# Automation, Globalization and Vanishing Jobs: A Labor Market Sorting View*

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**Abstract**

We show, theoretically and empirically, that the effects of technological change associated with automation and offshoring on the labor market can substantially deviate from standard neoclassical conclusions when search frictions hinder efficient matching between firms with heterogenous tasks and workers with heterogenous skills. Our key hypothesis is that better matches enjoy a comparative advantage in exploiting new technologies. It implies that technological change promotes employment when initial productivity is low so that firms and workers are not very selective in matching, whereas it hampers employment when initial productivity is high enough to make firms and workers sufficiently selective. Capturing task heterogeneity at the sectoral level and skill heterogeneity at the occupational level, we find empirical support to the model's predictions in a dataset covering 92 occupations and 16 sectors in 13 countries from 1995 to 2010.

*JEL: automation, offshoring, two-sided heterogeneity, positive assortativity, wage inequality, horizontal specialization, core-task-biased technological change.*

*Keywords:*

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# 1 Introduction

Automation and globalization are two of the most debated contemporary long-run trends. They are perceived as having a disruptive effect on the labour market with worrying implications for inequality in terms of both employment opportunities and wages across different groups of workers. Understanding their effects, their relative importance and their possible interactions is, therefore, of preeminent relevance and, as such, has attracted a lot of research.[1]

Conventional wisdom, based on neoclassical reasonings about technological progress, is that both trends are not going to have different effects from those of previous industrial revolutions as in the end both can be seen as two types of 'technological change'. With constant-return-to-scale technologies, competitive input markets and homothetic preferences, the neoclassical paradigm predicts that any improvement in the state of technology leads to an increase in labor productivity. In turn, higher labor productivity maps into higher wages, which raise demand so as to compensate the investment that fosters technological change in the first place. Labor demand, hence employment, cannot deviate from the long-run path dictated by the evolution of labor productivity. This argument is very general and stands also in the presence of skill-biased technological change (SBTC), whereby new technology complements workers with high skills, or routine-biased technological change (RBTC), whereby technology crowds out workers from repetitive tasks.[2] It highlights a win-win situation as the efficiency gains in production eventually trickle down to both capital owners and workers. If labor is the only factor of production and the relative price of investment goods declines, then workers as a whole gain from new technology. Moreover, if the supply of labor to different occupations is perfectly elastic, then all workers gain.[3]

People do observe, however, a number of facts (such as decreasing labor share, vanishing jobs especially in manufacturing, and increasing inequality) that might challenge the rosy neoclassical view. Concerns have been raised about the impact of automation on labor demand from various angles.[4] Similar concerns have also been raised with respect to offshoring as this is seen to work

[1]See e.g. Autor and Dorn [10], Goos et al. [32], Ottaviano et al. [45], Graetz and Michaels [33], Acemoglu and Restrepo [3], Dauth et al. [24] on the empirical side; Acemoglu and Autor [1], Aghion et al. [5], Acemoglu and Restrepo [2] and [4], Caselli and Manning [21] on the theoretical one.

[2]See, e.g., Acemoglu and Restrepo [2].

[3]Caselli and Manning [21].

[4]See for instance Bostrom [16], Brynjolfsson and McAfee [18], Goos et al [32], Ford [30], Susskind and Susskind [50], White House [52], Stone et al [49], Frey and Osborne [29], Caselli and Manning [21].

just like a new production technology.[5] More generally, some commentators fear that things are very different this time when compared with previous industrial revolutions.[6] All these concerns can be rationalized only if one departs from the neoclassical paradigm in that, from a theoretical viewpoint, any threat to wages and employment may be expected to come more from the impacts of new technology on the competitiveness of markets in the presence of various types of frictions than from changes in the production function in the presence of frictionless markets.[7]

Against this backdrop, the aim of the present paper is to show, theoretically and empirically, that the effects of technological change associated with automation and offshoring on the labor market can substantially deviate from the rosy neoclassical conclusions when search frictions hinder efficient matching between firms that need heterogenous tasks to be performed and workers who are endowed with heterogenous skills to perform those tasks. The type of heterogeneity we have in mind is 'horizontal' rather than 'vertical' as usually assumed in the literature on skill-biased or routine-biased technological change. In models of skill-biased technological change some tasks are more 'skill intensive' than others and some skills are 'higher' in a vertical scale than others. In the dominant case of positive assortative matching, high-skill workers end up performing more skill-intensive tasks. Skill-biased technological change then increases the relative demand of high-skill workers to the detriment of low-skill ones, boosting the skill premium. The same logic works in models of routine-biased technological change, the only difference being that the skill intensity of tasks is replaced by their 'routine intensity' and the high-low ranking of skills is replaced by a ranking in terms of routiness. Analogously, routine-biased technological change increases the relative demand of non-routine workers to the detriment of routine ones, boosting the non-routine premium.

While SBTC and RBTC are very relevant concepts, here we want to highlight additional effects of automation and offshoring that are at work independently from any vertical heterogeneity. From a theoretical point of view, our hypothesis is the following. With two-sided heterogeneity, firms and workers have 'ideal matches', that is, matches that produce the highest surplus. However, in the presence of search frictions, meetings do not necessarily lead to ideal matches. Hence, whenever

[5] Grossman and Rossi-Hansberg [34], Costinot and Vogel [23], Goos et al. [32], Ottaviano et al [45].
[6] Bowen [17], Akst [8], Brynjolfsson and McAfee [18], Autor [9].
[7] Caselli and Manning [21].

a firm and a worker meet with a less-than-ideal counterpart, they both face a trade-off between accepting the current match and leaving in search of a better match. A better match generates higher surplus but this gain has to be discounted as time is lost in search. That is why in equilibrium firms (workers) settle for an 'acceptance set' of workers (firms) with skills (tasks) that are 'good enough' for them, in the sense that they generate enough surplus. The intersection between the two acceptance sets determines the 'matching set' of productive matches that are implemented. The larger the acceptance sets and thus the matching set, the higher the inefficiency in production due to more 'mismatch' between tasks and skills. Meetings that are not converted into productive matches generate frictional unemployment.

Our hypothesis is then that technological change may increase the productivity of ideal matches relative to less-than-ideal ones, above and beyond any consideration of skill or routine bias. It may, therefore, make firms and workers more 'selective' reducing their acceptance sets as they become more willing to forgo the surplus of a less-than-ideal match while waiting for a better one. Increased selectivity is good for the productive efficiency of matches that are eventually formed as 'mismatch' in the matching set diminishes. However, as firms and workers are willing to sit longer on the fence waiting for better matches, unemployment rises. Moreover, for matches that are actually formed, ideal matches end up commanding a higher premium with respect to less-than-ideal matches. The result is that technological change leads to higher match productivity, but also lower employment and more wage inequality. This 'mismatch effect' interferes with the standard neoclassical forces and materializes as long as less-than-ideal skills and tasks become less substitutable with ideal ones. As ideal matches are the ones that define firms' and workers' core competencies, we use 'core-biased technological change' (CBTC) to label the way technology evolves in our conceptual framework.

We formalize our hypothesis through a growth model that, beyond neoclassical forces, features search frictions in the labor market and assortativity with two-sided heterogeneity of horizontally differentiated skills and tasks.[8] Workers and firms are risk-neutral and maximize lifetime discounted utility in continuous time. The matching process, based on a one-to-one relation, is governed by a canonical constant return to scale function.[9] Workers' skills and firms' tasks are uniformly and

[8]On this modeling of the labor market see Shimer and Smith [48] and, more recently, Hagedorn, Law and Manovskii [35].

[9]See Mortensen and Pissarides [43].

symmetrically distributed around a circle that describes the space of their heterogeneous characteristics. Due to search frictions, workers and firms do not match efficiently, but instead search and accept matches in an interval around their ideal ones. The distance between matched skill and task affects the production function of the match. This function is log-submodular in total factor productivity ('state of technology') and skill-task distance in the characteristics space ('mismatch') so that matches at lower distance ('better matches') have a comparative advantage in exploiting higher total factor productivity ('better state of technology').

In this context technological change increases the productivity of any given match ('neoclassical effect'), but also the degree of assortativity ('mismatch effect'). On the one hand, the first effect increases labor demand, hence raising employment. On the other hand, the second effect increases the cost of mismatch and induces workers and firms to search for longer time, which in turn reduces employment. We show that, due to these opposite effects, employment is an inverted U-shaped function of the state of technology. Low initial total factor productivity implies that firms and workers are not very selective to start with because the cost of mismatch is small. In this situation the neoclassical effect prevails so that employment rises as the state of technology improves. However, as technology keeps on improving, the cost of mismatch grows and firms as well as workers become increasingly selective and wait longer in search of better matches. Beyond a certain level of total factor productivity and thus of selectivity, the cost of mismatch becomes high enough that the mismatch effect starts dominating the neoclassical effect with employment falling as technology improves. Hence, technological change promotes employment when initial total factor productivity is low so that firms and workers are not very selective, whereas it hampers employment when initial total factor productivity is high enough to make firms and workers sufficiently selective.

Whether our theoretical mechanism operates in practice, and the mismatch effect is strong enough to reverse the neoclassical conclusions, is in the end an empirical issue. We tackle this issue by capturing skill heterogeneity at the occupational level and task heterogeneity at the sectoral level. We focus on 92 occupations at the 3-digits ISCO-88 level and 16 (out of 21) sectors according to the NACE Rev.2 classification.[10] To check that our findings are not driven by country specificities (such as labour market institutions), our dataset covers 13 European countries for the period $1995-2010$.

[10] We exclude occupations and sectors closely associated with public and agricultural activities.

The dataset includes information on employment from the European Labour Force Survey (EU-LFS) as well as automatability and offshorability indices at the beginning of the observation period, which we use as proxies for actual automation and offshoring in the subsequent years.

The analysis of this dataset reveals that the impact of automatability (defined as in Acemoglu and Autor [1]) on employment is negative and significant, and is amplified by its interaction with offshorability (defined as in Blinder and Krueger [15]): within industry-country occupations more exposed to automation and offshoring exhibit worse employment performance. For occupations with low initial offshorability, the change in employment is positive, though smaller when low initial offshorability is paired with higher initial automatability. Differently, for occupations with high initial offshorability, the change in employment is still positive when initial automatability is low, but becomes negative when initial automatability is high. This suggests that it is the combination of high automatability and high offshorability that mostly leads to vanishing jobs.

To investigate empirical relevance of the specific mechanism of the model, according to which automation and offshoring reduce employment through increased firms' and workers' selectivity, we construct an index of selectivity that can be computed with our data based on the notion of employers' and employees' matching set. The index proxies the size of this set through the 'sectoral specialization of occupations' (SSO) defined as the concentration of an occupation's employment across sectors. This index is meant to inversely capture the willingness of firms and workers to accept less-than-ideal matches so that selectivity is considered to be high (low) for larger (small) values of the SSO. Using this index we indeed find that automation and offshoring increase selectivity and, in turn, more selectivity decreases employment in our period of observation.

The rest of the paper is structured as follows. Section 2 introduces and solves the model. Section 3 presents the dataset, some descriptive statics and the regression results. Section 4 concludes.

## 2 A Model of 'Core-Biased Technological Change'

We want to investigate how technological progress, driven by automation and offshoring, affects employment and wage inequality when new technologies change the matching and sorting patterns between firms' heterogeneous tasks and workers' heterogeneous skills in the presence of search frictions.[11] We assume that firms in different sectors require different tasks to be performed and workers in different occupations provide different skills to perform those tasks. We model heterogeneity by placing tasks and skills in a characteristics space. In particular, we place firms and workers at different 'addresses' continuously distributed along a unit circle (i.e. with radius $1/2\pi$). Performing each task requires workers with the appropriate skill. There is an ideal match of each task with the most appropriate skill, which is the one with the same address as the task. The ideal match delivers the maximum achievable productivity. Less-than-ideal matches are also productive but their productivity decreases with the distance $d \in [0, 1/2]$ between their matched task's and skill's addresses along the circle. Minimum productivity thus corresponds to matches at distance $1/2$.

Matches between tasks and skills are not necessarily ideal as search frictions make firms and workers willing to accept less-than-ideal matches. In other words, search frictions induce 'mismatch' (measured by the equilibrum value of $d$) between tasks and skills, that is, divergence between the actual matches and the ideal ones. Technological change increases the productivity of any given match ('neoclassical effect') but also increases the relative productivity of ideal matches relative to less-than-ideal ones ('mismatch effect') thus raising the cost of mismatch.

The timing of events in the model is as follows. Workers and firms meet randomly. Next, and upon observing their types, they decide whether to match. Finally, based on the match surplus, they bargain wages according to the Nash protocol. The steady state pure strategy of each type of firm (worker) is to decide which workers (firms) to match with, taking the strategies of all other firms and workers as given.

## 2.1 Skill and Tasks

All agents are risk-neutral, infinitely lived and maximize the present value of their future income streams, discounted by the common discount factor $\rho$. Time is continuous. In terms of the distributions on the two sides of the labor market, we assume the following. There is a continuum of workers with heterogeneous skills indexed $x \in [0, 1]$ clockwise from noon ('skill address'). The

[11] Two-sided heterogeneity is featured in models of assortative matching à la Becker [13] and their applications to the labour market. Influential applications, including Shimer and Smith [48] and Hagedorn, Law and Manovskii [35], insert two-sided vertical heterogeneity and general assortativity into models with search and matching frictions. Differently from them, given the specific nature of our research question, we focus on production functions with positive assortative matching and two-sided horizontal heterogeneity.

distribution of skills features a uniform p.d.f. $g_w(x)$ and a measure $L$ of workers. Likewise, there is a continuum of firms with heterogeneous sector-specific tasks indexed $y \in [0,1]$ clockwise from noon ('task address'). The distribution of tasks features a uniform p.d.f. $g_f(y)$.

There is no asymmetric information in the model. All agents know their own type and the types of all potential partners they meet. Complementarity between workers' skills and firms' tasks induces labor market sorting, which means that for every worker (firm) an ideal firm (worker) exists and matching with this ideal partner maximizes surplus.[12] Search frictions, however, hamper the formation of these ideal matches.[13] This implies, first, that some meetings do not result in an employment relation, hence unemployment arises. Second, firms (workers) do not consider only workers (firms) with ideal skills (tasks), but are also willing to hire workers (be hired by firms) with skills (tasks) in a range centered around their ideal skills (tasks). This induces mismatch between skills and tasks, measured by their distance along the circle:

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

where the min function selects the shorter arc distance between clockwise and counterclockwise travels between $x$ and $y$ along the unit circle.

## 2.2 Production and Technological Change

Regarding production, we keep neoclassical assumptions so as to preserve the role of technological progress that increases total factor productivity, and thus workers and firms income. Specifically, we assume that production requires labor and capital, and that the technology frontier exhibits constant returns to scale with respect to both factors at the match level. Capital is endogenously accumulated. This serves the purpose of covering all neoclassical adjustment margins. By reducing the price of investment, an increase in productivity raises labor demand. In this respect, introducing capital is a conservative choice. If the cost of mismatch reduces employment, it will do so even in presence of a declining price of investment.

Matches are one-worker-one-job relationships. Then a firm's output is the sum of outputs of its matches.[14] Moreover, the measure of active firms in the labor market is governed by free entry.

[12] In absence of search or information frictions all workers and firms would be matched to their optimal partner as in Becker [13].

[13] See Shimer and Smith [48].

[14] We do not consider firm size and the complementarities between workers within the same firm as in Eeckhout

The functional form for production at match level is Cobb-Douglas:

$$f(d) = AK(d)^{\beta} L(d)^{1-\beta} \tag{2}$$

with $\beta \in (0,1)$, where $K(d)$ is capital, $L(d)$ is effective labor, $d$ is 'mismatch' as measured by distance (1) and $A > 0$ is the 'state of technology' as measured by total factor productivity.[15] For simplicity, we assume that automation and offshoring are two equivalent exogenous drivers of technological change. In the empirical analysis we will allow for richer patterns of interactions between them.

Mismatch implies that effective labor at match level declines with distance, which we capture by assuming the following functional form:

$$L(d) = \left(F - \frac{\gamma A^{\eta}}{2} d\right) L \tag{3}$$

where $L$ is the measure of workers we already introduced. Effective labor equals $F > 0$ for the ideal match ($d = 0$) and declines as $d$ increases until it reaches its minimum $\gamma A^{\eta}/4$ for the worst match ($d = 1/2$). The decline is steeper for better states of technology (larger $A$), the more so the larger $\eta > 0$. This captures our story according to which technological progress increases the losses from mismatch.

We endogenize capital accumulation by assuming that capital is supplied elastically at return $r = \rho$, which pins down capital's equilibrium marginal productivity:

$$\rho = \beta AK(d)^{\beta-1} L(d)^{1-\beta}. \tag{4}$$

This relation can be inverted to obtain

$$K(d) = \left(\frac{\beta A}{\rho}\right)^{\frac{1}{1-\beta}} L(d),$$

which, after substitution into (2) together with (3), allows us to write output at the match level as

$$f(d, A) = \varphi A^{\frac{1}{1-\beta}} \left(F - \frac{\gamma A^{\eta}}{2} d\right) \tag{5}$$

and Kircher[27]. While complementarity within the firms are certainly important, they are not immediately relevant for our purposes.

[15] $A$ subsumes all sources of produtivity gains. Let $b_K$, $b_L$ and $B$ capture capital-enhancing, labor-enhancing and Hicks-neutral technological change. With Cobb-Douglas technology we have $f(d) = B\,(b_K K(d))^{\beta}\,(b_L L(d))^{1-\beta}$, which can be rewritten as (2) after defining $A \equiv B\,(b_K)^{\beta}\,(b_L)^{1-\beta}$.

where $\varphi \equiv (\beta/\rho)^{\frac{\beta}{1-\beta}}$ is a constant bundling parameter and we have imposed $L = 1$ by choice of units. This expression highlights two channels through which technological change affects match output. First, output for the ideal match, $d = 0$, equals $\varphi A^{\frac{1}{1-\beta}} F$. In this case, better technology (larger $A$) univocally increases production, as it raises labour productivity by neoclassical forces. We will refer to this as the neoclassical 'productivity effect'. Second, output for less-than-ideal matches, $d \in (0, 1/2)$, decreases from $\varphi A^{\frac{1}{1-\beta}} F$ as mismatch $d$ increases. This happens with slope $f'(d) = -\gamma A^{\eta}/2 < 0$. Hence, for less-than-ideal matches better technology has the additional effect of increasing the cost of mismatch. We will refer to this as the 'mismatch effect'. If $\eta = 0$ held, this effect would vanish.[16]

Formally, the production function $f(d, A)$ is log-submodular in $d$ and $A$ as, for all $d' > d$ and $A' > A$, we have $f(d', A')f(d, A) < f(d, A')f(d', A)$ or equivalently $f(d', A')/f(d, A') < f(d', A)/f(d, A)$, i.e. by (5) we have

$$\left(d' - d\right) \left[\left(A'\right)^{\eta} - (A)^{\eta}\right] > 0. \tag{6}$$

In words, better matches (i.e. matches with lower $d$) have a comparative advantage in exploiting better states of technology (i.e. higher total factor productivity). This comparative advantage is stronger for larger $\eta$, hence when the impact of technology on the cost of mismatch is larger. If $\eta = 0$ held, log-submodularity would vanish.

To sum up, in this setup better technological opportunities (equivalently due to automation or offshoring) have two opposing effects on match surplus. They increase match productivity through $A^{\frac{1}{1-\beta}}$, but also increase the cost of mismatch through $A^{\eta}$ in (5). The latter effect materializes as long as less-than-ideal skills or tasks become less substitutable with the corresponding ideal ones. These are the ones that define firms' and workers' 'core competencies'. For this reason, we can use the term 'core-biased technological change' (CBTC) to label the way in which the state of technology evolves in our model. This is different from the concepts of 'routine-biased technological change' and 'skill-biased technological change' previously examined in the literature as discussed in the Introduction.

[16] See also see Gautier and Teulings [31] for similar considerations.

## 2.3 Search and Match

As already mentioned, workers and firms are infinitely lived, risk neutral, and maximize future income streams discounted at rate $\rho$. Workers and firms know their own type and the types of potential partners. Firms are either producing, labeled by $P$, or vacant, labelled by $V$. Workers are either employed, labelled by $E$, or unemployed, labelled by $U$, and the sum of employed and unemployed equals the labour force, $E + U = L = 1$. 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 homogenous-of-degree-one Cobb-Douglas matching function $M(U, V) = \vartheta U^{\xi} V^{1-\xi}$, where $\vartheta$ is matching efficiency, $U$ is unemployment, $V$ are vacancies and $\xi \in (0, 1)$ is the elasticity of new matches to unemployment.[17] In this setup the Poisson arrival rate can be derived as a function of aggregate labor market tightness $\theta = V/U$. We can then define $q_v(\theta) = M(U, V)/V = \vartheta\,(U/V)^{\xi} = \vartheta\theta^{-\xi}$ as the rate at which vacant firms meet unemployed workers and $q_u(\theta) = M(U, V)/U = \vartheta\,(V/U)^{1-\xi} = \vartheta\theta^{1-\xi}$ as the rate at which unemployed workers meet vacancies.

Firms face a cost $c$ of maintaining a job either filled or vacant. This is akin to a cost of capital. Unemployed workers' income is normalized to 0. Match surplus is shared according to the Nash bargaining solution with worker bargaining weight $\alpha \in (0, 1)$.[18] We impose zero outside options for both workers and firms.

Once matched, workers and firms decide whether to produce by comparing their shares of the match surplus with their outside options. Given the Nash bargaining protocol, risk-neutrality and zero outside option, workers of type $x$ accept a job of type $y$ if and only if

$$\Lambda(x) = \{y : S(x, y) \geq 0\} \tag{7}$$

holds, where $S(x, y)$ is the surplus of the match $(x, y)$, while $\Lambda(x)$ defines the workers' acceptance

[17] See Mortensen and Pissarides [43]. Our assumption departs from the non-linear matching function employed in models with two-sided heterogeneity à la Shimer and Smith [48]. In particular, our matching technology implies that congestion externalities arise for each task.

[18] We could consider alternative wage protocols, such as sequential auctions à la Postel-Vinay and Robin [46] or Lise and Robin [40], or also other competiitve wage protocols like in Moen [42]. However, for the purpose of our study, a simple rent sharing rule is appropriate.

set. Firms have a similarly defined acceptance set

$$\Omega(y) = \{x : S(x, y) \geq 0\}, \tag{8}$$

Given the two acceptance sets, the joint matching set $\Lambda(x) \cap \Omega(y)$ evaluates to

$$M(x, y) = \{x, y : S(x, y) \geq 0\}. \tag{9}$$

All sets are Borel measurable and depend also on the state of technology $A$. Matches can be destroyed by separations shocks, which we assume to happen with per-period probability $\delta$.

We restrict our attention to acceptance sets featuring positive assortative matching with uniformly distributed workers $x$ and thus also uniformly distributed firms $y$.[19] This case has the following appealing features from an analytical point of view. The values of unemployment and vacancies are identical for all worker and firm types respectively. Values of employment and production depend on the distance $d$ only. Also the Nash bargained wage $w(d)$ depends only on distance $d$. Workers and firms accept matches at some common maximum distance $d^*$ from their address. This implies that we can write the acceptance sets for workers as

$$\Lambda(x) = [y - d^*, y + d^*] \tag{10}$$

and for firms as

$$\Omega(y) = [x - d^*, x + d^*]. \tag{11}$$

### 2.4 Value Functions and Nash Bargaining

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:

$$\rho v_e(d) = w(d) - \delta(v_e(d) - v_u). \tag{12}$$

Analogously, the worker's discounted value of being unemployed $v_u$ satisfies

$$\rho v_u = 2q_u(\theta) \int_0^{d^*} (v_e(d) - v_u) dz, \tag{13}$$

As we have assumed zero outside option for the unemployed, the value of unemployment is given by the option value of future employment net of the value of unemployment. The worker obtains

[19] See Lemma 1 in Marimon and Zilibotti [41].

a job if he meets the firm (with contact rate $q_u(\theta)$), and if the worker's type falls in the matching set.

Next, the discounted value of a filled vacancy $v_p(d)$ equals what is left of the value of output after the wage and the maintenance costs have been paid:

$$\rho v_p(d) = (f(d) - w(d) - c) - \delta \left[ v_p(d) - v_v \right]. \tag{14}$$

Finally, the value of an unfilled vacancy $v_v$ satifies

$$\rho v_v = -c + 2q_v(\theta) \int_0^{d^*} (v_p(d) - v_v) dz, \tag{15}$$

where the right hand side corresponds to the option value of future employment net of the maintenance cost.

Given the foregoing value functions, we can write the general implicit expression for the surplus as:

$$S(d) = v_e(d) - v_u + v_p(d) - v_v \tag{16}$$

The set of equilibrium conditions is then completed by the free entry conditions for the value of a vacancy

$$v_v = 0, \tag{17}$$

the zero cut-off value of production

$$v_p(d^*) = 0 \tag{18}$$

and the steady state flow condition

$$2q_u(\theta)d^* = \frac{\delta E}{L - E}. \tag{19}$$

To summarize, an equilibrium is a distribution of matches and a wage equation satisfying: (i) the matching set (9); (ii) the Nash bargaining rule

$$(1 - \alpha) \left( v_e(d) - v_u \right) = \alpha \left( v_p(d) - v_v \right) \tag{20}$$

given the values determined by (12), (13), (14) and (15); (iii) all technological constraints (i.e. $E + U = L + 1$, $M(U, V) = \vartheta U^{\xi} V^{1-\xi}$, $q_v(\theta) = \vartheta \theta^{-\xi}$, $q_u(\theta) = \vartheta \theta^{1-\xi}$, $f(d) = \varphi A^{\frac{1}{1-\beta}} \left( F - \gamma A^{\eta} d/2 \right)$); (iv) the steady state flow condition (19); (v) the free entry condition (17); and (vi) the zero cut-off value condition (18).

## 2.5 Equilibrium and Horizontal Specialization

The set of equilibrium conditions can be solved analytically for employment $E$ and mismatch $d^*$. From the equilibrium levels of employment and mismatch it is also possible to derive the equilibrium wage schedule. The derivation of the analytical solution is presented in Appendix B. Hereby we focus instead on comparative statics as this is what will inform our empirical analysis. In particular, we discuss the impact of technological change on the equilibrium levels of employment and mismatch. To do this in a parsimonious way, we solve the model numerically. Parameter values are chosen from standard values in the literature and deliver empirically relevant levels of steady state employment and unemployment (see Appendix D).

Figure 1 shows results for the employment schedule (left panel) and mismatch schedule (right panel), while Figure 2 shows results for the wage schedule. Specifically, the left panel of Figure 2 plots the wages of top and bottom earners, who are the best-matched and worst-matched workers respectively. The right panel plots the ratio of top to bottom wage. Figure 2 therefore allows us to discuss also the model's implications for wage inequality.

Starting with Figure 1, the left panel shows that the model predicts that equilibrium employment $E$ is a non-monotone function of the state of technology $A$, increasing for small $A$ and decreasing for large $A$. The right panel shows that equilibrium mismatch $d^*$ is a decreasing function of the state of technology $A$. To see this, note that this panel has $1/d^*$ on the vertical axis, which is an inverse measure of the size of the firms' and workers' matching set or intuitively a direct measure of the 'selectivity' of their matching decisions. This notion will come handy in the empirical analysis.

The non-monotonicity of the employment schedule results from the balance of the opposite productivity and mismatch effects discussed above. Low initial total factor productivity implies that firms and workers are not very selective to start with (see right panel) because the cost of mismatch is small. In this situation the neoclassical productivity effect prevails so that employment rises as the state of technology improves. However, as technology keeps on improving, the cost of mismatch grows and firms as well as workers become increasingly selective and wait longer in search of better matches. Beyond a critical level of productivity and thus of selectivity, the cost of mismatch becomes high enough that the mismatch effect starts dominating the productivity effect with employment

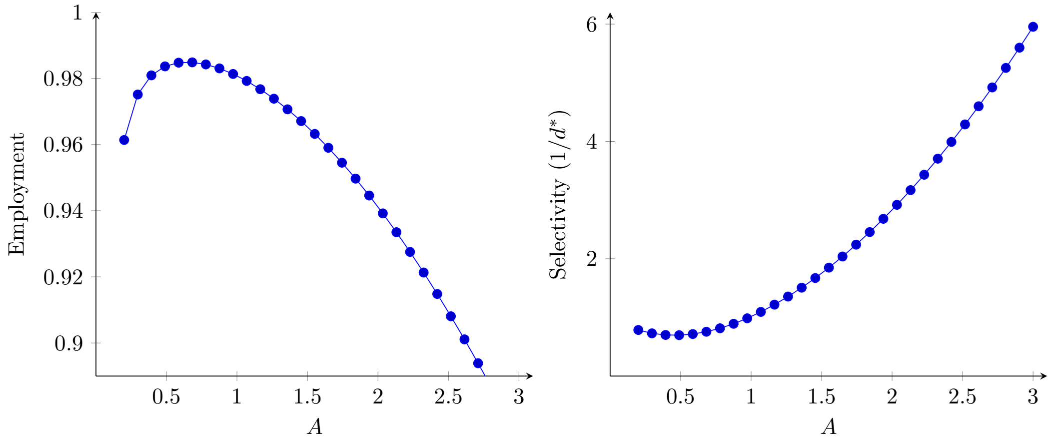


Figure 1: Effects of technological change on employment (left panel) and selectivity (right).

falling as technology improves. Hence, technological change promotes employment when initial total factor productivity and hence selectivity are low, whereas it hampers employment when initial total factor productivity is high enough to make firms and workers sufficiently selective.

Turning to Figure 2, the left panel shows that the wage of top earners is an increasing function of the state of technology $A$, while that of bottom earners is an inverted U-shaped function of the state of technology $A$. Moreover, even when the bottom wage rises, the top wage rises more. These features are explained by the fact that the rising mismatch cost is a burden for the worst matched workers but not for the best matched ones. The result is rising wage inequality as shown in the right panel of Figure 2.

Growing firms' and workers' selectivity as technology improves entails growing tasks' specialization across skills and skills' specialization across tasks. It is worthwhile noting that for high levels of specialization employment falls despite two forces that tend to dampen such fall. First, as total factor productivity increases, the price of capital falls. This raises labor demand. Second, as the cost of mismatch rises, firms' surplus falls, which on its own would lead firms to reduce their acceptance sets and this in turn would endogenously reduce mismatch.

To summarize, in our model core-biased technological change (associated with automation or offshoring) can have a detrimental impact on employment as less-than-ideal 'non-core' tasks/skills become less substitutable with ideal 'core' ones. This detrimental impact materializes as the state of technology improves as long as better matches of firms and workers have a comparative advantage in exploiting the new technologies. The mismatch effect of technological change is the novel element

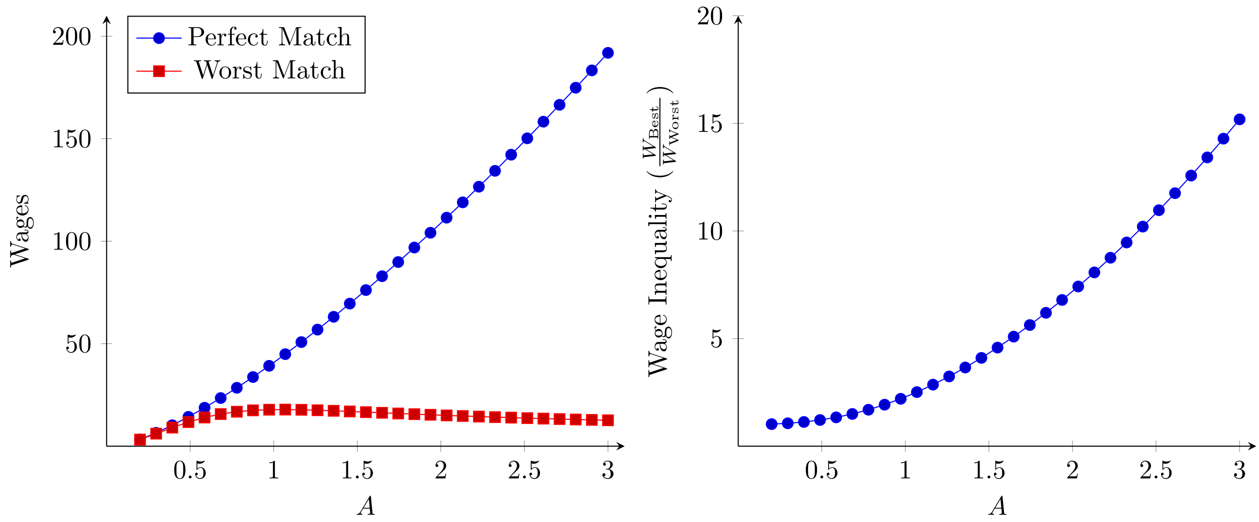


Figure 2: Effects of technological change on wages of top earners and bottom earners (left panel) and on their ratio (right panel).

in our model, which by counteracting neoclassical forces may induce jobs to vanish as the state of technology improves. It then remains an empirical question whether this new channel has any practical relevance, and is strong enough to alter the traditional neoclassical conclusions. We now show evidence that this may indeed be the case. In addition, while for simplicity we have not explicitly modelled any specific patterns of complementarity or substitutability between automation and offshoring, we will also shed light on those patterns.

### 2.6 Adding Vertical Specialization

Before looking at the data, a remark is in order. So far we have assumed full symmetry within skills and within tasks. This assumption has allowed us to highlight the key mismatch mechanism at work in our model through the quantitative discussion of a closed-form equilibrium solution. In reality, however, such symmetry does not necessarily hold as skills and tasks are not only horizontally but also vertically differentiated. In other words, some skills are higher than others and some tasks are more productive than others. In this section we extend our model to check the robustness of our mechanism to asymmetry. While the extended model will not be amenable to closed-form solution, the numerical investigation of its equilibrium properties shows that our mechanism is still at work and may be even reinforced in the presence of vertical differentiation.

To facilitate comparison with the original model, the simplest way to introduce vertical differentiation is to keep the distributions of workers and thus firms uniform along the circle while changing the production possibilities. In particular, we make two new assumptions. First, larger $x$ and larger $y$ are associated with higher workers' skills and more productive firms' tasks respectively. Second, the mismatch between a firm with task $y$ and a worker with lower-than-ideal skill $x < y$ is more costly in terms of foregone productivity than an equally distant mismatch with larger-than-ideal skill $x > y$ by a factor $\tau \geq 1$ (with $\tau = 1$ corresponding to the original symmetric case). In other words, for a given task and a given skill-task distance, employing an underskilled worker is more penalizing in terms of lost match surplus than hiring an overskilled one. This way the extended model also embeds a 'skill premium' in addition to the mismatch cost.[20]

The introduction of this asymmetry implies that the probability of forming a match now depends not only on the skill-task distance but also on the distribution of skills $x$ and tasks $y$ in the pools of unemployed workers and vacant firms respectively. Accordingly, the value $v_u(x)$ of being unemployed for a worker with skill $x$ now satisfies:

$$\rho v_u(x) = q_u(\theta) \int_{\tilde{y} \in \Omega(y)} d_v(\tilde{y}) \left( v_e(x, \tilde{y}) - v_u(x) \right) d\tilde{y}. \tag{21}$$

Analogously, the value of an unfilled vacancy $v_v(y)$ for a firm with task $y$ is given by:

$$\rho v_v(y) = -c + q_v(\theta) \int_{\tilde{x} \in \Lambda(x)} d_u(\tilde{x}) \left( v_p(\tilde{x}, y) - v_v(y) \right) d\tilde{x}. \tag{22}$$

Figures 3 and 4 report the equilibrium outcomes of the extended model for different degrees of asymmetry $\tau$ while holding the state of technology constant at $A = 2.5$. These outcomes are obtained numerically through value function iteration on a grid of workers' skills $x$ and firms' tasks $y$.[21] We then iterate over the surplus and matching density until they converge.

[20] Changing the production possibilities as we do and changing the distribution of either side of the labor market are anyway equivalent. This is due to the fact that one can think of workers' skills and firms' tasks as ranks in their respective productivity distributions. Since workers' and firms' types as well as the production function are unobserved, it is not possible to separately identify each of them. See Hagedorn, Law and Manovskii [35] and Katenga and Law [37] for a discussion of this point. Specifically, if the original distributions for skills and tasks are $H(x)$ and $G(y)$ respectively and the original production function is $\tilde{f}(\tilde{x}, \tilde{y})$, then we are simply performing the following transformation of the production function: $f(x, y) = f(F^{-1}(x), G^{-1}(y)$. The simplest example is in the 1-dimensional case, where $x \sim [0, 1]$ with $f(x) = 3x$ and $x \sim [0, 3]$ with $f(x) = x$ are observationally identical.

[21] Our numerical solution follows Hagedorn, Law and Manovski [35], who accommodate non-uniform distributions. They assume that the cost of posting vacancies adjusts so that the the mass of vacancies equals the mass of unemployed workers. Differently from them we solve for the number of vacancies using equation:

$$\rho V_v = -c + \frac{(1-\alpha) 2 q_v(\theta) \int_{y \in \Omega(y)} f(z) dz}{\delta + \rho + (1-\alpha) 2 q_b(\theta) + \alpha 2 q_u(\theta)}.$$

The three panels of Figure 3 depict the matching densities for different levels of $\tau = (0.85, 1, 1.15)$. Firms' tasks $y$ are displayed on the horizontal axis while workers' skills $x$ are displayed on the vertical axis. For all tasks and skills pairs, the panels show the simulated steady-state probabilities of being observed in a match. Blue areas are outside the matching sets of firms and workers so that the matching density of the corresponding pairs is zero. Color coding for the other areas goes from pale green to bright yellow in increasing order of matching density.

To interpret these color patterns recall that both tasks and skills are arranged along a circle $[0, 1]$. Panel (a) $\tau = 1$ corresponds to the original model, in which all addresses on the circle are symmetric and their ordering from noon is inconsequential. The circle is turned into segments along the panel's axes and we can see that each task $y$ on the horizontal axis has a symmetric matching interval centered around the ideal skill $x = y$ along the vertical axis. Vice versa, each skill $x$ on the vertical axis has a symmetric matching interval centered around the ideal task $y = x$ along the horizontal axis. Moreover, all feasible matches have equal density as shown by the uniformly yellow areas.

The other two panels correspond to scenarios in which the mismatch cost is asymmetric. In panel (b) we have $\tau = 1.15$ so that mismatch at a given distance is more costly than in panel (a) for underskilled workers (those with $x < y$), which our case of interest. For comparison, in panel (c) we look at the reverse case with $\tau = 0.85$ so that mismatch at given distance is more costly than in panel (a) for overskilled workers (those with $x > y$). The density patterns in these two panels are perturbed by the fact that our distance metric $d(x, y) = \min[x - y + 1, y - x]$ implies that very productive tasks at address $y$ just below 1 are very close along the circle to very low skills with address $x$ just above 0, which creates a strong incentive to match despite high matching cost per unit distance. Hence, to minimize the resulting distortions in the equilibrium density patterns, it is useful to focus on tasks and skills that are matched on the same round of the circle. This are the ones inside the inner dashed rectangles.

Comparing panels (a) and (b), we see that, going from $\tau = 1$ to $\tau = 1.15$, the lower blue band becomes thicker whereas the upper blue band is unchanged. This means that the matching set shrinks from below as the most underskilled matches are not feasible anymore. In addition to this adjustment at the extensive margin, we also observe an adjustment at the intensive margin due to the relative change in density for pairs that are still matched in favor of those between high skills and high productivity tasks (those in brighter yellow). Analogously, we observe the opposite evolution going from $\tau = 1$ to $\tau = 0.85$ as in this case underskilled matching becomes less costly.

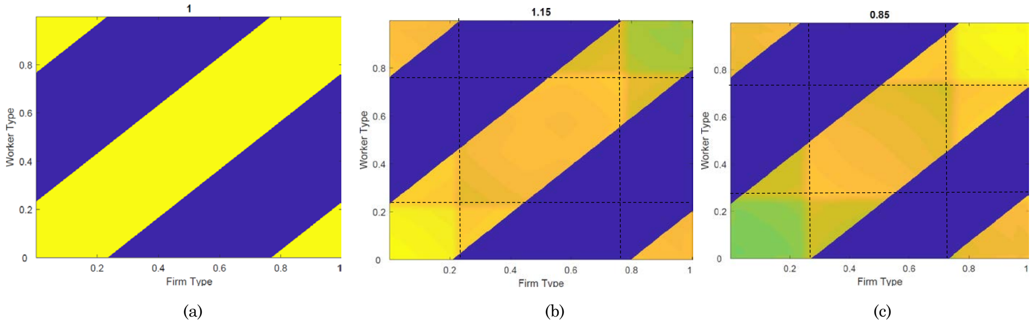


Figure 3: Matching set and matching density

Figure 4 shows how technology (measured by $A$) on the horizontal axis affects employment and selectivity on the vertical axes of panels (a) and (b) respectively. The figure confirms that, when the state of technology is good enough, the mismatch effect can dominate the productivity effect of technological change so that any further progress (larger $A$) not only increases selectivity in panel (b) but also employment in panel (a). Moreover, in the asymmetric case of interest ($\tau = 1.15$), the negative impact on employment is even stronger.

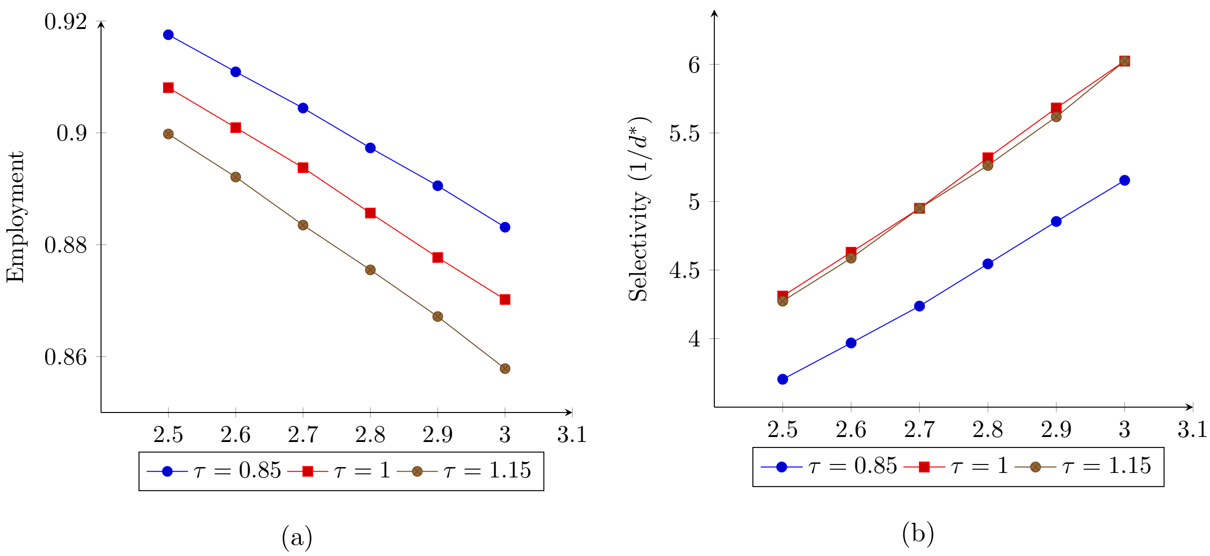


Figure 4: Effects on employment (left panel) and selectivity (right)

Overall, the economic mechanism highlighted in the original symmetric model is confirmed, and the associated results are even amplified for emploment in the extended asymmetric model as an additional vertical specialization effect reinforces the original horizontal specialization one. This is the way SBTC and CBTC interact in our framework.

# 3 Empirical Evidence: Insights from occupation-level data.

In this section we test some of the implications of our model according to which automation and offshoring drive a type of technological progress that is core-biased in that it increases firms' and workers' selectivity.

## 3.1 Data and Variables

We exploit the European Labour Force Survey (hereafter EULFS). This is an extensive cross-country dataset of national Labour Force Surveys that includes several variables at the occupational and sectoral level. We restrict the period of analysis to $1995-2010$ in order to include the maximum number of available countries and keep a consistent classification of occupations. We aggregate worker-level observations into country $\times$ sector $\times$ occupation $\times$ year cells. This way, we are able to analyse country, sectoral and occupational heterogeneities. Note that we will exploit long-differences between 1995 and 2010 assuming that a technological shock materializes between these two dates, as documented in other studies.[22] For the rest of the paper, the long-difference of a variable, $\Delta_{1995-2010}$, will be simply noted $\Delta$.

We focus on 92 occupations at the 3-digits 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. Following Goos et al. [32], occupations and sectors closely associated to public and agricultural activities are dropped. We also drop 3-digits ISCO occupations that are not precisely reported.[23]

We include 13 countries, among which we have both Anglo-Saxon and continental countries,

[22] For instance Chiacchio et al. (2018) show that the robot penetration in the EU28 has been multiplied by 3 between these two dates. They also document that the majority of this robot shock materialised in the period 1995-2007 compared to the period 2007-2015.

[23] In some cases, only 2-digits occupations are 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 6 countries in the sample.

making the analysis robust to local institutions or cultural trends.[24] The dataset mainly provides us with information about cell-level employment, number of employees, number of hours worked, number of unemployed workers, etc. Further details on the dataset are presented in Appendix A. We merge this dataset with variables capturing automatability and offshorability at the beginning of our observation period, which we use a proxies of actual automation and offshoring during the period. To measure automatability we use the 'routine task intensity' index (RTI, hereafter) as computed by Acemoglu and Autor [1]. This measure has been widely used in previous studies, such as Autor, Levy and Murnane [53], Autor and Dorn [11] and Goos et al. [32]. The U.S. Dictionary of Occupational Titles (DOT) provides information about the task contents of occupations. The RTI builds on this information and is determined by the difference between the log of Routine tasks and the sum of the log of Abstract and the log of Manual tasks in an occupation. Specifically, we adopt the refinement proposed by Lewandoski et al. [39]: $RTI = ln(RoutineCognitive + RoutineManual) - ln(NonroutineAnalytical + NonroutineInterpersonnal)$. The measure of the RTI is standardized in order to have mean equal to zero and standard deviation of one. We use a crosswalk to go from the SOC 2000 classification to the 4-digits ISCO88 classification before aggregating to the 3-digits ISCO88 classification (see Appendix A for additional details). For completeness, we compare the RTI with the alternative automatability measure constructed by Frey and Osborne [29], which is given by the probability of computerization based on a Gaussian process classifier. This alternative measure builds on the selection of solutions that engineers need to devise for specific occupations to be automated. Checking the correlation between the two measures, we find a large positive correlation between them, with only few exceptions for specific occupations.[25]

To measure offshorability three indices have been proposed in the literature: by Blinder [14], by Blinder and Krueger [15] (hereafter BK [15]) and by Acemoglu and Autor [1] (hereafter AA [1]). The first two indices build on questionnaires and qualitative observations. They are constructed by professional coders based on an occupational classification of workers.[26] For both measures

[24]These countries are Austria, Belgium, Germany, Denmark, Spain, France, Great Britain, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal. For these countries full time coverage is available.

[25]It is actually the goal of Frey and Osborne [29] to show that some non-routine occupations could be automated.

[26]See PDII: Princeton Data Improvement Initiative (`https://krueger.princeton.edu/pages/princeton-data-improvement-initiative-pdii`).

the authors propose a qualitative scale of offshorability, ranking occupations from 'Highly Non Offshorable' (1) to 'Highly Offshorable' (4). The difference between the two measures lies in the fact that Blinder [14] proposes a qualitative ranking of occupations according to their degree of offshorability, whereas BK [15] provides 4 categories of offshorability. The third measure by AA [1] is instead a quantitative index based on aggregating several ONET indicators.[27] In Appendix A we show that the correlations between the three offshorability measures are mostly positive. However, when Goos et al. [32] compare these offshorability indices with actual offshoring measures, they find that the indices by Blinder [14] and BK [15] are more reliable. Accordingly, we will use the BK index as our benchmark measure of offshorability. The matching procedure of occupations with our automatability and offshorability indices is detailed in Appendix A.

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 it can be solved algorithmically by a computer or a robot. Differently offshorability à la BK 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 market. As a result, while the correlation between our measures of automatability and offshorability is positive, there are important exceptions across occupations. These are reported in Appendix A.

### 3.2 Measuring selectivity

In the model presented above, firms in different sectors match with workers in different occupations. Each sector is seen as requiring different tasks to be performed while each occupation provides different skills to perform those tasks. The model shows that increasing automation have a positive effect on the matching quality that is detrimental to employment. Put differently, as automation increases, the selectivity increases, meaning that the size of the matching sets decreases. Using sectors to proxy 'tasks' and occupations to proxy 'skills', we define selectivity as the concentration of an occupation's employment across sectors, which we call the 'Sectoral Specialization of the

[27] This index is itself inspired by Firpo et al. [28]. The metric constructed is based on face to face discussions with employers in the following occupations: Assisting and Caring for Others, Performing for or Working Directly with the Public, Inspecting Equipment, Structures, or Material, Handling and Moving Objects, Repairing and Maintaining Mechanical Equipment, Repairing and Maintaining Electronic Equipment.

Occupation' (SSO hereafter). This is computed at the occupation $\times$ country level. Concentration in measured with the non-standardized Herfindhal index. With $\mathcal{O}$ the set of occupations, $\mathcal{O} = \{o_1, \ldots, o_{92}\}$, $\mathcal{K}$, the set of industries, $\mathcal{K} = \{k_1, \ldots, k_{11}\}$ and $s_{oki} = \frac{L_{oki}}{\sum_{k \in \mathcal{K}} L_{oki}}$ the share of share of each occupation in each industry, computed for each country:

$$SSO_{oi} = \sum_{k \in \mathcal{K}} s_{oki}^2$$

**Remark 1:** Note that a key feature of our selectivity index is that it is not standardized to account for the number of industries used in the estimation. Indeed, each occupation is not present in every sector. For a simple example, assume that an occupation is equally observed in 5 different sectors in 1995. Now assume that one occupation completely disappears from a sector in 2010 and that employment from this sector is equally reallocated to the 4 other sectors. It is then equally present in 4 sectors. A standardized Herfindahl index would be equal to zero in both cases, implying that selectivity has not changed between 1995 and 2010 for this occupation. However, it is key to our identification strategy that the change in selectivity in positive in this case, to account for the fact that employment in more concentrated between industries in 2010 than in 1995.

**Remark 2:** High SSO implies that few sectors account for a large share of the occupation's employment, while low SSO implies that employees in an occupation are similarly spread across many sectors. Accordingly, we see the SSO as inversely related to the size of the theoretical matching set. To investigate the robustness of our findings, we use also alternative measures of selectivity, in particular two traditional measures of 'mismatch': unemployment duration and education-based metrics of skill mismatch.

### 3.3 Descriptive Statistics

Table 1 presents descriptive statistics on the occupations aggregated at the 2-digit level. Occupations are ranked from the least to the most routine-intensive ones. 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 (i.e. the more routine-intensive ones). Among the ten most routine-intensive occupations, only Customer service clerks (42) and Sales and services elementary occupations (91) do not exhibit a fall in the share of hours. Column 2 reports the change in unemployment. For most occupations at the top of the table the unemployment rate falls. In particular, eight out of the ten least routine-intensive occupations experience a decrease in their unemployment rate between 1995 and 2010. It is worth noting that half of the ten most routine-intensive occupations experienced a decrease or a relative stability in their unemployment rate over the period. Notably, columns 4 and 5 reveal that there is no clear correlation between automatability and offshorability.

Figure 5 presents some simple graphical evidence on the direct effects of automatability on employment for different levels of offshorability. We aggregate our data at the cell level (country $\times$ sector $\times$ occupation $\times$ year) into occupation $\times$ year cells. Then we compute the log change in hours worked across the countries in our sample for each occupation: $\Delta ln(Hours)_o = ln(Hours)_o^{2010} - ln(Hours)_o^{1995}$. The 92 occupations are then divided into two groups according to median offshorability. The figure shows that the average change in total hours worked in an occupation decreases with automatability (grey dotted line). On average occupations that have low routine intensity in 1995 experience an increase in hours worked in the subsequent period. On the contrary, occupations with high automatability experience a negative change in the number of hours worked. This illustrates a reallocation of employment from routine to non-routine occupations.

The figure also confirms that automatability and offshorability are not capturing the same information. When occupations are partitioned in two groups according to their high or low offshorability, no clear relation appears with their routineness ranks. In particular, for occupations with a low offshorability (solid grey line) the change in hours worked does not seem to be related to the routineness of their tasks. For highly offshorable occupations (black line), there is a clear negative relation between the change in hours worked and automatability. For these occupations the decline in employment is stronger.

### 3.4 Empirical strategy

We test the relevance of the channels acting in the model in two steps:

1. As depicted in Figure 1, selectivity should increase with the level of technology. By regressing selectivity measures on the routine-intensity of an occupation as well as its offshorability, we confirm this theoretical finding.

Table 1: Descriptive statistics: occupations

| Occupations ranked by automation probability | $\Delta$ Share of hours (1) | $\Delta$ Unemployment rate (2) | Routine Task Intensity (3) | Offshorability (BK) (4) | Rank Offshorability (5) |
|---|---|---|---|---|---|
| Corporate managers (12) | 0.31 | -0.63 | -1.83 | -0.32 | 11 |
| Other professionals (24) | 0.79 | 0.26 | -1.70 | 0.21 | 7 |
| General managers (13) | 0.31 | -0.5 | -1.60 | -0.63 | 13 |
| Physical. mathematical. and engineering professionals (21) | 0.81 | -1.01 | -1.34 | 1.05 | 5 |
| Life science and health professionals (22) | 0.03 | -1.1 | -1.22 | -0.76 | 16 |
| Life science and health associate professionals (32) | 0.71 | -1.04 | -0.87 | -0.75 | 15 |
| Other associate professionals (34) | 0.66 | -0.26 | -0.76 | 0.10 | 8 |
| Physical and engineering science associate professionals (31) | 0.28 | -0.33 | -0.06 | -0.12 | 9 |
| Models. salespersons and demonstrators (52) | -0.62 | 1.03 | 0.21 | -0.89 | 18 |
| Personal and protective service workers (51) | 1.06 | -1.31 | 0.21 | -0.94 | 20 |
| Office clerks (41) | -0.31 | -1 | 0.27 | 0.40 | 6 |
| Extraction and building trades workers (71) | -0.45 | 2.67 | 0.32 | -0.93 | 19 |
| Metal. machinery. and related trade workers (72) | -0.73 | 0.06 | 0.39 | -0.45 | 12 |
| Customer services clerks (42) | 0.16 | -0.63 | 0.70 | -0.25 | 10 |
| Sales and services elementary occupations (91) | 0.66 | -1.58 | 0.88 | -0.81 | 17 |
| Laborers in mining. construction. manufacturing and transport (93) | -0.09 | 0.07 | 1.03 | -0.66 | 14 |
| Precision. handicraft. printing and related trades workers (73) | -0.48 | -0.95 | 1.04 | 1.66 | 2 |
| Drivers and mobile-plant operators (83) | -0.03 | 0.84 | 1.19 | -1.00 | 21 |
| Stationary-plant and related operators (81) | -0.24 | 0.91 | 1.20 | 1.59 | 3 |
| Other craft and related trade workers (74) | -1.73 | 0.28 | 1.46 | 1.15 | 4 |
| Machine operators and assemblers (82) | -1.46 | 0.91 | 1.48 | 2.35 | 1 |

Occupations are ranked from lowest probability of automation to highest. The automation probability and the offshorability indices are standardized to have a mean of 0 and a standard deviation of 1.

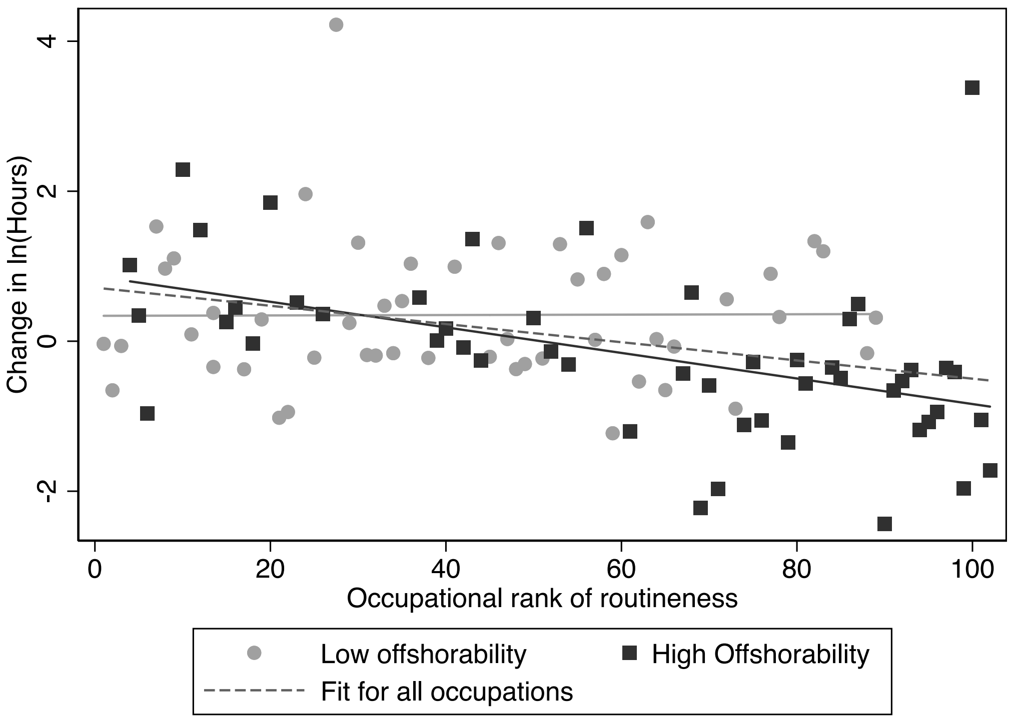


Figure 5: The impact of routineness and offshorability on labour hours

2. By increasing selectivity, technology has an adverse impact on employment. We explain the change in employment by the change in selectivity. To account for potential endogeneity, we build a *double Bartik* instrument (see Chodorow-Reich and Wieland, 2019).

**Step 1: From technology to selectivity.** The goal of these regressions is to establish the fact that more-routine occupations, *i.e.* occupations that are more likely to be automatized following a technology shock, experienced an increase in selectivity in the period 1995-2010. To this end we estimate the following equation:

$$\Delta SSO_{oi} = \alpha + \beta_1 RTI_o^{95} + \beta_2 Offshor_o^{95} + Z'_{oi}\mathbf{C} + mu_i + \epsilon_{oi} \tag{23}$$

where $\Delta SSO_{oi}$ is the change in SSO between 1995-2010, $RTI_o^{95}$ the initial routine task intensity, $Offshor_o^{95}$ the initial offshorability index and $\mathbf{C}$ is a vector of coefficients associated to a set of control variables $Z_{oi}$. Additionally we include country-level fixed effects ($\mu_i$) that account for any country-level shock. Table 2 column (1) reports the corresponding estimates. As predicted by the model, positive changes in RTI are associated with increases in selectivity, but is not statistically different from zero. Higher offshorability is instead statistically significant and affects selectivity negatively following the model's narrative. This shows that automation and offshoring are indeed two technologies that differently affect the matching between skills and tasks.

The specification in Equation (23) assumes the effect of routineness to be symmetric, Figure 5 shows that occupations with a high RTI experienced a decrease in employment while occupations with a low RTI experienced an increase of employment over the period. Therefore next we estimate a less restrictive model, where we explicitly allow for assymetric effects. We distinguish the case where the RTI is larger than the median RTI in the country ($RTI_o^H = RTI_o^{95} \times \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})}$) from the case where RTI is lower than the median ($RTI_o^L = RTI_o^{95} \times \left(1 - \mathbb{1}_{RTI_o^{95} > q_{50}(RTI_o^{95})}\right)$) and estimate:

$$\Delta ln(SSO_{oi}) = \alpha + \beta_1 RTI_o^H + \beta_2 RTI_o^L + \beta_3 Offshor_o^{95} + Z'_{oi}\mathbf{C} + mu_i + \epsilon_{oi} \tag{24}$$

While $\beta_1$ captures the effect of routineness, when routineness is high and the negative effect of routineness are more likely to materialize, $\beta_2$ will account for the effect of routineness where its positive effect is more likely to materialize.

This intuition is confirmed in column (2) of Table 2 where the effect of RTI in high RTI occupations is large, positive and significant while this effect is virtually zero for low-RTI occupations. It means that occupations that are the most at risk of automation at the beginning of the period experienced a large increase in selectivity between 1995 and 2010. This confirms a key result of the model: automation have an impact on matching sets. Taking into account the potential interactions between routineness and offshorability (column 3) does not affect this result.

In column (4) we return to the simple specification of equation 23 to further decompose the effect and uncover heterogenous effects. [28] We add the share of employment in an occupation in 1995 and its interaction with the RTI index. This allows to capture any differential effect affecting larger occupations at the country level. Column (4) reveals that heterogeneity in the effects of RTI on selectivity. The positively significant coefficient (note that the scale of this coefficient is largely dependent on the scale of the shares, that are very small) illustrates that the positive effect of RTI on selectivity is largely channelled through larger occupations.

[28] In order to keep parsimony in the number of coefficients estimated we prefer to estimate equation 23 instead of estimating 24

Table 2: Selectivity and technology.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | | $\Delta ln(SSO)$ | |
| $RTI_{95}$ | 0.0755 | | | 0.0312 |
| | (0.0522) | | | (0.0552) |
| $RTI^{H}_{95}$ | | 0.207** | 0.168* | |
| | | (0.100) | (0.0994) | |
| $RTI^{L}_{95}$ | | -0.0151 | 0.00885 | |
| | | (0.0792) | (0.0781) | |
| $Offshor._{95}$ | -0.0765* | -0.0923** | -0.123** | -0.0691 |
| | (0.0414) | (0.0432) | (0.0525) | (0.0427) |
| RTI $\times$ Offshor. | | | 0.0667 | |
| | | | (0.0470) | |
| $Share_{95}$ | | | | 0.0727 |
| | | | | (2.117) |
| $Share_{95} \times RTI_{95}$ | | | | 4.874*** |
| | | | | (1.596) |
| $SSO_{95}$ | -1.146*** | -1.231*** | -1.328*** | -1.156*** |
| | (0.184) | (0.189) | (0.203) | (0.183) |
| Observations | 1,063 | 1,063 | 1,063 | 1,063 |
| R-squared | 0.139 | 0.143 | 0.149 | 0.146 |
| Fixed effects | Country | Country | Country | Country |

Robust standard errors clustered at the occupation level in parentheses. Data is aggregated at the country $\times$ occupation level.
*** p<0.01, ** p<0.05, * p<0.1

**Step 2: From selectivity to employment.** We have first shown that automation-based technology increased selectivity between 1995 and 2010. According to the model narrative increases in selectivity have a negative impact on employment. To test this narrative we estimate the following equation:

$$\Delta ln(Hours_{oi}) = \gamma + \delta_1 \Delta ln(SSO_{oi}) + K'\mathbf{C_2} + \eta_i + \upsilon_{oi} \tag{25}$$

where $\Delta ln(Hours_{oi})$ is the long difference in total hours worked in occupation $o$ in country $i$, $\Delta SSO_{oi}$ the change in selectivity previously defined, $K'$ a matrix a control variables and $\mathbf{C_2}$ the vector of associated coefficients . We further include country fixed effect $\eta_i$ corresponds to country fixed effects.

The coefficients estimated in Equation (25) may be biased due to endogeneity concerns. The selectivity index is constructed using employment shares. This implies that there may be reverse causation from change in hours worked to change in selectivity. The sign of the bias is intricate given that it will ultimately depend on the distribution of employment between industries for a given occupation. We tackle this endogeneity concerns using an instrumental variable approach by constructing a so-called *Bartik instrument* or shift-share instrument. This is most used in the development and trade literature, but has also been recently used by Chodorow-Reich and Wieland (2019) in a labor market context to study local labor market reallocation and unemployment. Our proposed instrument follows their methodology as our instrument is also a so-called *double-Bartik*. In particular the instrument is constructed in two steps: First we compute the *Bartik-predicted change in employment* in a occupation-industry-country cell as the employment growth if that cell grew at exactly the same rate as employment in that occupation and industry in all other countries in our sample. In a second step we compute the Bartik-predicted selectivity using the shares computed in the first step to derive the Herfindahl index.
More formally, the predicted employment in 2010 is $\widehat{L^b_{oik,2010}} = g^b_{o,-i,k,2010} \times s_{o,i,k,1995}$ with $g^b_{o,-i,k,2010}$ the average growth rate of a occupation-industry pair in all other countries of the sample (denoted by the index $-i$) and $s_{o,i,k,1995}$ the employment of occupation $o$ in sector $k$ in country $i$ in 1995. The *Bartik-predicted* SSO for year 2010 is then: $\widehat{SSO^b_{oi,2010}} = \sum_{k\in\mathcal{K}} (\hat{s}^b_{oik,2010})^2$ with $\hat{s}^b_{oik,2010}$ being the share of predicted employment of occupation $o$, in sector $k$, in country $i$ in 2010. Our instrument is then the log change in predicted SSO:

$$\widehat{\Delta SSO^b_{oi}} = ln\left(\frac{\widehat{SSO^b_{oi,2010}}}{SSO_{oi,1995}}\right)$$

We use the *Bartik-predicted* change in specialization as the included instrument and further include the predicted occupation-industry employment growth ($\Delta ln(L^b) = ln(\frac{L_{oi,1995}}{\widehat{L^b_{oik,2010}}})$) from the leave-one-out estimates as a control variable for unobserved variation in employment due to any secular occupation-industry specific trends in employment shared across countries (see Chodorow-Reich and Wieland, 2019).

Results are displayed in table 3. We display different specifications that use different sets of controls or fixed effects. Importantly in each case (columns 2, 3 and 5) the Kleinberger-Paap F-statistic is large and largely above the Montiel-Pflueger robust weak instrument test critical values (Montiel and Pflueger, 2013 and Pflueger and Wang, 2015 for Stata implementation). The associated first-stage estimates are displayed in the first line of the table. They are positive and significant for each IV regressions.

In the first column, the OLS regression shows a negative and significant effect of an increase in selectivity on employment. The predicted growth of occupation's employment in other countries is positively linked to employment, as expected. In column (2), we implement our double Bartik strategy to control for endogeneity concerns. The coefficient estimated is negative and close than the OLS coefficient. It is also a bit less precisely estimated, leading to an estimate significant at the 10% level. In column (3), we see that the coefficient on the change in selectivity is rather constant when controlling for occupation level factors, including the initial routineness. This variable controls for the direct effect of automation on employment. The IV regression in column (4) confirms the robustness of this finding with a negative and significant coefficient for the change in selectivity. We include occupation fixed effects together with country fixed effects in column (5). These fixed effects control for any occupation-level determinants of the change in employment that is common to all countries in the sample. The coefficient estimated is now negative, significant and larger than the OLS estimate in column (1).

Additional estimation results are displayed in table 4. In column (1), we restrict the sample to positive increases in selectivity. This way, we are able to isolate the specific effect of an increase in selectivity *versus* a decrease in selectivity. For our narrative to be confirmed, we need to observe a decrease in employment following an exogenous increase in selectivity. The coefficient estimated in column (1) for the change in selectivity is negative and significant. It is also larger in absolute value than the coefficient estimated on the full sample in column (4). The same remarks hold when we include occupation-level fixed effects in column (2). The employment growth in other countries is not significant any more when we add the fixed effects. This is driven by the limited scope for variation within occupation of this variable.

Table 3: Selectivity and employment I

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | $\Delta ln(Hours)$ | | |
| First Stage | | 1.780*** | | 1.789*** | 1.925*** |
| | | (0.127) | | (0.139) | (0.204) |
| $\Delta ln(SSO)$ | -0.160*** | -0.161* | -0.169*** | -0.267*** | -0.446*** |
| | (0.0417) | (0.0852) | (0.0349) | (0.0658) | (0.0809) |
| $\Delta ln(L^b)$ | 0.266*** | 0.266*** | 0.297*** | 0.302*** | 0.0697 |
| | (0.0640) | (0.0647) | (0.0629) | (0.0650) | (0.0883) |
| $RTI_{95}$ | | | -0.226*** | -0.225*** | |
| | | | (0.0425) | (0.0427) | |
| $Offshor._{95}$ | | | 0.0719 | 0.0668 | |
| | | | (0.0562) | (0.0578) | |
| RTI × Offshor. | | | -0.178*** | -0.181*** | |
| | | | (0.0447) | (0.0453) | |
| FE | Country | Country | Country | Country | Country Occup. |
| Instrument | No | Bartik | No | Bartik | Bartik |
| Observations | 1,073 | 1,073 | 1,062 | 1,062 | 1,073 |
| K-P F-Test 1st | | 196.6 | | 165.1 | 88.71 |

Robust standard errors clustered at the occupation level in parentheses.
Data is aggregated at the country × occupation level.
*** p<0.01, ** p<0.05, * p<0.1

We now want to establish a more direct link between change in selectivity and initial routineness, this would help to show that it is really the automation channelled through a change in selectivity that affects negatively employment. As before, we separate our RTI variable at the country-level median and interact it with the change in selectivity. We now have to deal with two endogenous variables that are constructed by interacting our instrument with $RTI_{95}^{H}$ and $RTI_{95}^{L}$. The fact of having two endogenous variables and two instruments naturally reduces the Kleinberger-Paap F statistic. In column (3) to (6), this first stage F-statistic is always above the threshold proposed by Stock and Yogo (2005) to identify weak instruments.[29] Column (3) reveals that the effect of selectivity estimated before is mainly driven by large routine occupations experiencing an increase in selectivity. This confirm that the *mismatch effect* plays an important role in explaining the employment decrease. This result holds when we restrict the sample to increases in selectivity only in column (4) and when we replicate columns (3) and (4) with occupation fixed effects.

This set of regressions provides result in line with the theory predictions: more routine-intensive occupations experienced an increase in selectivity,i.e. a decrease in the matching sets, between 1995 and 2010. This increase in selectivity then has a negative effect on employment, even controlling for the direct effect of automation on employment.

### 3.5 Alternative Measures of Selectivity

In this subsection, we provide an alternative strategy to identify the effect of technology on matching. Instead of relying on a theory-based measure, we rely on more standard metrics of mismatch.

**Alternative 1: Educational mismatch** We measure educational mismatch, over-education and under-education, by comparing each worker's education in terms of years to the educational level of his peers (as defined by occupation, sector or country) at the date of the observation. The worker is considered as over-educated (under-educated) when his or her educational level is above (below) the average in its occupation, industry, country and 10-year cohort by more than

[29] In our context, this threshold for a bias of 10% is 7.03.

Table 4: Selectivity and employment II

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | $\Delta ln(Hours)$ | | | |
| $\Delta ln(SSO)$ | -0.339*** | -0.694*** | | | | |
| | (0.101) | (0.151) | | | | |
| $\Delta ln(SSO) \times RTI^{H}_{95}$ | | | -0.343*** | -0.507*** | -0.357*** | -0.714** |
| | | | (0.119) | (0.159) | (0.126) | (0.288) |
| $\Delta ln(SSO) \times RTI^{L}_{95}$ | | | 0.105 | 0.0594 | 0.244** | 0.241** |
| | | | (0.107) | (0.112) | (0.0973) | (0.109) |
| $\Delta ln(L^{b})$ | 0.223*** | -0.145 | 0.326*** | 0.248*** | 0.113 | -0.0954 |
| | (0.0845) | (0.109) | (0.0700) | (0.0764) | (0.0846) | (0.116) |
| $RTI_{95}$ | -0.194*** | | | | | |
| | (0.0511) | | | | | |
| $Offshor._{95}$ | 0.0445 | | 0.00564 | 0.0340 | | |
| | (0.0644) | | (0.0521) | (0.0606) | | |
| RTI $\times$ Offshor. | -0.182*** | | -0.205*** | -0.147*** | | |
| | (0.0507) | | (0.0394) | (0.0485) | | |
| FE | | ISCO3 | | | ISCO3 | ISCO3 |
| Instrument | Bartik | Bartik | Bartik | Bartik | Bartik | Bartik |
| $\Delta ln(SSO) > 0$ | Yes | Yes | | Yes | | Yes |
| Observations | 558 | 563 | 1,062 | 558 | 1,073 | 563 |
| K-P F-Test 1st | 90.11 | 63.88 | 24.31 | 17.93 | 9.593 | 11 |

Robust standard errors clustered at the occupation level in parentheses.
Data is aggregated at the country × occupation level.
*** p<0.01, ** p<0.05, * p<0.1

2 standard deviations (see e.g. Hartog [54] for a similar definition). To make our estimates of mismatch more precise avoiding the case of a small number of observations in a cell (that would bias our measure), we aggregate the observations at the 2-digit ISCO level. In order to be able to compute the mismatch metrics, these regression are realized on the long difference between 1998 and 2010.

Intuitively, as automation takes place, employers become more picky and want to select better (in the sense of the match output) employees. In consequence we should observe a decrease of under-education, *id est*, employees relatively less qualified that the average employee in the occupation. The effect on over-education is ambiguous. Indeed, matching output decreases if the employee is "too skilled" for the a given task. However, recent literature on matching in the labor market suggests that worker type increases with education (see Lochner and Schultz, 2016). Following this fact, one could imagine that pickier employers would match with more educated workers. The effect on educational mismatch is then also undetermined.

**Alternative 2: Unemployment duration** The fact that employers become more selective should have a direct impact on unemployment duration since matches are less likely to happen. Especially, increase in selectivity should end up in an increase in the unemployment duration in a cell. Defining unemployment at the cell level in not straightforward as cells are defined based on having an activity. In order to proxy unemployment duration in a cell, we assign unemployed workers to the cell of their last job. Again we aggregate the occupations observations at the 2-digits ISCO level in order to make the estimations of the left-hand side variable more precise. Note that France and Netherlands are not present in these regressions since the information provided for these countries does not allow us to compute unemployment duration.

**Results** We run the following econometric estimation:

$$\begin{aligned}\Delta Y_{oik} =& \alpha + \beta_1 RTI_o + \beta_2 Offshorability_o \\ &+ \beta_3 (Offshorability_o \times RTI_o) + \mu_{ik} + \epsilon_{oik}\end{aligned} \tag{26}$$

where $\Delta Y_{oik}$ stands for the long difference on variable $Y$, which will be either educational mismatch, over-education, under-education or unemployment duration. Standards errors are clustered at the occupation × country level. All estimations are weighted by initial employment shares and all right-hand side variables are standardized so their mean equals zero and their standard deviation equals one.

Table 5 reports the corresponding results. In column (1), we observe a negative but non-significant estimate of the RTI on mismatch. We cannot conclude from this result. We then decompose mismatch between under-education in column 2 and over-education in column 1.

Columns 2 and 3 reveal that the most automatable occupations as of 1998 experienced a decrease in the under-education rate and an increase in the over-education rate. The opposite pattern is associated with offshorability. Note also the complementarity between automation and offshoring in column 2. The effect of automation on under-education corresponds to what was expected. As explained before, the effect of RTI on over-education was not determined. Results indicate that more routine-intensive occupations experienced an increase in over-education. This is in line with employers becoming pickier associated with a positive link between employee type and education.

Column 4 shows that automatability is associated with an increase in unemployment duration. This provides further evidence that automation may induce firms and workers to wait and search for longer. Overall, these results are in line with our theoretical framework and confirm the results obtained with a theory-driven measure of selectivity.

Table 5: Impact of technology on educational mismatch and unemployment duration

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Δ Mismatch | Δ Under-educ. | Δ Over-educ. | Δ Unemp. duration |
| $RTI_{95}$ | -0.0347 | -0.00340*** | 0.00305*** | 0.0409* |
| | (0.0984) | (0.000742) | (0.000778) | (0.0243) |
| $Offshor._{95}$ | 0.0532 | 0.00220** | -0.00167** | -0.0183 |
| | (0.114) | (0.000858) | (0.000795) | (0.0319) |
| $RTI_{95} \times Offshor._{95}$ | -0.290*** | -0.00177** | -0.00113 | 0.0454 |
| | (0.111) | (0.000814) | (0.000805) | (0.0328) |
| Observations | 1,915 | 1,915 | 1,915 | 905 |
| R-squared | 0.236 | 0.143 | 0.235 | 0.183 |
| Fixed effects | Country-Industry | | | |

Robust standard errors clutered at the occupation × country level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

### 3.6 Aggregate effects

In this section we propose a back-of-the-envelope calculation of the aggregate effects of technological change on employment, after a brief discussion of the related literature.

Acemoglu and Restrepo (2018) with US data and Chiacchio et al. (2018) with European data have found a negative effect of industrial robots on aggregate employment. These papers study whether the displacement effect of technology is larger than its employment enhancing productivity effect. In both papers the displacement effect of robot exposure exceeds the productivity gains and make the aggregate effect of technology on employment negative. It is important to note that the two papers use a specific technology shock, that is, the increase in robot exposure. As defined in their papers, robots do not cover all cases of automation. In particular, automation through the routinization of computer tasks is not taken into account. When Autor and Salomons (2018) adopt a broader measure of technology, they find a positive effect of technology on aggregate employment. Using changes in TFP at the industry level across European countries, Asian countries and the US to capture technological change, they allow for many channels to be potentially relevant: own-industry effects (expected to have a negative impact on employment) as well as cross-industry input-output effects, between-industry shifts and final demand effects (all expected to have a positive impact on employment). Overall, they find that technological change increases aggregate employment but decreases the labour share. Closer to the spirit of our analysis, Salomons et al. (2019) investigate the labor demand and employment effects of routine-biased technological change (RBTC) and show that its effect on aggregate employment in the EU is positive. Both Autor and Salomons (2018) and Salomons et al. (2019), however, do not offer country-by-country estimations.

Here we adopt a less structural approach than all these papers. Specifically, in order to estimate the employment effect of technological change, we build the counterfactual outcome, in which technological change has no effect on employment, by using the estimated parameters and fixed effects of an econometric model to create a prediction of the change in employment when the impact of initial automatability is shut down. For this strategy to be effective, we need an econometric model that can explain a large share of the variation in employment changes. We therefore aggregate our occupations at the 2-digits level so as to be able to exploit the within-occupation cross-country and cross-industry variation of automatability. Accounting for the share of employment of each 3-

digits occupation collapsed to 2-digits occupations allows us to add occupation-specific fixed effects in the estimation.

The econometric model we run is:

$$\Delta ln(Hours_{oik}) = \beta_1 RTI^{95}_{oik} + \beta_2 Off^{95}_{oik} + \beta_3 RTI^{95}_{oik} \times Off^{95}_{oik} + \mu_{ik} + \mu_{oi} + \epsilon_{okc} \tag{27}$$

where $\mu_{ik}$ and $\mu_{oi}$ are industry $\times$ country and occupation $\times$ industry fixed effects respectively. We also allow the effect of the RTI on employment to depend on the extent of occupation routineness by splitting the variable $RTI^{95}_{oik}$ into two variables $RTI^{H}_{oik}$ and $RTI^{L}_{oik}$ depending on whether the RTI is above or below the median level of routineness in a country $\times$ industry pair. Lastly, we control for the average education level in a cell and the relative size of the cell. Specification (27) partly captures the displacement effect of technological change as long as we observe decreasing employment in routine-intensive occupations and increasing employment in non-routine-intensive occupations. It also partly captures the productivity effect of technological change as long as the gains in low-routine occupations are allowed to differ from the losses in high-routine occupations.

Then, for each country $k$, we use the aggregate employment changes $\ln\left(\widehat{H^k_{10}/H^k_{95}}\right)$ predicted by (27) to construct the predicted aggregate hours worked in 2010, which we denote by $\widehat{H^k_{10}}$. Specifically, imposing $\ln\left(\widehat{H^k_{10}/H^k_{95}}\right) = \ln\left(\widehat{H^k_{10}}/H^k_{95}\right)$, we obtain

$$\widehat{H^k_{10}} = H^k_{10} \exp\left(\ln\left(\widehat{\frac{H^k_{10}}{H^k_{95}}}\right) - \ln\left(\frac{H^k_{10}}{H^k_{95}}\right)\right) \tag{28}$$

where all terms on the right-hand side are either observed ($H^k_{95}$ and $H^k_{10}$) or estimated ($\ln\left(\widehat{H^k_{10}/H^k_{95}}\right)$) from (27).

For the estimated $\beta_1$ the comparison of predicted and actual outcomes tells us how much we should believe 'statistically' in the counterfactual. The correlation between predicted and actual employment *changes* in a cell is 0.53. However, the correlation between predicted and actual employment *levels* is 0.98. The quality of this prediction increases for higher levels of predicted employment, while it falls to 0.17 in the first quartile (rank correlation of 0.46). Figure 6 plots the distribution of observed and predicted changes in employment (left panel) and employment (right panel) in 2010.

For the counterfactual in which the impact of automatability on employment is shut down, we replace the estimated $\beta_1$ with $\beta_1 = 0$. The counterfactual employment of country $k$ in 2010 in

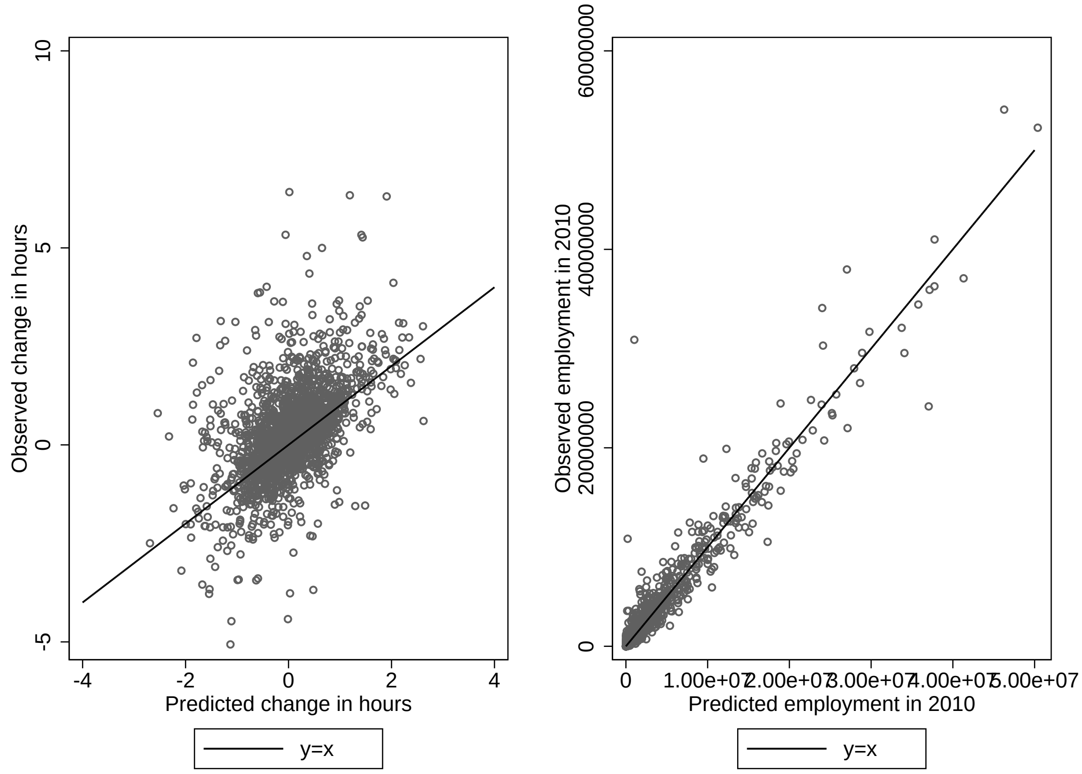


Figure 6: Predicted and observed outcomes

denoted $\widetilde{H}^k_{10}$. In Table 6 we consider two types of predictions for the impacts of automatability on aggregate employment across countries. Column $\Delta_1$ compares the observed employment in 2010 ($H^k_{10}$) with the correspoding counterfactual employment ($\widetilde{H}^k_{10}$): $\Delta_1 = H^k_{10} - \widetilde{H}^k_{10}$. Column $\Delta_2$ compares the predicted employment in 2010 ($\widehat{H^k_{10}}$) with the corresponding counterfactual employment ($\widetilde{H}^k_{10}$) to account for the fact that our prediction may not be totally in line with observed employment : $\Delta_2 = \widehat{H^k_{10}} - \widetilde{H}^k_{10}$.

Table 6 highlights the heterogenous effects of automatability on employment across countries. In both columns, a negative aggregate effect is found for Germany, Spain and Greece while it is positive for all other countries. When comparing the predicted and counterfactual outcomes, we also find a negative effect in Austria, France, Italy, Luxembourg and Portugal. Assuming that an employee works 35 hours a week for 45 weeks a year, the negative effect in the first column for Germany corresponds to a loss of 4585 jobs in 2010. Hence, we can conclude that, according to our back-of-the-envelope, the aggregate impact of automation on employment is either positive or slightly negative for all countries in our sample despite large negative developments for specific occupations.

Table 6: Predicted impact of automation on aggregate employment

| Country | Number of hours | |
|---|---|---|
| | Observed - Counterfactual $\Delta_1$ | Predicted - Counterfactual $\Delta_2$ |
| AUT | 5588166 | -3400177 |
| BEL | 4682215 | 2741240 |
| DEU | -7083773 | -15680964 |
| DNK | 3544136 | 51327 |
| ESP | -33149281 | -39131725 |
| FRA | 13787699 | -10408017 |
| GBR | 65426662 | 6381045 |
| GRC | -3572807 | -5935122 |
| IRL | 12653495 | 1409682 |
| ITA | 39957419 | -20904866 |
| LUX | 436904 | -69497 |
| NLD | 12442593 | 4042058 |
| PRT | 10267282 | -10856301 |

# 4 Conclusions

There are growing concerns about the negative impacts of automation and offshoring on employment and wage inequality. As long as both phenomena are to be interpreted as technological changes, traditional neoclassical arguments imply that those concerns are unfounded. We have shown, theoretically and empirically, that the effects of technological change associated with automation and offshoring on the labor market can substantially deviate from standard neoclassical conclusions when search frictions hinder efficient matching between firms with heterogenous tasks and workers with heterogenous skills.

Our key hypothesis is that better-matched workers and firms enjoy a comparative advantage in exploiting new technologies. This way technological change has two effects on employment, one benign and one detrimental. The first produces a standard increase in labor productivity at match level. The second raises the cost of mismatch making firms and workers more selective with respect to matching opportunities. As a result, technological change promotes employment when initial productivity is low so that firms and workers are not very selective in matching, whereas it hampers employment when initial productivity is high enough to make firms and workers sufficiently selective.

Capturing task heterogeneity at the sectoral level and skill heterogeneity at the occupational level, we have found empirical support to our mechanisms in a dataset covering 92 occupations and 16 sectors in 13 countries from 1995 to 2010. Automation increases selectivity and reduces employmen, the more so for highly offshorable occupations. At the aggregate level, however, the impact of automation on employment is either positive or slightly negative for all countries in our sample despite large negative developments for specific occupations.

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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 individuals 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, Great Britain, 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 et al. [32], 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); marketoriented skilled agricultural and fishery workers (ISCO-88: 61); agricultural, fishery and related labourers (ISCO-88: 92).[30] Finally, our data contains information, virtually complete, at the cell level for 92 occupations, in 16 sectors.

Table 7 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 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%).

Table 7: Database Coverage (in % of official Eurostat figures)

| Country | # of employees | # of unemployed workers |
|---|---|---|
| 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% | - |
| Great Britain | 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 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.

[30] These occupations respectively account for 0.12%, 0.27%, 0.53%, 0.39% and 0.07% observations in the sectors kept.

### 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) (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. [31] 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 8, we compute the correlation coefficient between these measures. The correlation between Blinder and BK indexes is large while for both indices the correlation with the AA measure is quite low.

Table 8: Correlation table between offshorability measures

| | AA (2011) | Blinder (2009) | BK (2013) |
|---|---|---|---|
| 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 Manning et al. (2013) compare different offshorability index with actual offshorability measures. Blinder/BK types of measures seem more reliable. We consider these two

[31] This index is inspired by Firpo et al., 2009

measures as our preferred ones, using the BK index in our baseline regressions.

## A.2 Automation

We proxy the probability of future automation of an occupation using the RTI measure constructed by Autor and Dorn (2013) [10]. This measure correlates with the one provided by Frey and Osborne (2017). Using the files by Autor and Acemoglu [1] and the definition of the RTI by Lewandowski et al. (2017) we compute the RTI index based on DOT data.[32] 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-digits ISCO88 classification and then aggregate it to the three-digits ISCO88 classification. At this level the correlation between the RTI ('routineness') and measure by Frey and Osborne ('probability of automation') is 0.77 (see figure 7). However, the two variables diverge for some occupations.

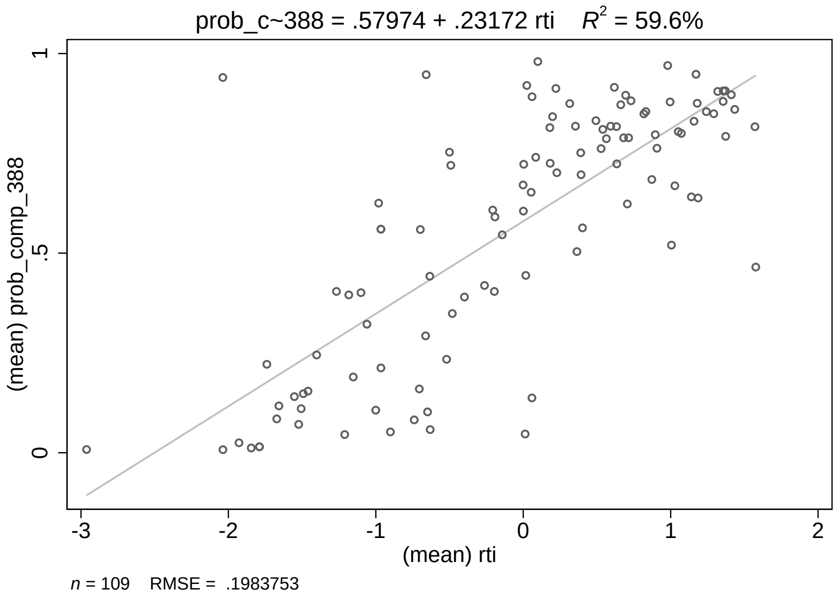


Figure 7: Correlation between automation probability and routiness

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

[32]Lewandowski et al. (2017) slightly modify the RTI definition compared to Autor and Dorn (2013) in order to adapt it to the use of ONET data instead of DOT data: $RTI = ln(RoutineCognitive + RoutineManual) - ln(Nonroutineanalytical + nonroutineinterpersonnal)$.

time. We relax this assumption by only assuming that the RTI of a 3-digits ISCO occupation is fixed. This way we are able to observe the evolution in the automatability by country, industry and occupation.

### A.3 Link between automation probability and offshorability

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 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 8 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 (73: Precision, handicraft, printing and related trades workers; 81: Stationary-plant and related operators; 82: machine operators and assemblers), other 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 take the unweighted average probability of automation to aggregate our measure at the 3-digits 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-digits ISCO level. Finally, when necessary, we obtain the measure of routine task intensity and offshorability

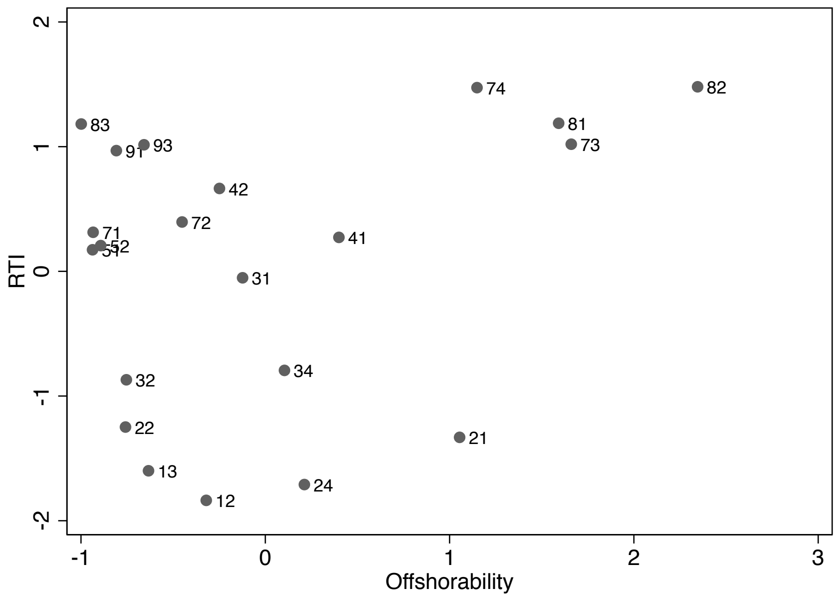


Figure 8: Automation probability and Offshorability (BK, 09)

at the 2-digits ISCO level by collapsing (with appropriate weights) all observations at the 3-digits level in their corresponding 2-digits ISCO occupation.

# B Derivation of Value Functions

Time is discrete. The value function of an employed worker being in a match with a firm at distance $d$ reads:

$$V_t^E(d) = w_t(d) + (1-\rho)\left[(1-\delta)V_{t+1}^E(d) + \delta V_{t+1}^U\right],$$

where on the right-hand side the first term is the wage the worker currently earns and the second term is the discounted value of still being employed tomorrow if the current match survives (with probability $(1-\delta)$) and the value of unemployment when the match gets destroyed exogenously (probability $\delta$). Rewriting in $\Delta$ units of time gives

$$V_t^E(d) = \Delta w_t(d) + (1-\Delta\rho)\left[(1-\Delta\delta)V_{t+\Delta}^E(d) + \Delta\delta V_{t+\Delta}^U\right],$$

where flow variables are now simply a share $\Delta$ of the flows. Dividing through by $\Delta$ and rearranging terms yields:

$$\frac{V_t^E(d) - V_{t+\Delta}^E(d)}{\Delta} = w_t(d) - (\rho + \delta - \rho\Delta\delta)V_{t+\Delta}^E(d) + (1-\Delta\rho)\delta V_{t+\Delta}^U.$$

Taking the limit $\lim_{\Delta\to 0}$ then gives the continuous-time value functions, where time subscripts are inessential since we consider stationary steady-states only and lower case letters will be used for continuous time value functions:

$$\rho v_e(d) = w(d) - \delta\left(v_e(d) - v_u\right).$$

The value of being unemployed can be derived in the same fashion:

$$V_t^U = (1-\rho)q_u(\theta)2\int_0^{d^\star} V_{t+1}^E(z)dz + (1-\rho)q_u(\theta)2\int_{d^\star}^1 V_{t+1}^U(z)dz + (1-\rho)\left(1-q_u(\theta)\right)V_{t+1}^U.$$

With probability $q_u(\theta)$ a given worker meets a firm at distance $d$. If this firm is acceptable (i.e. $-d^\star < d < d^\star$, the value of being employed at that firm is $V_{t+1}^E(d)$. Note that symmetry over the circle implies that integration from $-d^\star$ to $d^\star$ is equivalent to taking twice the integral from 0 to $d^\star$. If the match is unacceptable the value is $V_{t+1}^U$ (second term). With probability $(1-q_u(\theta))$ the worker does not meet a firm. Adding and subtracting $(1-\rho)q_u(\theta)2\int_0^{d^\star} V_{t+1}^U dz$, we have

$$V_t^U = (1-\rho)q_u(\theta)2\int_0^{d^\star}\left(V_{t+1}^E(z) - V_{t+1}^U\right)dz + (1-\rho)V_{t+1}^u$$

Following the same steps as above then yields:

$$\rho v_u = q_u(\theta)2\int_0^{d^\star}\left(v_e(z) - v_u\right)dz.$$

The value of a vacancy ($V_V$) and a filled vacancy ($V_P(d)$) can be derived analogously.

# C Model Solution

We detail here the analytical steps needed to solve the full system of the model's equilibrium conditions. We start with merging the value functions. Specifically we first derive an expression for the workers' surplus by subtracting (12) from (13):

$$\rho\left(v_e(d) - v_u\right) = w(d) - \delta\left(v_e(d) - v_u\right) - 2q_u(\theta)\int_0^{d^*}\left(v_e(z) - v_u\right)dz \tag{29}$$

$$\begin{aligned}
\rho\int_0^{d^*}\left(v_e(z) - v_u\right)dz &= \int_0^{d^*} w(z)dz - \delta\int_0^{d^*}\left(v_e(z) - v_u\right)dz - 2q_u(\theta)\int_0^{d^*}\left(v_e(z) - v_u\right)dz \\
\left(\rho + \delta + 2q_u(\theta)\right)\int_0^{d^*}\left(v_e(z) - v_u\right)dz &= \int_0^{d^*} w(z)dz \\
\int_0^{d^*}\left(v_e(z) - v_u\right)dz &= \frac{\int_0^{d^*} w(z)dz}{\rho + \delta + 2q_u(\theta)}
\end{aligned}$$

Next, we find an expression for the firms' surplus. To this purpose we subtract (14) from (15):

$$\rho\left(v_P(d)-v_v\right)=\left(f(d)-w(d)-c\right)-\delta\left(v_p(d)-v_v\right)+c-2q_v(\theta)\int_0^{d^*}\left(v_p(z)-v_v\right)dz \tag{30}$$

$$\rho\int_0^{d^*}\left(v_p(z)-v_v\right)dz=\int_0^{d^*}\left(f(z)-w(z)\right)dz-\delta\int_0^{d^*}\left(v_p(z)-v_v\right)dz-2q_v(\theta)\int_0^{d^*}\left(v_p(z)-v_v\right)dz$$

$$\int_0^{d^*}\left(v_p(z)-v_v\right)dz=\frac{\int_0^{d^*}\left(f(z)-w(z)\right)dz}{\rho+\delta+2q_v(\theta)}$$

To find the expression for wages we substitute the workers' and firms' surpluses into the Nash bargaining rule (20):

$$\begin{aligned}(1-\alpha)\left(v_e(d)-v_u\right)&=\alpha\left(v_p(d)-v_v\right)\\(1-\alpha)\int_0^{d^*}\left(v_e(z)-v_u\right)dz&=\alpha\int_0^{d^*}\left(v_p(z)-v_v\right)dz\\(1-\alpha)\frac{\int_0^{d^*}w(z)dz}{\rho+\delta+2q_u(\theta)}&=\alpha\frac{\int_0^{d^*}\left(f(z)-w(z)\right)dz}{\rho+\delta+2q_v(\theta)}\\(1-\alpha)\frac{w(z)}{\rho+\delta+2q_u(\theta)}&=\alpha\frac{\left(f(z)-w(z)\right)}{\rho+\delta+2q_v(\theta)}\\\frac{1-\alpha}{\alpha}\frac{\rho+\delta+2q_v(\theta)}{\rho+\delta+2q_u(\theta)}w(z)&=f(z)-w(z)\\\left(1+\frac{1-\alpha}{\alpha}\frac{\rho+\delta+2q_v(\theta)}{\rho+\delta+2q_u(\theta)}\right)w(z)&=f(z)\end{aligned} \tag{31}$$

This leads to:

$$\begin{aligned}w(z)&=f(z)\left(1+\frac{1-\alpha}{\alpha}\frac{\rho+\delta+2q_v(\theta)}{\rho+\delta+2q_u(\theta)}\right)^{-1}\\&=\frac{\alpha\left(\delta+\rho+2q_u(\theta)\right)f(z)}{\delta+\rho+(1-\alpha)\,2q_v(\theta)+\alpha 2q_u(\theta)}\end{aligned} \tag{32}$$

Next, we substitute the firms' share of surplus into the value of a vacancy (15):

$$\begin{aligned}\rho v_v&=-c+2q_v(\theta)\int_0^{d^*}\left(v_p(z)-v_v\right)dz\\&=-c+2q_v(\theta)\frac{1-\alpha}{\alpha}\int_0^{d^*}\left(v_e(z)-v_U\right)dz\end{aligned} \tag{33}$$

We express the value of a vacancy in (29) by substituting wages, (32):

$$\int_0^{d^*} (v_e(z) - v_u)\, dz = \frac{\int_0^{d^*} w(z)dz}{\rho + \delta + 2q_u(\theta)} \tag{34}$$

$$= \frac{\left(1 + \frac{1-\alpha}{\alpha}\frac{\rho+\delta+2q_v(\theta)}{\rho+\delta+2q_u(\theta)}\right)^{-1}}{\rho + \delta + 2q_u(\theta)}$$

$$= \frac{\alpha \int_0^{d^*} f(z)dz}{\delta + \rho + (1-\alpha)\, 2q_v\,(\theta) + \alpha 2q_u\,(\theta)}$$

Thus, using (34) and (33) implies:

$$\rho v_v = -c + 2q_v(\theta)\frac{1-\alpha}{\alpha}\int_0^{d^*} (v_e(z) - v_u)\, dz \tag{35}$$

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

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

Using the definition of the probability of finding a job

$$q_u(\theta) = \frac{M(U,V)}{U}$$

and the steady state flow condition

$$2d^* q_u(\theta) = 2d^* \frac{M(U,V)}{U} = \frac{\delta E}{L-E} \tag{36}$$

$$q_u(\theta) = \frac{\delta E}{2d^*(L-E)} \tag{37}$$

we find:

$$M(U,V) = \vartheta U^{\xi} V^{1-\xi} = \frac{\delta E}{2d^*}$$

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

which, once substituted into the labour market tightness, gives:

$$q_v(\theta) = \frac{M(U,V)}{V} = \frac{\delta E}{2d^* \left(\frac{\delta E}{2d^* \vartheta U^{\xi}}\right)^{\frac{1}{1-\xi}}} \tag{38}$$

$$= \frac{(\delta E)^{1-\frac{1}{1-\xi}}}{(2d^*)^{\frac{-\xi}{1-\xi}} (\vartheta U^{\xi})^{-\frac{1}{1-\xi}}} \tag{39}$$

$$= \vartheta^{\frac{1}{1-\xi}} \frac{(\delta E)^{-\frac{\xi}{1-\xi}}}{(2d^*\,(L-E))^{\frac{-\xi}{1-\xi}}}$$

$$= \vartheta^{\frac{1}{1-\xi}} \left(q_u(\theta)\right)^{-\frac{\xi}{1-\xi}}. \tag{40}$$ [33]

Thus, substituting (36) and (38) in (35) gives:

$$\begin{aligned} \rho v_v &= -c + \frac{(1-\alpha)\, 2q_v(\theta) \int_0^{d^*} f(z)dz}{\delta + \rho + (1-\alpha)\, 2q_v\,(\theta) + \alpha 2q_u\,(\theta)} \\ &= -c + \frac{(1-\alpha)\, 2\vartheta^{\frac{1}{1-\xi}}\,(\delta E)^{-\frac{\xi}{1-\xi}}\,(2d^*\,(L-E))^{\frac{\xi}{1-\xi}} \int_0^{d^*} f(z)dz}{\delta + \rho + (1-\alpha)\, 2\vartheta^{\frac{1}{1-\xi}}\,(\delta E)^{-\frac{\xi}{1-\xi}}\,(2d^*\,(L-E))^{\frac{\xi}{1-\xi}} + \alpha 2\delta E/\,(2d^*\,(L-E))} \end{aligned} \tag{41}$$

where integrating implies the following aggregate production over equilibrium matches:

$$\begin{aligned} \int_0^{d^*} f(z)dz &= \int_0^{d^*} \varphi A^{\frac{1}{1-\beta}} \left(F - \frac{\gamma A^\eta}{2} d\right) dz \\ &= \varphi A^{\frac{1}{1-\beta}} \left(F - \frac{\gamma A^\eta}{4} d^*\right) d^* \end{aligned}$$

Hence, substituting the above into (41), we obtain an equation in unknown $E$ and $d^*$:

$$c = \frac{(1-\alpha)\, 2\vartheta^{\frac{1}{1-\xi}}\,(\delta E)^{-\frac{\xi}{1-\xi}}\,(2d^*\,(L-E))^{\frac{\xi}{1-\xi}} \left[\varphi A^{\frac{1}{1-\beta}} \left(F - \frac{\gamma A^\eta}{4} d^*\right) d^*\right]}{\delta + \rho + (1-\alpha)\, 2\vartheta^{\frac{1}{1-\xi}}\,(\delta E)^{-\frac{\xi}{1-\xi}}\,(2d^*\,(L-E))^{\frac{\xi}{1-\xi}} + \alpha 2\delta E/\,(2d^*\,(L-E))}$$

A second equation in the same unknowns can be obtained by substituting the flow of employment and zero profit condition into the value of a filled vacancy (14):

$$\begin{aligned} \rho v_p(d^*) &= (f(d^*) - w(d^*) - c) - \delta\,(v_p(d^*) - v_v) \\ 0 &= f(d^*) - w(d^*) - c \\ w(d^*) &= f(d^*) - c \end{aligned} \tag{42}$$

which together with (32) evaluated at $d^*$:

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

gives:

$$\begin{aligned} f(d^*) - c &= \frac{\alpha\,(\delta + \rho + 2q_u(\theta))\, f(d^*)}{\delta + \rho + (1-\alpha)\, 2q_v(\theta) + \alpha 2q_u(\theta)} \\ c &= \left(1 - \frac{\alpha\,(\delta + \rho + 2q_u(\theta))}{\delta + \rho + (1-\alpha)\, 2q_v(\theta) + \alpha 2q_u(\theta)}\right) f(d^*) \\ c &= (1-\alpha)\, \frac{\delta + \rho + 2q_v(\theta)}{\delta + \rho + 2\,(1-\alpha)\, q_v(\theta) + 2\alpha q_u(\theta)} f(d^*) \end{aligned}$$

Thus, substituting (36) and (38) we get:

$$c=(1-\alpha)\frac{\delta+\rho+2\vartheta^{\frac{1}{1-\xi}}\left(\delta E\right)^{-\frac{\xi}{1-\xi}}\left(2d^{*}\left(L-E\right)\right)^{\frac{\xi}{1-\xi}}\left[\varphi A^{\frac{1}{1-\beta}}\left(F-\frac{\gamma A^{\eta}}{2}d\right)\right]}{\delta+\rho+2\left(1-\alpha\right)\vartheta^{\frac{1}{1-\xi}}\left(\delta E\right)^{-\frac{\xi}{1-\xi}}\left(2d^{*}\left(L-E\right)\right)^{\frac{\xi}{1-\xi}}+2\alpha\delta E/\left(2d^{*}\left(L-E\right)\right)}$$

This is the second equation in unknown $E$ and $d^{*}$. To sum up, the equilibrium outcome solves the following 2 equations in the 2 unknown $E$ and $d^{*}$:

$$c=\frac{\left(1-\alpha\right)2\vartheta^{\frac{1}{1-\xi}}\left(\delta E\right)^{-\frac{\xi}{1-\xi}}\left(2d^{*}\left(L-E\right)\right)^{\frac{\xi}{1-\xi}}\left[\varphi A^{\frac{1}{1-\beta}}\left(F-\frac{\gamma A^{\eta}}{4}d^{*}\right)d^{*}\right]}{\delta+\rho+\left(1-\alpha\right)2\vartheta^{\frac{1}{1-\xi}}\left(\delta E\right)^{-\frac{\xi}{1-\xi}}\left(2d^{*}\left(L-E\right)\right)^{\frac{\xi}{1-\xi}}+\alpha2\delta E/\left(2d^{*}\left(L-E\right)\right)}$$

$$c=(1-\alpha)\frac{\delta+\rho+2\vartheta^{\frac{1}{1-\xi}}\left(\delta E\right)^{-\frac{\xi}{1-\xi}}\left(2d^{*}\left(L-E\right)\right)^{\frac{\xi}{1-\xi}}\left[\varphi A^{\frac{1}{1-\beta}}\left(F-\frac{\gamma A^{\eta}}{2}d\right)\right]}{\delta+\rho+2\left(1-\alpha\right)\vartheta^{\frac{1}{1-\xi}}\left(\delta E\right)^{-\frac{\xi}{1-\xi}}\left(2d^{*}\left(L-E\right)\right)^{\frac{\xi}{1-\xi}}+2\alpha\delta E/\left(2d^{*}\left(L-E\right)\right)} \tag{43}$$

i.e. in more compact notation:

$$q_u=\frac{\delta E}{\left(2d^{*}\left(L-E\right)\right)},\ q_u'(E)>0 \tag{44}$$

$$c=(1-\alpha)\frac{2\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}}\left[\varphi A^{\frac{1}{1-\beta}}\left(F-\frac{\gamma A^{\eta}}{4}d^{*}\right)d^{*}\right]}{\delta+\rho+2\left(1-\alpha\right)\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}}+2\alpha\left(q_u\right)} \tag{45}$$

$$c=(1-\alpha)\frac{\delta+\rho+2\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}}\left[\varphi A^{\frac{1}{1-\beta}}\left(F-\frac{\gamma A^{\eta}}{2}d\right)\right]}{\delta+\rho+2\left(1-\alpha\right)\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}}+2\alpha\left(q_u\right)}=c \tag{46}$$

with $\varphi=(\beta/\rho)^{\frac{\beta}{1-\beta}}$.

With the equilibrium values of $E$ and $d^{*}$ we can also evaluate the wage. Using the profit function (32) and (40) we get:

$$w(d)=\frac{\alpha\left(\delta+\rho+2q_u(\theta)\right)\left[\varphi A^{\frac{1}{1-\beta}}\left(F-\frac{\gamma A^{\eta}}{2}d\right)\right]}{\delta+\rho+2\left(1-\alpha\right)\vartheta^{\frac{1}{1-\xi}}\left(q_u\right)^{-\frac{\xi}{1-\xi}}+2\alpha(q_u)}.$$

# D Parameter Values

Table 9 reports the parameter values used in Section 2.5

| Parameter | Description | Value |
|---|---|---|
| $\alpha$ | Bargaining Weight | 0.5 |
| $\rho$ | Patience | 0.05 |
| $\delta$ | Per-period Seperation Shock | 0.1 |
| $\xi$ | Matching Function Elasticity | 0.5 |
| $\vartheta$ | Matching Function Constant | 0.5 |
| $\beta$ | Capital share in CB | 0.3 |
| $F$ | Max. Productivity | 20 |
| $\gamma$ | Mismatch Cost Param. 1 | 25 |
| $\eta$ | Mismatch Cost Param. 2 | 2 |
| $c$ | Vacancy Cost | 1 |

Table 9: Parameter