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Automation when skills are bundled

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Automation when skills are bundled[a]

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Abstract

Automation affects workers because it affects the return to their skills when performing different tasks. I propose a general equilibrium model of occupational choice and technological change which takes two important labor market features into account: (i) automation happens to tasks and (ii) workers have bundled skills. Equilibrium skill returns vary across tasks, and the impact of automation on skill returns is task-specific. I find that, to a first-order approximation, skill returns depend only on the relative skill allocation in each task. In equilibrium, automation reduces employment in the task subjected to automation so long as tasks are gross complements. This reduction in employment increases both tasks' intensity in the skill used intensively in the automated task. This increased intensity is coupled with a universal decline in the return to the skill used intensively in the automated task. Conversely, the return to the other skill increases in both tasks.

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1 Introduction

Is automation good or bad for workers? On the one hand, automation increases productivity, but on the other, it means machines replace humans in their work tasks. Although a large literature explains how the mix between capital and labor in tasks is altered by automation, precisely how this affects individual workers, and the value of their skills, is not known. This paper seeks to answer the following question: How does automation affect workers who have bundled skills?

Bundled skills means each worker has an indivisible package of skills, which she supplies to one occupation. That is, she does not employ her cognitive skills as an office clerk, while simultaneously employing her psychological skills as a care worker. Rather, she chooses one occupation where she uses all her skills to produce output.

Apart from its intuitive and realistic appeal,[1] this idea rationalizes the empirical observation that skills are paid differently across occupations (Deming 2017, Edin et al. 2022). In other words, the law of one price for skills does not hold. Furthermore, these skill prices' growth rates also vary between occupations (Ibid.). Skill bundling is one plausible explanation for occupation-specific skill prices: when a worker cannot freely place each skill in the occupation paying the highest price, occupations can compensate low payments for one skill by higher payments in another.

Given these observations, it is natural to ask how automation affects skill prices, and whether it can account for their changes over time. Automation, one of the most salient aspects of technological progress, is the process whereby machines start performing tasks that could previously only be performed by human labor. Depending on which skills are particularly useful in the automated tasks, automation clearly has the potential to change skill prices and thus wages in different and potentially interesting ways. My goal in this paper is to build a general equilibrium model that can speak to these issues.

I provide a unified framework which explains how labor-replacing automation affects skill prices in different occupations, and thereby workers, in the presence of skill bundling. The model follows the Roy (1951) tradition where workers select into occupations based on comparative advantage. I use the standard division of occupations (or tasks)[2] into routine and non-routine, where I let automation happen in the routine occupation, just as in classical models of labor replacing automation such as those by Acemoglu & Autor (2011) and Acemoglu & Restrepo (2018*b*). The main innovation compared to these models is skill bundling, which implies skill prices vary across tasks (occupations). I allow for two skills, and I compare the skill prices for these two skills in the different tasks as routine tasks are automated.

First, I note that skill prices in my model – the marginal productivities of skills – are different from the skill returns obtained when estimating a log wage regression. I provide a link between these two concepts.

The skill prices for both skills in both tasks increase with automation of the routine task, although the price of the skill used intensively in the routine task falls in *relative* terms compared to the other skill price. My model also allows decomposition of the skill prices, and as such I can explore the mechanisms behind the changes in skill prices. Skill prices in the routine task benefit from

[1] 7.8 percent of employed persons in the US held multiple jobs in 2018 (Bailey & Spletzer 2020). However, one can imagine that even if workers have multiple jobs, their skill package is an innate feature of their person. They will use this package to perform whichever tasks are given to them in each occupation or job.

[2] In this paper, I use the simplifying assumption that a task equals an occupation. It is possbile to extend the model to allow occupations to consist of a bundle of tasks.

increased labor productivity, while skill prices in the non-routine task increase because of the relative scarcity of this task. The relative scarcity appears as routine task output increases when it becomes cheaper to produce.

The skill returns obtained from estimating a log wage regression, to a first approximation, depend only on relative skill allocation. That is, automation affects estimated skill returns only insofar as it affects reallocation of skills between tasks.

I find that automation reduces the return to the skill used intensively in the automated, routine task (when tasks are gross complements). The return to the other skill increases. This change in skill returns is in equilibrium coupled with reallocation of skills from the routine to the non-routine task, which means that the mix of skills changes in both tasks.

This is mirrored in the empirical patterns I show in Section 5.2. Over the sample period, employment has shifted from routine to non-routine occupations, and skill prices of psychological skills increased relative to cognitive skill prices.[3]

I devise an estimation procedure to calibrate the full model to data on skills, wages and occupations – variables that exist in the Swedish micro data I can access. I note that skills observed in the data might be mismeasured versions of or imperfect proxies for the true skills that the labor market values. With a reasonably general formulation of measurement error, I show how to obtain the "true" skills and skill returns from the observed skills and estimated skill returns from the data. However, the calibration to Swedish data proves difficult due to weak sorting on the skills observed in the data into the occupational categories I study (routine and non-routine). Instead, I demonstrate that the calibration procedure works well for a simulated data set, and will proceed with future work to explore other ways in which the model can be fitted to data.

I connect two important strands of literature: the task-based models of automation and the literature exploring returns to skills across occupations.

Firstly, task-based models, developed by Autor et al. (2003), Acemoglu & Autor (2011) and Acemoglu & Restrepo (2018*a*), have shaped the understanding of routine-biased technological change (RBTC): machines replace human labor mainly in *routine* tasks. Automation therefore has the potential to reduce demand for workers employed in routine tasks. Indeed, routine workers have experienced declining demand in the US (Autor et al. 2006, Cortes 2016) and in Europe (Goos & Manning 2007, Goos et al. 2014). These task-models, in their current form, leave open the question of how the value of workers' different skills develop when a task is automated.

Secondly, the evolution of skill prices is a topic of recent interest: both Deming (2017) and Edin et al. (2022) demonstrate that the returns to non-cognitive (or psycho-social) skills have risen over the last decades in the US and Sweden, respectively.[4] Furthermore, there is broad understanding that skill prices differ between occupations (or tasks) (Autor & Handel 2013, Fredriksson et al.

[3] In Section 5.2 I show that cognitive skills are paid more in routine occupations, and psychological skills are paid more in non-routine occupations.

[4] A related literature describes the evolution of tasks (or skill requirements) within occupations. Atalay et al. (2020) use job ads published large US newspapers to extract task content of occupations from 1940-2000, and find that within-occupation changes in tasks are at least as important as employment reallocation when explaining the decline in routine tasks in the US. Spitz-Oener (2006) presents evidence on increasing skill requirements in German occupations from 1979-1999. Cortes et al. (2021) document how high-paid jobs have experienced larger increases in the importance of social task, compared to other occupations. This impacts sorting: people who have comparative advantage in social skills (e.g. women) have moved into high-paying jobs to a higher degree than people who do not (e.g. men).

2018), which may be a consequence of skill bundling (Rosen 1983, Heckman & Scheinkman 1987, Firpo et al. 2011). In this paper, I study the consequences of automation for skill prices.

Skill bundling has received renewed attention recently. Lindenlaub (2017) describes how changes in complementarity between workers' skills and the skill requirements of jobs can create job polarization, and I complement her paper by explicitly considering labor-replacing automation and its effect on skill prices.

Two other contemporary papers on skill bundling are relevant for this paper. Firstly, Edmond & Mongey (2020) provide a similar model to the one presented in this paper, and they explore under what conditions the bundling constraint binds. The bundling constraint is the constraint posed by the rule that skills cannot be sold one-by-one, and Edmond & Mongey (2020) asks what type of technological change makes a *bundled* equilibrium (i.e. occupation-specific skill prices) more or less likely. They look at how that affects inequality within and between occupations. Secondly, Choné & Kramarz (2021) consider how sorting is affected by new ways to unbundle skills – temp agencies, "gig job" platforms and the like.

I complement both these papers by considering labor-replacing automation, which has had particular success in explaining RBTC, and its impact on skill prices. In contrast, Edmond & Mongey (2020) look at factor-augmenting technological change, and Choné & Kramarz (2021) look at explicitly unbundling technological advances.

The model I construct carries many similarities with Acemoglu & Restrepo's (2018*a*, 2018*b*, 2019) model. My main innovation is that I consider workers with bundled skills. But I also differ in that I have two tasks, and that workers are endowed with multiple skills that are useful in both tasks. The resulting model thus features skill prices that vary across tasks, while payment to labor in previous models of labor-replacing automation – such as the ones by Acemoglu & Autor (2011) and Acemoglu & Restrepo (2018*a*, 2018*b*, 2019) – is characterized by one wage rate for each type of worker: w_R for routine workers and w_N for non-routine workers, for instance.

Models with varying skill prices – such as the one by Autor & Handel (2013) – are usually partial equilibrium models, which do not consider the impact of sorting on labor payment. Edmond & Mongey (2020), on the other hand, consider a general equilibrium model, similar to mine, but they do not include labor replacing automation.

This paper is structured as follows: In Section 2, I present the model. Thereafter, in Section 3, I present comparative statics. Section 4 describes how to accommodate commonly estimated skill prices in the model, and present comparative statics on these estimated skill prices. In Section 5, I present some empirical patterns from the Swedish data. Section 6 concludes.

2 A model with labor-replacing automation and bundled skills

Brief overview The economy consists of consumers, who are workers, intermediate firms and final good firms. Workers supply skills to intermediate firms, who produce one task each (task output is denoted by X_τ) and pay wages to households. The task output X_τ is purchased by final good firms, who use it to produce a final good Y. They convert some of the final good to capital K, which they rent back to intermediate firms. The rest is sold as consumption to households. Both types of firms are competitive and owned by households.

2.1 Worker earnings and occupational choice

I start by describing how workers sort into occupations and what their earnings are. This section highlights the main novelty of my model: workers choose *one* occupation (task) where they apply *all* their skills. Consequently, skill prices may vary between tasks in equilibrium.

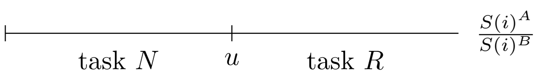
Each worker (consumer), indexed by i, is endowed with an $\mathcal{S}$ dimensional vector of non-negative skills: $S(i) = \{S(i)^1, S(i)^2, ..., S(i)^{\mathcal{S}}\}$. Here, I consider two skills, and I call them A and B. Skills are bundled, which means a worker cannot supply individual skills to different occupations. One occupation, in this context, is one task.[5] The worker's occupational choice is therefore a discrete choice of a task τ from a set of available tasks. For ease of exposition, I consider two tasks, which I call R and N – think of routine and non-routine tasks. Each unit of skill is paid its marginal product in each task,[6] so worker i's earnings are

$$W_\tau(i) = \sum_s \omega_\tau^s S^s(i) \tag{1}$$

where ω_τ^s is the price paid to worker skills in task τ. As posited by Autor & Handel (2013), and as explained in Heckman & Scheinkman (1987), there is no single skill price across the economy since labor is bundled. Instead, skill prices depend on the task in which skills are employed.

For there to be positive employment in all tasks, no task can have skill prices that strictly dominate those in another occupation – a task that pays A skills more than another occupation must have a lower price of B skills. If it were not so, the occupation that paid lower prices to both A and B would not get any workers.[7] In order to demonstrate the workers' choice graphically below, I assume that skill A is paid more in routine tasks, and that skill B is paid more in non-routine tasks.

Workers will choose a task τ in which $W_\tau(i) \geq W_{\tau'}(i)$ for all $\tau' \neq \tau \in \mathbb{T}$. In the case with two skills, workers can be characterized on a line representing their ratio of skills $s(i)^A/s(i)^B$. In the case of two tasks: routine R and non-routine NR, if skill A is paid more in task R, and vice versa for skill B, I can characterize the workers' choice graphically as follows:



Workers to the left of the cutoff u prefer the non-routine task, since they have comparative advantage in the skill which is paid relatively well in the non-routine task (B). Workers to the right of the cutoff choose the routine task since they have comparative advantage in the other skill (A). The cutoff between tasks is defined by

$$u \equiv \frac{\omega_N^B - \omega_R^B}{\omega_R^A - \omega_N^A} \tag{2}$$

since workers on the cutoff are indifferent between tasks, i.e. they have

$$\omega_N^A S^A(i) + \omega_N^B S^B(i) = \omega_R^A S^A(i) + \omega_R^B S^B(i). \tag{3}$$

Rearranging Equation (3) results in the cutoff in Equation (2). Here, let us assume skill A is paid more in R than in N, and skill B is paid more in N than in R. This ensures both numerator and denominator are positive in 2.

[5] It is possible to extend the model to include multiple tasks in each occupation.

[6] This is because within an occupation (task), skills can be unbundled. See section 2.4 for more details.

[7] This is akin to proposition 1 from Autor & Handel (2013). Proposition 2 of the same paper says that there cannot be uniformly positive cross-occupation covariance between task returns for all task pairs, which, for the case of two occupations, means the same as proposition 1.

The supply of a skill in each task is simply the sum of skills of those who choose to work in each task, namely[8]

$$S_\tau^s = \int_{i\in\tau} S^s(i)di.$$

2.2 From skills to efficiency units of labor

Skills are the innate abilities of a worker – her human capital. She applies these skills to a task, where they are differently productive depending on the task. Let us define efficiency units of labor in task R as the following constant-elasticity-of-substitution (CES) aggregate of skills:

$$L_R = \left[\alpha_R^{1/\varepsilon} S_R^{A\,\frac{\varepsilon-1}{\varepsilon}} + (1-\alpha_R)^{1/\varepsilon} S_R^{B\,\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$$

where α_R defines the weight of skill S^A in the "production" of R labor. This "production function" thus represents a mapping between skills – innate features of workers – to tasks – building blocks of production. There is a similar production function for L_N, where α_N denotes the importance of A skills in task N.

2.3 Intermediate firms: Production

Intermediate firms specialize in one task group: routine or non-routine tasks. The routine and non-routine task groups consist of a continuum of smaller, intermediate tasks. For instance, the routine task group may include such tasks as typing, operating machinery in a predictable manner, counting, recording, etc. The non-routine task group may include such tasks as cleaning, managing, planning, childminding, etc. Each task group is an aggregate of these smaller, intermediate tasks, as in Acemoglu & Restrepo (2018*b*):

$$X_R = \left[\int_0^1 x_R(j)^{\frac{\eta-1}{\eta}} dj\right]^{\frac{\eta}{\eta-1}}$$

and similarly for task group N. A fraction (b_t^R, b_t^N) of task groups R and N respectively can be performed by machines, and the rest must be performed by labor. For now, let (b_t^R, b_t^N) be constant over time, and drop the time subscript. In the tasks that can be performed by machines, capital and labor are perfect substitutes. Thus, task j in task group R is produced as follows (this follows Acemoglu & Restrepo 2018*b*):

$$x_R(j) = \begin{cases} \lambda k_R(j) + l_R(j) & \text{if automatable, i.e. } j \in [0, b_R] \\ l_R(j) & \text{otherwise, i.e. } j \in (b_R, 1] \end{cases} \tag{4}$$

[8] To solve the model given some distribution of skills, I reformulate this integral: Skills are jointly distributed according to some pdf $f(S(i)^A, S(i)^B)$. Given the cutoff u, I compute the skill supply of to each task as the double integrals

$$\begin{aligned} S_R^A &= \int_0^\infty \int_0^{uS^B(i)} S(i)^A f(S^A(i), S^B(i)) dS^A(i) dS^B(i) \\ S_R^B &= \int_0^\infty \int_{S^A(i)/u}^\infty S^B(i) f(S^A(i), S^B(i)) dS^B(i) dS^A(i) \\ S_N^A &= S^A - S_R^A \\ S_N^B &= S^B - S_R^B, \end{aligned}$$

where there are two tasks, and A is used more intensively in the routine task, and B in the non-routine task.

and similarly for intermediate tasks in task group N. λ is a capital augmenting productivity factor. Intermediate tasks are equally productive in the production of the routine task X_R (and similarly for the non-routine task output X_N), as evident from equation 4, so each intermediate task is produced in the same amount: $x_\tau(j) = x_\tau \ \forall j \in [0,1]$. If firms automate all automatable tasks, task group R is produced as follows:

$$X_R = \left[b_R^{1/\eta}(\lambda K_R)^{\frac{\eta-1}{\eta}} + (1-b_R)^{1/\eta} L_R^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$$

where capital letters L_R, K_R denote the total amount of labor and capital, respectively, that task R employs:

$$\begin{aligned} L_R &= (1-b_R)l_R(j) && \forall j \in [b_R, 1] \\ K_R &= b_R k_R(j) && \forall j \in [0, b_R]. \end{aligned}$$

2.4 Intermediate firms: Firm problem

Intermediate firms produce one task τ each, which they sell to final good firms at price p_τ. There are many homogeneous intermediate firms within each task τ, meaning that intermediate firms are price takers. Capital is supplied by final good firms at the constant rate r. Skills are supplied to each task in bundles, but within the task, skills are unbundled. That is, within an occupation, workers can supply different skills to different sub-tasks along the task interval described in Section 2.3 above. For instance, a machine operator might use manual dexterity when managing a machine's moving parts, and analytical skill when assessing how to mend a faulty piece of equipment. Each skill thus commands a task specific price ω_τ^s for skill s in task τ.

Now, allow intermediate firms to automate *up to* the technological frontier. Denote an intermediate firm's optimal automation level as b_τ^* and the technological frontier as b_τ. Recall equation 4. Allowing firms to automate up to b_τ means that firms choose whether to use capital or labor in the tasks in the $[0, b_\tau]$ interval.

Intermediate firms are symmetric within a task, so we can treat them as one representative firm. Intermediate firms maximize profits by choosing capital, degree of automation – what share of tasks to be produced by capital – and labor. Each intermediate firm chooses labor in the sense that they demand certain skills to perform their task. The firm problem for an R producing intermediate firm is

$$\begin{aligned} \max_{\{K_R, S_R^A, S_R^B, b_R^*\}} \quad & p_R X_R - rK_R - \omega_R^A S_R^A - \omega_R^B S_R^B \\ \text{s.t.} \quad & X_R = \left[{b_R^*}^{1/\eta}(\lambda K_R)^{\frac{\eta-1}{\eta}} + (1-b_R^*)^{1/\eta} L_R^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \\ & L_R = \left[\alpha_R^{1/\eta} {S_R^A}^{\frac{\varepsilon-1}{\varepsilon}} + (1-\alpha_R)^{1/\varepsilon} {S_R^B}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}} \\ & b_R^* \le b_R \end{aligned}$$

and similarly for a firm producing the N task. Consequently, the first order conditions for capital, skills and automation are given by

$$r = p_R \left(\frac{b_R^* \lambda^{\eta-1} X_R}{K_R} \right)^{1/\eta} \tag{5}$$

$$\omega_R^A = p_R \left(\frac{(1-b_R^*) X_R}{L_R} \right)^{1/\eta} \left(\frac{\alpha_R L_R}{S_R^A} \right)^{1/\varepsilon} \tag{6}$$

$$\omega_R^B = p_R \left(\frac{(1-b_R^*) X_R}{L_R} \right)^{1/\eta} \left(\frac{(1-\alpha_R) L_R}{S_R^B} \right)^{1/\varepsilon} \tag{7}$$

$$\mu_R = p_R \left(\frac{X_R^{1/\eta}}{\eta - 1} \right) \left[\left(\frac{\lambda K_R}{b_R^*} \right)^{\frac{\eta-1}{\eta}} - \left(\frac{L_R}{1-b_R^*} \right)^{\frac{\eta-1}{\eta}} \right], \tag{8}$$

and similarly for N. μ_R is the Lagrange multiplier attached to the inequality constraint $b_R^* \leq b^R$. First, consider the case when $\mu_R = 0$. This implies that the chosen level of automation b_R^* may be below the constraining b_R. Solving for b_R^* gives

$$b_R^* = \frac{\lambda K_R}{\lambda K_R + L_R}. \tag{9}$$

Intermediate firms will automate up until the point where the automated share of tasks equals the share of effective capital inputs. If instead $\mu_R > 0$, then the ratio of capital inputs to total inputs will be larger than b_R. This means intermediate firms want to automate *more* than technology allows, and the constraint binds. There will be complete automation of automatable tasks: $b_R^* = b_R$. Intuitively, the more abundant capital is, the more firms want to automate. Then, they are more likely to hit the technological frontier b_R. On the other hand, if labor is abundant, it will be cheaper to use human labor than machines, and firms will automate less than technology allows.

2.5 Final good firms

Final good firms purchase tasks X_τ from intermediate firms at price p_τ. They convert it into the homogeneous final good Y via the following CES aggregate, where σ is the elasticity of substitution between tasks:

$$Y = \left[\beta^{1/\sigma} X_R^{\frac{\sigma-1}{\sigma}} + (1-\beta)^{1/\sigma} X_N^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$

The parameter β represents the importance of routine tasks in the economy, compared to non-routine tasks which have importance $1-\beta$.

The final good firms then convert this final good into capital at the fixed rate γ or to the consumption good C at rate 1. They rent the capital back to intermediate firms at rate r and sell the consumption good to consumers at price $\tilde{P}$. Their firm problem is thus

$$\max_{\{K, C, X_\tau\}} rK + \tilde{P}C - \sum_\tau p_\tau X_\tau \tag{10}$$

$$\text{s.t.} \quad Y = \left[\beta^{1/\sigma} X_R^{\frac{\sigma-1}{\sigma}} + (1-\beta)^{1/\sigma} X_N^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{11}$$

$$Y \geq C + \frac{K}{\gamma}. \tag{12}$$

Defining the optimal price index as $P = \left[\beta^{\frac{1}{1-\sigma}} p_R^{1-\sigma} + (1-\beta)^{\frac{1}{1-\sigma}} p_N^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$, the first order conditions imply that the price for the consumption good $\tilde{P} = P$.[9] The first order conditions define the demand for tasks X_τ and the supply of capital K as follows:

$$\begin{aligned} p_R &= \left(\frac{\beta Y}{X_R}\right)^{1/\sigma} P \\ p_N &= \left(\frac{(1-\beta)Y}{X_N}\right)^{1/\sigma} P \\ r &= \frac{P}{\gamma}. \end{aligned}$$

I set the final consumption good as the numeraire in the model, meaning I normalize $P = 1$.

2.6 Consumption

There is a unit mass of consumers i. They derive utility from consumption only, which they purchase from final good firms at price $\tilde{P}$ using their income $I(i)$. All consumers are workers, and they own all firms, all of which have zero profits. Their income $I(i)$ is therefore $I(i) = \sum_s w^s_{\tau(i)} S^s(i)$, where $\tau(i)$ is the task chosen by worker i. This implies that each individual consumes $C(i) = \sum_s w^s_{\tau(i)} S^s(i)/\tilde{P}$. Summing over all individuals i to obtain $C = \sum_\tau \sum_s \omega^s_\tau S^s_\tau/\tilde{P}$ means that all labor income is spent on consumption.

2.7 Equilibrium

Given some joint distribution of skills, $\{S^s(i)\}_{s=A,B}$, an equilibrium is an allocation $\{S^s_\tau, K_\tau\}_{\tau=R,N;s=A,B}$ and a set of prices $\{p_\tau, \omega^s_\tau\}_{\tau=R,N;s=A,B}$, automation levels $\{b^*_\tau\}_{\tau=R,N}$ and a cutoff $\{u\}$ such that individuals (workers who are also consumers) and firms (intermediate and final good) optimize and markets clear subject to the production functions and the bundling constraint. It is characterized

[9] Below, I show that $P = \tilde{P}$. The first order conditions are as follows:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial K} &= r - \mu/\gamma = 0 \\ \frac{\partial \mathcal{L}}{\partial C} &= \tilde{P} - \mu = 0 \\ \frac{\partial \mathcal{L}}{\partial X_R} &= -p_R + \mu\left(\frac{\beta Y}{X_R}\right)^{1/\sigma} = 0 \\ \frac{\partial \mathcal{L}}{\partial X_N} &= -p_N + \mu\left(\frac{(1-\beta)Y}{X_N}\right)^{1/\sigma} = 0 \end{aligned}$$

where constraint 11 is inserted to 12, and μ represents the Lagrange multiplier attached to that constraint. Now, define

$$P = \left[\beta^{\frac{1}{1-\sigma}} p_R^{1-\sigma} + (1-\beta)^{\frac{1}{1-\sigma}} p_N^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

and note that from the first order conditions, $\tilde{P} = \mu$. Substitute for p_R and p_N using the first order conditions to obtain

$$\begin{aligned} P &= \tilde{P}\left[\beta^{\frac{1}{1-\sigma}} \left(\frac{\beta Y}{X_R}\right)^{\frac{1-\sigma}{\sigma}} + (1-\beta)^{\frac{1}{1-\sigma}} \left(\frac{(1-\beta)Y}{X_N}\right)^{\frac{1-\sigma}{\sigma}}\right]^{\frac{1}{1-\sigma}} \\ &= \tilde{P}\left[\beta^{1/\sigma} X_R^{\frac{\sigma-1}{\sigma}} + (1-\beta)^{1/\sigma} X_N^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{1-\sigma}} Y^{1/\sigma} \\ &= \tilde{P} Y^{-1/\sigma} Y^{1/\sigma} \\ \Rightarrow P &= \tilde{P}\ \square. \end{aligned}$$

by the following equations:

$$r = p_\tau \left(\frac{b_\tau^* \lambda^{\eta-1} X_\tau}{K_\tau} \right)^{1/\eta} \tag{13}$$

$$\omega_\tau^A = p_\tau \left(\frac{(1-b_\tau^*) X_\tau}{L_\tau} \right)^{1/\eta} \left(\frac{\alpha_\tau L_\tau}{S_\tau^A} \right)^{1/\varepsilon} \tag{14}$$

$$\omega_\tau^B = p_\tau \left(\frac{(1-b_\tau^*) X_\tau}{L_\tau} \right)^{1/\eta} \left(\frac{(1-\alpha_\tau) L_\tau}{S_\tau^B} \right)^{1/\varepsilon} \tag{15}$$

$$p_\tau = \left(\frac{Y}{X_\tau} \right)^{1/\sigma} P \tag{16}$$

$$S_\tau^s = \int_{i \in I(\tau)} S^s(i) di \tag{17}$$

$$u = \frac{\omega_N^B - \omega_R^B}{\omega_R^A - \omega_N^A} \tag{18}$$

$$b_\tau^* = \begin{cases} \frac{\lambda K_\tau}{\lambda K_\tau + L_\tau} & \text{if this ratio} < b_\tau \\ b_\tau & \text{otherwise,} \end{cases} \tag{19}$$

for $\tau = \{R, N\}$. This means I have 15 equations to solve for 15 unknowns. In the 15 equations above, I also make use of the following nine variables: $\{L_\tau, X_\tau, Y, C, K, P, r\}$, which are determined according to the nine equations below:

$$L_\tau = \left[\alpha_\tau^{1/\varepsilon} S_\tau^{A\ \frac{\varepsilon-1}{\varepsilon}} + (1-\alpha_\tau)^{1/\varepsilon} S_\tau^{B\,\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{20}$$

$$X_\tau = \left[b_\tau^{*\ 1/\eta} (\lambda K_\tau)^{\frac{\eta-1}{\eta}} + (1-b_\tau^*)^{1/\eta} L_\tau^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{21}$$

$$Y = \left[\beta^{1/\sigma} X_R^{\frac{\sigma-1}{\sigma}} + (1-\beta)^{1/\sigma} X_N^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{22}$$

$$C = \sum_\tau \sum_s \omega_\tau^s S_\tau^s / P \tag{23}$$

$$K = \sum_\tau K_\tau \tag{24}$$

$$P = \left[\sum_\tau p_\tau^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{25}$$

$$r = P/\gamma. \tag{26}$$

3 Results: Skill prices and comparative statics

3.1 Parameters of the model

In this section, I present and motivate the choice of parameter values of the model.

First, Table 1 presents the automation levels I set for the initial period: I assume 10 percent of all tasks in the routine task group are automatable, and I assume no automation in the non-routine task. The qualitative results are unchanged if I set the automation level in the non-routine task to some low non-zero number, such as 10 percent, throughout.

The second panel in Table 1 refers to the skill distribution. Skills in the model are log-normally distributed, normalized around a zero mean and with unit variance. I set the covariance between log skills to 0.6.[10]

[10]The covariance between the log skills I observe in the data (see below in Section 5.1) is 0.3, and with a simple measurement error structure, I conclude that the true covariance should be somewhat larger. Say observed skills

The third panel in Table 1 includes the rental rate of capital, constructed as the difference between the nominal interest rate and inflation, plus some depreciation. The final good price is normalized to one, and the conversion rate between final good and capital is thus determined by the inverse of the rental rate.

The fourth panel in Table 1 presents the important elasticities of substitution in the three layers of production in the model. I set the elasticity of substitution between capital and labor within each task at $\eta = 0.7$. This number is taken from the estimate of the capital-labor elasticity of substitution in US manufacturing by Oberfield & Raval (2014). They conclude that this value has been steady for the last 45 years before their study. Another piece of suggestive evidence is from Acemoglu & Restrepo (2019), who write that the elasticity of substitution between capital and labor in a sector is probably below but close to one (p.12). I view the tasks or occupations in my model as akin to sectors, although it might be that the elasticity of capital and labor is slightly higher within an occupation than within a whole sector.[11]

I set the elasticity of substitution between routine and non-routine tasks to a relatively low value of $\sigma = 0.4$. The tendency for elasticities of substitution to become smaller with higher aggregation was documented by Diewert (1974) and has intuitive rationale: In the overall economy, when producing a final good, there should be a high degree of complementarity between different factors of production (in this case, tasks), to square with a sense of diversity of the economy. In other words, the production of the final goods of the whole economy needs more than one factor of production. For the main results, it is important that the elasticity of substitution between tasks (σ) does not surpass one, but I will discuss what happens when it does (see Section 4.4 and Figure 6).

Lastly, I construct the "production function" for efficient labor units as Cobb-Douglas in skills, i.e. I set the elasticity of substitution ε between skills to one. As evident in Section 4.4, this does not affect the qualitative conclusions from the model.

The fourth and last panel describes the weights I attach to the cognitive skill in the "production" of labor in each task. I assume skill A is more important in the routine task, and skill B more important in the non-routine task. Given the ordering of these weights (i.e. that $\alpha_R > \alpha_N$), the absolute numbers are not important for the qualitative results. I bound these parameters in (0,1), so that each skill is at least somewhat useful in both tasks.

Calibration to Swedish data I calibrate three parameters of the model. Using data on the ratio of machinery to gross-domestic product in Sweden in 1996, I find an appropriate value for capital-augmenting productivity λ. I use the weight on routine tasks in the economy β to match the

relate to true skills in the following way:

$$s_i^{A,obs} = a_A s_i^{A,true} + a_{A,\epsilon}\epsilon_{A,i} \quad \forall i$$
$$s_i^{B,obs} = a_B s_i^{B,true} + a_{B,\epsilon}\epsilon_{B,i} \quad \forall i$$

Then the covariance of true skills is

$$\rho = cov(s_i^{A,true}, s_i^{B,true}) = \frac{cov(s_i^{A,obs}, s_i^{B,obs})}{a_A a_B}$$

so that if $a_A a_B < 1$, covariance between true skills exceeds the covariance observed in data. More specifically, if the product $a_A a_B = 0.5$, for instance if the signal in observed skill A is 0.75 ($a_A = 0.75$), and the signal in skill B is two thirds ($a_B = 2/3$), the true covariance is twice the observed.

[11] As a rule of thumb, the substitutability between factors increases the deeper down in the model layers you go. However, this might not always be true. It might be easier to switch from workers to machines in a whole industry than in a single occupation.

Table 1: Parameters

Parameter		Value	Source or comment
$b_{R,1996}$	Automation level of routine tasks, initial period	0.1	Some low, non-zero initial level of automation
$b_{N,1996}$	Automation level of non-routine tasks, initial period	0	No automation in the non-routine task
μ^A	Mean of log A skills	0	Normalization
μ^B	Mean of log B skills	0	Normalization
$\sigma^{2,A}$	Variance of log A skills	1	Normalization
$\sigma^{2,B}$	Variance of log B skills	1	Normalization
ρ	Covariance between log skills	0.6	Covariance between the two observed skills in data (cognitive and psychological) is 0.3
r_{1996}	Rental rate	0.0903	Swedish real price of capital = nominal rate - inflation + depreciation, constructed using data from The Riksbank (2021), Statistics Sweden (2021*b*) and Corbo & Strid (2020)
P	Final good price	1	Normalization
γ	Productivity of final good in producing capital	1/0.0903	$\gamma = P/r$ from Equation (26)
σ	Elasticity of substitution (EoS) between R and NR	0.4	"Top layer" in model i.e. final good production, selected to have lowest EoS
η	EoS between K and L within a task	0.7	Oberfield & Raval (2014), Acemoglu & Restrepo (2019)
ε	EoS between skills within a task	1	Cobb-Douglas
α_R	Weight on A skills in R	0.7	R is intensive in A skills
α_N	Weight on A skills in N	0.3	N is intensive in B skills

Notes: The skill parameters in the second panel refer to the logged skills from the model: they are normally distributed (by construction of the military test scores), and normalized to have zero mean and unit variance. The bottom panel describes the weights on skill A in Equation (20).

employment share of routine occupations in 1996. Lastly, I determine the size of the automation parameter in the final period $b_{R,2013}$ by matching the employment share in routine occupations in 2013.

Calibration of the full model (i.e. calibration also of the parameters in Table 1) is, in principle, possible, as described in Section 5.3.

3.2 How does automation affect skill prices? Comparative statics

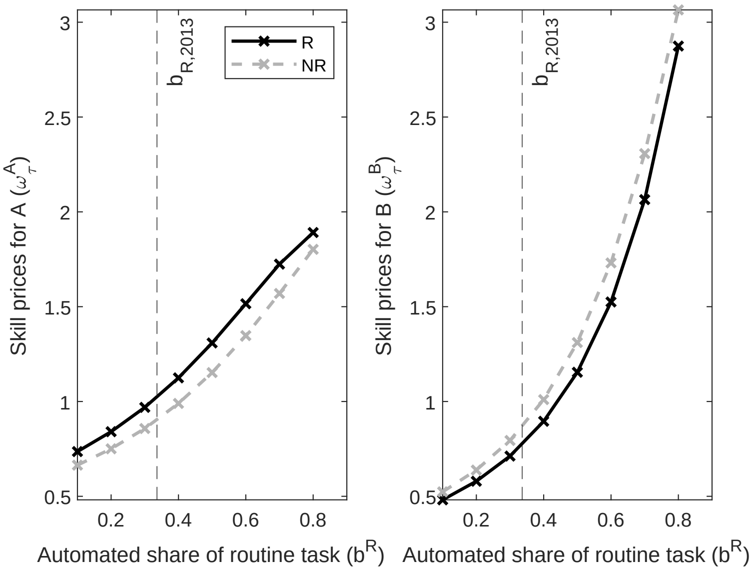
The level of skill prices of both skills increase in both tasks when the routine task is automated, as evident from Figure 1. However, in relative terms, the A skill becomes less valuable in both tasks: Figure 2 exhibits a decline in the relative price of A compared to B in both tasks.

Going back to the *level* of skill prices, recall that the skill price is the product of three marginal products (see Equations (14) and (15)). Logging the skill price, we can thus decompose it into a

Table 2: Parameters and matched moments

Parameter		Estimated value	Matched moment	Data (1996)	Model
λ	Capital-augmenting productivity	1.10	Capital-Output ratio K/Y	0.3881	0.3880
β	Weight on routine tasks	0.74	Employment share in routine occupations	0.7227	0.7227
Parameter		Estimated value	Matched moment	Data (2013)	Model
$b_{R,2013}$	Automation level of routine tasks, final period	0.34	Employment share in routine occupations	0.6264	0.6128

Notes: The top panel includes parameters calibrated for the initial period. The bottom panel includes the automation rate calibrated to match the change in routine employment in my sample over the study period (1996-2013). The automation level of non-routine tasks is kept at the initial level of $b_N = 0$. The capital price r is kept at the initial period level, $r_{1996} = 0.0903$. Recalibrating $b_{R,2013}$ after changing r to $r_{2013} = 0.0367$ (and γ accordingly), results in $b_{R,2013} = 0.3047$. The data source for capital and output is Statistics Sweden (2021*c*, 2021*a*). Details on the data used for computing employment shares can be found in Section 5.1.

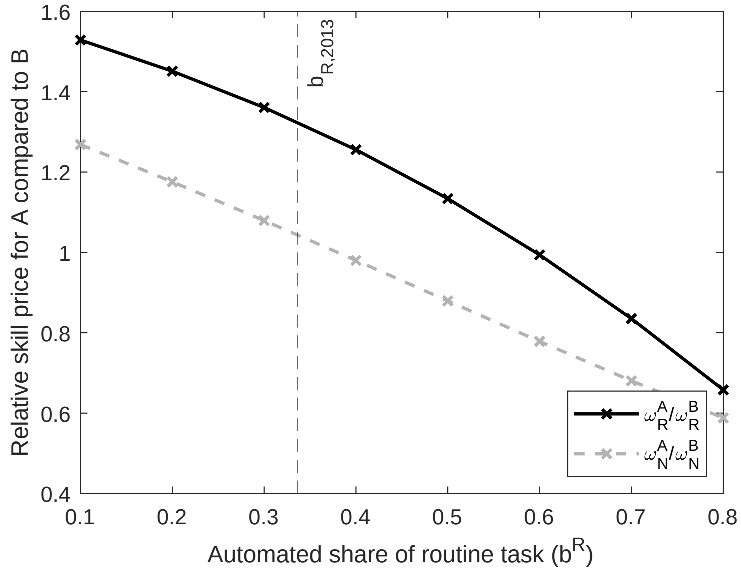


Notes: The figure plots the skill prices in the different tasks against automation level of task R. $b_N = 0$ throughout, and the parameters are as specified in Tables 1 and 2. The dashed, vertical line represents the final period automation level in R. The black solid line refers to the routine task R, and the gray dashed line refers to the non-routine task NR. The same graph for logged skill prices is presented in Figure B.1.

Figure 1: Skill prices and automation

sum of the logged marginal products.

$$\ln \omega_\tau^s = \ln \frac{\partial Y}{\partial X_\tau} + \ln \frac{\partial X_\tau}{\partial L_\tau} + \ln \frac{\partial L_\tau}{\partial S_\tau^s} \tag{27}$$



Notes: The figure plots the relative skill prices in the different tasks against automation level of task R. $b_N = 0$ throughout, and the parameters are as specified in Tables 1 and 2. The dashed, vertical line represents the final period automation level in R. The black solid line refers to the routine task R, and the gray dashed line refers to the non-routine task NR.

Figure 2: Relative skill prices and automation

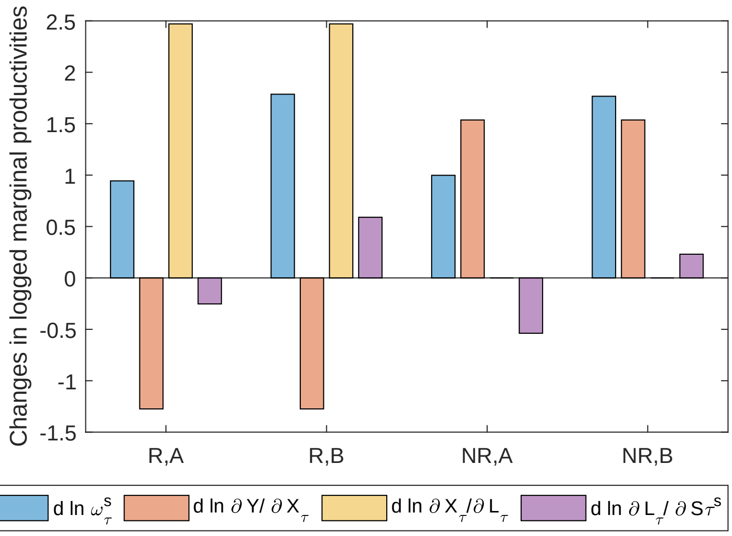
In Figure 3, I demonstrate the change in skill prices as the sum of the change in each term of Equation (27), as automation in the routine task goes from 10 to 80 percent. The first thing to note is that within a task (R or NR), the orange bars are of the same size. That is, the marginal productivity of the task in final output production ($\frac{\partial Y}{\partial X_\tau}$) are the same within each task. The same applies to the yellow bars, which represent the marginal productivity of labor in producing a task ($\frac{\partial X_\tau}{\partial L_\tau}$). The only term that varies between skills is the marginal productivity for each skill in the efficiency labor inputs – the purple bars representing $\frac{\partial L_\tau}{\partial S^s_\tau}$.

The routine task output becomes *less* productive in producing final output: $\frac{\partial Y}{\partial X_R}$ declines. This is because automation enables cheaper production of the routine task. This increases the production, which means diminishing marginal returns to the routine task. In contrast, non-routine task is now *more* productive in the final good production: $\frac{\partial Y}{\partial X_N}$ increases, since the growth in final output Y is more than proportional to the increase in non-routine output.

Two opposing forces affect the marginal productivity in labor in the routine task, as it is being automated (Acemoglu & Restrepo 2018*b*). First, the displacement effect: automation means labor is pushed into fewer tasks, so that their marginal productivity declines. But second, the productivity effect has the potential to *increase* labor productivity in the automated task group. The productivity effect appears as the now cheaper, automated task is demanded in higher quantity, requiring more of all factors of its production – including labor. In this case, and for a large range of possible parameter values in the model, the productivity effect dominates the displacement effect in the routine task.[12]

[12] As in the Acemoglu & Restrepo (2018*a*) model, the displacement effect may dominate when the threshold condition for automation is close to holding with equality. That is, when firms are "on the fence" on whether or not to automate. This is intuitive: if the cost saved by automation is small (i.e. firm are close to indifference

The changes in the marginal productivity of skills in "producing" efficiency labor units are driven by reallocation across the two tasks: as employment in the routine task declines, the ratio of A-to-B skills increase in both tasks. This change in skill intensity might seem puzzling at a first glance. How can *both* occupations become more intensive in A? But it is clear when considering the line in Section 2.1 along which workers are sorted according to their skill ratio S_i^A/S_i^B. Workers to the left of the cutoff work in the non-routine task, and workers to the right of the same cutoff work in the routine task. When labor demand in the routine task declines, the cutoff moves rightward. Generalists – those who were previously close to the border between the occupations – move. The stayers in the routine task are more specialized in skill A, and the movers to the non-routine task have higher A-to-B ratio than the incumbent non-routine workers. Because of diminishing marginal productivity, this increase in the S_τ^A/S_τ^B ratio in both tasks reduce the marginal productivity of A skills, and increase it for B skills. This is depicted in the purple bars in Figure 3.



Notes: The figure demonstrates the changes in the elements of Equations (14) and (15), when automation in the routine task goes from $b_R = 0.1$ to $b_R = 0.8$. In the appendix, Figure B.2 shows the same figure for a smaller change in automation (b_R goes from 0.1 to 0.3). $b_N = 0$ throughout, and the parameters are as specified in Tables 1 and 2.

Figure 3: Decomposing the change in skill prices

Comparative statics on the remaining variables from the model are depicted in Appendix B.

4 Results: Skill returns and comparative statics

The marginal productivities of skills in tasks – the ω_τ^s – are one way to describe skill prices. However, when researchers try to measure skill returns, the common procedure is to run a regression

between automating and not), the productivity gains are small, so the productivity effect vanishes. In the context of my model, this case may occur when the optimal automation level b_τ^* as described in Equation (9) is close to the technologically constraining level of automation, b_τ. This is related to Acemoglu & Restrepo's (2018*b*) result that we should worry more about the "so-so" innovations than the large automative innovations, in terms of their potential to decrease wages.

of the following form:[13]

$$\ln W_{i,\tau} = \pi_\tau + p_\tau^A s_i^A + p_\tau^B s_i^B + \epsilon_{i,\tau} \tag{28}$$

Where the left-hand side has the logged wage for person i in occupation τ, and the skills s_i^A, s_i^B are normally distributed around a zero mean and with unit variance in the population. The constant π_τ is an occupation-specific premium, and skill returns are found by estimating the occupation-specific p_τ^A, p_τ^B parameters.[14]

In this section, I first explain how I map the wage equation from my model to a wage equation in the form of Equation (28) in Section 4.1, using a first-order Taylor approximation. In Section 4.2 I show that, to a first approximation, skill returns depend only on the allocation of skills in the different occupations. I continue to describe comparative statics results in Section 4.3 and discuss their interpretation in Section 4.4.

4.1 Mapping the model wage equation to a log wage regression equation

In the model, an individual worker i's wage in task (occupation) τ is a function of the workers' skills S_i^s (Equation (1)), *the logged values of which* are normally distributed around zero mean and with unit variance in the population.

Recall that Equation (28) features normally (rather than log normally) distributed skills. Thus, I rewrite the wage Equation (1) as follows

$$W_\tau(i)(s^A(i), s^B(i)) = \omega_\tau^A \exp(s^A(i)) + \omega_\tau^B \exp(s^B(i))$$

where the lower case skills s_i^s are normally distributed around a zero mean and with unit variance. I log linearize the wage around the mean skills in each task $(\bar{s}_\tau^A, \bar{s}_\tau^B)$ to get

$$\begin{aligned}\ln W_\tau(i)(s^A(i), s^B(i)) \approx{}& \ln\left[\omega_\tau^A \exp(\bar{s}_\tau^A) + \omega_\tau^B \exp(\bar{s}_\tau^B)\right] \\ &+ \frac{\omega_\tau^A \exp(\bar{s}_\tau^A)}{\omega_\tau^A \exp(\bar{s}_\tau^A) + \omega_\tau^B \exp(\bar{s}_\tau^B)}(s_i^A - \bar{s}_\tau^A) + \frac{\omega_\tau^B \exp(\bar{s}_\tau^B)}{\omega_\tau^A \exp(\bar{s}_\tau^A) + \omega_\tau^B \exp(\bar{s}_\tau^B)}(s_i^B - \bar{s}_\tau^B)\end{aligned}$$

Collecting terms, and adding in the residual approximation error, I obtain

$$\begin{aligned}\ln W_\tau(i)(s^A(i), s^B(i)) ={}& \underbrace{\pi_\tau}_{\text{Occupational premium}} + \underbrace{\frac{\omega_\tau^A \exp(\bar{s}_\tau^A)}{\omega_\tau^A \exp(\bar{s}_\tau^A) + \omega_\tau^B \exp(\bar{s}_\tau^B)}}_{\text{skill return for } A \text{ in } \tau} s^A(i) \\ &+ \underbrace{\frac{\omega_\tau^B \exp(\bar{s}_\tau^B)}{\omega_\tau^A \exp(\bar{s}_\tau^A) + \omega_\tau^B \exp(\bar{s}_\tau^B)}}_{\text{skill return for } B \text{ in } \tau} s^B(i) + \underbrace{\epsilon_\tau(i)}_{\text{Approximation error}}\end{aligned} \tag{29}$$

where

$$\begin{aligned}\pi_\tau = \ln\left[\omega_\tau^A \exp(\bar{s}_\tau^A) + \omega_\tau^B \exp(\bar{s}_\tau^B)\right] &- \frac{\omega_\tau^A \exp(\bar{s}_\tau^A)}{\omega_\tau^A \exp(\bar{s}_\tau^A) + \omega_\tau^B \exp(\bar{s}_\tau^B)}\bar{s}_\tau^A \\ &- \frac{\omega_\tau^B \exp(\bar{s}_\tau^B)}{\omega_\tau^A \exp(\bar{s}_\tau^A) + \omega_\tau^B \exp(\bar{s}_\tau^B)}\bar{s}_\tau^B\end{aligned}$$

[13] This form of regression is used in e.g. Deming (2017), Edin et al. (2022) and Fredriksson et al.'s working paper version from 2015 (published version from 2018). Also, Autor & Handel (2013) use a regression of the same form, but use the regressors "task inputs" instead of skills as they do not have access to skills data.

[14] A note on the terminology used: I call the ω_τ^s *skill prices*, since they are the wage increase *in levels* from an increase in skill level S_i^s for the individual worker (see Equation (1)). In contrast, the p_τ^s parameters represent the *percentage change* (or, more accurately, the *log change*) in wages for a worker when her skills increase by some percentage (or, again, some log change) (recall that $s_i^s = \ln S_i^s$). I call these p_τ^s parameters *skill returns*.

In Equation (29), log wage depends linearly on skills and an occupation (or task) specific premium, and some approximation error. Note that the skill returns implied by this approximation range between zero and one, and sum to one within each task.[15]

4.2 What affects skill returns?

I rewrite the skill prices from Equation (29) as follows

$$\text{skill return}_\tau^A = \left(1 + \frac{\omega_\tau^B \exp(\bar{s}_\tau^B)}{\omega_\tau^A \exp(\bar{s}_\tau^A)}\right)^{-1} \tag{30}$$

$$\text{skill return}_\tau^B = \left(\frac{\omega_\tau^A \exp(\bar{s}_\tau^A)}{\omega_\tau^B \exp(\bar{s}_\tau^B)} + 1\right)^{-1} \tag{31}$$

and I note that the ratio of $\frac{\omega_\tau^B}{\omega_\tau^A}$ can be obtained from the first-order conditions Equations (6) and (7) as follows:

$$\frac{\omega_\tau^B}{\omega_\tau^A} = \left(\frac{1-\alpha_\tau}{\alpha_\tau}\right)^{1/\varepsilon} \left(\frac{S_R^A}{S_R^B}\right)^{1/\varepsilon}. \tag{32}$$

So I can substitute for Equation (32) in Equations (30) and (31) to get

$$\text{skill return}_\tau^A = \left(1 + \left(\frac{1-\alpha_\tau}{\alpha_\tau}\right)^{1/\varepsilon} \left(\frac{S_\tau^A}{S_\tau^B}\right)^{1/\varepsilon} \frac{\exp(\bar{s}_\tau^B)}{\exp(\bar{s}_\tau^A)}\right)^{-1} \tag{33}$$

$$\text{skill return}_\tau^B = \left(\left(\frac{\alpha_\tau}{1-\alpha_\tau}\right)^{1/\varepsilon} \left(\frac{S_\tau^B}{S_\tau^A}\right)^{1/\varepsilon} \frac{\exp(\bar{s}_\tau^A)}{\exp(\bar{s}_\tau^B)} + 1\right)^{-1}. \tag{34}$$

Thus, skill returns depend only on the skill allocation among tasks: the conditional mean of logged skill in each task, and the ratio of total skills. In Section 4.3, I explain how automation affects the size of tasks, which in turn affects the skill ratios in each task.

4.3 What happens when routine tasks are automated? Comparative statics

Automation of the routine task leads to declining returns to the skill used intensively in the routine task: The return to skill A thus decreases in both tasks. The return to skill B, on the other hand, increases in both tasks. Figure 4 depicts this in two panels: on the left, the return to skill A, and on the right, the same for skill B. The dashed line represents the final period automation level in the routine tasks.

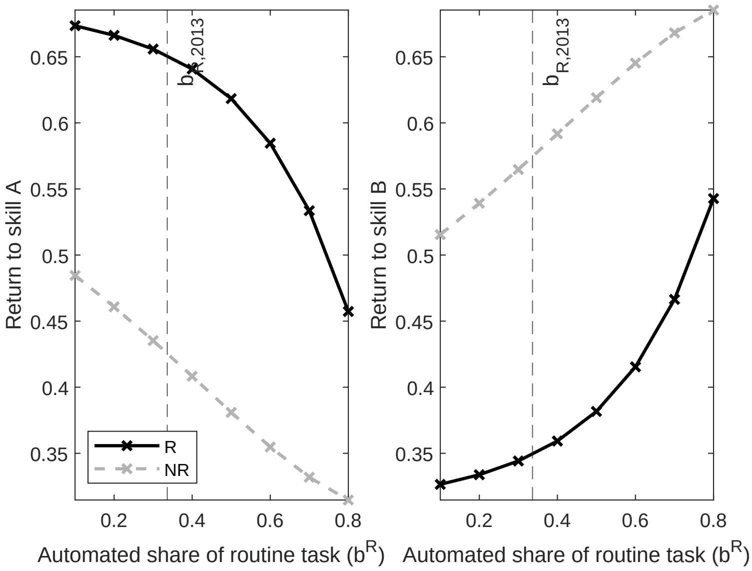
From Equations (33) and (34), we know that automation affects skill returns insofar as it affects skill ratios. Figure 5 shows that automation does bring about reallocation that affects skill ratios: Employment in the routine task declines, and both tasks become more intensive in skill A, as described in Section 3.2.

4.4 Understanding the results

Automation of the routine task induces three moments to change in equilibrium:

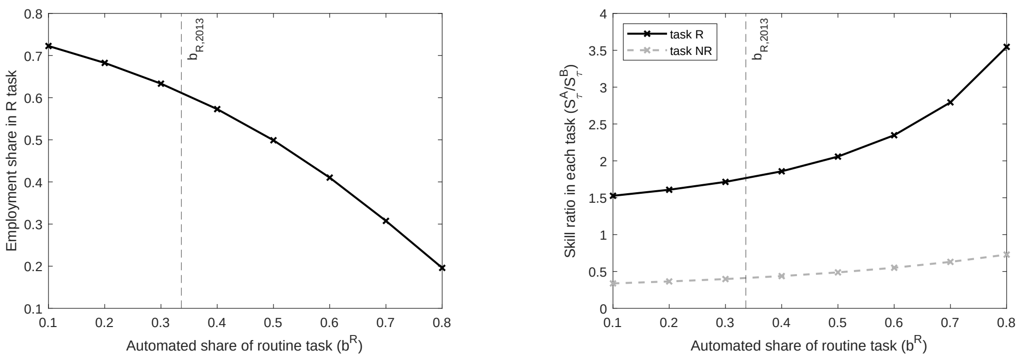
1. A decline in employment in the routine task group,

[15]When estimating skill returns in the data, there is no reason to expect them to sum to one. In Appendix A.1, I outline a procedure to retrieve the skill returns from regression coefficients in a log wage regression, given some structure of measurement error in skills.



Notes: Skill returns are constructed as a first-order approximation, according to the procedure in Section 4.1. $b_N = 0$ throughout, and the parameters are as specified in Tables 1 and 2. The dashed, vertical line represents the final period automation level in R. The black solid line refers to the routine task R, and the gray dashed line refers to the non-routine task NR.

Figure 4: Skill returns



(a) Employment share of the routine task

(b) Ratio of A to B skills in the two tasks

Figure 5: Reallocation of workers and skills between tasks

Notes: $b_N = 0$ throughout, and the parameters are as specified in Tables 1 and 2. The dashed, vertical line represents the final period automation level in R. The black solid line refers to the routine task R, and the gray dashed line refers to the non-routine task NR.

2. A higher A-to-B skill ratio in both tasks, and
3. Declining A and increasing B skill returns

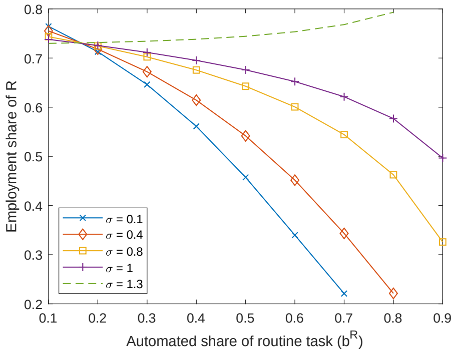
In this section, I describe this result in more detail, and explain what parameters are important for the result.

1. A decline in employment in the routine task group So long as routine and non-routine tasks are gross complements – i.e. $\sigma \leq 1$ – automation reduces employment in the routine task, as shown in Figure 6a. Automation makes the routine task cheaper to produce, so more is demanded and produced. Because of gross complementarity, this increases the marginal productivity of the *other* input in final good production, namely the non-routine task. The non-routine task therefore absorbs labor that was previously employed in the routine task, since its increasing marginal product implies higher payments to factors (in this case, only labor, since the non-routine task is not automated at all). In all, therefore, employment increases in the non-routine task even though the *task output* increases more in the automated, routine task.

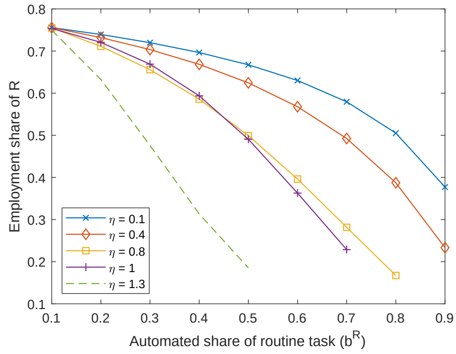
The reverse is true when tasks are gross substitutes. Then, the increased production of routine tasks *reduces* the marginal productivity of non-routine tasks, meaning that the routine task absorbs some non-routine workers.

The other important elasticity of substitution is the one between capital in labor in each task (η), depicted in Figure 6b. However, in this case, a higher substitutability between factors mean employment declines *faster* with automation. If it is easy to replace labor by machines, then automation has large effects on the routine task: Machines replace labor at a high rate, and employment in R shrinks quickly. Thus, η does not affect the sign of the effect of automation on employment.

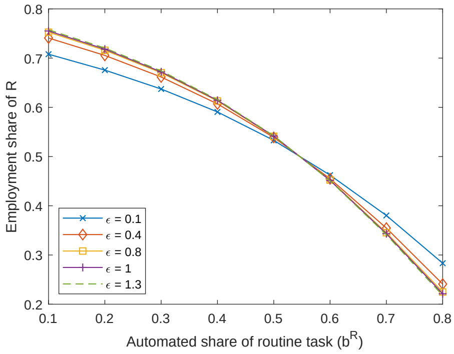
Figures 6c to 6e demonstrate that the substitutability between skills within labor production ε, the capital augmenting productivity λ and the capital price r all have a close-to-zero impact on automation's effect on R employment.



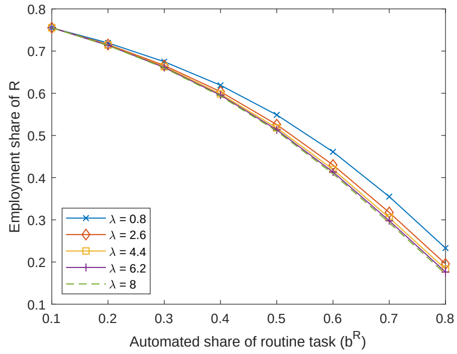
(a) Different values of EoS between R and NR, σ



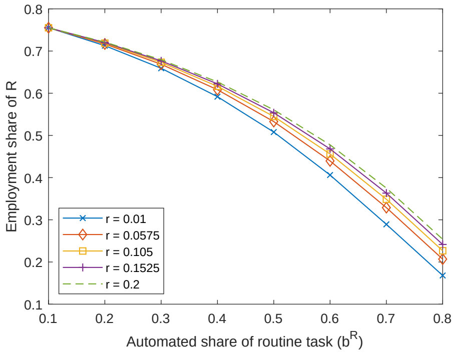
(b) Different values of EoS between K and L in each task, η



(c) Different values of EoS between A and B skills in "production" of efficient labor units, ε



(d) Different values of the capital-augmenting productivity, λ



(e) Different values of the price of capital, r

Notes: $b^{NR} = 0$ throughout, and the parameters are as specified in Tables 1 and 2.

Figure 6: Employment share of R under automation: Robustness to changes in parameter values

2. A higher A-to-B skill ratio in both tasks This occurs mechanically and concurrently as the decline in routine employment, so long as there is density around the cutoff along the S_i^A/S_i^B distribution. Consider moving the cutoff depicted in Section 2.1 to the right, so that the non-routine occupation increases in size and the routine occupation declines in size. Unless there is zero mass around the cutoff, the ratio of total A-to-B skills will increase in both occupations.[16]

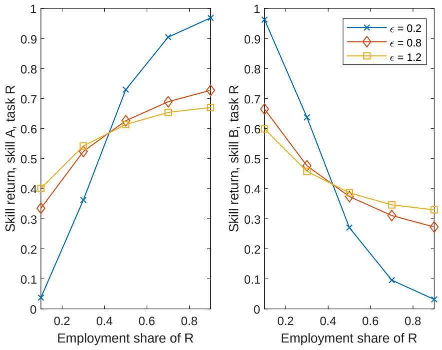
3. Declining A and increasing B skill returns The change in routine employment, which brings about the change in skill intensity, must in equilibrium be coupled with a decline in the A skill return, and an increase in the B skill return. This is, however, not immediately clear when looking at Equations (33) and (34). The equations state that skill returns are fully determined by the skill ratios, but the functional form is complicated, and I therefore look at the comparative statics from the numerical exercise I display above.

I find that for a large variation of values of the relevant parameters – the parameters from Equations (33) and (34) that have the potential to affect the impact of skill ratios on returns – skill returns for A decline and skill returns for B increase as the employment share of the routine task declines (and the A-to-B ratio thereby increases). I plot this result in Figure 7. Figures 7a and 7b demonstrate the skill return response to variation in the employment share of R for different values of ε – the elasticity of substitution between the two skills in the production of efficient labor units. In the row below, in Figures 7c and 7d, I vary the covariance between skills, ρ. The third parameter from Equations (33) and (34) is α_τ, representing the weight of A skills in task τ. But since it is bounded in (0,1), it will not affect the *sign* of the change in skill returns as skill ratios change.

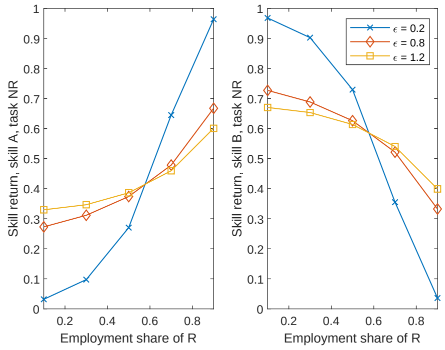
When skills are highly substitutable – i.e. when ε is high – changes in the A-to-B skill ratio have a relatively small impact on estimated skill returns. Loosely speaking, as the routine employment share declines, and thus the A-to-B ratio increases, the productivity of A declines relatively *little* when skills are substitutable, since skill A is good at substituting for skill B. Thus, the force of diminishing marginal productivity is diluted, but never (unless ε approaches infinity) vanishes.

Turning to ρ: When A and B skills are highly correlated – i.e. when ρ is high – small changes in the employment share are associated with small changes in the A-to-B skill ratio in each task. Imagine the two-dimensional skill distribution when the correlation is almost 1. Then, all workers are located close to the 45 degree line. The cutoff between tasks (occupations) must go somewhere in the mass of these workers, and a minuscule move of the cutoff will lead to large shifts in the number of workers employed in each task. The curve where $\rho = 0.95$ in Figures 7c and 7d demonstrate a case like this. Here, changes in the employment share are associated with small changes in the A-to-B skill ratio and thus low impact on estimated skill returns.

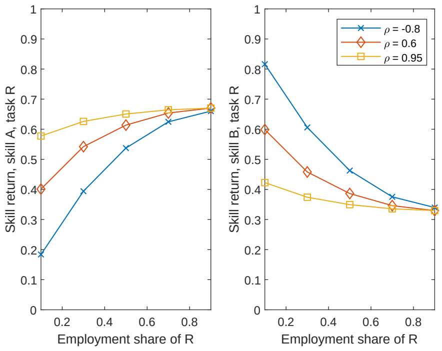
[16]Note that there is always non-zero mass around the cutoff. If there were not, then the payment to one skill in one task could decline without losing any workers.



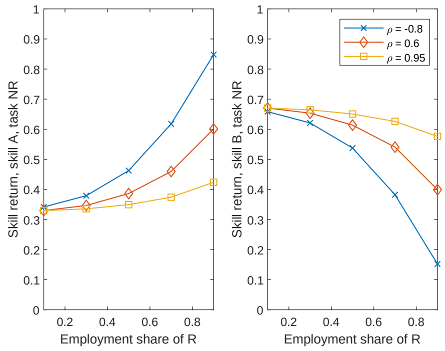
(a) Task R, different values of EoS between A and B skills in "production" of efficient labor units, ε



(b) Task NR, different values of EoS between A and B skills in "production" of efficient labor units, ε



(c) Task R, different values of skill covariance, ρ



(d) Task NR, different values of skill covariance, ρ

Notes: $b^{NR} = 0$ throughout, and the parameters are as specified in Tables 1 and 2 (apart from the parameter I let vary in each panel). NB that the employment share of the routine task is on the x-axis. This means that going right along the x-axis implies *less* automation. The variances of skills A and B both equal 1, so the covariance ρ is bounded between -1 and 1.

Figure 7: Skill returns under automation: Robustness to changing parameter values

5 Labor demand, skill returns and sorting in the data

5.1 Data and sample

The main sample The main sample covers the age groups 38-42, following Edin et al. (2022). The first reason is data availability: The availability of skill data is large for males born 1951-1975. Therefore, I exclude other cohorts, as well as females. The sample period is 1996-2013, meaning that workers older than 45 would be missing in the first year in the sample. In the later sample years, skill data for workers younger than 38 is scarce. The second reason for the sample choice is that age affects skill returns (Nybom 2017). Using a small age window makes age controls redundant, and simplifies interpretation of regression coefficients in the log wage regression.

The main sample is also limited to private sector firms. Like Edin et al. (2022), I deem it reasonable that the market forces are more pronounced here than in the large public sector. Furthermore, I exclude occupations requiring higher education from the main sample. The main reason is that the current form of my model does not allow for vertical sorting. That is, no occupation can be uniformly *better* (as in, paying more for all skills) than another. By restricting my attention to occupations that do not require higher education, I limit myself to a more homogeneous sample where sorting on comparative (rather than absolute) advantage is reasonable. Excluded occupations are (SSYK96 1-digit code in brackets) Managers (1), Occupations requiring advanced higher education (2) and Occupations requiring higher education (3).[17]

Wages and occupation Wages and occupation information come from the Wage Structure Statistics, an annual survey of Swedish firms. All public sector firms are included (but excluded from my main sample, as stated above), as well as a random sample of private sector firms. All firms with 500 employees or more are included, and other firms in the economy are randomly selected to participate. In total, around 8700 firms with around 50 percent of all employees (18-66 years old) are included, and around 20 percent of participating firms are exchanged for other firms each year. Private sector firms are surveyed in September.

I classify occupations into two large groups to mimic the task groups routine and non-routine. I compute the routine-intensity index developed by Autor et al. (2003) for each three-digit occupation, and then I split the occupations into routine or non-routine depending on whether they have a higher or lower than average routine index.[18]

Skills Skills are measured at enlistment to military service, where health exams, cognitive and physical tests, as well as an interview with a psychologist were performed. All information in this section is retrieved from Lindqvist & Vestman (2011), who wrote the mandatory reading on how skills measured at the Swedish enlistment tests affect labor market earnings. They were, to my knowledge, the first to do so.

I use males born 1951-1975 in my main sample, and at the time when they enlisted, it was mandatory to do so for males in Sweden. Normally, enlistment occurred when the men were 18-19 years old. During the sample cohorts' early adulthood, almost all males went to military service after enlistment, conditional on good scores on the health exam. It is worth noting that it was not possible to avoid service by performing badly on the cognitive, psychological or physical tests. Rather, these tests were used to determine what position the person were to assume during his military service.

I use two aggregated measures of skills: cognitive and psychological (or non-cognitive, or psychosocial). The cognitive skills are measured in a test with four parts: *synonyms* measure verbal skill, *inductions* measure logical skill, *metal folding* measures spatial skill, and *technical comprehension* measures technical skill.

The conscript's psychological skill (called non-cognitive skill in Lindqvist & Vestman (2011) and

[17] I show the results also for a sample including *all* occupational groups (also those requiring higher education) in the appendix: Figures B.6 to B.8 display results for this expanded sample.

[18] The routine index for occupation m computed as $rti_m = \text{routine}_m/(\text{abstract}_m + \text{manual}_m)$ where routine, abstract and manual refer to task content as recorded in O*NET. For details, see Autor et al. (2003). The mean of this value for the 104 three-digit occupations is 1.42, and 41 occupations are then classified as routine. If I were to use the log of the routine index, the mean would be 0.67, and 45 occupations would be classified as routine. 12 occupations differ in their classification depending on whether they are classified with the rti_m or the $\log(rti_m)$. They are (classification under non-logged rti_m in brackets): 123 Other specialist managers (NR), 242 Legal professionals (NR), 246 Religious professionals (NR), 341 Finance and sales associate professionals (NR), 342 Business service agents and trade brokers (NR), 514 Other personal services workers, 713 Building finishers and related trades workers (R), 714 Painters, building structure cleaners and related trades workers (R), 723 Machinery mechanics and fitters (R), 724 Electrical and electronic equipment mechanics and fitters (R), 833 Agricultural and other mobile-plant operators (NR), 915 Garbage collectors and related labourers (NR). In this paper, I use the non-logged routine index to classify occupations.

Edin et al. (2022), may also be conceived as psycho-social skill) is evaluated during a 25 minute interview with a psychologist. The psychologist is to determine how able the conscript is to perform his duties in the military during his service. Skills that are highly valued in this interviews are social skills, "willingness to assume responsibility; outgoing character; persistence; emotional stability, and power of initiative" (Lindqvist & Vestman 2011:108). In accordance with Lindqvist & Vestman (2011), I argue that these capabilities are likely rewarded in the labor market, too, and in fact I (and they) find that they are. More details on the interview procedure, and other things related to the enlistment tests, can be found in Lindqvist & Vestman (2011).

5.2 The evolution of labor demand, skill returns, and sorting in Sweden 1996-2013

In my main sample, skill returns are higher for cognitive skills in the routine occupation, and for psychological skills in the non-routine occupation, as seen in Figure 8. This figure also demonstrates how the return to psychological skills increased substantially over the sample period, particularly in the non-routine occupation, leading to diverging returns for psychological skills. Cognitive skill returns, on the other hand, converged over the sample period, here, too, driven by an increasing skill return in the non-routine occupation.

However, the standard routine-biased technological change literature cannot explain why the price of psychological skills increased more than the cognitive skills. Nor can it speak to the fact that skills are useful, but to varying degrees, in both occupations, as demonstrated by the positive skill returns for both skills in both occupations. My model provides theoretical underpinnings to both these facts.

We might speculate that, on the basis of my model, the psychological skill returns increased due to automation: Psychological skills seem to be intensively used in the non-routine – and thus the non-automated – task. Suggestive evidence of this would be that routine employment declined, and both occupations became more intensive in the cognitive skill as a result. The demand for routine labor did indeed decline in Sweden (as in many other countries) between 1996 and 2013, as demonstrated by Figure 9.[19]

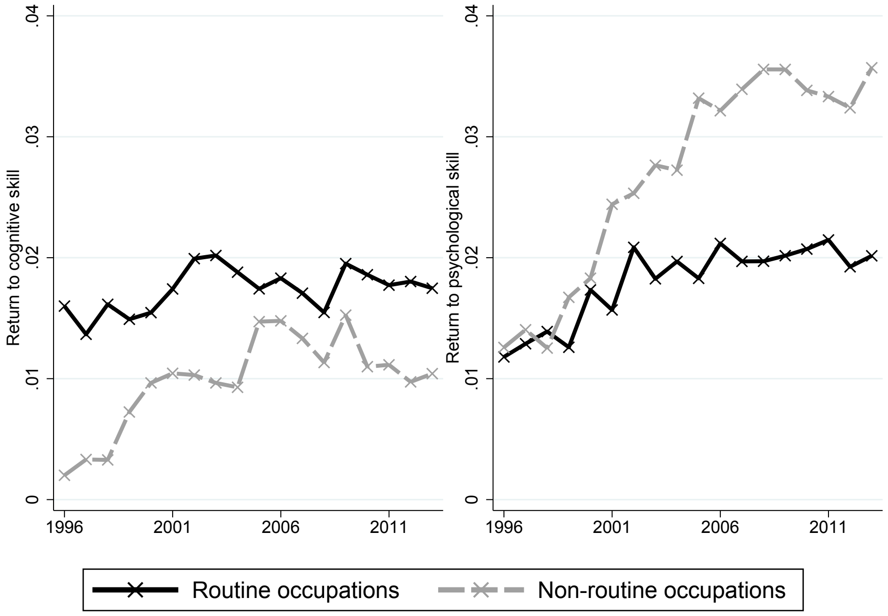
However, although skill returns changed over the sample period, and the routine occupations declined in size, there is no clear evidence that sorting changed. The mean skills in each occupation seem relatively stable over the sample period, according to Figure 10. This is at odds with the model prediction that a change in skill returns, in equilibrium, is coupled with changes in the skill mix in each task. I will discuss this feature of the data available to me in the next section.

5.3 Bringing the model to the data: Potential calibration

The model that this paper presents could be used to understand how automation may account for some of the observed changes in skill returns. A first step is to estimate the skill returns described in Section 4, given data on skills, (logged) wages and occupations (which are proxies for tasks). However, as most researchers will note, these estimated skill returns will rarely sum to one, as they should according to Equation (29).

One reason for this discrepancy between estimated skill returns and those implied by the model is that skills in the data are mismeasured versions of or imperfect proxies for the *true* skills that the

[19] One thing that my model could not speak to, is the increase in both skill returns in the non-routine occupation, compared to both skill prices in the routine occupation.



Notes: The graphs plot estimated coefficients from a pooled OLS regression of log wages on skill measures and occupation fixed effects for the routine and non-routine occupation, with no other covariates. Skill measures are standardized to be normally distributed with zero mean and unit variance in each year. Figure B.5 plots values with confidence intervals. The data consists of a large, representative sample of the Swedish workforce (Wage Structure Statistics). The sample consists of males aged between 38-42, in occupations with no higher education requirements, who work in the private sector. The number of workers is 35,330 in 1996 and 28,285 in 2013. Routine occupations are those 3-digit occupations with higher routine-intensity index (Autor et al. 2003) than average. The equivalent graph for a sample including all education categories can be found in Figure B.6.

Figure 8: Returns to cognitive and psychological skills in Sweden 1996-2013

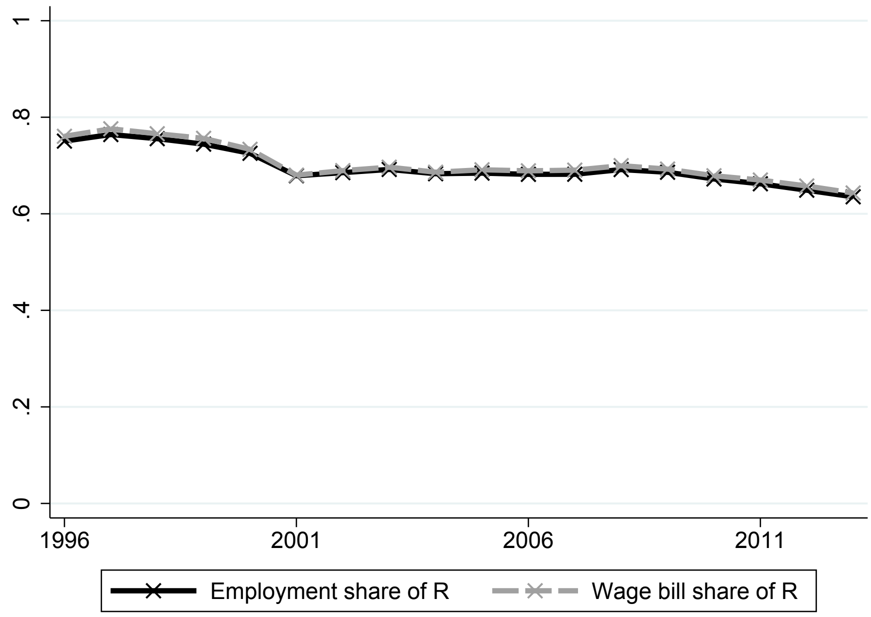
labor market values. In order to impose some structure on potential measurement error, I assume that the skills I observe in the data (cognitive and psychological) are linear functions of the true skills, as follows:

$$s_i^{c,obs} = a_{cc}s_i^{c,true} + a_{cp}s_i^{p,true} + a_{c,\epsilon}\epsilon_{c,i} \quad \forall i$$
$$s_i^{p,obs} = a_{pc}s_i^{c,true} + a_{pp}s_i^{p,true} + a_{p,\epsilon}\epsilon_{p,i} \quad \forall i.$$

The measurement error is uncorrelated with occupation. True skills are jointly distributed with mean zero, unit variance and some covariance parameter ρ. Errors are jointly distributed with mean zero, unit variance and zero covariance. The parameters preceding true skills $(a_{cc}, a_{cp}, a_{pc}, a_{pp})$, I call "skill signal", and the parameters preceding the errors $(a_{c,\epsilon}, a_{p,\epsilon})$ are called "skill noise". Note that I assume that the true skills are called cognitive (superscripted with c) and psychological (p) here, but I could also call them A and B, or cognitive and manual, or any other division I find theoretically plausible.

Given this structure of measurement error in skills, I can derive equations that relate the estimated regression coefficients from the log wage regression with the "true" skill returns as described in Equation (29).

In Appendix A, I provide a method for a full calibration of the model to the data on skills and estimated skill returns. I show that, if the data is generated in accordance with the model described in Section 2, the calibration procedure retrieves the correct parameter values, even for this quite flexible formulation of the measurement error in skills.



Notes: The data consists of a large, representative sample of the Swedish workforce (Wage Structure Statistics). The sample consists of males aged between 38-42, in occupations with no higher education requirements, who work in the private sector. The number of workers is 35,330 in 1996 and 28,285 in 2013. Routine occupations are those 3-digit occupations with higher routine-intensity index (Autor et al. 2003) than average. The equivalent graph for a sample including all education categories can be found in Figure B.7.

Figure 9: Employment and wage bill share of routine occupations in Sweden 1996-2013

However, as demonstrated in Figure 10, although skill prices differ between occupations, sorting on comparative advantage seems weak. Firstly, it does not change over time in response to skill price changes, and secondly, the mean skills are very similar in the two occupations. In essence, mean skills seem not to be related to the skill prices,[20] indicating that sorting on comparative advantage is weak in the sample period, at least on the dimensions I study, namely the sorting of cognitive and psychological skills into routine and non-routine occupations. This weak link between skill prices and sorting in Sweden 1996-2013 prevents successful calibration of the moments proposed by the model and the ones observed in the data.

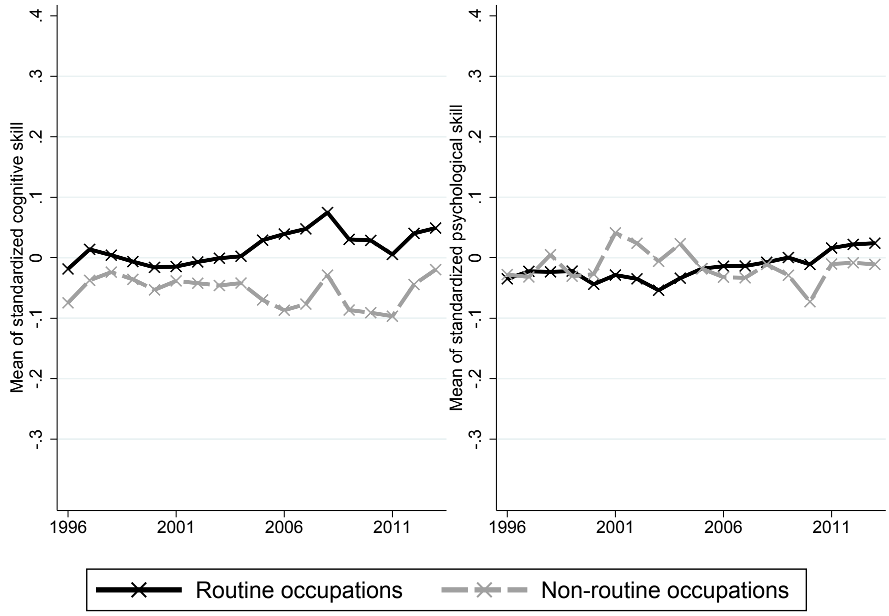
6 Discussion and conclusion

I have presented a model to understand how automation affects skill returns when workers' skills are bundled. In the model, workers choose one occupation (task), and employ all their skills there to produce output. This delivers occupation-specific skill prices, as observed in the data (both by previous researchers and in this project).

I note that the marginal productivities of skills in my relatively standard model are not directly comparable to skill returns usually estimated in data. Apart from providing a direct link between the two, I also investigate comparative statics responses to automation in both these moments.

Although marginal productivities all increase in response to automation, they increase for different reasons, which I explore by decomposing the marginal productivities of skills in tasks into their

[20] Results from a regression of mean skills on skill prices available upon request.



Notes: The graphs plot the mean skills in each occupation. Skill measures are standardized to be normally distributed with zero mean and unit variance in each year. The data consists of a large, representative sample of the Swedish workforce (Wage Structure Statistics). The sample consists of males aged between 38-42, in occupations with no higher education requirements, who work in the private sector. The number of workers is 35,330 in 1996 and 28,285 in 2013. Routine occupations are those 3-digit occupations with higher routine-intensity index (Autor et al. 2003) than average. The equivalent graph for a sample including all education categories can be found in Figure B.8.

Figure 10: Mean of cognitive and psychological skills in Sweden 1996-2013

constituent parts.

As for the estimable skill returns, the return to the skill used intensively in the automated task declines, and the return to the other skill increases. This is directly linked to reallocation of skills across tasks: When automation happens to one task (occupation), employment in that occupation declines, so long as tasks are gross complements. The relocation of labor to the non-automated occupation means that the skill intensity in both occupations change: both become more intensive in the skill used intensively in the automated task. In equilibrium, this is coupled with changes in the estimated skill returns: the return to the skill used intensively in the automated task declines, and the return to the other skill increases.

This qualitative result is robust to changing many parameter values, but if the elasticity of substitution between tasks (σ in the model) surpasses one – that is, if tasks become gross substitutes – the routine task increases in employment when it is being automated. This leads to a reversal of the qualitative result: now, the skill used intensively in the automated task *increases* in value, while the other skill return declines.

Although I have devised a calibration and estimation procedure, the Swedish data I have used display too low levels of sorting on comparative advantage in order for calibration to be successful. We might speculate that sorting between routine and non-routine tasks depend on some unobserved skill, such as manual skills (including physical strength, manual dexterity etc.). Instead of calibrating to the Swedish data, I demonstrate, in Appendix A, that the calibration procedure works well for simulated data generated by the model data generating process. Future work will focus on exploring ways in which I can calibrate my model to data: either from other countries (such as using the National Longitudinal Study of Youth from the US), or using additional data from Sweden, such as manual skills from enlistment tests.

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A Estimation procedure

In this section, I present an estimation procedure to retrieve model parameters. First, I present some assumptions on the measurement errors in skills, which are needed to map true to observed moments. Then, I go through the estimation procedure in steps. I also test the procedure on simulated data, and Figures B.10 and B.11 demonstrate that the procedure works well.

As described in the data section (Section 5.1), I observe cognitive and psychological skills from military enlistment tests. I will, in this section, therefore talk about skill A as *cognitive skill* and skill B as *psychological skill*. Additionally, I observe annual earnings, so that I can run a regression of log of (real) earnings on the skill measures. Since I count only those with full-time employment, I hereafter call log earnings log wage.

A.1 Mapping between model skill returns and regression coefficients

The skill return estimates I get from the log wage regressions are not necessarily identical to the skill returns as approximated by the Taylor procedure in Section 4.1. Recall that the skill returns in the Taylor approximation (Equation (29)) sum to one, which regression coefficients from a log wage regression may or may not. One reason for which this discrepancy occurs may be measurement error in skills.

This section outlines a procedure to estimate what I call the *true* skill returns – the ones approximated by the Taylor approximation, which relate directly to my model – using the estimated regression coefficients I obtain from the data, given a reasonably general formulation of measurement error in skills.

True model From the Taylor approximation in section 4.1 we have

$$\ln W(i) = w(i) = \alpha_R + p_R s(i)^{c,true} + (1-p_R)s(i)^{p,true} + e(i) \quad \forall i \in R \tag{35}$$

$$\ln W(j) = w(j) = \alpha_N + p_N s(j)^{c,true} + (1-p_N)s(j)^{p,true} + e(j) \quad \forall j \in N \tag{36}$$

where R and N are the routine and non-routine tasks (occupations), and c and p stand for the cognitive and psychological skills, respectively. The true skills are not observed. Instead, we observe the following:

$$s(i)^{c,obs} = a_{cc}s(i)^{c,true} + a_{cp}s(i)^{p,true} + a_{c,\epsilon}\epsilon(i)_c \quad \forall i \tag{37}$$

$$s(i)^{p,obs} = a_{pc}s(i)^{c,true} + a_{pp}s(i)^{p,true} + a_{p,\epsilon}\epsilon(i)_p \quad \forall i \tag{38}$$

The measurement error is thus uncorrelated with occupation. True skills are jointly distributed with mean zero, unit variance and some covariance parameter ρ. Errors are jointly distributed with mean zero, unit variance and zero covariance. The parameters preceding true skills $(a_{cc}, a_{cp}, a_{pc}, a_{pp})$, I call "skill signal", and the parameters preceding the errors $(a_{c,\epsilon}, a_{p,\epsilon})$ are called "skill noise".

Regression equation The estimated equations are

$$\ln W_i = w_i = \delta_{R,0} + \delta_{R,c}s_i^{c,obs} + \delta_{R,p}s_i^{p,obs} + e_i \quad \forall i \in R$$
$$\ln W_j = w_j = \delta_{N,0} + \delta_{N,c}s_j^{c,obs} + \delta_{N,p}s_i^{p,obs} + e_j \quad \forall j \in N$$

where I now index using subscripts to indicate that workers in the data are discrete rather than on the continuous (0,1) interval. Using the Frisch-Waugh-Lovell Theorem, I define the ordinary least squares estimator as follows:

$$\hat{\delta}_{R,c} = \frac{cov(w_R, \tilde{s}^c_R)}{v(\tilde{s}^c_R)} \tag{39}$$

where $\tilde{s}^c_R$ are the residuals from a projection of $s^{c,obs}_R$ onto $s^{p,obs}_R$:

$$\tilde{s}^c_R = s^{c,o}_R - \frac{cov(s^{c,o}_R, s^{p,o}_R)}{v(s^{p,o}_R)} s^{p,o}_R \tag{40}$$

where I shortened the superscript *obs* to *o* (and will shorten *true* to *t* below) to avoid excessive clutter. Below, I also drop the R subscript, and note that all the derivations apply to both occupations' OLS estimates (R and N) – just insert the relevant occupations' parameters into the equations. First, look at the denominator of $\hat{\delta}_{R,c}$ in Equation (39): substitute for Equation (40) to get

$$v(\tilde{s}^c) = v(s^{c,o}) - \frac{cov(s^{c,o}, s^{p,o})^2}{v(s^{p,o})} \tag{41}$$

where, as I explained above, all variables refer to occupation-specific variables. I compute the variances and the covariances between the observed skills by substituting for Equation (37),[21] but to reduce clutter, let us keep them as they are in Equation (41) for now.

The numerator is slightly more involved. Substitute for w using the true model Equation (35), and for $\tilde{s}^c$ using Equation (40) to get

$$\begin{aligned} cov(w, \tilde{s}^c) &= cov(\alpha + p s^{c,true}_i + (1-p) s^{p,true}_i + e_i, s^{c,o} - \frac{cov(s^{c,o}, s^{p,o})}{v(s^{p,o})} s^{p,o}) \\ &= p\ cov(s^{c,t}, s^{c,o}) - p\frac{cov(s^{c,o}, s^{p,o})^2}{v(s^{p,o})} cov(s^{c,t}, s^{p,o}) \\ &\qquad (1-p) cov(s^{p,t}, s^{c,o}) - (1-p)\frac{cov(s^{c,o}, s^{p,o})^2}{v(s^{p,o})} cov(s^{p,t}, s^{p,o}). \end{aligned}$$

Substituting for Equations (37) and (38), I compute the covariances between observed and true skills.[22] I keep the variances and covariance of observed skills as they are (to reduce clutter, but knowing that I can substitute for the equations in Footnote 21), and collect terms. Then, the numerator of Equation (39) is

$$\begin{aligned} cov(w, \tilde{s}_c) = \frac{1}{v(s^o_p)} \Bigg(& p\Big[\sigma^2_{c,s}(v(s^o_p)a_{cc} - cov(s^o_p, s^o_c)a_{pc}) + \rho(v(s^o_p)a_{cp} - cov(s^o_p, s^o_c)a_{pp})\Big] \\ & + (1-p)\Big[\sigma^2_{p,s}(v(s^o_p)a_{cp} - cov(s^o_p, s^o_c)a_{pp}) + \rho(v(s^o_p)a_{cc} - cov(s^o_p, s^o_c)a_{pc})\Big]\Bigg). \end{aligned} \tag{42}$$

[21] The variances and covariance of observed skills are as follows:

$$\begin{aligned} v(s^{c,o}) &= a^2_{cc}\sigma^2_{c,s} + a^2_{cp}\sigma^2_{p,s} + a^2_{c,\epsilon}\sigma^2_{c,\epsilon} + 2a_{cc}a_{cp}\rho \\ v(s^{p,o}) &= a^2_{pc}\sigma^2_{c,s} + a^2_{pp}\sigma^2_{p,s} + a^2_{p,\epsilon}\sigma^2_{p,\epsilon} + 2a_{pc}a_{pp}\rho \\ cov(s^{c,o}, s^{p,o}) &= a_{cc}a_{pc}\sigma^2_{c,s} + a_{cp}a_{pp}\sigma^2_{p,s} + \rho(a_{cc}a_{pp} + a_{cp}a_{pc}) \end{aligned}$$

[22] The covariances between observed and unobserved skills are

$$\begin{aligned} cov(s^t_c, s^o_c) &= a_{cc}\sigma^2_{c,s} + a_{cp}\rho \\ cov(s^t_c, s^o_p) &= a_{pc}\sigma^2_{c,s} + a_{pp}\rho \\ cov(s^t_p, s^o_c) &= a_{cp}\sigma^2_{p,s} + a_{cc}\rho \\ cov(s^t_p, s^o_p) &= a_{pp}\sigma^2_{p,s} + a_{pc}\rho \end{aligned}$$

In conclusion, the regression coefficient estimated in the data, $\hat{\delta}_c$, can be expressed in terms of model parameters as follows – where I divide Equation (42) by Equation (41):

$$\hat{\delta}_c = \Bigg(p\Big[\sigma^2_{c,s}(v(s^o_p)a_{cc} - cov(s^o_p, s^o_c)a_{pc}) + \rho(v(s^o_p)a_{cp} - cov(s^o_p, s^o_c)a_{pp})\Big]$$
$$+(1-p)\Big[\sigma^2_{p,s}(v(s^o_p)a_{cp} - cov(s^o_p, s^o_c)a_{pp}) + \rho(v(s^o_p)a_{cc} - cov(s^o_p, s^o_c)a_{pc})\Big]\Bigg)\frac{1}{v(s^o_p)v(s^o_c) - cov(s^o_p, s^o_c)^2}. \tag{43}$$

Going through the corresponding procedure for the psychological skill coefficient, I get

$$\hat{\delta}_p = \Bigg(p\Big[\sigma^2_{c,s}(v(s^o_c)a_{pc} - cov(s^o_p, s^o_c)a_{cc}) + \rho(v(s^o_c)a_{pp} - cov(s^o_p, s^o_c)a_{cp})\Big]$$
$$+(1-p)\Big[\sigma^2_{p,s}(v(s^o_c)a_{pp} - cov(s^o_p, s^o_c)a_{cp}) + \rho(v(s^o_c)a_{pc} - cov(s^o_p, s^o_c)a_{cc})\Big]\Bigg)\frac{1}{v(s^o_p)v(s^o_c) - cov(s^o_p, s^o_c)^2}. \tag{44}$$

Recall that all parameters, except the a parameters, are occupation (or task) specific. Although I have normalized the total skill distribution to have zero mean and unit variance, the distribution of skills within an occupation will not have those properties. These variances must be estimated. However, the measurement error will, because it is independent from true skills, be uncorrelated with occupational choice, and thus the error variances in the equations above equal one.

A.2 First step of estimation: Estimate skill returns, skill distribution and selection rule

In this step, I estimate the skill returns, the distribution of skills and the selection rule. In order to map true skill distributions to observed skill distributions, I also need the “skill signals” and “skill noise” parameters described in Appendix A.1. The parameters I estimate in this step are listed in Table A.1.

Table A.1: Parameters, first step of estimation

Parameter	Notation
Covariance between true cognitive and psychological skills	ρ
Cutoff	u
Return to cognitive skills in R	p_R
Return to cognitive skills in NR	p_N
Skill signal CC	$a_{cc,s}$
Skill signal CP	$a_{cp,s}$
Skill signal PC	$a_{pc,s}$
Skill signal PP	$a_{pp,s}$
Skill noise, cognitive	$a_{c,\epsilon}$
Skill noise, psychological	$a_{p,\epsilon}$

The selection rule in the model boils down to a cutoff between the two occupations. This, together with the total skill distribution, determines the size, the mean skills and the variance-covariance matrix of skills of each occupation. I observe these moments, listed in Table A.2, but not the *true* ones, since skills are mismeasured. Additionally, I also “observe” the estimated regression coefficients from the log wage regression. These are, according to Equations (43) and (44), related to the true skill returns, the distribution parameters and the skill signals.

First, I make a guess of each of the ten parameters listed in Table A.1. Then, using the skill signal and noise parameters, I construct the implied *observed* skill moments: the unconditional variance-covariance matrix, and the conditional means, variances and covariance.[23] That is: what would the observed skill variance and covariance in each occupation be, if my guessed parameters were correct? I also construct the regression coefficients according to Equations (43) and (44). I then minimize the sum of squared deviations of these moments from the data moments (in Table A.2),[24] using `fmincon`.

Lastly, it is worth noting that this first step of estimation uses no assumptions or equations from my model as presented in Section 2.[25] Instead, I assume a specific shape of measurement error, as described in Appendix A.1, and I use the Frisch-Waugh-Lovell theorem to compute the regression coefficients in terms of parameters, given the measurement error structure. The estimation is overidentified, since there are 13 equations to solve for 10 unknowns.

Table A.2: Moments, first step of estimation

Moment	Notation	Relevant equation(s)
Mean of observed cognitive skills in R	$\exp(\mathbb{E}s_R^{cog})$	Equation (37)
Mean of observed psychological skills in R	$\exp(\mathbb{E}s_R^{psy})$	Equation (38)
Share of workers in R		
Variance in observed cognitive skills in R	$v(s_R^{cog,obs})$	Equation (37) and Footnote 21
Variance in observed psychological skills in R	$v(s_R^{psy,obs})$	Equation (38) and Footnote 21
Covariance between observed cognitive and psychological skills in R	$cov(s_R^{cog,obs}, s_R^{psy,obs})$	Equations (37) and (38) and Footnote 21
Variance in observed cognitive skills in the whole sample	$v(s^{cog,obs})$	Equation (37) and Footnote 21
Variance in observed psychological skills in the whole sample	$v(s^{psy,obs})$	Equation (38) and Footnote 21
Covariance between observed cognitive and psychological skills in the whole sample	$cov(s^{cog,obs}, s^{psy,obs})$	Equations (37) and (38) and Footnote 21
Coefficient on cognitive skills in R	$\hat{\delta}_{c,R}$	Equation (43)
Coefficient on psychological skills in R	$\hat{\delta}_{p,R}$	Equation (44)
Coefficient on cognitive skills in NR	$\hat{\delta}_{c,N}$	Equation (43)
Coefficient on psychological skills in NR	$\hat{\delta}_{p,N}$	Equation (44)

Test of the procedure I test this estimation method in the following way: I pretend I know the true values of the parameters listed in Table A.1. Using these assumed parameters, I construct

[23] "Conditional" moments refer to moments within each occupation, while "unconditional" refers to moments covering the whole sample of workers.

[24] I say "data moments" here, but as explained in the main part of the paper, I do not succeed in performing this procedure using actual, Swedish data. Success here means ability to match the chosen moments. Instead, I test the procedure on simulated data, described below.

[25] This is not strictly true: I use the information from my model that true skill prices sum to one – this comes from the Taylor expansion of the log wages.

assumed moments from Table A.2. These are the moments I would observe in the data, if the assumed parameters were true.

Then, I forget about my assumed parameters. I guess parameters, construct new moments, and use `fmincon` to equalize these new moments with the moments computed from the assumed parameters.

I do this procedure 100 times – each time with a new, random set of assumed parameters. I ask whether or not my procedure retrieves the parameters I assumed, and the plots in Figures B.10 and B.11 suggest that, in most cases, I do. This suggests that the estimation works well. If there were indeed data generated by the data generating process my model implies, I would be able to retrieve the true, unobserved parameters that generated the data.

A.3 Second step of estimation: Estimate model skill weights

Recall that skill returns as found in the Taylor expansion can be rewritten as in Equations (33) and (34), meaning that the skill returns are functions of the skill ratios in each task and the parameters α_τ and ε. In this step, I use the skill distributions estimated in Step 1 (Appendix A.2) to construct skill ratios,[26] which I use to compute skill returns in accordance with Equations (33) and (34). I then minimize the distance between these skill returns and the ones estimated in Step 1, by adjusting the α parameters. The ε is assumed to be one, so that the technology that converts skill to labor units is Cobb-Douglas.

Table A.3: Moments and parameters

Moment	Notation	Relevant equation(s)
Return to cognitive skills in R	p_R	Equations (33) and (34)
Return to cognitive skills in NR	p_N	Equations (33) and (34)
Parameter	Notation	
Weight of cognitive skills in R labor units	α_R	
Weight of cognitive skills in NR labor units	α_N	

Notes: The sum of the squared deviation from the observed moments is minimized by adjusting the parameters. The α parameters are constrained to be between 0 and 1. $\varepsilon = 1$. The skill returns are estimated in Step 1, described above in Appendix A.2.

[26] One alternative is to use the actual, observed skills from the data, and convert them into the "*true*" skill ratios using skill signals and skill noise parameters. For the ratio $\frac{\exp(\bar{s}_\tau^{psy})}{\exp(\bar{s}_\tau^{cog})}$, it is relatively easy. Here, I just take the observed skill means from the data, convert them to *true* skill means using equations Equations (37) and (38), and then exponentiate. However, the ratio $\frac{S_\tau^{cog}}{S_\tau^{psy}}$ is slightly trickier. Here, I must exponentiate the data skills *before* summing them, and I need to apply the skill noise and skill signal parameters, as well as a random error to each individual worker. It would look something like this:

$$\begin{aligned} S_\tau^{cog,true} &= \sum_{i\in\tau} exp(s_i^{c,true}) \\ &= \sum_{i\in\tau} exp((s_i^{c,obs} - a_{cp}s_i^{p,obs} - a_{c\epsilon}\epsilon_{i,c})/a_{cc}) \end{aligned}$$

A.4 Third step of estimation: Estimate the task weight, automation parameter, elasticities of substitution and the capital augmenting factor of the model

To complete estimation of parameters of the model, I select parameters in Table A.4 to match the moments in the same table. In order to do so, I guess parameters, solve the model fully using the equilibrium equations in Section 2.7, and iterate until the model solution implies the moments I observe in data (in the cases of K/Y and employment share) or have already estimated in Steps 1 and 2 (in the case of the remaining three moments).

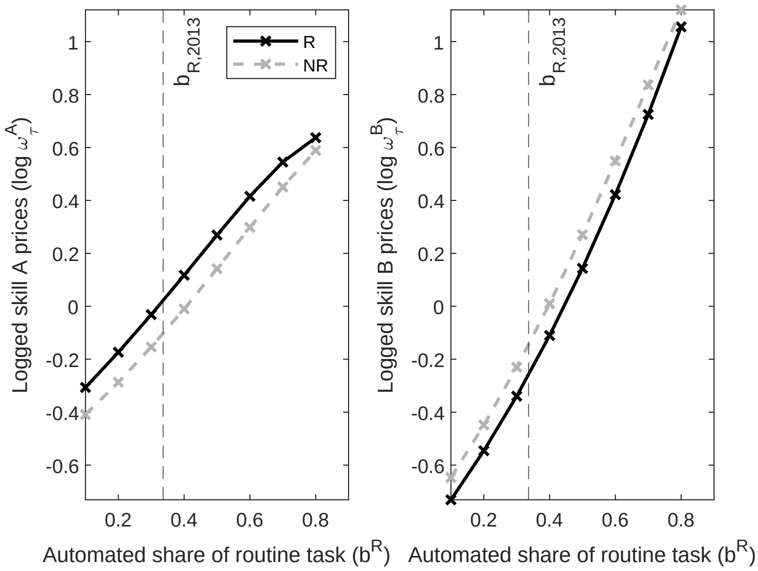
While the capital-output ratio has a clear connection to the capital-augmenting factor λ, and the employment share of routine workers to the task weight β and the automation rate b_R, as evident in Figure B.9, the other three moments are intricately linked to the full solution of the model.

Table A.4: Moments and parameters

Moment	Notation
Capital-Output ratio	K/Y
Employment share of R	
Ratio between skill prices in R*	$\omega_R^{cog}/\omega_R^{psy}$
Ratio between skill prices in NR*	$\omega_N^{cog}/\omega_N^{psy}$
Cutoff**	u
Parameter	**Notation**
Capital-augmenting factor	λ
Weight of routine tasks in the economy	β
Automated share of tasks in R in 1996	$b_{R,1996}$
EoS between tasks R and NR	σ
EoS between capital and labor	η

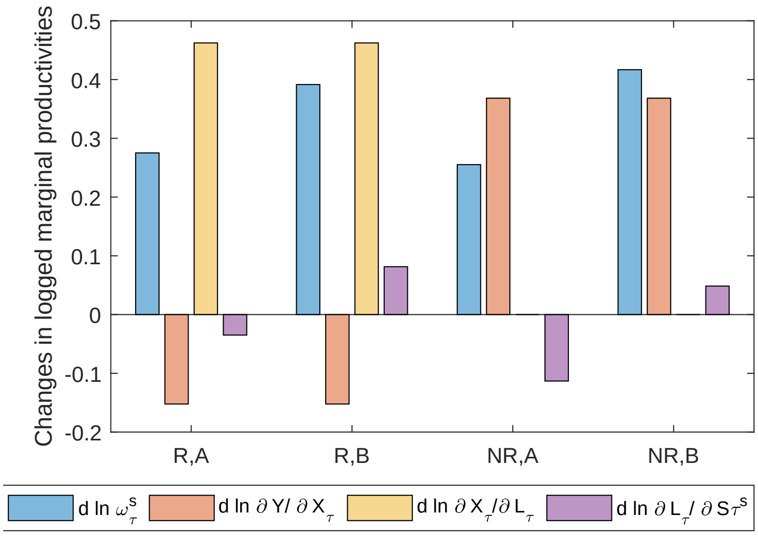
Notes: The sum of the squared deviation from the observed moments is minimized by adjusting the parameters. * means moment is recorded from estimation in Step 2 (Appendix A.3). ** means moment is recorded from estimation in Step 1 (Appendix A.2). EoS means elasticity of substitution. No "relevant equations" are listed, since these moments are all determined jointly by the equilibrium equations in Section 2.7.

B Auxiliary figures



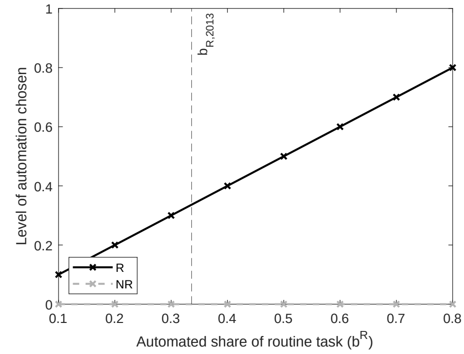
Notes: The figure plots the logged skill prices in the different tasks against automation level of task R. $b_N = 0$ throughout, and the parameters are as specified in Tables 1 and 2. The dashed, vertical line represents the final period automation level in R. The black solid line refers to the routine task R, and the gray dashed line refers to the non-routine task NR.

Figure B.1: Logged skill prices and automation

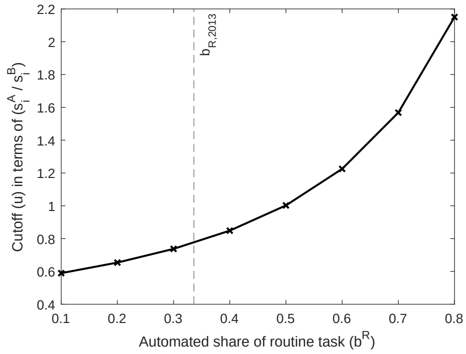


Notes: The figure demonstrates the changes in the elements of Equations (14) and (15), when automation in the routine task goes from $b_R = 0.1$ to $b_R = 0.3$. $b_N = 0$ throughout, and the parameters are as specified in Tables 1 and 2.

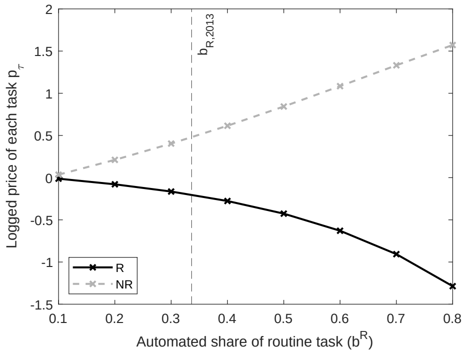
Figure B.2: Decomposing the change in skill prices



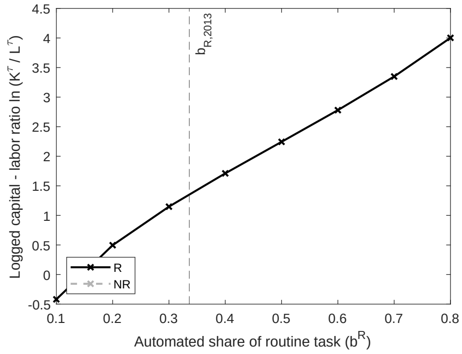
(a) Optimal automation level



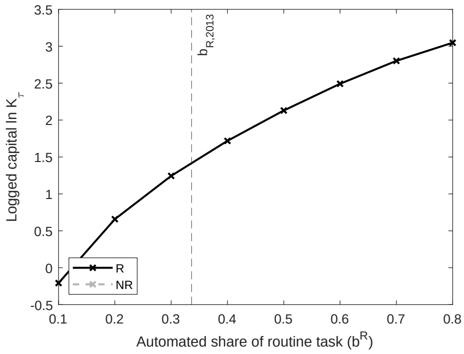
(b) Cutoff between routine and non-routine task in terms of skill ratio S_i^A/S_i^B



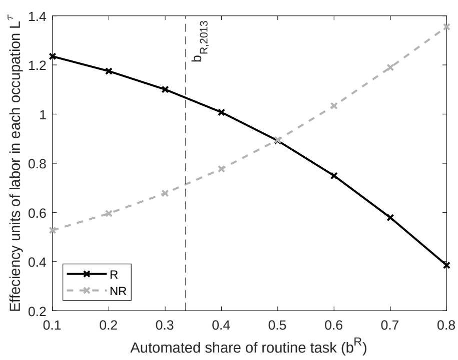
(c) Logged task price p_τ



(d) Logged capital - labor ratio

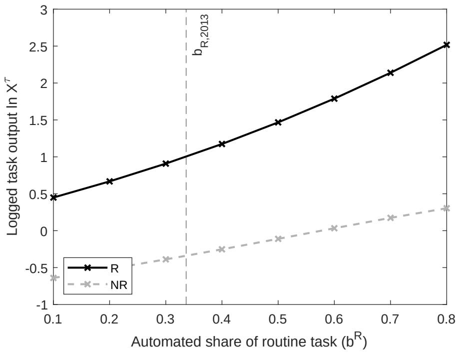


(e) Logged capital levels K_τ

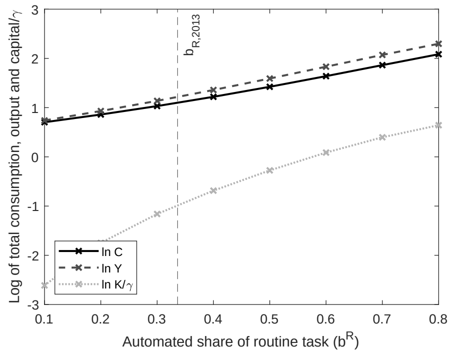


(f) Effective labor input L_τ

Figure B.3: Comparative statics, other variables



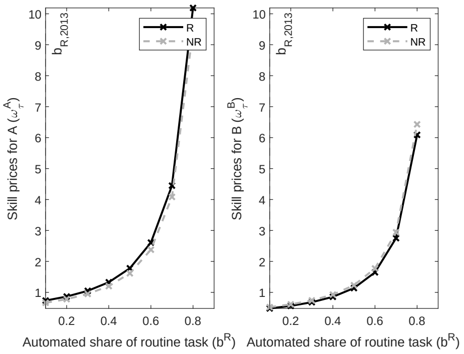
(g) Logged task output X_τ



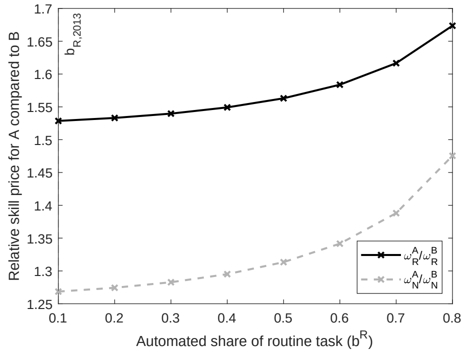
(h) Logged total consumption, output and capital

Notes: $b_N = 0$ throughout, and the parameters are as specified in Tables 1 and 2. The dashed, vertical line represents the final period automation level in R.

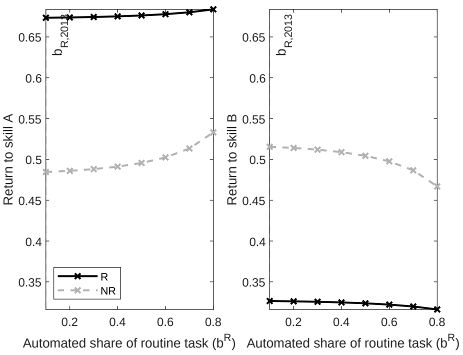
Figure B.3: Comparative statics, other variables



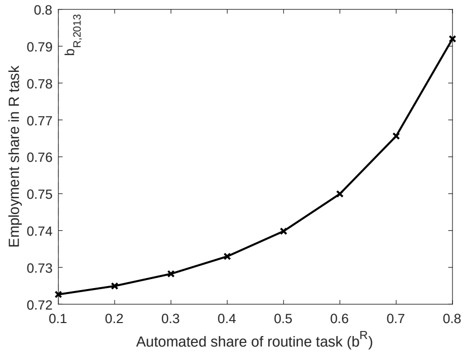
(a) Skill prices



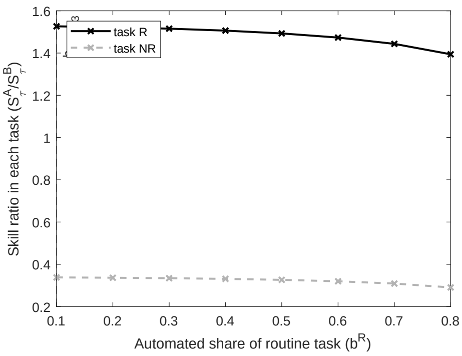
(b) Relative skill prices



(c) Skill returns



(d) Employment share of the routine task



(e) Ratio of A to B skills in the two tasks

Notes: $b_N = 0$ throughout, and the parameters are as specified in Table 1, except that $\sigma = 1.3$. I recalibrate λ and β to be $\lambda = 1.1014$ and $\beta = 0.7363$. In this case, since employment in R increases as routine tasks are automated, the only b_R that is consistent with the final period's employment share is the initial level of $b_R = 0.1$.

Figure B.4: Key moments of the model under automation when tasks are gross substitutes ($\sigma = 1.3$)

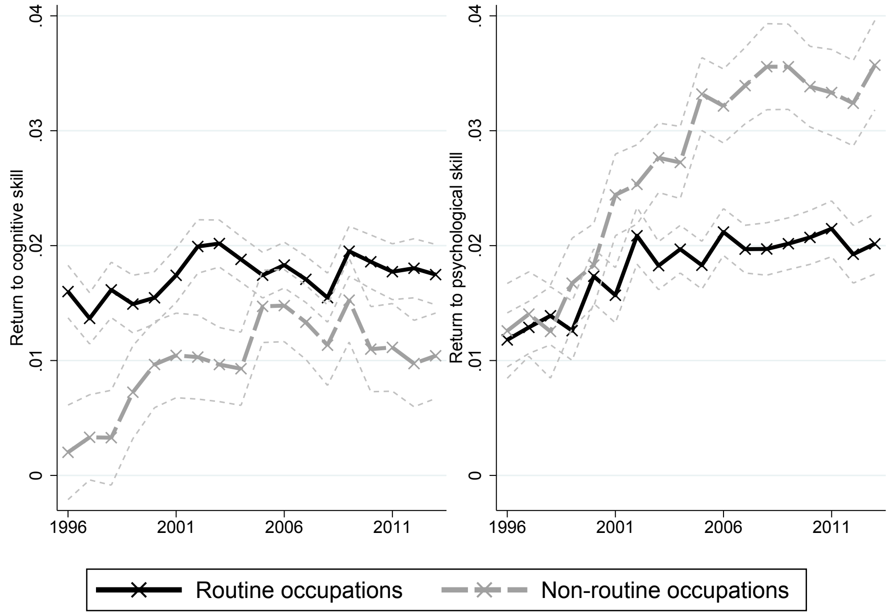


Figure B.5: The returns to cognitive and psychological skills in Sweden including confidence intervals

Notes: The graphs plot estimated coefficients from a pooled OLS regression of log wages on skill measures. Skill measures are standardized within each cohort, to be normally distributed with zero mean and unit variance. The graph includes 95 percent confidence intervals. The data consists of a large, representative sample of the Swedish workforce (Wage Structure Statistics). The sample consists of males aged between 38-42, in occupations with no higher education requirements, who work in the private sector. The number of workers is 35,330 in 1996 and 28,285 in 2013. Routine occupations are those 3-digit occupations with higher routine-intensity index (Autor et al. 2003) than average.

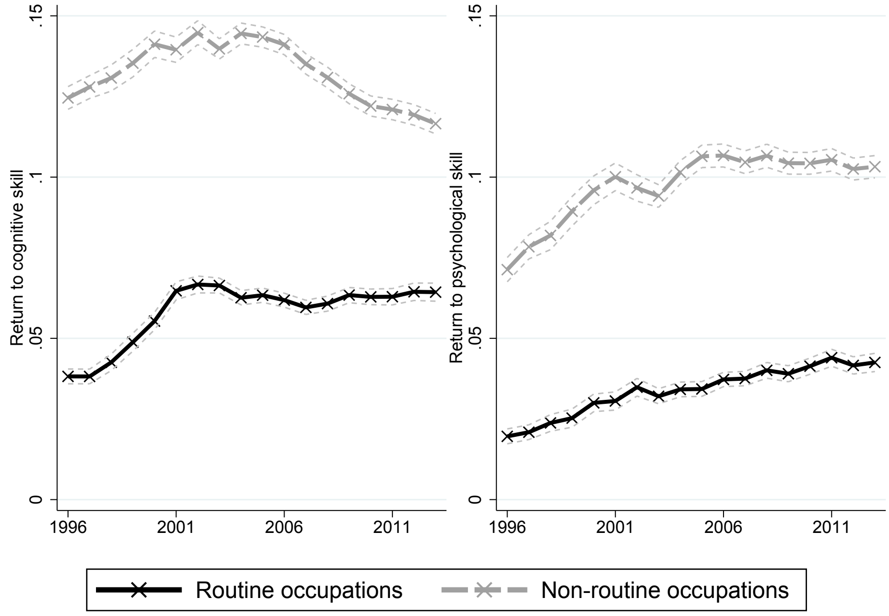


Figure B.6: Sample including all education categories: The returns to cognitive and psychological skills in Sweden 1996-2013

Notes: The graphs plot estimated coefficients from a pooled OLS regression of log wages on skill measures. Skill measures are standardized to be normally distributed with zero mean and unit variance in each year. The graph includes 95 percent confidence intervals. The data consists of a large, representative sample of the Swedish workforce (Wage Structure Statistics). The sample consists of males aged between 38-42 who work in the private sector. The number of workers is 55,683 in 1996 and 58,696 in 2013. Routine occupations are those 3-digit occupations with higher routine-intensity index (Autor et al. 2003) than average.

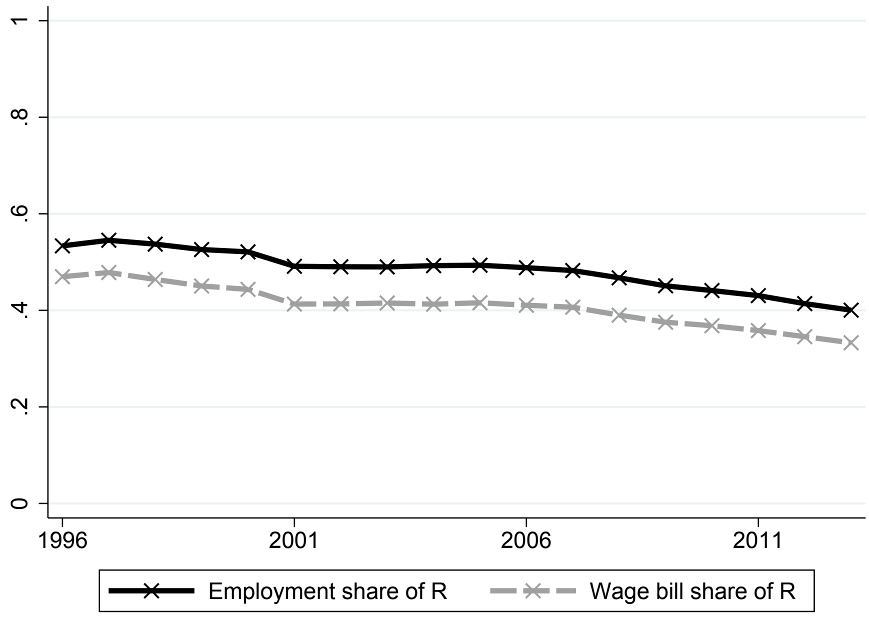


Figure B.7: Sample including all education categories: Employment and wage bill share of routine occupations in Sweden 1996-2013

Notes: The data consists of a large, representative sample of the Swedish workforce (Wage Structure Statistics). The sample consists of males aged between 38-42 who work in the private sector. The number of workers is 55,683 in 1996 and 58,696 in 2013. Routine occupations are those 3-digit occupations with higher routine-intensity index (Autor et al. 2003) than average.

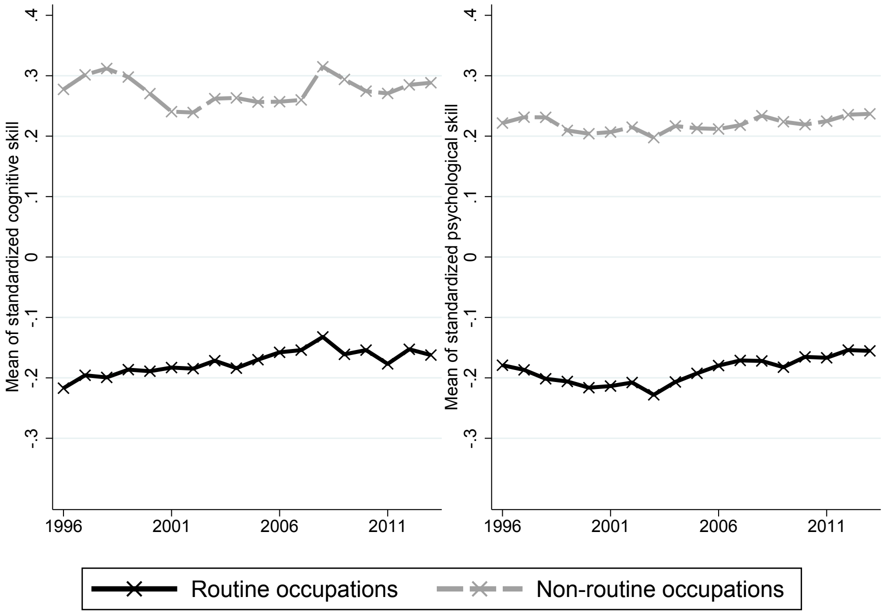
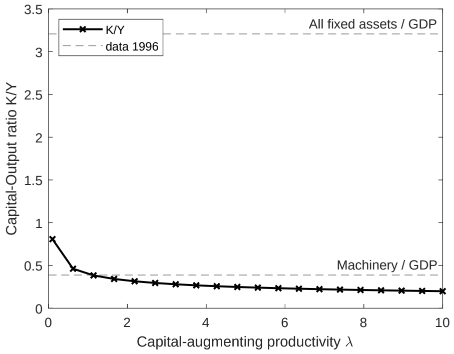
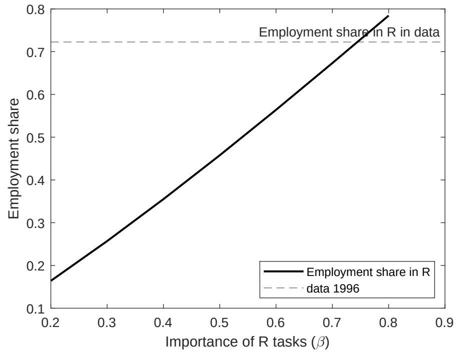


Figure B.8: Sample including all education categories: Mean of cognitive and psychological skills in Sweden 1996-2013

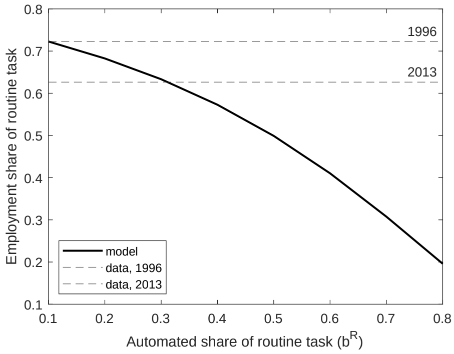
Notes: The graphs plot the mean skills in each occupation. Skill measures are standardized to be normally distributed with zero mean and unit variance in each year. The data consists of a large, representative sample of the Swedish workforce (Wage Structure Statistics). The sample consists of males aged between 38-42 who work in the private sector. The number of workers is 55,683 in 1996 and 58,696 in 2013. Routine occupations are those 3-digit occupations with higher routine-intensity index (Autor et al. 2003) than average.



(a) Capital-Output ratio as a function of the capital-augmenting factor λ



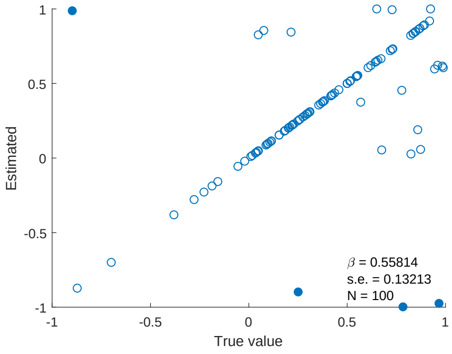
(b) Employment share in routine tasks as a function of the routine task weight β



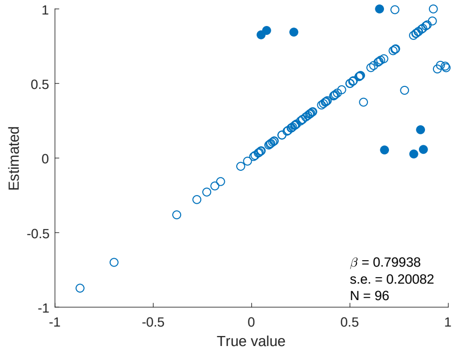
(c) Employment share in routine tasks as a function of automation of the routine task b_R

Figure B.9: Moments' dependence on selected parameters

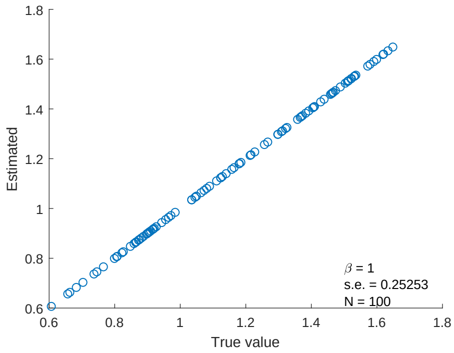
Notes: Automation levels are $(b_R, b_N) = (0.1, 0)$, and other parameters than those varied in each panel are as specified in Tables 1 and 2. Data on capital come from Statistics Sweden (2021*c*), data on output comes from Statistics Sweden (2021*a*), data on employment come from the sources listed and explained in Section 5.1.



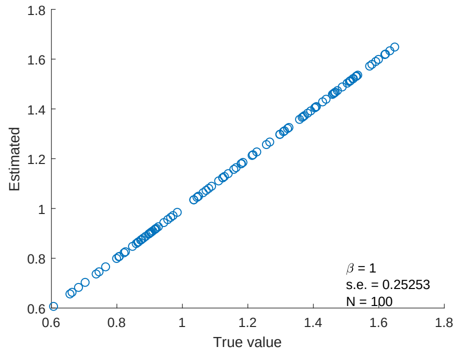
(a) Skill covariance ρ, including outliers



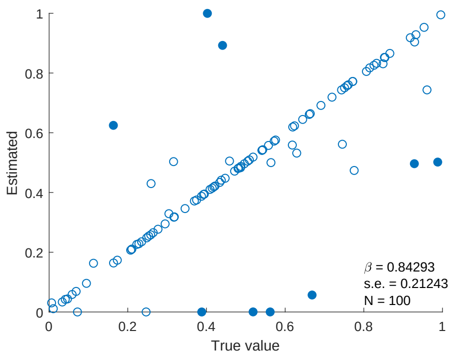
(b) Skill covariance ρ, excluding outliers



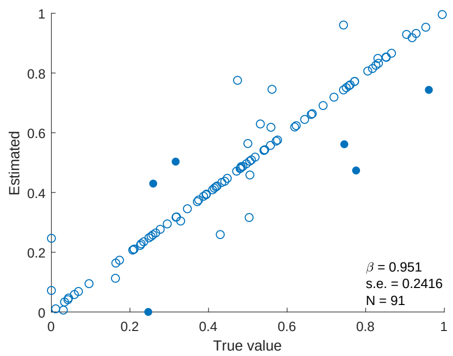
(c) Cutoff u, including outliers



(d) Cutoff u, excluding outliers

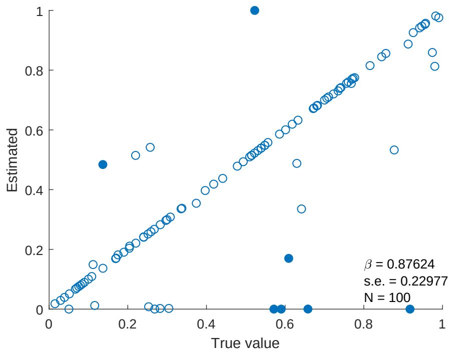


(e) Skill price for cog in R p_R^{cog}, including outliers

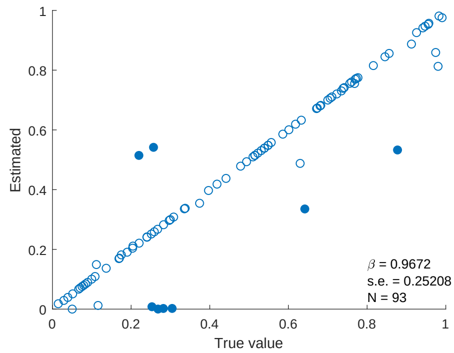


(f) Skill price for cog in R p_R^{cog}, excluding outliers

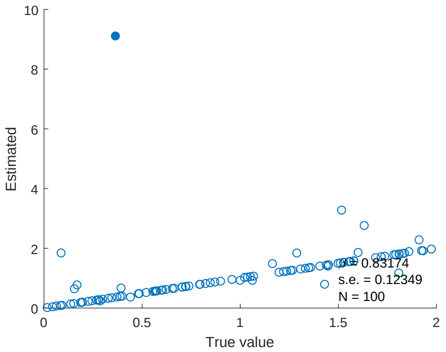
Figure B.10: Testing the estimation procedure: Scatter plots of estimated parameters on true parameters



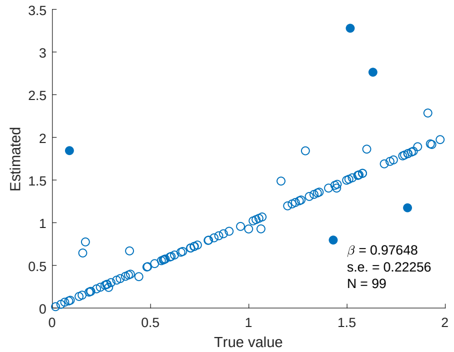
(g) Skill price for cog in NR p_R^{cog}, including outliers



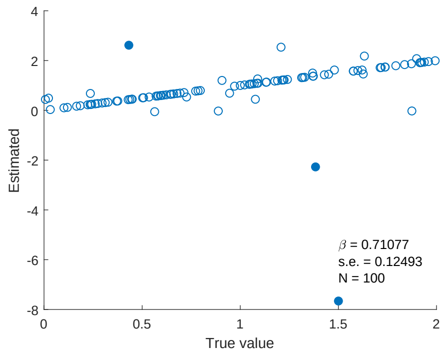
(h) Skill price for cog in NR p_R^{cog}, excluding outliers



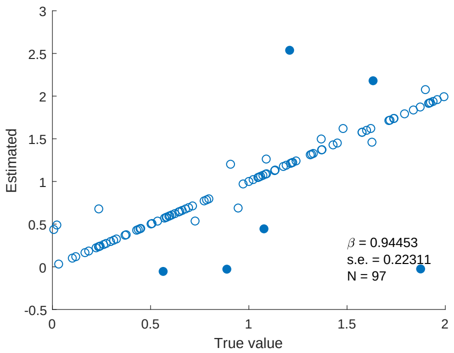
(i) Skill signal CC a_{cc}, including outliers



(j) Skill signal CC a_{cc}, excluding outliers

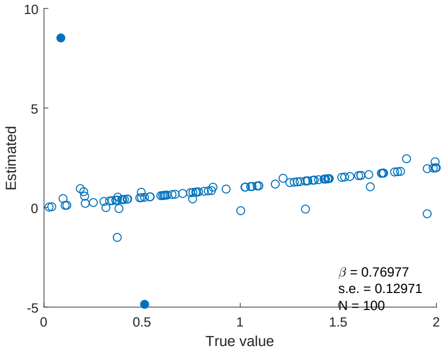


(k) Skill signal CP a_{cp}, including outliers

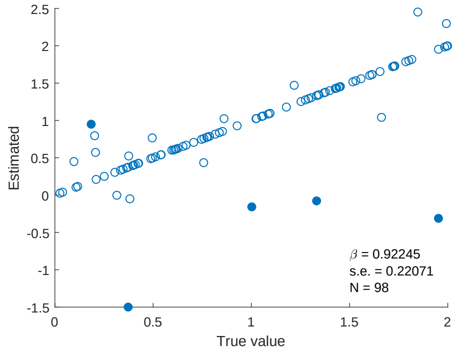


(l) Skill signal CP a_{cp}, excluding outliers

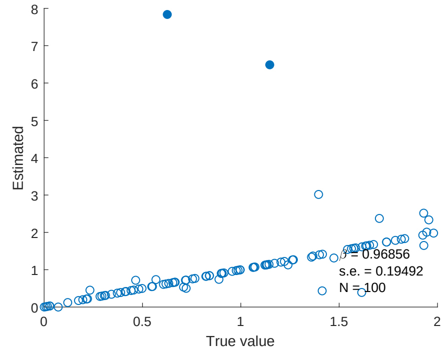
Figure B.10: Continued: Testing the estimation procedure: Scatter plots of estimated parameters on true parameters



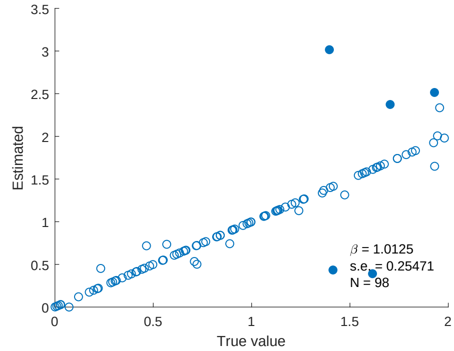
(m) Skill signal PC a_{pc}, including outliers



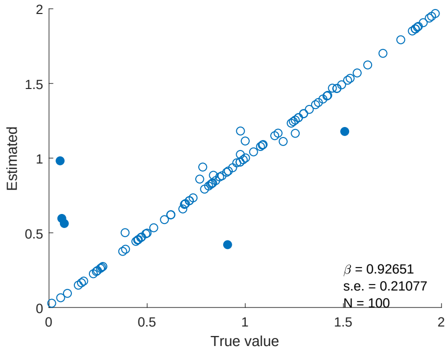
(n) Skill signal PC a_{pc}, excluding outliers



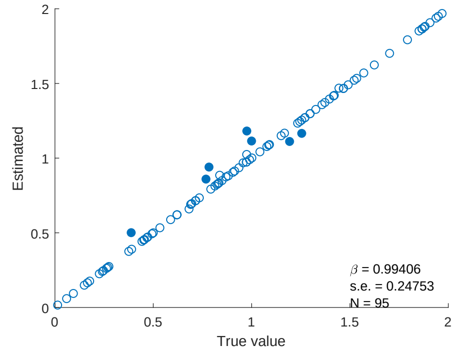
(o) Skill signal PP a_{pp}, including outliers



(p) Skill signal PP a_{pp}, excluding outliers

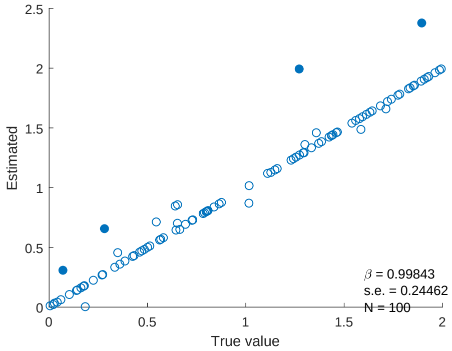


(q) Skill noise C $a_{\epsilon,c}$, including outliers

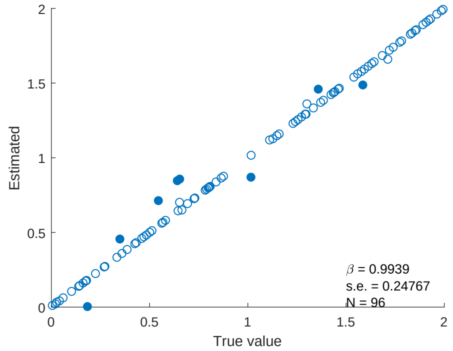


(r) Skill noise C $a_{\epsilon,c}$, excluding outliers

Figure B.10: Continued: Testing the estimation procedure: Scatter plots of estimated parameters on true parameters



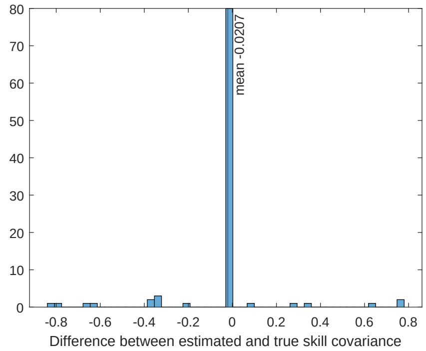
(s) Skill noise P $a_{\epsilon,p}$, including outliers



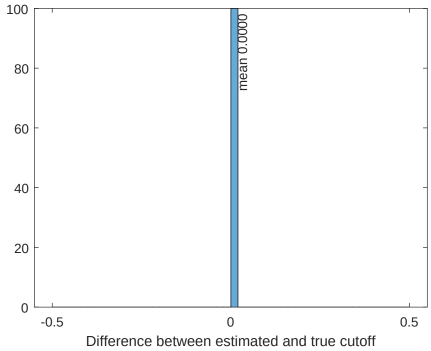
(t) Skill noise P $a_{\epsilon,p}$, excluding outliers

Figure B.10: Continued: Testing the estimation procedure: Scatter plots of estimated parameters on true parameters

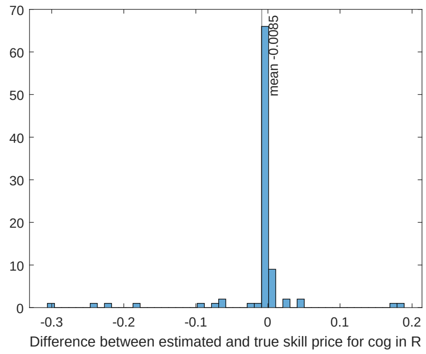
Notes: The graphs plot the estimated parameter on the true parameter value, where the parameter values are drawn randomly 100 times. In the right column, outliers (defined by Matlab's function `regress`, using `rint`) are excluded. The blue, filled-in markers on the left-hand side are those that are excluded on the right-hand side. The blue, filled-in markers on the right-hand side are defined as outliers in the same way, but they are included in the estimation of slope and standard errors displayed on the right-hand side.



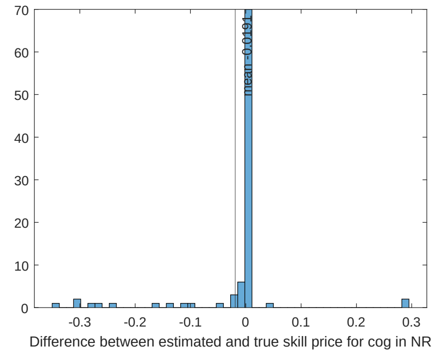
(a) Skill covariance ρ, excluding outliers



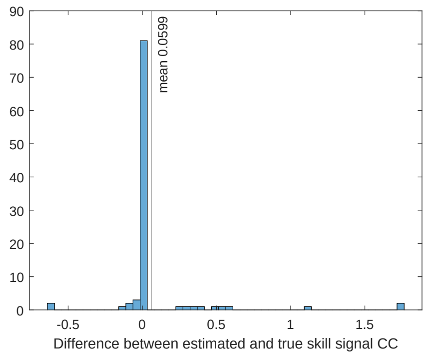
(b) Cutoff u, excluding outliers



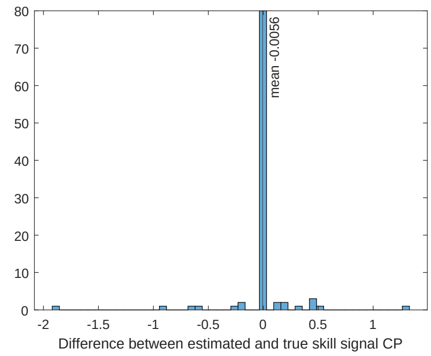
(c) Skill price for cog in R p_R^{cog}, including outliers



(d) Skill price for cog in NR p_R^{cog}, excluding outliers

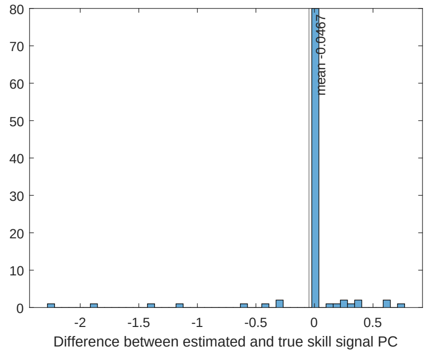


(e) Skill signal CC a_{cc}, excluding outliers

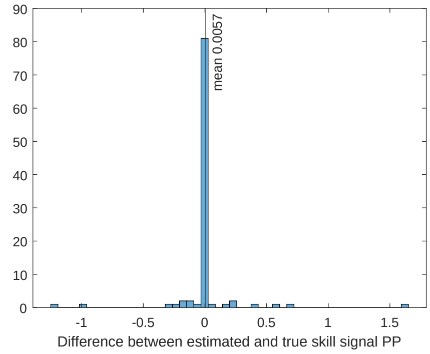


(f) Skill signal CP a_{cp}, excluding outliers

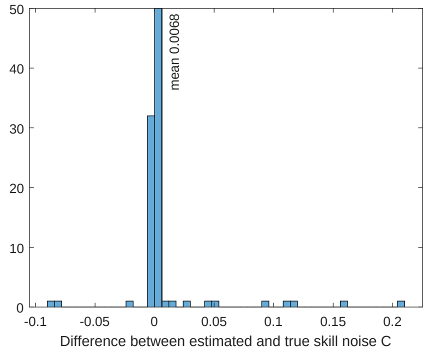
Figure B.11: Testing the estimation procedure: Histograms of the difference between estimated parameters and true parameters



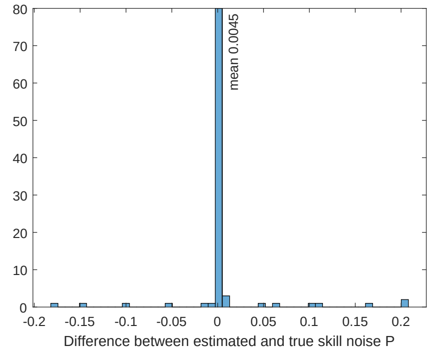
(g) Skill signal PC a_{pc}, excluding outliers



(h) Skill signal PP a_{pp}, including outliers



(i) Skill noise C $a_{\epsilon,c}$, excluding outliers



(j) Skill noise P $a_{\epsilon,p}$, excluding outliers

Figure B.11: Continued: Testing the estimation procedure: Histograms on estimated parameters

Notes: The histograms plot the difference between the estimated parameter and the true parameter value, where the parameter values are drawn randomly 100 times. Outliers (defined by Matlab's function `regress`, using `rint`) are excluded.