

To summarize, for standard parameter values drawn from the literature, if better matches between firms and workers have a comparative advantage in exploiting automation, our model reproduces the observed effects of automation and offshoring on our three measures of selectivity. The model then implies that automation reduces employment by increasing workers' and firms' selectivity. If worse matches between firms and workers have a comparative advantage in exploiting offshoring, it also predicts that offshoring raises employment by decreasing workers' and firms' selectivity. Lastly, if matches with a higher degree of automation have a comparative advantage in exploiting offshoring, the model predicts that offshorability reinforces the impact of automation. These predictions are consistent with the automation paradox discussed in Section 2 and what we called "core biased technological change".

5 Conclusion

Automation and offshoring may affect a country's workers employment opportunities and wages in two main ways. As some tasks are automated or offshored, these tasks are not performed by the country's workers any longer and the demand for their services falls. This is the negative "substitution effect", which leads to reduced employment opportunities and wages. Nonetheless, reallocating tasks from the country's workers to automated systems or foreign workers may also promote production efficiency, which in turn allows production activities to expand with a beneficial impact on employment opportunities and wages. This is the positive "productivity effect", which may cause employment and wages to rise.

With regard to the substitution effect, existing studies mainly focus on the impact of automation on capital-labor substitution, which is particularly relevant for the adoption of robots and machines in production. They have highlighted that different workers are affected differently depending on their education ("skill-biased technological change") or the routineness of their tasks ("routine-biased technological change").

In the present chapter we have investigated the possible existence of an additional negative effect of automation on workers' employment opportunities and wages. As automation intensifies, specialized knowledge ("core competencies") becomes increasingly salient above and beyond what would be needed by the education content of tasks or their degree of routineness. As a result, workers and firms become more selective in matching their specialized skills and tasks. We have called this aspect of automation "core-biased technological change" (CBTC), and argued that something similar could be relevant also for offshoring: the more sophisticated a country's global value chains are, the more crucial may be the contribution of specialized knowledge by the country's workers.

We have looked for evidence consistent with CBTC in occupational data for European industries. We have found that automation reduces employment opportunities. More interestingly for the purposes of our analysis, automation also increases workers' and firms' selectivity as captured by longer unemployment duration, less skill-task mismatch, and more concentration of specialized knowledge in specific tasks. This does not happen in the case of offshoring, though offshoring reinforces the effects of automation.

We have shown that a labor market model with two-sided heterogeneity and search frictions can rationalize our empirical findings as long as one is willing to assume that better matches between firms and workers have a comparative advantage in exploiting automation, worse matches between firms and workers have a comparative advantage in exploiting offshoring, and matches with a higher degree of automation have a comparative advantage in exploiting offshoring. Directly testing these properties has not been possible with the occupational data used in this chapter, and we leave it to future research exploiting matched employer-employee data with detailed information in skills and tasks.

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A Data Description

We use the annual files of the European Labour Force Survey (EULFS) made available by Eurostat. This survey combines labour force surveys conducted at the national level in European countries. It has the advantage to provide harmonized information on basic labour markets variables. Our final database corresponds to *country* \times *industry* \times *occupation* \times *year* cells. The information on the sector is based on the broad NACE sectors (21 sectors in the NACE Rev.2 classification) and the information on the occupation is based on the 3-digits ISCO-88 classification. The EULFS is used to derive the number of employed and unemployed workers in each cell by collapsing individual observations using the provided weighting coefficients. We also use the EULFS to compute the unemployment duration in each cell.

Construction of the variables We keep the employed people as defined by the ILO criteria and derived by Eurostat. It is less common to compute unemployment at the *sector* \times *occupation* level since workers can be mobile across sectors and occupations. We define unemployment in a given sector and a given occupation as the number of unemployed people who had this precise occupation in this precise sector. This measure corresponds to the true and unobservable unemployment rate at the *sector* \times *occupation* level if workers do not move across sectors and occupations.

Dataset selection We restrict our dataset to the 13 following countries: Austria, Belgium, Germany, Denmark, Spain, France, United Kingdom, Greece, Ireland, Italy, Luxembourg, Netherlands and Portugal. This group of countries corresponds to all countries that provided data at least from 1995. It is important to note that France and the Netherlands do not provide enough information to compute the unemployment rate at the cell level. Following Goos, Manning and Salomons (2014), we also drop the following industries: Agriculture, Forestry, Fishing (A); Mining and Quarrying (B), Public Administration and Defence and Compulsory Social security (O); Education (P) and Extra-territorial organizations and bodies (U). These sectors corresponds to public sectors and agricultural sectors. They account for 26% of all jobs in our sample. The following occupations, closely associated to the sectors deleted are also dropped from the sample: Legislators and senior officials (ISCO-88: 11); teaching professionals (ISCO-88: 23); teaching associate professionals (ISCO-88: 33); market-oriented skilled agricultural and fishery workers (ISCO-88: 61); agricultural, fishery and related labourers (ISCO-88: 92).²⁹ Finally, our data contains information, virtually complete, at the cell level for 92 occupations, in 16 sectors.

Table 4.A1 sums up the coverage of our database relative to official statistics. According to official Eurostat statistics, we cover around 70% of the employment in each country, except for Luxembourg for which we only cover 58.5% of the employment. This is due to the fact that Luxembourg is a small country with a large institutional sector driven by the presence of some European institutions. Our coverage of unemployment is a bit less precise, going from 36.2% of official unemployment numbers in Italy to 69.6% in Denmark. This is principally due to

Table 4.A1 Database Coverage (in % of official Eurostat figures)

| <i>Country</i> | <i># of employees</i> | <i># of unemployed workers</i> |
|----------------|-----------------------|--------------------------------|
| Austria | 70.9% | 56.1% |
| Belgium | 70.5% | 51.5% |
| Germany | 75.4% | 62.3% |
| Denmark | 73.3% | 69.6% |
| Spain | 70.5% | 61.1% |
| France | 69.1% | - |
| United Kingdom | 74.2% | 59.8% |
| Greece | 61.1% | 42.3% |
| Ireland | 66.5% | 51.1% |
| Italy | 71.8% | 36.2% |
| Luxembourg | 58.5% | 44.0% |
| Netherlands | 68.0% | - |
| Portugal | 69.8% | 38.6% |

the lack of precise reporting of the last job for unemployed people and to dropped industries. Especially the coverage is very low for Portugal in 1995 (around 10%).

The time frame of our analysis corresponds to 1995–2010 in order to include the maximum number of countries. Our analysis stops in 2010 because after this date, a change in the occupation classification (ISCO-88 to ISCO-08) prevents us from accurately representing changes in the time series.

A.1 Offshorability

Three different measures of offshorability are proposed in the literature: by Blinder (2009), by Blinder and Krueger (2013, hereafter BK) and by Acemoglu and Autor (2011, hereafter AA). In the first two cases, the authors propose a qualitative scale of offshorability, ranking occupations from “Highly Non-Offshorable” (1) to “Highly Offshorable” (4) following Blinder (2009). Blinder then proposes a qualitative ranking of occupations according to their degree of offshorability. BK only provide 4 categories. AA propose a quantitative index of offshorability based on ONET.³⁰ Their measure aggregates several ONET indicators: Face to face discussions, Assisting and Caring for Others, Performing for or Working Directly with the Public, Inspecting Equipment, Structures, or Material, Handling and Moving Objects, 0.5*Repairing and Maintaining Mechanical Equipment, 0.5*Repairing and Maintaining Electronic Equipment.

While Blinder and BK measures are based on questionnaires and qualitative observations about offshorability; the AA measure is not. The two types of measures are likely to diverge for some occupations. In Table 4.A2, we compute the correlation coefficient between these measures. The correlation between Blinder and BK indices is large while for both indices the correlation with the AA measure is quite low.

Table 4.A2 Correlation Table between Offshorability Measures

| | <i>AA (2011)</i> | <i>Blinder (2009)</i> | <i>BK (2013)</i> |
|------------------------|------------------|-----------------------|------------------|
| Acemoglu-Autor (2011) | 1 | – | |
| Blinder (2009) | 0.34 | 1 | – |
| Blinder-Krueger (2013) | 0.25 | 0.94 | 1 |

For instance, Models, Salespersons and Demonstrators (code 52) is an occupation classified among the five most offshorable occupations according to the AA index while it is ranked as Highly Non-Offshorable by Blinder (2009). Teaching professionals (code 23) are also in the same situation. On the contrary, Machine operators and assemblers (code 82) are ranked as offshorable in Blinder (2009) while being ranked as a low offshorability activity by the AA index.

In their data appendix Goos, Manning and Salomons (2014) compare different offshorability index with actual offshorability measures. Blinder/BK types of measures seem more reliable. We consider these two measures as our preferred ones, using the BK index in our baseline regressions.

A.2 Automatability

We proxy the probability of future automation of an occupation using the RTI measure constructed by Autor and Dorn (2009). This measure correlates with the one provided by Frey and Osborne (2013). Using the files by Acemoglu and Autor (2011) and the definition of the RTI by Lewandowski et al. (2017) we compute the RTI index based on DOT data.³¹ The measure of the RTI is standardized in order to have a mean of zero and a standard error of one. We use a crosswalk to go from SOC 2000 classification to 4-digit ISCO-88 classification and then aggregate it to the 3-digit ISCO-88 classification. At this level the correlation between the RTI (“routineness”) and measure by Frey and Osborne (“probability of automation”) is 0.77 (see Figure 4.A1). However, the two variables diverge for some occupations.

To assess the evolution of routine jobs across countries and industries, Dao et al. (2017) also use an index of “routineness” fixed for the nine 1-digit ISCO-88 occupations. They then assume that the partition of jobs within 1-digit ISCO occupations is fixed among countries, industries and time. We relax this assumption by only assuming that the RTI of a 3-digit ISCO occupation is fixed. This way we are able to observe the evolution in the automatability by country, industry and occupation.

A.3 Relation Between Offshorability and Automatability

In this subsection we document that automatability and offshorability are not trivially correlated. First, conceptually the two concepts are different. Offshorability is defined as “the ability to perform one’s work duties (for the same

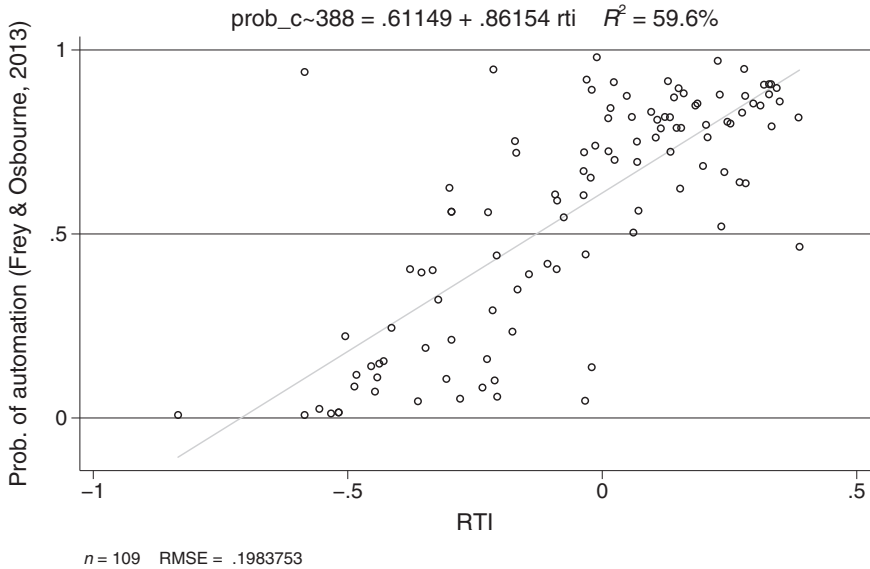


Figure 4.A1 Correlation between Automation Probability and Routineness

employer and customers) in a foreign country but still supply the good or service to the home market” (Blinder and Krueger, 2009) while the automatability is more strictly linked to the routineness of a task, its possibility to be solved algorithmically, etc. Figure 4.A2 documents the correlation between the two variables. There is a global positive correlation, but the figure also highlights the diversity of RTI/offshorability combinations. Especially some occupations are both offshorable and routine-intensive (42: Customer service clerks; 73: Precision, handicraft, printing and related trades workers; 74: Other craft and related trade workers; 81: Stationary-plant and related operators; 82: machine operators and assemblers). Others are not routine intensive but offshorable (21: Physical, mathematical and engineering science professional) while some are protected from offshorability but at risk of automation (83: Drivers and mobile-plant operators; 91: sales and services elementary occupations; 93: labourers in mining, construction, manufacturing and transport). Finally, some occupations are both protected from automation and from offshorability (12: corporate managers; 13: general managers; 22: life science and health professionals). Note, however, that the scope of occupations that are not routine intensive but offshorable is very limited.

A.4 Merging Procedure

Our matching strategy could be decomposed as follows: i) We only keep the observations before 2011, ii) we compute the RTI for each 4-digit ISCO-88 using official crosswalks, iii) we average the probabilities of automation when many SOC occupations are matched into a single ISCO occupation, iv) we

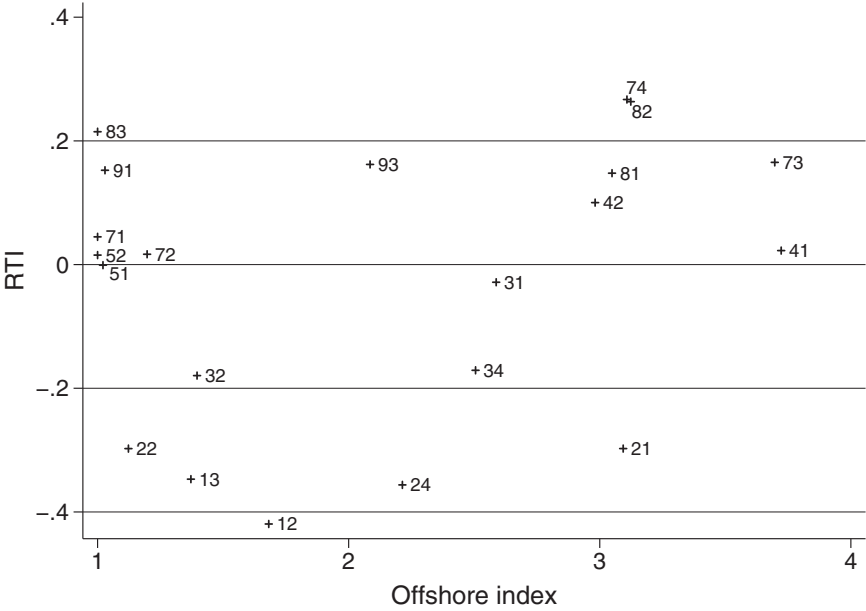


Figure 4.A2 Automation Probability and Offshorability (BK, 09)

take the unweighted average probability of automation to aggregate our measure at the 3-digit ISCO-88 levels, v) we match each occupation with its RTI, vi) we proceed in the same way to assign RTI and offshorability indexes to occupation reported at the 2-digit ISCO level. Finally, when necessary, we obtain the measure of routine task intensity and offshorability at the 2-digit ISCO level by collapsing (with appropriate weights) all observations at the 3-digit level in their corresponding 2-digit ISCO occupation.

B Model Solution

This Appendix provides a detailed derivation of (10), (11) and (12) in the main text. The steady state equilibrium is characterized by the following equations:

Surplus function:

$$s(d, A, \Omega) = \Phi B^{\frac{1}{1-\beta}}(1 - A)(1 - \Omega) \left\{ \frac{1}{4} F(1 + A)(1 + \Omega) - \right. \quad (16)$$

$$\left. \frac{1}{4} [\gamma_a(1 + A) + \gamma_\omega(1 + \Omega)] d \right\}, \quad (17)$$

where we occasionally omit the dependence on A and Ω for brevity.

Matching function:

$$M(U, V) = \vartheta U^\xi V^{1-\xi}. \quad (18)$$

Resource constraint:

$$E + U = L = 1. \quad (19)$$

Flow condition:

$$2d^* M(U, V) = \delta E. \quad (20)$$

Meeting probabilities:

$$q_v = M(U, V)/V = \vartheta(U/V)^\xi. \quad (21)$$

$$q_u = M(U, V)/U = \vartheta(V/U)^{1-\xi}. \quad (22)$$

Optimality conditions:

$$\rho v_E(d) = w(d) - \delta(v_E(d) - v_U), \quad (23)$$

$$\rho v_P(d) = (s(d) - w(d) - c) - \delta(v_P(d) - v_v), \quad (24)$$

$$\rho v_U = 2q_u \int_0^{d^*} (v_E(z) - v_U) dz, \quad (25)$$

$$\rho v_V = -c + 2q_v \int_0^{d^*} (v_P(z) - v_v) dz. \quad (26)$$

Bargaining outcome:

$$(1 - \alpha)(v_E(d) - v_U) = \alpha(v_P(d) - v_v). \quad (27)$$

Free entry condition:

$$v_V = 0. \tag{28}$$

Zero cutoff value condition:

$$v_P(d^*) = 0. \tag{29}$$

From this system of 13 equations in 13 unknowns ($E, U, V, M, q_v, q_u, w, v_E, v_P, v_U, v_V, s, d^*$), (10) and (11) can be obtained as follows. Subtract (25) from (23) to obtain:

$$\int_0^{d^*} (v_E(z) - v_u) dz = \frac{\int_0^{d^*} w(z) dz}{\rho + \delta + 2q_u(\theta)}. \tag{30}$$

Subtract (26) from (24) to obtain:

$$\int_0^{d^*} (v_P(z) - v_V) dz = \frac{\int_0^{d^*} (s(z) - w(z)) dz}{\rho + \delta + 2q_v(\theta)}. \tag{31}$$

Substitute into the integral of (27)

$$(1 - \alpha) \int_0^{d^*} (v_E(z) - v_U) dz = \alpha \int_0^{d^*} (v_P(z) - v_V) dz \tag{32}$$

to obtain:

$$w(z) = \frac{\alpha(\delta + \rho + 2q_u(\theta))s(z)}{\delta + \rho + (1 - \alpha)2q_v(\theta) + \alpha 2q_u(\theta)}. \tag{33}$$

Substitute (27) into (26) to obtain:

$$\rho v_V = -c + 2q_v(\theta) \frac{1 - \alpha}{\alpha} \int_0^{d^*} (v_E(z) - v_U) dz. \tag{34}$$

Substitute (33) into (30) to obtain:

$$\int_0^{d^*} (v_E(z) - v_u) dz = \frac{\alpha \int_0^{d^*} s(z) dz}{\delta + \rho + (1 - \alpha)2q_v(\theta) + \alpha 2q_u(\theta)}. \tag{35}$$

Hence (34) and (35) imply:

$$\rho v_V = -c + \frac{(1 - \alpha)2q_v(\theta) \int_0^{d^*} s(z) dz}{\delta + \rho + (1 - \alpha)2q_v(\theta) + \alpha 2q_u(\theta)} \quad (36)$$

Using (20) and (19) in (22) gives:

$$q_u = \frac{M(U, V)}{U} = \frac{\delta E}{2d^*(L - E)}. \quad (37)$$

Using (20) and (19) gives

$$V = \left(\frac{\delta E}{2d^* \mathfrak{G} U^\xi} \right)^{\frac{1}{1-\xi}},$$

which, once substituted into (21), gives:

$$q_v = \mathfrak{G}^{\frac{1}{1-\xi}} (\delta E)^{-\frac{\xi}{1-\xi}} (L - E)^{\frac{\xi}{1-\xi}} (2d^*)^{\frac{\xi}{1-\xi}}, \quad (38)$$

or equivalently

$$q_v = \mathfrak{G}^{\frac{1}{1-\xi}} (q_u)^{-\frac{\xi}{1-\xi}}. \quad (39)$$

Substituting (39) into (33) gives (12) in the main text:

$$w(d) = \frac{\alpha(\delta + \rho + 2q_u)}{\delta + \rho + 2(1 - \alpha)\mathfrak{G}^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u} s(d).$$

Now substitute (39) into (36) to obtain:

$$\rho v_V = -c + \frac{2(1 - \alpha)\mathfrak{G}^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} \int_0^{d^*} s(z) dz}{\delta + \rho + 2(1 - \alpha)\mathfrak{G}^{\frac{1}{1-\xi}}(q_u)^{-\frac{\xi}{1-\xi}} + 2\alpha q_u}. \quad (40)$$

Hence using the free entry condition $v_v = 0$, (40) becomes:

$$\frac{2(1 - \alpha)g^{1-\frac{1}{\zeta}}(q_u)^{-\frac{\zeta}{1-\zeta}} \int_0^{d^*} s(z) dz}{\delta + \rho + 2(1 - \alpha)g^{1-\frac{1}{\zeta}}(q_u)^{-\frac{\zeta}{1-\zeta}} + 2\alpha q_u} = c, \tag{41}$$

which is (10) in the main text where (17) implies:

$$\int_0^{d^*} s(x, A, \Omega) dx = \Phi B^{\frac{1}{1-\beta}}(1 - A)(1 - \Omega) \frac{1}{4} d^* \left\{ F(1 + A)(1 + \Omega) - \frac{1}{2} [\gamma_a(1 + A) + \gamma_\omega(1 + \Omega)] d^* \right\}$$

Finally, substitute the free entry condition and (29) into (24) to obtain

$$w(d^*) = s(d^*) - c,$$

which, together with (17) evaluated at d^*

$$w(d^*) = \frac{\alpha(\delta + \rho + 2q_u)s(d^*)}{\delta + \rho + 2(1 - \alpha)q_v + 2\alpha q_u},$$

gives:

$$(1 - \alpha) \frac{\delta + \rho + 2q_v}{\delta + \rho + 2(1 - \alpha)q_v + 2\alpha q_u} s(d^*) = c.$$

Substituting (39) gives:

$$(1 - \alpha) \frac{\delta + \rho + 2g^{1-\frac{1}{\zeta}}(q_u)^{-\frac{\zeta}{1-\zeta}}}{\delta + \rho + 2(1 - \alpha)g^{1-\frac{1}{\zeta}}(q_u)^{-\frac{\zeta}{1-\zeta}} + 2\alpha q_u} s(d^*) = c, \tag{42}$$

which is (11) in the main text where

$$s(d^*, A, \Omega) = \Phi B^{\frac{1}{1-\beta}}(1 - A)(1 - \Omega) \left\{ \frac{1}{4} F(1 + A)(1 + \Omega) - \frac{1}{4} [\gamma_a(1 + A) + \gamma_\omega(1 + \Omega)] d^* \right\}$$

and

$$q_u = \frac{\delta E}{2d^*(1 - E)}.$$

given $L = 1$.

C Parameter Values

Table 4.C1 reports the parameter values used in Section 4

Table 4.C1 Parameters

| <i>Parameter</i> | <i>Description</i> | <i>Value</i> |
|------------------|------------------------------|--------------|
| α | Bargaining Weight | 0.5 |
| ρ | Patience | 0.04 |
| δ | Per-period Separation Shock | 0.05 |
| ξ | Matching Function Elasticity | 0.5 |
| ϑ | Matching Function Constant | 0.4 |
| β | Capital share in CB | 0.33 |
| c | Vacancy Cost | 1 |
| F | Max. Productivity | 115 |
| B | Factor Aug. Technology | 25.5 |
| γ_A | Mismatch penalty A | 115 |
| γ_B | Mismatch penalty Ω | -53 |

Notes: Table 4.C1 shows parameter values used for the numerical example in the main text. Parameter values are standard values drawn from Hagedorn, Law and Manovskii (2017) except for the mismatch penalty parameters whose values have been chosen in order to deliver empirically relevant equilibrium rates of employment. As we do not model endogenous separations we choose a higher separation rate compared to Hagedorn, Law and Manovskii (2017) and closer to Fujita and Ramey (2012).

Notes

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- 1 See, for example, Autor and Dorn (2009), Ottaviano, Peri and Wright (2013), Goos, Manning and Salomons (2014), Graetz and Michaels (2018), Acemoglu and Restrepo (2020a), Dauth et al. (2017) on the empirical side; Acemoglu and Autor (2011), Aghion, Jones and Jones (2017), Acemoglu and Restrepo (2018b) and Acemoglu and Restrepo (2018a), Caselli and Manning (2019) on the theoretical one. Most of these studies tend to focus more on the effects of either automation or globalization (for instance Grossman and Rossi-Hansberg, 2008, Costinot and Vogel, 2010 or Costinot, Vogel and Wang, 2012) than on their interactions. Empirical assessments of their simultaneous effects across US regions can be found, for example, in Autor, Dorn and Hanson (2013, 2015) and with a global perspective, both theoretically and empirically, in, for example, Arkolakis et al. (2018).
- 2 See, for instance, Acemoglu and Restrepo (2018b) and Acemoglu and Restrepo (2018a) and, on employment, also Bostrom (2014), Brynjolfsson and McAfee (2014), Goos, Manning and Salomons (2014), Ford (2015), Susskind and Susskind (2015), White House (2016), Stone (2016), Frey and Osborne (2013), Caselli and Manning (2019), Acemoglu and Restrepo (2019), Acemoglu, Lelarge and Restrepo (2020), and Acemoglu and Restrepo (2020b) and Fornino and Manera (2019) regarding the reversability of capital investments.
- 3 See Section 2 for concrete examples.
- 4 See, e.g., Grossman and Rossi-Hansberg (2008), Costinot and Vogel (2010), Ottaviano, Peri and Wright (2013), Goos, Manning and Salomons (2014).

- 5 For example, in the offshoring model by Antras, Garicano and Rossi-Hansberg (2006), cross-country hierarchical teams are formed where less skilled countries specialize in production and more skilled countries specialize in problem solving. In the model of global value chains by Antras, Garicano and Rossi-Hansberg (2006), in which production of the final good is sequential and subject to mistakes, countries with lower probabilities of making mistakes at all stages specialize in later stages of production.
- 6 In the wake of Costinot and Vogel (2010) the underlying idea is that, while a sector may cover a rich menu of occupations, these include a submenu of “core occupations” that are disproportionately concentrated in the sector.
- 7 The 2018 Talent Shortage Survey by ManpowerGroup covers 39,195 employers across six industry sectors in 43 countries and territories: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, China, Colombia, Costa Rica, Czech Republic, Finland, France, Germany, Greece, Guatemala, Hong Kong, Hungary, India, Ireland, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Panama, Peru, Poland, Portugal, Romania, Singapore, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, UK and USA.
- 8 In spring 2014 the European Centre for the Development of Vocational Training of the European Union (Cedefop) undertook the first European skills and jobs survey (ESJS), a large-scale primary data collection of about 49,000 adult employees in 28 EU Member States. Cedefop Eurofound (2018) summarizes many of the insights gained by closer empirical scrutiny of this new European data set.
- 9 Koren, Csillag and Köllö (2020) also find that the productivity of workers assigned to new machines rises and their wages increase but become more unequal.
- 10 Following Goos, Manning and Salomons (2014), occupations and sectors closely associated with public and agricultural activities are dropped. We also drop 3-digit ISCO occupations that are not precisely reported. These occupations are dropped from the final sample. This corresponds to 1.1% of total hours worked in the sample and this only affects six countries in the sample.
- 11 For instance, Chiacchio, Petropoulos and Pichler (2018) shows that robot penetration in the EU28 has tripled over this period and particularly between 1995–2007 relative to the years 2007–2015. A similar pattern can be observed for offshoring as measured by foreign direct investment and intermediates trade in the WTO and UNCTAD statistics.
- 12 We follow the definition of Lewandowski et al. (2017): $RTI_o = \ln(\text{Routine Cognitive}_o + \text{Routine Manual}_o) - \ln(\text{Non-Routine Analytical}_o + \text{Non-Routine Interpersonal}_o)$. Throughout we standardize RTI to have a mean equal to zero and a standard deviation of one.
- 13 The measure used by Frey and Osborne (2013) builds on the selection of solutions that engineers need to devise for specific occupations to be automated and it is given by the probability of computerization based on a Gaussian process classifier.
- 14 The index of Blinder (2009) is constructed in the same way, but it reports a qualitative ranking of occupations according to their degree of offshorability.
- 15 We obtain data from the Princeton Data Improvement Initiative (<https://krueger.princeton.edu/pages/princeton-data-improvement-initiative-pdii>). The matching procedure of occupations with our automatability and offshorability indices is detailed in Appendix A. Throughout we standardize the BK index to have a mean equal to zero and a standard deviation of one.
- 16 We aggregate our data at the cell level (country \times sector \times occupation \times year) into occupation \times year cells and for each occupation we compute the log change in

hours worked across the countries in our sample: $\Delta \ln(Hours_o) = \ln(Hours_o^{2010}) - \ln(Hours_o^{1995})$.

- 17 The paper by Bonfiglioli, Crinò, Gancia, and Papadakis (2021) in this volume studies the effect of imported industrial robots on US local labor markets between 1990 and 2015, unveiling empirical patterns consistent with “reshoring” whereby imported robots substitute foreign workers more than US workers. Related to our Figure 4.1, after classifying occupations in terms of their “replaceability” (by robots) and “offshorability”, they show in their Table 5 that the employment changes in non-replaceable occupations are uncorrelated with robot exposure regardless of offshorability. This holds also for replaceable occupations if they are also offshorable, whereas the correlation is negative if they are non-offshorable. It should be noted, however, that, while in a robustness check they measure “offshorability” as we also do, our measure of “automatability” based on routine intensity as in Acemoglu and Autor (2011) is quite different from their measure of “replaceability” based on robot application categories as in Graetz and Michaels (2018). Moreover, “reshoring” seems to be less relevant in Europe than in the US (De Backer et al., 2016; Kinkel, Dewanti and Zimmermann, 2017; Vanchan, Mulhall and Bryson, 2018).
- 18 The results on educational mismatch may resonate with the implications of traditional models of SBTC, but there is a crucial difference. In those models the demand of workers with higher education rises and the demand of workers with lower education falls in occupations more exposed to technological change. Yet, typically this is not connected to the evolution of over/under education.
- 19 Matches are one-worker-one-job relationships, and therefore we do not consider the complementarities between workers within the same firm as in Eeckhout and Kircher (2018). While complementarities within the firms are certainly important, they are not immediately relevant for our purposes.
- 20 In the absence of search or information frictions all workers and firms would be matched to their optimal partner as in Becker (1973).
- 21 See Mortensen and Pissarides (1994). Our assumption departs from the non-linear matching function employed in models with two-sided heterogeneity à la Shimer and Smith (2000). In particular, our matching technology implies that congestion externalities arise for each task.
- 22 If the outside option were positive, workers would simply search for longer periods of time.
- 23 See Appendix B for detailed derivations.
- 24 While we do not dwell on the determination of A and Ω , it would be straightforward to explicitly endogenize them by specifying the costs of automation and offshoring. Most naturally, A and Ω would be determined as decreasing functions of those costs. Comparative statics results would then be stated with respect to the cost parameters driving the choice of A and Ω rather than with respect to A and Ω . As this would not add much insight to the analysis, we prefer to keep the costs of automation and offshoring in the background and discuss the comparative statics with respect A and Ω .
- 25 See Appendix C for additional details.
- 26 To give some idea about the quantitative consistency of the calibrated model with the motivating evidence, consider deviations from point $A = 0.2$ and $\Omega = 0.2$ in the left panel of Figure 4.2 (i.e. black line). Increasing A to 0.35 corresponds to an increase in concentration of 8% comparable to the estimated increase of 8% in response to a 1 standard deviation increase in automatability (RTI) reported in Table 4.2. Similarly, in the right panel of Figure 2 increasing Ω to 0.35 (with $A = 0.2$) translates to a 17% decrease in selectivity in the model which is comparable to the estimated 12% drop in SSO in response to a 1 standard

deviation increase in offshorability. Similarly, consider decreasing A from 0.2 to 0.05, that is moving from the black to the dotted line in the right panel of Figure 4.2, while keeping $\Omega = 0.35$: selectivity decreases by roughly 30% relative to the case of $A = 0.2$ and $\Omega = 0.2$. This is comparable to empirically predicted drop in SSO by 27% when offshorability increases and automatability decreases by 1 standard deviation respectively. A similar exercise based on unemployment duration in Figure 4.3 reveals that the magnitude of the model's predictions roughly aligns with the estimated effects; mapping over- and under-education to a suitable model-analogue for interpretation is, however, difficult.

- 27 For instance, the left panel of Figure 4.5 clearly shows that, after denoting equilibrium employment by $E(A, \Omega)$, for $A' > A$ and $\Omega' > \Omega$ with $\Omega = 0.05$ and $\Omega' = 0.2$, we have $E(A', \Omega')/E(A', \Omega) > E(A, \Omega')/E(A, \Omega)$. This derives from the fact that $E(A, \Omega')$ is a flatter function of A than $E(A, \Omega)$. While less visible, the same applies to the right panel.
- 28 For instance, the left panel of Figure 4.6 clearly shows that, after denoting the equilibrium wage ratio by $W(A, \Omega)$, for $A' > A$ and $\Omega' > \Omega$ with $\Omega = 0.05$ and $\Omega' = 0.2$, we have $W(A', \Omega')/W(A', \Omega) > W(A, \Omega')/W(A, \Omega)$. While less visible, the same applies to the right panel of Figure 4.6. In Figure 4.6 the wage of the best match is an order of magnitude larger than the wage of the worst match. While this gap between the two extremes of the wage distribution may look unrealistically large, comparing the 75% and 25% percentiles reveals that the wage in the former percentile is only about twice as large as that in the latter percentile.
- 29 These occupations respectively account for 0.12%, 0.27%, 0.53%, 0.39% and 0.07% observations in the sectors kept.
- 30 This index is inspired by Firpo, Fortin and Lemieux (2011)
- 31 Lewandowski et al. (2017) slightly modify the RTI definition compared to Autor and Dorn (2009) in order to adapt it to the use of ONET data instead of DOT data: $RTI = \ln(\text{Routine Cognitive} + \text{Routine Manual}) - \ln(\text{Non-Routine Analytical} + \text{Non-Routine Interpersonal})$.