Worker Skills, Firm Dynamics, and Productivity*

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Abstract

We develop a general equilibrium model of firm dynamics with multiple labour skills to analyse the productivity implications of skill shortages. Firms employ cognitive, interpersonal, and manual skills in both operational and overhead tasks, with sectoral variation in skill intensities, and within sector firm size heterogeneity due to idiosyncratic technology draws. Calibrated to UK data, the model reveals that cognitive skills are a binding constraint on productivity. A reduction in the supply of cognitive skills lowers labour productivity at all levels – firms, sectors, and in the aggregate. About half of the sectoral effects are due to changes in the within-sector distribution, whereby larger firms grow in relative size but become less productive. Sectoral heterogeneity in skill intensities amplifies these effects.

Keywords: multi-dimensional skills; skills shortages; firm dynamics; productivity

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1 Introduction

Skills shortages are a widely discussed labour market phenomenon with potentially far-reaching consequences for productivity. For instance, after the recovery from the Covid-19 recession, labour shortages became apparent in the UK where the number of job vacancies reached record highs in many industries (House of Lords, Economic Affairs Committee, 2022). Difficulties to hire employees with the right set of skills might suppress firms' output and (labour) productivity[1], as managers might be forced to allocate tasks to those who are not well-suited to perform these tasks.[2] Taking a more macroeconomic point of view, we expect that skills shortages to not just affect individual firms in isolation, but that competition over the scarce inputs results in changes in the distribution of firms, potentially affecting industrial sectors differentially. To understand the macroeconomic impact of skills shortages, all these effects need to be taken into account.

In this paper, we develop a quantitative general equilibrium model of firm dynamics that incorporates multiple types of worker skills, each utilised with varying intensities across sectors. Our framework builds on the Hopenhayn (1992) model of firm heterogeneity and dynamics, extended to include multiple skill types, which are employed in both production (operations labour) and overhead tasks. We calibrate the model using UK data on the skill composition of employment, firm size/productivity distributions, and firm entry statistics. We then simulate skill supply shocks to examine their impact on labour productivity across firms, sectors, and at the aggregate level.

Our analysis is motivated by the observation that skills are multi-dimensional. Following Lise and Postel-Vinay (2020), we focus on three dimensions of skills — cognitive, interpersonal, and manual — and introduce these into a model of firm dynamics. We note that categorising skills by these three types is different to splitting workers

[1]Throughout this paper when we write productivity we mean labour productivity unless stated otherwise.

[2]Jane Gratton, the Head of People Policy at the British Chambers of Commerce, recently expressed this concern as 'Because [firms] got staff shortages at lower levels in the organisation, qualified staff and higher skilled staff are doing lower-level work, which is taking their eye off the productivity goal. And also, they cannot release staff for training.' (Has Britain Stopped Working? – the Bottom Line, BBC).

into low and high skilled by wages or by education. We see in the data for instance that amongst the highest paid occupations the interpersonal skill intensity is the highest, with the intensity of cognitive skills only in second place. As we discuss below, our results reveal that variations in the supply of these two skills have quantitatively different effects, implying that pooling interpersonal and cognitive skills together as a single 'high skill' would be misleading in an analysis of skills shortages. While we do not model workers' labour supply as a bundle of multi-dimensional skills, in our framework firms' labour demand is multi-dimensional in cognitive, manual, and interpersonal skills, and we evaluate how variations in the aggregate skills supplies impacts firms and productivity.

In principle, the framework could accommodate any number of industrial sectors, but for the quantitative model we concentrate on two broad sectors: production and professional services (including technology and media)[3]. Contrasting these two sectors is particularly interesting as they are markedly distinct; they differ in tasks, value added per worker, and in the characteristics of worker skills. Although both sectors have broadly similar shares of cognitive skills among their workers (with professional services having moderately higher shares), the production sector is far more manual-intensive, while professional services rely much more heavily on interpersonal skills. The two sectors differ vastly in their firm size distribution too, with professional services having a much larger share of small employers than the production sector (see data in Figure 5).

Despite these differences in skill intensities, the sectors compete over the same pool of workers' skills. Through general equilibrium linkages, shocks to the aggregate skill composition impact firms in all sectors via changes in relative prices, firm entry, and employment composition, which in turn will shape the firm size distribution and impact overall productivity.

Our central finding is that cognitive skills currently represent a binding constraint on productivity in the UK economy, whereas interpersonal skills hardly do, despite being intensively used in high wage occupations. A reduction in the supply of cognitive skills lowers labour productivity at all levels – firms, sectors, and in the aggregate.

[3] These two broad sectors account for more than half of the value added in the UK private sector.

While effects via firm exit are minimal, the main impacts arise from effects within and between active firms, including through firm entry. First, the average productivity of firms declines as their employment mix tilts away from the scarcer skill. Second, within sectors, there are differential effects across firm size: larger firms grow in relative size but also become less productive. This change across the distribution of active firms further depresses sectoral and aggregate productivity.

Most of the response to cognitive skill shortages stems from heterogeneity in how intensively the three distinct skills are used in operations.[4] In contrast, heterogeneity in how intensively the distinct skills are used in overhead labour has negligible explanatory power in the effects of skills shortages on productivity loss. Similarly, initial differences in the supply of each skill play a limited role in determining how subsequent skill supply shocks affect productivity.

Our paper connects several strands of economic literature. First, we build on the recent literature that emphasises the multi-dimensional nature of skills — describing individuals' abilities across a range of tasks. Weinberger (2014) and Deming (2017) highlight the importance of interactions between social and cognitive skills for wages and productivity. Lindenlaub (2017) and Deming (2023) demonstrate how multi-dimensional skills shape worker sorting and the wage structure. We draw on this literature and, following Lise and Postel-Vinay (2020), focus on three types of skills: cognitive, manual, and interpersonal. However, our analysis differs: we study how the allocation of skills across heterogeneous firms affects productivity. Girsberger, Koomen, and Krapf (2022) also consider these three skill dimensions and analyse how workers' skill acquisition influences productivity and employment transitions in the context of heterogeneous workers. In contrast, we focus on the firm side of the market, examining how aggregate skill supplies shape firm dynamics and productivity outcomes.

Second, our paper contributes to the literature on firm heterogeneity. Hopenhayn (1992) and Hopenhayn and Rogerson (1993) provide the canonical model of firm entry, exit, and dynamics under idiosyncratic productivity shocks. We extend this frame-

[4]To avoid confusion between firm production and the production sector, we use the term 'operations' to refer to the former.

work by moving beyond a homogeneous labour input to examine the implications of skill heterogeneity. Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) demonstrate that the allocation of inputs across firms can have substantial effects on aggregate productivity. While our model differs in structure, we pursue a related idea by analysing how the allocation of scarce skills across heterogeneous firms shapes labour productivity. Mukoyama, Takayama, and Tanaka (2025) develop a model that incorporates multiple tasks (occupations) into the Hopenhayn (1992) and Hopenhayn and Rogerson (1993) framework. Although the model setups are similar, our focus differs: they examine the effects of firing costs on worker reallocation across occupations (where workers are ex ante homogeneous but moving workers across occupations is costly), whereas we study skills shortages in an environment with heterogeneous workers (but no firing costs). Gottlieb, Poschke, and Tueting (2025) study the role of skill endowments in explaining cross-country differences in firm dynamics. Similar to our work, they incorporate multiple skill types into the Hopenhayn (1992) and Hopenhayn and Rogerson (1993) framework. However, while their skill types are defined by differences in educational attainment, ours are based on workers' underlying abilities. Moreover, whereas they introduce a productivity-correlated returns-to-scale parameter and goods market distortions, we abstract from these features and instead focus on cross-industry variation in the effects of skill shocks by modelling distinct industries with sector-specific parameters.

Third, we relate to the literature on skills mismatch. Şahin, Song, Topa, and Violante (2014) quantify the impact of mismatch on unemployment, while Guvenen, Kuruscu, Tanaka, and Wiczer (2020) and Baley, Figueiredo, and Ulbricht (2022) examine how multi-dimensional mismatch affects productivity, abstracting from within-firm complementarities. In contrast, there is not mismatch in our model. We take a different approach: we specify sector-specific production functions in which firms use multiple skill types, allowing for substitution between them. This enables us to analyse how firm and sectoral dynamics respond to aggregate skills supply shocks, capturing within-firm adjustments in skill use.

In the next section we briefly present some stylized facts that suggests that skills shortages are indeed multi-dimensional and vary by industry. We then develop in section 3 our quantitative general equilibrium model of heterogeneous firms with multiple skills. After calibrating the model against detailed UK data in section 4, we evaluate in section 5 the role of cognitive, manual, and interpersonal skills for labour productivity. The final section concludes.

2 Motivating Facts

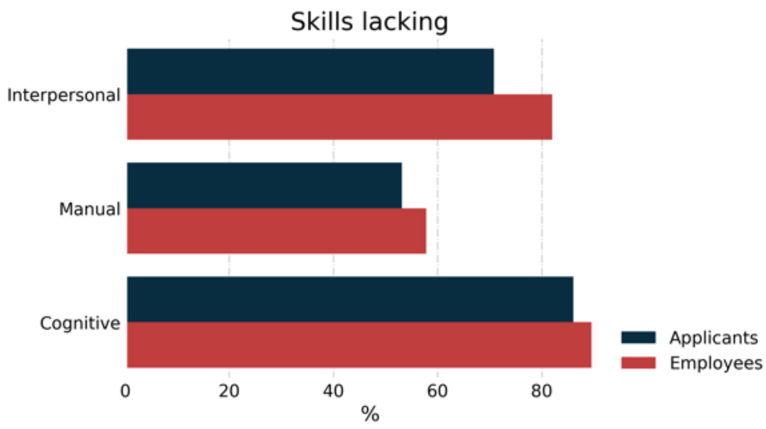
To motivate our analysis of skills shortages, we draw on data from the ONS Employer Skills Survey for the year 2022. This survey, conducted by the Office for National Statistics (ONS), collects establishment-level information from UK employers on a range of issues related to workforce skills, including whether current employees or job applicants are perceived to lack specific types of skills.

We classify the reported skills into three categories: cognitive, interpersonal, and manual skills. As discussed in the introduction, we focus on these three dimensions following Lise and Postel-Vinay (2020) and other recent work such as Girsberger et al. (2022). To provide suggestive evidence on skills shortages, we group the detailed skill items from the Employer Skills Survey into these categories through a manual mapping based on the ONS skill descriptions.[5] The detailed mapping is provided in Appendix D.

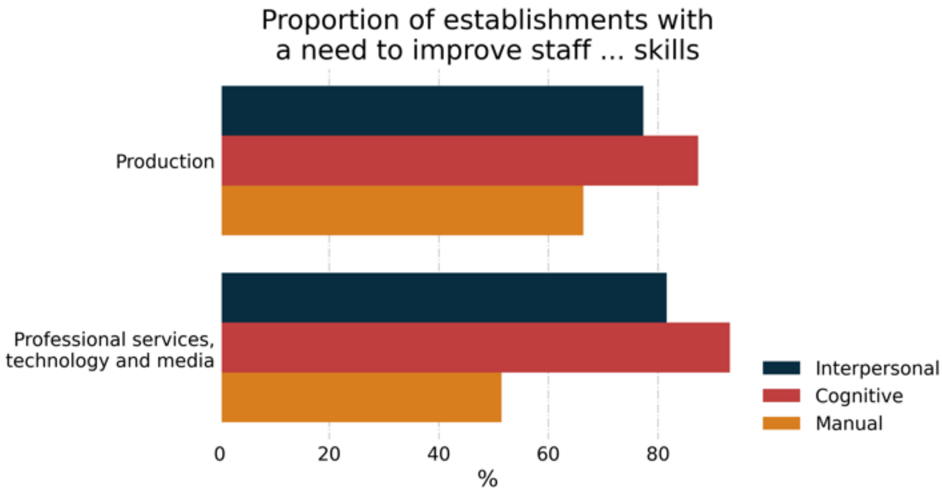
Figure 1a presents the prevalence of reported skill gaps among current employees and job applicants, by skill category. While shortages are reported across all skill types, lacking cognitive skills are the most prevalent, followed by interpersonal skills. This pattern suggests that a simple one-dimensional treatment of labour inputs is obscuring an analysis of skills.

Figure 1b breaks down reports of a need to improve workers' skills across the three dimensions by sector, distinguishing between employers in the production sector and those in professional services (including technology and media). Cognitive and interpersonal skill shortages are reported at broadly similar rates across both sectors. However, the need to boost workers' manual skills is substantially more pronounced

[5]For the calibration of our model, we construct skill shares by combining data from the Annual Population Survey on occupational employment shares (by industry) with the occupational skill requirements reported in Lise and Postel-Vinay (2020); see Section 4 for details.



(a) By Skill Category



(b) By Sector (for Current Employees)

Figure 1: Reported Skill Shortages in the UK

Source: ONS Employer Skills Survey 2022 and authors' calculations. The top figure: the survey asks about the skills found difficult to obtain from applicants. For example, "Soft / people skills found difficult to obtain from applicants (SUMMARY): Instructing, teaching or training people" (as quoted from the ONS Employer Skills Survey 2022). The survey also about employee skills which need improving. For example, "Soft / people skills that need improving (SUMMARY): Customer handling skills." We first group skills (the specific skills which come after ':') into three major groups: interpersonal skills, manual skills, and cognitive skills (the grouping is in the Appendix). Then we calculate, among the establishments which report having a skills shortage vacancy (a different question), the proportion of establishment which also report having found at least one of the skills in a skill group difficult to obtain (the bars labelled as 'Applicants'). We also calculate, among the establishment which report at least one instance of lack of proficiency among staff (a different question), the proportion of establishments which report having found at least of the skills in a skill group that needs improving (the bars labelled 'Employees'). The results are reported for the entire economy. The bottom figure reports the results by sector (the industry grouping we used in our calibration).

in the production sector. The cross-sector variation in the survey responses suggests that skill intensities might differ. When we turn to the Annual Population Survey to calibrate our quantitative model in Section 4, we indeed find that the production sector is more manual skill-intensive, which reinforces the importance of accounting for both the multidimensional nature of skills and sectoral heterogeneity in any analysis of skill shortages.

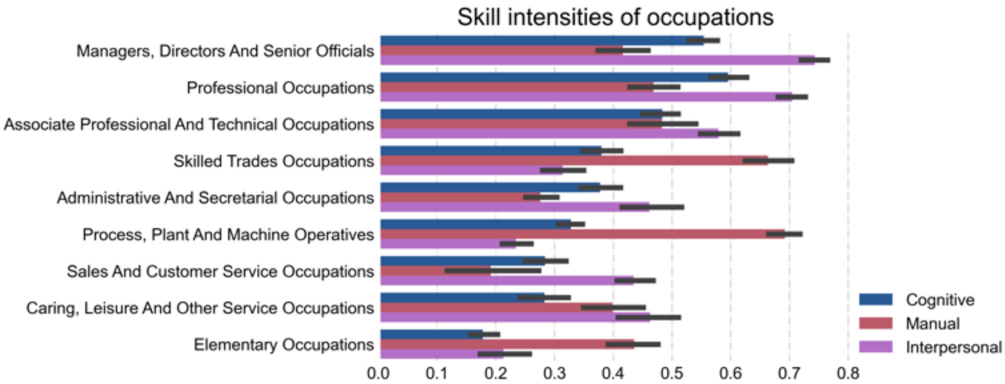


Figure 2: Skill Use by Occupation

Source: Lise and Postel-Vinay (2020) and authors' calculations. The figure shows the means and 95% confidence intervals (black bars) of skill intensities of major occupations. The figure is constructed by taking averages of 4-digit occupation skill intensities from Lise and Postel-Vinay (2020) at the major occupation group level.

Another way of gauging the importance of these three skills is to look at their prevalence in different occupations. Figure 2 shows the intensity of each skill by 1-digit occupation groups, ranked by average wages (in descending order)[6]. This graph is constructed by taking averages of 4-digit occupation skill intensities from Lise and Postel-Vinay (2020) at the major occupation group level. While the use of cognitive skills increases broadly with the rank of occupations, it is interpersonal skills that are the most important skill in the highest paid occupation (managers, directors and senior officials). At the same time, the use of interpersonal (and of manual) skills is not monotonic in occupation rank. These patterns highlight the nuanced nature of skills and the need to move beyond workers based on educational attainment alone.

[6]Occupations are ranked in descending order of 2023 mean full-time gross hourly wages from the UK Annual Survey of Hours and Earnings (ASHE).

3 Model of Firm Dynamics with Multiple Skills

To study the productivity implications of variations in the aggregate supplies of skills, we develop a general equilibrium model with firm dynamics. We introduce into the Hopenhayn (1992) and Hopenhayn and Rogerson (1993) model the novel feature that labour is differentiated by skill types. Following Lise and Postel-Vinay (2020) we consider cognitive, manual, and interpersonal skills. We further add a two sector structure: production and professional services (including technology and media). Within each sector, firms are heterogeneous due to (Hicks-neutral) technology differences and operate under decreasing returns to scale to produce a homogenous sector-specific good. Sectoral output is consumed by a representative household with CES preferences across goods. The equilibrium is competitive, with free firm entry (subject to fixed costs) and exit, where all firms and consumers take prices and wages as a given.

The aggregate labour supply of each skill we take as exogenous because our interest lies in the endogenous assignment of skills to each (active) firm and in how this shapes productivity. Changes in the skill supply will alter wage rates for each of the skills, employment in each firm, entry and exit of firms, sectoral output prices and GDP, and thereby also labour productivity at all levels.

3.1 Model setup

We index sectors by j and firms by k. To ease notation, we omit the time index for now, and only introduces it as t in dynamic equations. Each labour skill is perfectly mobile across firms and sectors, such that there is a single wage rate w_i for each skill for $i \in \{C, M, I\}$ (cognitive, manual, and interpersonal skills, respectively).

Firms. Firms combine the various labour skills using a CES aggregator for production under decreasing returns to scale and in the presence of some fixed costs. We follow Hopenhayn (1992) in setting up the firm dynamic structure. Within a sector firms differ in idiosyncratic productivity in a Hicks-neutral technology way. Idiosyncratic productivity is drawn upon entry from a sector-specific distribution G_j and subsequently evolves according to an AR(1) process. Firms face fixed entry costs, denominated in units of the sector's output they seek to enter. They also face each period a fixed operating cost, which we set up as an overhead labour cost as a linear combination over the three skills. Firms make optimal decisions, including whether to exit at the end of the period (before the realization of next period's productivity). The mass of active firms is therefore endogenous.

Output of firm k in industry j is given by:

$$y_{kj} = s_{kj} L_{kj}^{\theta}, \quad \text{where } \theta < 1, \tag{1}$$

$$L_{kj} = \left(\sum_i \phi_{j,i}^{1/\sigma} n_{k,i}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}, \tag{2}$$

$i \in \{C, M, I\}$ denotes cognitive, manual, and interpersonal skill types, and σ is the elasticity of substitution across skills. The returns to scale parameter θ is below one such that firms have increasing marginal costs. Higher values of the Hicks-neutral technology parameter s_{kj} result —at given inputs— in lower (marginal) production cost. As in equilibrium all firms in a sector face the same product price p_j, which implies that firms with higher s_{kj} are larger in terms of value-added and composite employment. Consequently within a sector the distribution of firm size is closely linked to the distribution of s_{kj} amongst the active firms, where both firm size and idiosyncratic productivity distributions are endogenous. While the firms' technology evolves according to an $AR(1)$ as

$$\log(s_{t+1}) = (1-\rho)\mu_j + \rho \log(s_t) + \varepsilon_{t+1}, \text{ with } \varepsilon \sim N(0, \sigma_j^2) \text{ and } 0 < \rho < 1, \tag{3}$$

firms decide optimally at the end of each period (after production took place, but before the realization of next period's draw) whether to stay or exit the market. As we will see below, because of overhead fixed costs this structure implies a threshold productivity, such that firms with $s_{kjt} < s_{jt}^*$ leave. It is always the least productive firms that leave, but what the critical value s_{jt}^* is determined in general equilibrium.

Our approach differs from Hopenhayn (1992) in two key ways. First, in our model L_k is not a one-dimensional labour input but a CES composite of the three distinct skill types: interpersonal, cognitive, and manual. Second, the fixed cost of operations stems from the overhead labour required. We model this as a (time-invariant) linear combination across the skills, parametrised as $C_{f,j} \sum_i n_{f,i} w_i$, where w_i the (time-varying) equilibrium wage for skill i and $\{n_{f,i}\}$ the required units of overhead labour. $C_{f,j}$ is a scaling parameter that determines the overall size of the overhead labour requirement in sector j.

The optimal choices by firms are all static apart from the exit decision. As we show in the appendix, firm k's optimal demand for each skill i used in production of output satisfies

$$n_{kij} = \phi_{j,i} \left(\frac{w_j}{w_i} \right)^{\sigma} L_{kj} \text{ for } i \in \{C, M, I\}, \tag{4}$$

where $w_j = \left(\sum_i \phi_{j,i} w_i^{1-\sigma} \right)^{1/(1-\sigma)}$ is the unit cost of composite labour L_{kj} in sector j, with the property that $\sum_i w_i n_{k,i} = w_j L_{jk}$. In the following we refer to these demands for labour skills, as inputs to the production of output, as a firm's *operations labour* demand (one for each skill). These $\{n_{kij}\}$ are variable amounts reflecting the optimization by firm k, in contrast to the fixed overhead labour ($\{n_{f,i}\}$) required for firms to be active. We see that the skill shares in the operations labour mix of a firm reflects relative wages for each skill (w_i) and skill intensities ($\phi_{j,i}$), where the latter vary across sectors (j).[7]

The optimal size of a firm, in terms of composite labour (2) and output (1), is given by

$$L_{kj} = \left(\frac{p_j s_{kj} \theta}{w_j} \right)^{\frac{1}{1-\theta}} \tag{5}$$

$$y_{kj} = s_{kj}^{\frac{1}{1-\theta}} \left(\frac{p_j \theta}{w_j} \right)^{\frac{\theta}{1-\theta}}. \tag{6}$$

Since within a sector only s_{kj} varies across firms and $0 < \theta < 1$, firms with higher technology draws have in equilibrium larger overall employment, larger employment in each skill, and larger value-added compared to other firms in their sector.

The dynamic part in the firm optimization problem stems from deciding whether to exit the market at the end of the period, before next period's productivity has been realized. This dynamic problem can be represented a value function. To ease the

[7]The composite wage index w_j is sector-specific, even though the wage rates for each skill are common across sectors, because the skill intensities $\{\phi_{j,i}\}_i$ differ by sector.

notation, we omit the firm index k from the choice variables and the sector index j from the value function, and use primes to denote next period values:

$$v(s, p_j, \{w_i\}) = \max_L p_j s L^\theta - C_{f,j} \sum_i n_{f,i} w_i - w_j L + \beta \max\{0, E_s v(s', p_j', \{w_i'\})\}, \quad (7)$$

where w_j is the unit cost of labour in industry j, p_j the sectoral output price, w_i is the wage rate for skill type i, and $n_{f,i}$ is the share of skill type i in overhead labour. If a firm decides to exit the market, it receives a scrap value of 0. If it decides to stay, it gets the continuation value $E_s v(s', p_j', \{w_i'\}) = E\left[v(s', p_j', \{w_i'\})|s\right]$ where the expectation for the next period value over possible productivity realizations s', is conditional on the current value of technology s. Under the $AR(1)$ process for firm productivity (3), $E_s v(s', p_j', \{w_i'\})$ is monotonically increasing in s, and due to the fixed overhead labour costs it is negative for small s and positive only for sufficiently high s. Firms with productivity $s < s^*$ exit the market where the critical threshold productivity is such that $E_{s^*} v(s', p_j', \{w_i'\}) = 0$, while firms with $s \geq s^*$ stay.

We summarised the decisions of incumbent firms above. Left to describe are the entry dynamics. As typical in the Hopenhayn model, we assume that potential entrants pay an upfront entry cost and draw a productivity afterwards. The entrants are therefore not ex ante selected.[8] Specifically, we assume that potential entrants pay a cost of entry, $C_{e,j}$, in units of their industrial sector's output. Entering firms then draw their initial (log) productivity from a log-normal distribution G_j with mean $\mu_{e,j}$ and variance $\sigma_{e,j}^2$. Following the traditional Hopenhayn model, entrants, unlike incumbents, do not face a further fixed cost to operate in their first period in the market. Therefore, the value of entry is

$$v_e(p_j, \{w_i\}) = \int_s \left(v(s, p_j, \{w_i\}) + C_{f,j} \sum_i n_{f,i} w_i \right) dG(s). \quad (8)$$

Households. Workers belong to a representative household. The household supplies $\{N_i\}_{i \in C,M,I}$ units of labour inelastically, owns the firms and collects their profits (net

[8] Ex post, some firms that enter will make losses. Nonetheless, they will produce in their initial period, as this is optimal for minimising losses. If $E_s v(s') < 0$ they will leave the economy after one period, just like the other firms discussed above.

of entry costs) and consumes output of each sector to maximise utility. We assume preferences over the sectoral goods are given by

$$U = \left(\sum_j \eta_j^{1/\epsilon} C_j^{(\epsilon-1)/\epsilon} \right)^{\epsilon/(\epsilon-1)}.$$

The household maximises utility by choosing consumption of each good C_j subject to the budget constraint

$$\sum_j p_j C_j \leq \sum_i w_i N_i + \Pi. \tag{9}$$

Optimal choices imply

$$\frac{C_i}{C_j} = \frac{\eta_i}{\eta_j} \left(\frac{p_j}{p_i} \right)^{\epsilon}. \tag{10}$$

3.2 Equilibrium

We solve for a stationary competitive equilibrium in which the distribution of firms and prices are constant over time. Firms and household optimise, and prices are such that all markets clear.

Let F_j denote the stationary distribution of incumbent firms over productivity draws s in sector j and M_j^f be the total mass of firms in industry j. G_j is the probability distribution over idiosyncratic productivity s from which new entrants draw. The equilibrium is such that:

- Given prices $\{p_j\}$ and wage rates $\{w_i\}$ potential entrants make optimal entry decisions in each sector, resulting in a measure M_j^e of entrants to sector j, such that free entry equates the value of entry to the cost of entry

  $$v_{e,j}(p_j, \{w_i\}) = p_j C_{e,j}$$

  where the entry cost $C_{e,j}$ is in units of output of the sector chosen by the entrants.

- Given prices $\{p_j\}$ and wage rates $\{w_i\}$ firms choose labour demand for each skilled labour and decide on whether to stay in the market.

- Given prices $\{p_j\}$ and wage rates $\{w_i\}$ households make consumption decisions.
- The market of goods clears for each sector j:

$$M_j^f \int_s y_j(s) dF_j(s) + M_j^e \int_s y_j(s) dG_j(s) - C_{e,j} M_j^e = C_j,$$

  where M_j^e is the measure of entrants, each of whom pays the sectoral output entry cost $C_{e,j}$.

- The labour market for each skill i clears

$$\sum_j \left[M_j^f \int_s n_{j,i}(s) dF_j(s) + M_j^f C_{f,j} n_{f,i} + M_j^e \int_s n_{j,i}(s) dG_j(s) \right] = N_i \text{ for } i \in \{C, M, I\},$$

  where the total labour demand for a skill is the sum across all sectors and comprised of the operations labour demand by incumbent firms (first integral), the overhead labour by incumbents, and the operations labour demand by new entrants (last term).

4 Calibration

For the quantitative analysis we calibrate our general equilibrium model to match various aspects of the UK data over 2009–2023. Our strategy for calibrating the firm dynamics part is similar to Hopenhayn, Neira, and Singhania (2022); additionally we incorporate the three labour skills. We externally calibrate some parameters and choose the remaining ones to match in the stationary equilibrium key aspects of the UK economy. Given our research angle, we specifically target statistics on skill intensities, firm size distributions in terms of employees, firm entry, productivity and survival, and sectoral value-added shares.

We use multiple datasets from the Office for National Statistics and UK Government to collect relevant targets for the UK economy. We target averages of available data over the years 2009 to 2023, but due to data availability the sample period used for each target differs (see Table A2 in Appendix A). The list of datasets and the information collected is

- Business Population Estimates for the United Kingdom (BPE) — mean employment of sectors and size distribution of firms,
- Business demography, quarterly, UK Statistical Bulletins — mean entrant employment.
- Business demography, annual UK, — entry rate, entry rate of employer firms, 5-year survival rate of entering firms
- Annual Business Survey (ABS) — average labour productivity of industrial sectors, the relative productivity of 250+ employee firms
- UK National Accounts, The Blue Book — GVA shares
- Annual Population Survey (APS) — occupation shares of industries

The first four sources give us information about firms by industry. Across datasets, we assign industries consistently to our two sectors: production and professional services (including technology and media). Due to differences in industry coding across datasets, we assign media and technology throughout to professional services, as this aggregation gives us a consistent definition of sectors across the datasets. Then we use the generated firm-level statistics by sectors as calibration targets. We proceed similarly with sectoral data on gross value-added (from the national accounts) and on labour productivity (from the ABS).

The last data source is the Annual Population Survey (APS). From this household survey, we construct in a first step occupational employment shares by industries. We then multiply these by occupational requirements for cognitive, manual, and interpersonal skills from Lise and Postel-Vinay (2020), which gives us the skill shares in employment in each sector. We also use this approach to construct the aggregate labour supplies for each skill, which we construct by summing across all workers.

We start the model parametrisation by fixing some parameters based on the literature. From Hopenhayn et al. (2022) we take the elasticity of output with respect to overall labour as 0.64, and the persistence of Hicks-neutral technology in the $AR(1)$ process as 0.984. The elasticity of substitution across the sectoral consumption goods

	Definition	Value	Source
θ	Elasticity of output w.r.t. labour	0.64	Hopenhayn et al. (2022)
ρ	Persistence of AR(1) productivity	0.984	Hopenhayn et al. (2022)
σ	b/w skills substitutability	0.73	Adachi (2025)
ϵ	sectoral consumption substit.	0.2	Bárány and Siegel (2020)
$\{N_i\}$	labour supply by skill (C, M, I)	0.201, 0.201, 0.198	labour force, times APS skill shares
$\{n_{f,i}\}$	overhead skill shares (C, M, I)	0.32, 0.25, 0.43	skill shares of managerial occ in APS

Table 1: Externally Calibrated Parameters

we take from Bárány and Siegel (2020) as 0.2, but we point out that this value has virtually no effect on our results (see robustness checks in section 5.3). More important is the production elasticity of substitution between skills. While papers focusing at aggregate level substitution between worker skill types have found values above one, at the firm level the evidence points to values less than one, which implies that the different skills are complements. We follow Adachi (2025) and set the elasticity between cognitive, manual, and inter-personal skills to 0.73.

	Definition	Target
$\{\phi_{j,i}\}_i$	Skill intensities	Skill shares
$C_{e,j}$	Cost of entry	Entry rate
$C_{f,j}$	Scale of overhead labour requirements	Rel. productivity of 250+ employee firms
μ_j	Mean of productivity $AR(1)$ process	Relative productivity of industries
σ_j^2	Variance of productivity $AR(1)$ process shocks	5-year survival rate
$\mu_{e,j}$	Mean of entrant productivity distribution	Mean employment of entrants
$\sigma_{e,j}^2$	Variance of entrant productivity distribution	Mean employment of sectors
η_j	Industry intensity in consumption	Gross value added shares

(a) Parameters to be Calibrated (by sector)

	Production	Prof serv, tech & media
ϕ_c	0.55	0.57
ϕ_m	0.20	0.12
ϕ_i	0.25	0.30
C_f	1.28	1.59
C_e	47.47	41.20
μ_i	-3.18	-3.93
σ_i	0.29	0.32
μ_e	-0.06	1.23
σ_e	0.95	0.55
η	0.31	0.69

(b) Calibrated Values

Table 2: Calibration Parameters

We compute the labour supplies of the various skills and their share in overhead labour directly from APS data. We construct the former by multiplying the labour force participation rate of roughly 60 percent by the aggregate skill shares, which we compute by multiplying occupational shares from the APS with skill intensities from Lise and Postel-Vinay (2020). That is, we multiply 0.6 by the C, M, I shares of $[0.335, 0.335, 0.33]$ to obtain the per capita labour supply by skill as $0.2011, 0.2011, 0.1978$ respectively. For the required overhead labour in each skill, we proceed by viewing the overhead requirement as the need to have managers. We then compute the skill shares among workers in managerial occupations and use these as the overhead skill shares $n_{f,i}$. Table 1 lists all externally calibrated parameters.

We are then left with 10 parameters for each industrial sector, shown in Table 2a, which we calibrated in general equilibrium against an equal number of targets in the data. We choose these to minimize the distance between the model-implied values and the data targets of Table 3. The table further shows the model statistics generated by the resulting calibrated parameters (whose values we report in Table 2b).

Our calibrated model replicates the targeted moments very well. The only exception is a slight under-prediction of relative productivity for large firms in the production sector. The model does also reasonably well in replicating some untargeted moments: it generates the general patterns of firms' business shares by employment size bands. We show these (alongside results from experiments) in Figure 5 below as "Benchmark" model outcomes. Comparing these against the data, we see that the calibrated model qualitatively perfectly mimics the distribution of business shares across employment bands in each sector. Quantitatively, the model and data shares are very close in professional services, while in the production sector the model somewhat understates the share in the 1–4 employee band, but nonetheless gets the relative sizes broadly right.

In Table 3 we can also see that the two sectors are indeed different in terms of the data we are targeting. Compared to production, the average firm in professional services (including technology and media) has lower employment and relies more on cognitive and interpersonal skills. In the professional services sector, there is more frequent entry of firms and their average survival rates are higher. Compared to production, professional services account for a larger share of gross value-added (GVA)

	Data		Model	
	Production	Prof serv, tech & media	Production	Prof serv, tech & media
Mean employment	20.73	11.16	20.87	11.15
Mean entrant employment	4.08	2.51	4.06	2.51
Entry rate (employer)	0.10	0.12	0.10	0.12
5-year survival rate	0.39	0.44	0.40	0.44
GVA share	0.41	0.59	0.41	0.59
Rel. industry productivity	0.98	1.03	0.97	1.02
Rel. productivity of 250+	1.20	1.19	1.06	1.14
Cognitive share	0.31	0.35	0.31	0.35
Manual share	0.40	0.27	0.41	0.28
Interpersonal share	0.28	0.37	0.28	0.37

Table 3: Data and Model Moments in Calibration

in the economy, and the sectors' labour productivity is slightly higher.[9] The sectoral differences in the data we target are reflected in the parameters obtained through the model calibration. Table 2b shows that the two sectors differ in various dimensions: (i) in the production skill intensities $\{\phi_{j,i}\}$ (reflecting skill shares), (ii) overhead labour fixed costs $C_{f,j}$ (higher in professional services where the typical firm is smaller), (iii) entry costs $C_{e,j}$ (lower in professional services where entry is more frequent), (iv) the parameters of the productivity process for incumbents and (v) of entrants (all feed on to relative productivity within and across sectors, survival rates, and employment distribution within a sector), as well as (vi) the consumption intensities (matching sectoral value-added shares).

By giving a realistic firm size distributions, matching cross sectional facts, and replicating the allocation of skills to industries well, the model provides a suitable laboratory to simulate productivity effects induced by aggregate skill supply shifts. Given the sectoral differences we established here, we can expect to see differential responses across the sectors.

[9] Note that the construction of these sectoral shares and relative industry productivity for the calibration is based on an economy from which all other sectors were excluded.

5 Quantitative Results

5.1 The Effects of Variations in the Aggregate Skills Supplies

In this section, we use our quantitative model to analyse the effects of changes in the aggregate supply of skills on (labour) productivity, which we calculate as the real output over the number of employees (including both operations and overhead labour), whether at the firm or sector level. Productivity effects can occur due to adjustments in various margins. When a skill becomes scarcer, the higher wage rate for this skill alters the skills mix at the firm level and at the same time firms' production costs. As a consequence, some firms may decide to exit, others to enter the market, and the number of active firms changes. But there will also be reallocations between incumbent firms and between the industrial sectors. These effects are non-trivial, since in our model calibration industrial sectors differ in skills intensities, fixed costs, and underlying productivity processes. All these endogenous adjustments feed onto the measure of and distribution of active firms, sectoral productivity, and ultimately aggregate labour productivity or GDP per worker.

Exercise	Cognitive	Manual	Interpersonal
Benchmark	0.2011	0.2011	0.1978
-10% shock to cognitive	0.1810	0.2111	0.2079
-10% shock to manual	0.2112	0.1810	0.2079
-10% shock to interpersonal	0.2110	0.2110	0.1781

Table 4: Labour Supply Scenarios

We exogenously reduce the inelastic supply of each skill, one at a time, to examine the productivity consequences of skills shortages. This table shows the labour supply in our benchmark economy and in the three exercises (one for each skill).

Specifically, we conduct exercises in which we reduce the supply of a labour skill, one at a time, by 10% percent and increase the supply of the other types equally, such that the total labour supply remains constant but only the skills composition changes.[10] We consider such skills composition shocks as we want to evaluate consequences of skills shortages amongst the workforce of a given size (and not confound this with

[10]Suppose the supply of cognitive labour is reduced by 10%, which corresponds to an x percentage points decrease in the cognitive share in total labour supply. To keep the total labour supply constant we, then, increase the supply of manual and interpersonal labour by $x/2$ percentage points each.

changes in amount of overall labour available, which in this model with decreasing returns and fixed costs would have effects by itself). In essence, the shocks are to the average worker's shares of cognitive, manual, or interpersonal skills. Table 4 shows the exact numbers for three scenarios.

Such an aggregate skills composition shock naturally alters relative wages across the different skill types in order to restore equilibrium in labour markets. As firms' labour demand and production costs are impacted, the distribution of the mass of active firms changes, both due to reallocations between incumbents and due to effects on firm entry and exit. These changes occur in all sectors. But due to the various layers of structural sectoral differences, which we discussed in the model calibration in section 4, not to the same extent. This implies differential changes in sectoral output prices as well. We report all the effects on equilibrium wages and prices in Appendix Table A3. Here, we focus on the effects on labour productivity.

Sectoral level. We start by reporting the effects on sectoral real labour productivity in Table 5. We compute this as the value-added (or output) of a sector divided by its total employment.[11] Additionally, we report an aggregated real labour productivity index in the last column, which we construct by adding the sectors' value-added under the initial benchmark economy's prices and dividing by the sum of sectors' employments.

	Sectors		**Aggregated**
Exercise	Production	Prof. Services	
Benchmark	1.619	2.960	1
-10% shock to cognitive	1.533	2.826	0.951
-10% shock to manual	1.686	3.038	1.032
-10% shock to interpersonal	1.623	2.988	1.006

Table 5: Sectoral and Aggregated Real Labour Productivity

Real productivity in each sector is calculated as real total output (of incumbent and entrant firms) over total employment (including both operations and overhead labour) in the sector. We calculate aggregate productivity as the sum of real value added of sectors (calculated at benchmark economy prices) over total employment. We normalized the productivity in the benchmark economy to 1.

[11] In terms of model objects, we compute real labour productivity in sector j as

$$\frac{M_j^f \int_s y_j(s)dF_j + M_j^e \int_s y_j(s)dG_j}{\sum_{i\in C,M,I}\left[M_j^f \int_s n_{j,i}(s)dF_j + M_j^f C_{f,j} n_{f,i} + M_j^e \int_s n_{j,i}(s)dG_j\right]}$$

Depending on what skill becomes scarcer, productivity effects can be positive or negative. Recall that the shocks we consider are changes in the aggregate supply shares of the different skills, as we keep the total labour supply constant.

When the aggregate cognitive skill supply share falls, labour productivity in production and in professional service alike declines, both by roughly 5 percent. The aggregate productivity falls by roughly that amount. However, a reduction in the share of manual skills causes an increase in the labour productivity of both sectors, with an increase of about 4.1 percent in production compared to 2.4 percent in professional services. Finally, a change in the interpersonal skill share hardly affects either sector's productivity.

These results directly establish that the skills composition of the economy matters. Our quantitative model suggests that currently, cognitive skills are in shortage, as if the average worker had a higher share of cognitive skills, productivity would increase in all sectors and in the aggregate. In contrast, manual skills are in abundance — reducing their relative supply would boost productivity. The counterfactual simulation of the manual supply shock also highlights that lowering the manual skill share would benefit the production sector more than the professional services.

The above table shows the results on each sectors' real labour productivity (measured in the sector's own units of output). For cross-sector comparisons, we also construct revenue productivities and compute their ratios to the aggregate economy (spanning the model's two sectors). Appendix Table A5 reports these results. The productivity changes in this table reflect reflect changes in not only in real productivity but also in relative sectoral prices.

In the following we disentangle the productivity effects within each sector to establish how they arise. The overall sectoral effect stems from within-firm changes, changing firm sizes (reallocations between incumbents), entry and exit.

Decomposing sectoral productivity. We first use an Olley and Pakes (1996) style decomposition of a sector's aggregate labour productivity into an (unweighted) average of productivity at the firm level and the covariance between the firms' employment share and their productivity.

$$Productivity_j = \overline{Productivity_j} + \sum_{k \in j} (\omega_{kj} - \overline{\omega_j}) \left(Productivity_{kj} - \overline{Productivity_j}\right) \quad (11)$$

where the weights ω_{kj} are the shares of firm k in total employment (across all skills) in sector j. $\overline{Productivity_j}$ denotes the mean productivity across all firms in the sector and $\overline{\omega_j}$ is the mean employment share.[12] Comparing across model simulations the simple mean, the first term in (11), captures what happens to mean productivity across firms (when all are given equal weight regardless of their size), whereas the covariance, the second term in the equation, changes when firm sizes change systematically with productivity across firms. This covariance term captures the assignment of employment to firms that vary in their labour productivity. It captures the impact of the joint distribution of firms' size and productivity to aggregated productivity, and it increases if the correlation between firms' employment shares and their labour productivity increases. An increase in the covariance therefore indicates a change in the allocation of labour to the more productive firms (all within a sector).[13]

Table 6 shows the results of this decomposition. We see that variations in supplies impact both components (mean productivity and the covariance term) in qualitatively the same way, whether considering manual or cognitive skills. The effects of cognitive and manual skills reductions on sectoral productivities, as found above, are therefore driven by both within-firm and between-firm changes, all of which go in the same direction. However, there are some quantitative differences. For instance, in the case of cognitive skill shocks, changes in the allocation account for 55 percent of the labour productivity effects in the production sector, but only about 40 percent in professional services. Later we investigate reasons for these differential responses across sectors.

For interpersonal skill supply variations, whose effects are small at the sectoral level, we observe two opposing forces. A reduction in the aggregate share of interpersonal skills increases mean productivity in each sector, but it decreases the covariance

[12]Note, this holds since the sector's aggregate labour productivity $Productivity_j$ can be expressed as the sum of firms' employment shares and their labour productivity as $\sum_{k \in j} \omega_{kj} Productivity_{kj}$.

[13]In this simple decomposition, the covariance captures the productivity contributions of resource allocation amongst all active firms. In the detailed analysis below we isolate the effects of firm exit and re-allocations between incumbent firms.

Exercise	Production	Prof. Services
Benchmark	0.914	1.958
-10% shock to cognitive	0.875	1.877
-10% shock to manual	0.941	2.001
-10% shock to interpersonal	0.926	1.984

(a) Mean Productivity

Exercise	Production	Prof. Services
Benchmark	0.705	1.003
-10% shock to cognitive	0.658	0.949
-10% shock to manual	0.745	1.036
-10% shock to interpersonal	0.697	1.004

(b) Covariance of Productivity and Employment

Table 6: Olley-Pakes Decomposition of Sectoral Labour Productivity: Average vs Allocation Across Firms

This table shows the Olley-Pakes decomposition of sectoral labour productivity according to (11). The first component, top panel, is the (unweighted) mean productivity at the firm level; the second component, bottom panel, is the covariance between firms' employment share and their labour productivity.

term in the production sector, i.e. the extent to which larger firms have higher labour productivity is reduced. Once again, this highlights the importance of distinguishing between skill types and industrial sectors when drawing conclusions about productivity.

Firm level. Since both within- and between-firm margins are important for sectoral outcomes, we now examine the mechanisms at the firm level.

One crucial driver of productivity in the average firm might be the exit threshold s^*, the value of the idiosyncratic Hicks-neutral technology below which firms exit the market. A reduction in this threshold, for instance, implies that more low productivity firms remain in the sector, which, all else equal, suppresses average and aggregated productivity. Table 7 shows how this exit threshold changes in response to skills composition shocks.

Shocks to the skills supplies alter the thresholds in both sectors in the same direction. However, all changes in the exit threshold are relatively small, suggesting that changes to the marginal firm staying or exiting the market play only a minor role.

Exercise	Production	Prof. Services
Benchmark	0.783	2.247
-10% shock to cognitive	0.781	2.238
-10% shock to manual	0.777	2.246
-10% shock to interpersonal	0.795	2.269

Table 7: Exit Threshold

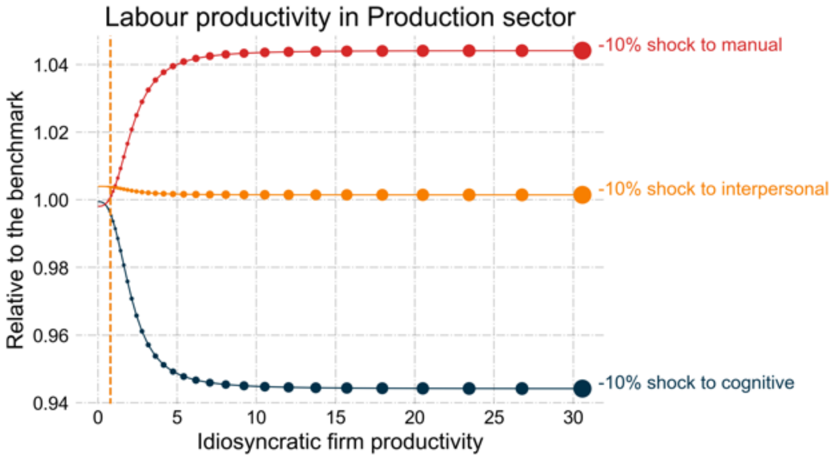
This table shows the idiosyncratic productivity values below which incumbent firms exit the market at the end of the period, for each sector and exercise.

Moreover, comparing with the results of Tables 6a, we see that average productivity does not always change in the same direction as the threshold. This discrepancy points out that changes in the exit threshold are not the main driver of sectoral labour productivity dynamics. In fact, as the impacts on the thresholds are so small, the contributions of the firms leaving the market after a shock are very minor. Nonetheless because there are considerable effects on sectoral productivity, analysing the effects of skills supply variations in a dynamic general equilibrium model of firms is still important.

The fact that the direct effect of firm exits is so small suggests that other channels play a much more significant role. These include the impact on employment within each active firm (via changes in wage rates), alterations in firm entry behaviour (through the value of entry), and shifts in the joint distribution of employment and idiosyncratic productivity among active firms (driven by differential responses of heterogeneous firms).

We now consider the cross-sectional impacts across active firms. We begin with analysing the effects of the skills shocks to the labour productivity distribution across firms. Recall that all within sector heterogeneity between firms is due to realizations in the Hicks-neutral technology term. Figure 3 plots labour productivity as a function of a firm's idiosyncratic technology s_k for each skill supply shock, relative to the corresponding labour productivity in the absence of the shock. Note that the mass of firms across the s_k space is not uniform, but determined by the (endogenous) mass distributions of active firms in each sector. The figure shows in the dashed vertical lines also the exit threshold, which barely changes across the scenarios (as in Table 7).

Figure 4 plots the corresponding behaviour of firm employment as a function of



(a) Production Sector

(b) Professional Services Sector

Figure 3: Labour productivity distribution across firm types

Labour productivity (of incumbent firms) for each idiosyncratic firm technology, s, in different economies relative to the benchmark economy. The dashed vertical lines represent the (sector-specific) idiosyncratic threshold s^* below which firms exit the market. Circle sizes are proportional to the total employment in incumbent firms with the corresponsing idiosyncratic productivity type.

firm technology in each sector.[14] Within a sector, as seen in (5) and (6), firms with higher technology draws are larger in terms of output, total employment, and, as indicated by (4), also in the employment of each skill.[15]

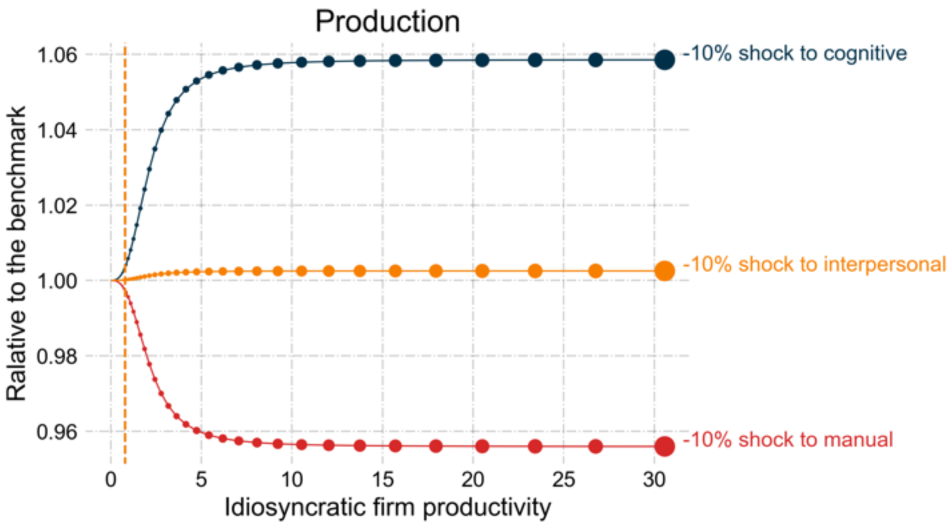
These figures demonstrate that firms' responses vary across idiosyncratic technology realizations, and thus firm size. For instances, reductions in the aggregate supply of manual skills increase labour productivity in all sectors, as we reported in Table 5, but Figure 3 at the firm level shows that this effect is much more pronounced among higher-productivity firms. Conversely, a reduction in the cognitive skill share lowers labour productivity in all sectors and firms, but the impact increases with idiosyncratic firm productivity.

The differential impacts by firm size arise from overhead labour requirements. These imply that part of an incumbent firm's labour cost is fixed, and when shocks occur firms can only adjust parts of the overall employment, the operations labour used in production. Since within a sector, firms differ only in terms of idiosyncratic technology, skill supply shocks have uniform effects on firms' variable operations labour inputs. As the supply of cognitive skills falls, they become more expensive (see Appendix Table A3). The change in relative wages is common to all firms, thereby shifting the skill mix in operations labour, as shown in (4), by an identical amount. This, in turn, alters the ratio of output to operations labour by the same factor for all active firms within a sector. Since cognitive skills are relatively scarce, a reduction in their supply results in a uniform decline in the ratio of output to operations labour across all active firms in a sector (plotted in Appendix Figure A1).

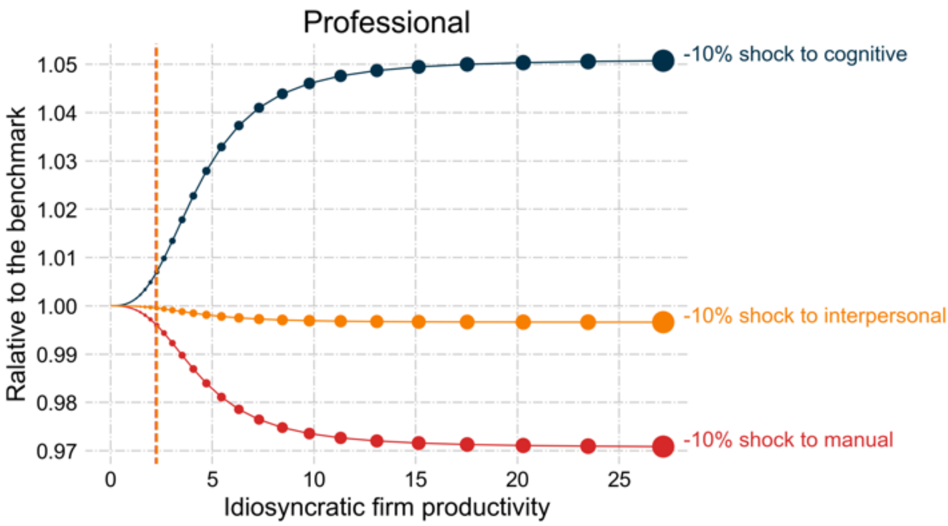
Yet, there is a differential impact on firms' labour productivity, which is the ratio of output to the *overall* numbers of workers, i.e., the *sum of overhead and operations* employment. For very large firms, labour overheads are negligible, and their labour productivity closely tracks the ratio of output per unit of operations labour, which is approximately equal to the ratio of output to overall employment. However, for smal-

[14]Since skills intensities and wages are common to all firms within a sector, a firm's total operations employment share (within the sector) is identical to the operations employment share in each skill.

[15]The idiosyncratic technology differences create heterogeneity in firms' output and employment, with these two outcomes moving together across s_k realizations, as seen in (5) and (6). However, the slope of the output-employment relationship across firms changes with the real unit labour cost w_j/p_j (shown in Appendix Table A3), and thus in response to skill supply shocks, see Appendix Figure A2. The change in the gradient can be understood by comparing (5) and (6), noting that $0 < \theta < 1$.



(a) Employment Distribution - Production



(b) Employment Distribution - Prof. Services

Figure 4: Employment distribution across firm types

Incumbent firm employment for each idiosyncratic firm technology, s, in different economies relative to the benchmark economy. The dashed vertical lines represent the (sector-specific) idiosyncratic threshold s^* below which firms exit the market. Circle sizes are proportional to the total employment in incumbent firms with the corresponsing idiosyncratic productivity type.

ler firms labour productivity is less tightly linked to output per operations worker. In very small firms, where almost all employment is in overheads, there is a larger disconnect between changes in operations labour (which directly affects output) and overall employment. Changes in operations labour affect both the numerator and the denominator of the output-to-overall-employment and of the output-to-operations-employment ratios. However, in smaller firms the former ratio, which is the labour productivity of the firm, moves much less. Consequently, the overhead labour requirements imply that a contraction in the supply of cognitive skills results in a greater reduction in labour productivity for large firms than for small firms.

Looking more carefully at Figure 3, we see one difference between the impact of shocks to manual and interpersonal skills on the distribution across firms. Throughout the effects are positive for active firms (with $s > s^*$). But while typically the shocks impact larger firms' labour productivity more strongly, a reduction in the interpersonal skill share has relatively stronger impact on small firms, but only in the production sector. Recall that for large firms' labour overheads are negligible, therefore productivity dynamics are mainly driven by changes in operations labour. Moreover, a reduction in the interpersonal skill supply increases the output of each firm. After the reduction in the interpersonal skill supply, operations labour for each firm in the professional sector falls by approximately 0.3%, which results in a larger productivity increase in large firms. The pattern is different in the production sector; here a reduction in the supply of the interpersonal skills leads to an increase in operations employment in all firms. Consequently the productivity of large firms in the production sector goes up at a lower rate than the productivity of smaller firms.

It is important to bear in mind that these graphs represent the distribution of firms by type, where firms are classified according to their technology draw. The mass of firms in each type is shaped by the exogenous productivity processes and the endogenous entry and exit dynamics that result in the stationary distributions of active firms. By applying the distribution of incumbents F_j and entrants G_j, we get the cross-sectional distributions of outcomes. Figure 5 shows the shares of firms grouped by employment bracket.

The differential behaviour of firms by size also has implications for their labour

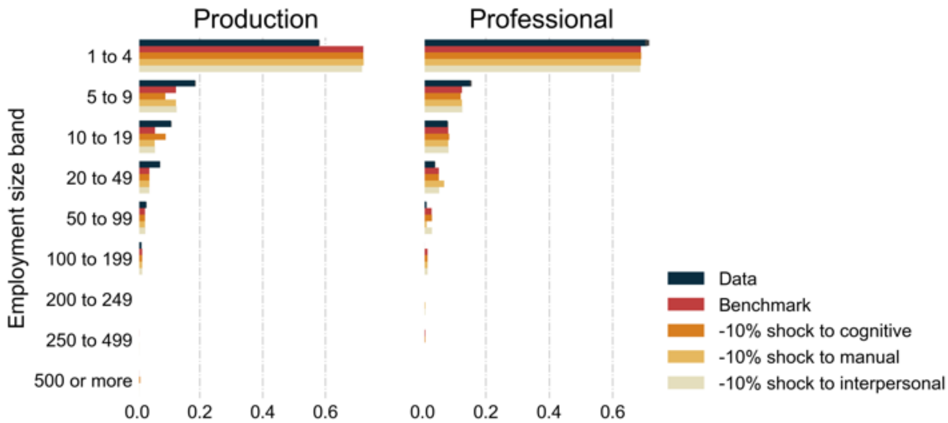
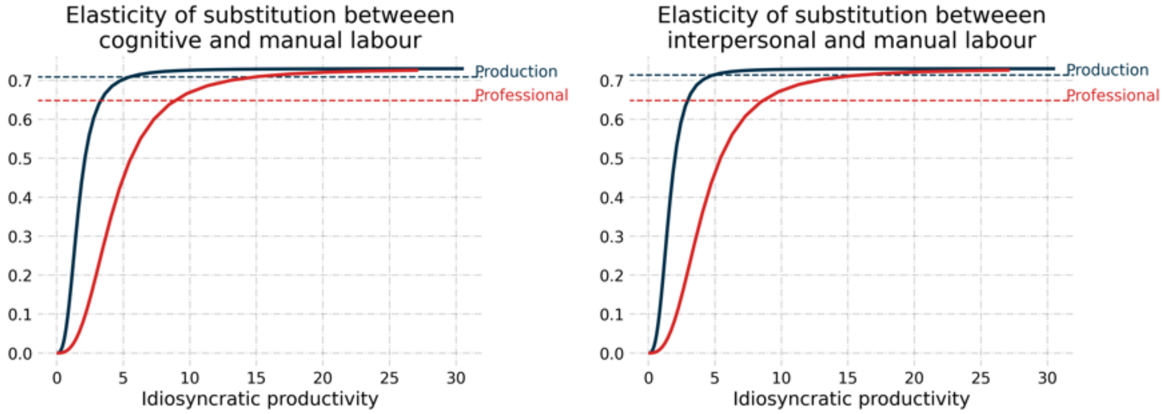


Figure 5: Business Share by Employment Size Band

Each bar shows the measure of firms (both incumbent and entrant) with the number of employees in that band relative to the total measure in the sector. The data bars are calculated using Business Population Estimates dataset. Since employment in the data is discrete, but continuous in the model, firms with employment between two consecutive labels are counted in the first label. For example, the 1 to 4 band contains firms with employment in the range $[1, 5)$.

demand responses. Figure 4 already revealed that skill supply shocks affect the distribution of employment across firms within a sector. For instance, a reduction in the cognitive skill supply shifts employment towards larger firms. In large firms, which are those with a high idiosyncratic technology s, overhead labour is only a small portion of overall employment. As a result, their labour demand for the various skills is highly responsive to changes in relative wages, with an elasticity of relative skill demand that approaches the structural parameter σ that represents the elasticity of substitution in *operations labour* (2). In contrast, for firms with a low technology draws, labour demand is much less elastic. These firms are smaller and a large share of their employment is tied to overhead labour, which cannot be substituted. For these firms, the elasticity of substitution between skills in *total labour demand* is much smaller than σ.

In Figure 6, we plot the derived substitution elasticities across skill types, computed from our quantitative model, against the firms' idiosyncratic technology. In both sectors, the derived firm-level relative labour demand elasticity increases monotonically, ranging from 0 to 0.73. The lowest value applies to firms that are so small (due to low s) that –if they are operating– they virtually hire only overhead labour. The upper limit to which the derived elasticity converges is 0.73, which is the value of the structural elasticity of substitution σ for operations labour in (2). This is the elasticity



(a) Cognitive vs Manual

(b) Interpersonal vs Manual

Figure 6: Derived Elasticities of Substitution

Notes: Solid lines show the firm-level elasticity of substitution for incumbents; dashed lines show the implied industry-wide average.

for firms that are so large that overhead labour accounts for a negligibly small share of total employment. For any given value of idiosyncratic technology, the elasticity is lower in professional services, the sector with the higher overhead labour requirement (see Table 2b for $C_{f,j}$). This is one of the key factors driving cross-sector differences in the response to shocks in the skills composition.

Reallocations between firms. The differential responses across firms of different sizes imply reallocations between firms. Some of the aggregate skill composition shocks induce reallocations of employment to larger firms, while other shocks shift employment to smaller firms. These reallocations are manifested in the covariance component of the Olley-Pakes decomposition, shown in Table 6b. Consider, for instance, variation in the aggregate share of cognitive skills in labour supply. As established earlier, cognitive skills are relatively scarce, so a reduction in their supply lowers labour productivity in all sectors and firms. While operations labour within a sector is equally affected, the impact on total employment varies across firms due to the overhead labour requirements. Figures 3 and 4 show that firms with higher idiosyncratic technology are getting larger, yet they are getting less productive. In the new equilibrium labour productivity in larger firms is decreased by more than in smaller firms. As a result, the covariance between firms' overall employment and labour productivity declines. The cross-firm results in Figures 3 and 4 therefore illustrate how the changes in the allocation component of the Olley-Pakes decomposition, shown in Table 6 occur.

Taking stock. Shocks to the aggregate skills composition systematically alter labour productivity across all sectors. A reduction in the relative supply of cognitive skills lowers labour productivity in all sectors and firms. This result suggests that cognitive skills are relatively scarce, while manual skills are abundant, and interpersonal skills are moderately so.

When we analyse the impact of a reduction in the share of cognitive skills in detail, we see that there are several channels through which productivity is adversely affected. It leads to a uniform decline in the ratio of output to operations labour across all active firms in a sector (see Figure A1). This occurs because the shock tilts the skills mix in (variable) operations labour away from the now relatively more expensive cognitive skill, by a factor that is identical to all firms in a sector.

However, due to fixed overhead labour requirements the overall effects on firms vary by firm size, which itself is monotonically increasing in idiosyncratic productivity. Consequently the size distribution of firms in equilibrium changes: more employment is allocated to larger firms but whose labour productivity is reduced. This reallocation has a further negative effect on sectoral productivity. Changes in the exit thresholds, however, are rather small, indicating only a minor direct effect from firm exits. In contrast, shocks to manual skills lead to the opposite pattern.[16]

Our quantitative model further highlights that, in general equilibrium, a reduction of the cognitive skill supply has a twofold negative impact on labour productivity: (i) by reducing average firm-level productivity, and (ii) by altering the within-sector firm distribution – specifically, increasing the relative size of large firms, which, however, become less productive.

There are sectoral differences, however. For example, interpersonal skill shortages affect the allocation of labour to heterogeneous firms differently across sectors. Another difference lies in the relative contributions of changing allocations versus within-firm productivity changes. While in the production sector changes in the allocation of

[16] By and large, the effects of interpersonal skills shocks mimic those of manual skills, though some impacts are minimal and, in a few instances, with the opposite sign.

resources across firms account for 55 percent of the labour productivity effects, this contribution is only 40 percent in professional services.

5.2 Understanding the causes of differential effects by skill

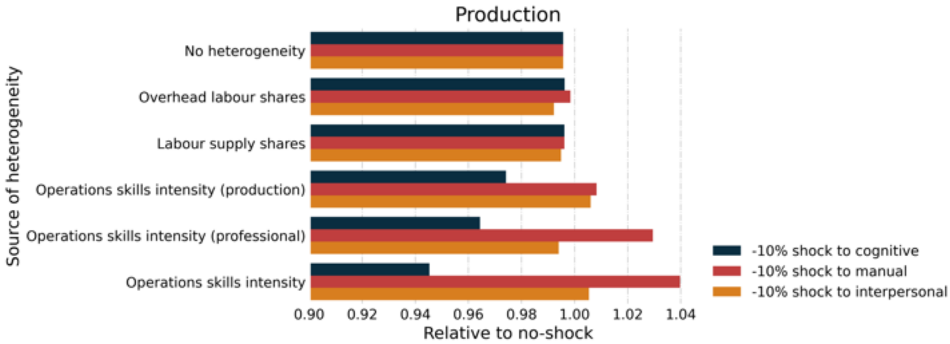
To better understand the sectoral differences and pinpoint the sources of the differential effects by skill, we now remove from the model structure all heterogeneity in skills, including how they are used in the various sectors.

Departing from our baseline calibration (Table 2b), we impose (i) homogeneous operations skills intensities across the three skills i and all sectors j by setting $\phi_{i,j} = 1/3$, (ii) identical skill intensities in overhead labour $n_{f,i} = 1/3$, and (iii) identical aggregate skills supply $N_i = 0.2$. This results in perfectly symmetric skills. The economy's sectors still differ due to variations in the idiosyncratic productivity processes for incumbent and entering firms, but these differences are 'skill-neutral,' as they only influence the firm size distribution and not the skill composition of employment. We then re-introduce skill heterogeneity, adding one feature at a time.

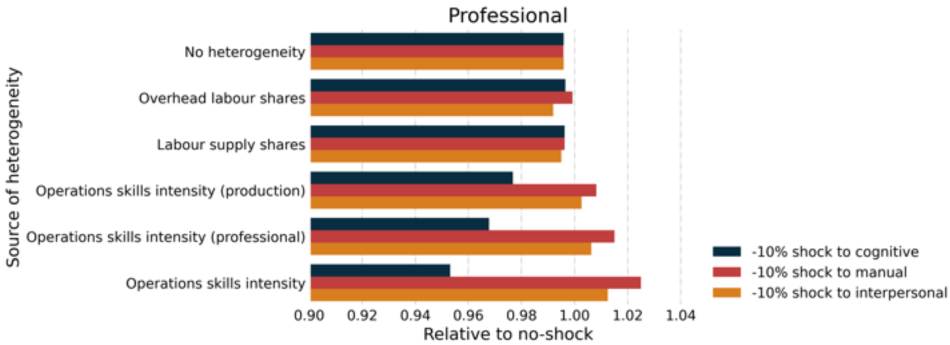
Figure 7 shows the results from this exercise.[17] By far, most of the differences across skills shocks originate from sectoral differences in operations skills intensities. The effect of toggling this element of heterogeneity dwarfs all other sources. Differences in skills intensities in overhead labour or in the aggregate skills supplies (by themselves) have only modest impacts on the economy's response to shocks to the skills composition. In contrast, heterogeneity in operations skills intensities across skills and sectors, (the last set of bars in Figure 7) accounts for nearly all of the benchmark model's response to a shock in cognitive skills. When we remove the differences in operations skills intensities from just one sector at a time (the two penultimate sets of bars), the responsiveness to skill supply shocks decreases, but remains substantial.

This result seems intuitive, as all firms compete for the same pool of skills for operations labour, not just those within a single sector. If a skill, such as cognitive skills, is already relatively scarce due to discrepancies between firms' skill intensities and the aggregate skill supply composition, a further reduction in its supply only exacerbates

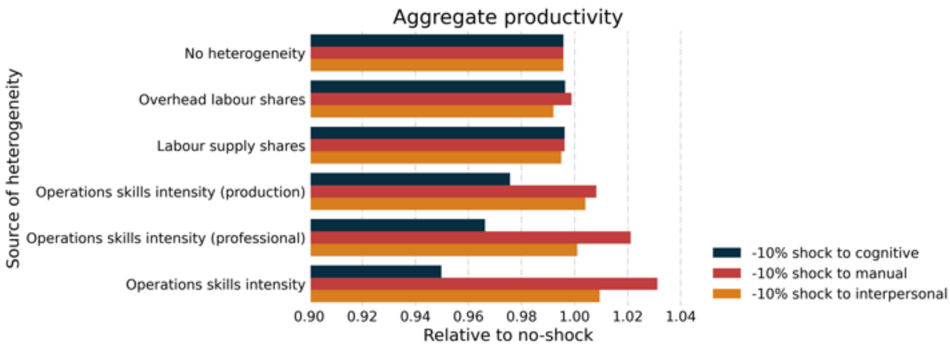
[17] Alternatively, the results can be reorganized by skill shocks, as shown in Appendix Figure A3.



(a) Production Sector Labour Productivity



(b) Professional Services Labour Productivity



(c) Aggregated Labour Productivity

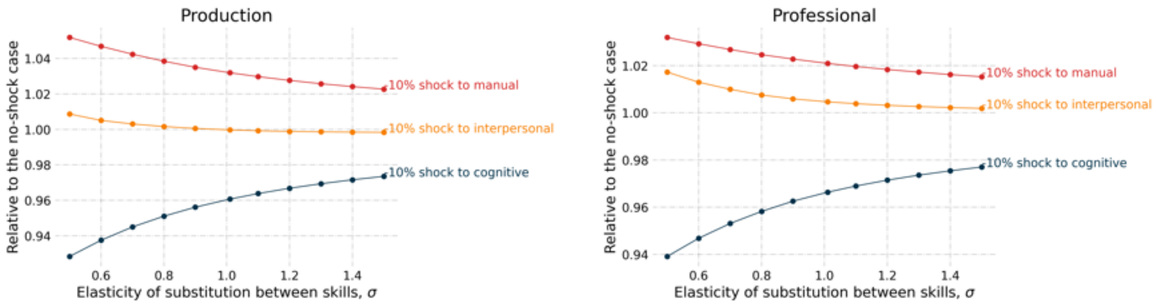
Figure 7: Effect Heterogeneity by Source

In these exercises we begin by removing all skills heterogeneity from the model and introduce one type of heterogeneity at a time. For each type of heterogeneity we conduct three exercises where we shock the supply of each skill, one at a time. We then calculate the sectoral and aggregate productivity in each exercise relative to the corresponding productivity in the 'no-shock' case. Note that the 'no-shock' case is not the benchmark economy but it refers to the economy with the corresponding heterogeneity but no skill supply shock. In the last three experiments, we vary the 'operations skills intensity', first only in the production sector '(production)', then only in professional services '(professional)', and finally in both sectors.

that scarcity. As a result, labour productivity declines, regardless of whether the original scarcity was driven by the skill intensities in one sector or the other. However, the results also show that when heterogeneity in operations skills intensities exists across sectors, the impact on labour productivity is more pronounced.

5.3 Sensitivity and Robustness

Here we briefly show that our results are robust across some of the parameters we fixed outside the calibration.



(a) Production Sector

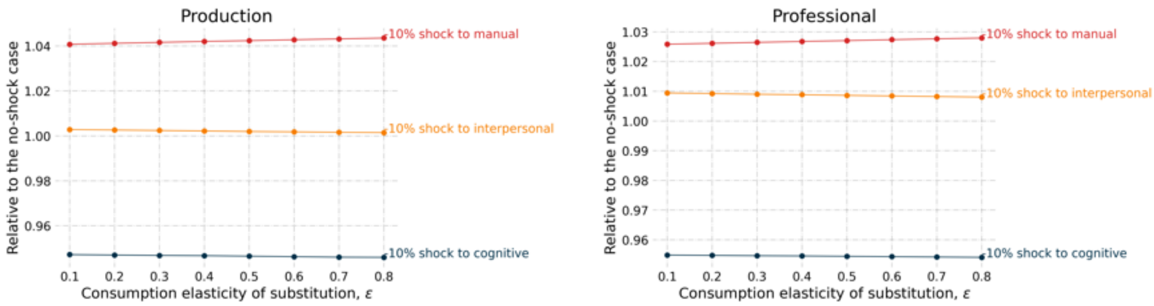
(b) Professional Services

Figure 8: Comparative Statics: Role of σ for Sectoral Labour Productivity

This graph shows labour productivity for alternative values of the elasticity of substitution between skills in production, σ. The benchmark parametrisation is $\sigma = 0.73$.

Figure 8 shows how the model's response to skills shocks varies with the elasticity of substitution between skills in operations labour. Our baseline value is $\theta = 0.73$, based on Adachi (2025). This is a plausible value for the firm level elasticity where we expect the various skills to be complements, so $\theta < 1$. Nonetheless, we also consider much higher values including the range where the three skills are substitutes (as often found at the macro-level). We can see that higher values somewhat mute the responsiveness of labour productivity to skill shocks, but they do not change fundamentally, not even when skills become substitutes (i.e., $\theta > 1$).

In Figure 9 we plot how the effects of the skills supply shocks depend on the elasticity of substitution between sectoral consumption goods, ε. We see this value plays almost no role for the quantitative results.



(a) Production Sector (b) Professional Services

Figure 9: Comparative Statics: Role of ε for Sectoral Labour Productivity

This graph shows labour productivity for alternative values of the elasticity of substitution between sectoral consumption goods, ε, on the horizontal axis. The benchmark parametrisation is $\varepsilon = 0.2$.

6 Conclusions

Our findings underscore the importance of accounting for the multi-dimensional nature of skills shortages. Our model-based analysis suggests that, in the current UK economy, a shortfall in cognitive skills is holding back labour productivity. That is, cognitive skills are relatively scarce, whereas manual skills are in abundance, and interpersonal skills moderately so.

One implication is that aggregate metrics on worker skills may be misleading in debates about overall productivity. Identifying bottlenecks requires measuring skills along multiple dimensions. Our analysis points to cognitive skills as the critical constraint. Similarly, aggregate productivity measures may obscure substantial heterogeneity in how firms and sectors are affected by skill shortages.

Indeed, we find that incorporating sectors in the analysis is important, as sectoral variation in operations skills intensities amplifies the impact of cognitive skill shortages, not only in the aggregate but across all sectors.

Furthermore, our general equilibrium model with firm dynamics reveals that a shortage of cognitive skills depresses labour productivity in two ways: (i) by reducing average firm-level productivity, as the operational skill mix shifts away from the scarce cognitive skill, and (ii) by distorting the within-sector firm size distribution, whereby larger firms grow in relative size but become less productive.

To our knowledge, this second channel has not been emphasised in the existing literature and emerges directly from the model we develop in this paper. It underscores the importance of incorporating firm dynamics into the analysis of skill shortages. Therefore skills shortages may play an even larger role in limiting aggregate productivity than previously recognised.

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Appendix

A Data

Industry Code/Label	Industry Group
A Agriculture, forestry and fishing	Production
B Mining and quarrying	Production
C Manufacturing	Production
D Electricity, gas, air cond supply	Production
E Water supply, sewerage, waste	Production
J Information and communication	Professional services, technology and media
L Real estate activities	Professional services, technology and media
M Prof, scientific, technical activ.	Professional services, technology and media
F Construction	Construction
G Wholesale, retail, repair of vehicles	Trade, transportation and hospitality
H Transport and storage	Trade, transportation and hospitality
I Accommodation and food services	Trade, transportation and hospitality
K Financial and insurance activities	Finance
N Admin and support services	Other Services
O Public admin and defence	Government, education and healthcare
P Education	Government, education and healthcare
Q Health and social work	Government, education and healthcare
R Arts, entertainment and recreation	Other Services
S Other service activities	Other Services

Table A1: Mapping of Industry Labels to Industry Groups

Dataset	Sample Period
Business Population Estimates for the United Kingdom (BPE)	2013-2023
Business demography, quarterly, UK Statistical Bulletins	2017-2022
Business demography, annual, UK, all firms	2009-2022
Business demography, annual, UK, employer firms	2014, 2020, 2022
UK National Accounts, The Blue Book	1990-2021
Annual Business Survey (ABS)	2000-2021
Annual Population Survey (APS)	2011-2020

Table A2: Sample periods of the datasets in the calibration

B Derivations

Firms' optimization We can break down an incumbent firm's problem into a static and dynamic part. In the following we focus on an individual firm and therefore drop firm (k) and sector (j) indices. Future value are denoted by a prime ($'$).

In the static part, firms minimize variable costs. This entails choosing the amount of each skilled labour input for a given composite labour L as described by (2):

$$\min \sum_i w_i n_i \text{ s.t. } L = \left(\sum_i \phi_{j,i}^{1/\sigma} n_i^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}, \text{ where } i \in \{C, M, I\}.$$

Denoting the Lagrange multiplier by λ, the first order conditions require

$$w_i = \lambda L^{1/\sigma} \phi_{j,i}^{1/\sigma} n_i^{-1/\sigma} \text{ for } i \in \{C, M, I\}.$$

or after rearranging

$$n_i = \lambda^\sigma L \phi_{j,i} w_i^{-\sigma} \text{ for } i \in \{C, M, I\}.$$

Substituting this into (2) solves for the Lagrange multiplier, which due to the properties of the cost minimization problem, equal to the unit cost of composite labour w

$$w_j \equiv \lambda = \left(\sum_i \phi_{j,i} w_i^{1-\sigma} \right)^{1/(1-\sigma)}. \tag{12}$$

This composite labour unit cost index w is such that

$$\sum_i n_i w_i = w_j L. \tag{13}$$

A firms' optimal variable demand for each skill i satisfies

$$n_i = \phi_{j,i} \left(\frac{w}{w_i} \right)^\sigma L \text{ for } i \in \{C, M, I\}. \tag{14}$$

The skill shares in the labour mix of a firm therefore reflects relative wages for each skill (w_i) and skill intensities ($\phi_{j,i}$), which vary across sectors (j).

The second part to the static optimization by firms is to choose the labour composite L, pinning down the firm's overall size in terms of employment. Note, in our model this is not a dynamic decision making problem, as L is not a state variable (in the absence of any labour adjustment costs) — profits in the subsequent period, and thus the continuation value in the value function, do not depend on its current value. The optimal amount of composite labour L is therefore the one that maximise flow profits in each period. Given (13), it solves $\max_L p_j s L^\theta - C_{f,j} \sum_i w_i n_{f,i} - w_j L$, requiring

$$L = \left(\frac{p_j s \theta}{w_j} \right)^{\frac{1}{1-\theta}}, \tag{15}$$

in turn this implies for firm output (1)

$$y = s^{\frac{\theta}{1-\theta}} \left(\frac{p_j \theta}{w_j} \right)^{\frac{\theta}{1-\theta}}. \tag{16}$$

Since within a sector, only s varies across firms, and $0 < \theta < 1$, firms with higher technology draws have in equilibrium larger employment and value-added shares compared to others in their sectors.

The dynamic part in the firm optimization problem stems from deciding whether to exit the market at the end of the period, before next period's productivity has been realized. This dynamic problem can be represented by the following value function

$$v(s, p_j, w_j, \{w_i\}) = \max_L p_j s L^\theta - C_{f,j} \sum_i w_i n_{f,i} - w_j L + \beta \max\{0, E_s v(s', p'_j, w'_j, \{w'_i\})\},$$

where w_j is the unit cost of labour in industry j (as defined in (13)), p_j the price of the homogenous good in sector j, w_i is the wage rate for skill type i, and $n_{f,i}$ is the share of skill type i in overhead labour. If a firm decides to exit the market, it receives a scrap value of 0, if it decides to stay the continuation value $E_s v(s', p'_, w'_j, \{w'_i\} j)$ where the expectation is conditional on the current productivity s. Under the $AR(1)$ process for firm productivity (3), $E_s v(s', p'_j, w'_j, \{w'_i\})$ is an increasing function in s, that is the expected future value of the firm increases in current productivity. Because of the fixed overhead labour costs $C_{f,j} \sum_i w_i n_{f,i}$, flow profits are negative for firms that are relatively small. Given the results of the static optimization, small firms making flosses are those with low s. Therefore, $E_s v(s', p'_j, w'_j, \{w'_i\})$ is not only monotonically increasing in s, but also negative for small s and positive only for sufficiently high s. Firms with productivity $s < s^*$ exit the market where the critical productivity is such that $E_{s^*} v(s') = 0$ leave, while firms with $s \geq s^*$ stay.

C Additional Results

Exercise	Cognitive	Manual	Interpersonal
Benchmark	1	0.171	0.415
-10% shock to cognitive	1	0.136	0.327
-10% shock to manual	1	0.215	0.414
-10% shock to interpersonal	1	0.171	0.527

(a) Wages

Exercise	Production	Prof. Services
Benchmark	0.449	0.257
-10% shock to cognitive	0.412	0.236
-10% shock to manual	0.464	0.262
-10% shock to interpersonal	0.476	0.275

(b) Sectoral Output Prices

Exercise	Production	Prof. Services
Benchmark	0.596	0.647
-10% shock to cognitive	0.547	0.596
-10% shock to manual	0.616	0.66
-10% shock to interpersonal	0.630	0.69

(c) Sectoral Unit Labour Cost (w_j)

Exercise	Production	Prof. Services
Benchmark	1.326	2.519
-10% shock to cognitive	1.326	2.522
-10% shock to manual	1.327	2.519
-10% shock to interpersonal	1.356	2.636

(d) Real Sectoral Unit Labour Cost (w_j/p_j)

Table A3: Wages and Prices in the Counterfactuals

Note, $w_c = 1$ by normalization.

Exercise	Production	Prof. Services
Benchmark	0.255	0.345
-10% shock to cognitive	0.256	0.344
-10% shock to manual	0.252	0.348
-10% shock to interpersonal	0.256	0.344

(a) Overall Employment

	Production Employment		Overhead Employment	
Exercise	Production	Prof. Services	Production	Prof. Services
Benchmark	0.241	0.302	0.014	0.043
-10% shock to cognitive	0.243	0.303	0.013	0.041
-10% shock to manual	0.238	0.303	0.015	0.045
-10% shock to interpersonal	0.242	0.301	0.014	0.043

(b) Production vs Overhead Employment

Table A4: Sectoral Employment

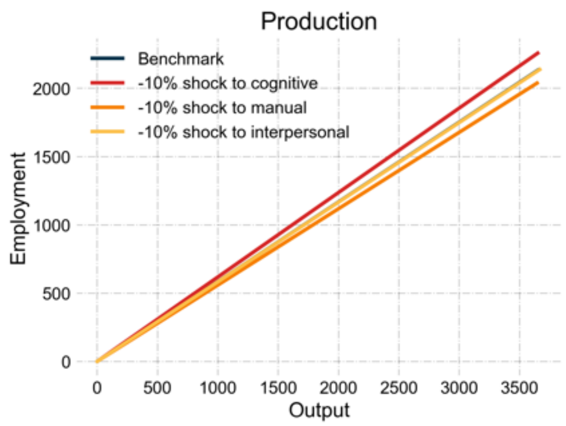
Exercise	Production	Prof. Services
Benchmark	0.975	1.019
-10% shock to cognitive	0.969	1.023
-10% shock to manual	0.991	1.007
-10% shock to interpersonal	0.965	1.026

Revenue productivity in industry j over the revenue productivity in the economy.

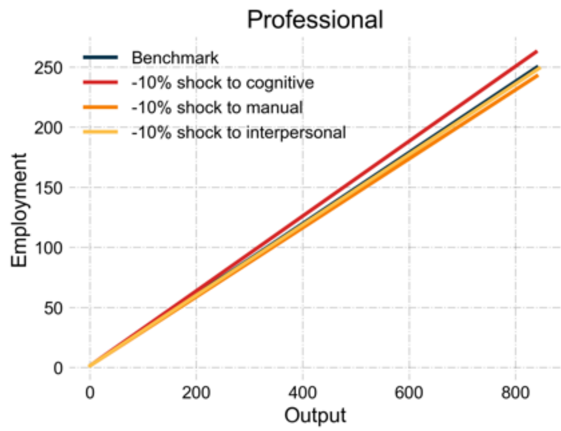
Table A5: Relative Sectoral Revenue Productivity

Exercise	Production	Prof. Services
Benchmark	20.875	11.149
-10% shock to cognitive	22.004	11.618
-10% shock to manual	19.926	10.861
-10% shock to interpersonal	21.235	11.183

Table A6: Mean Firm Employment

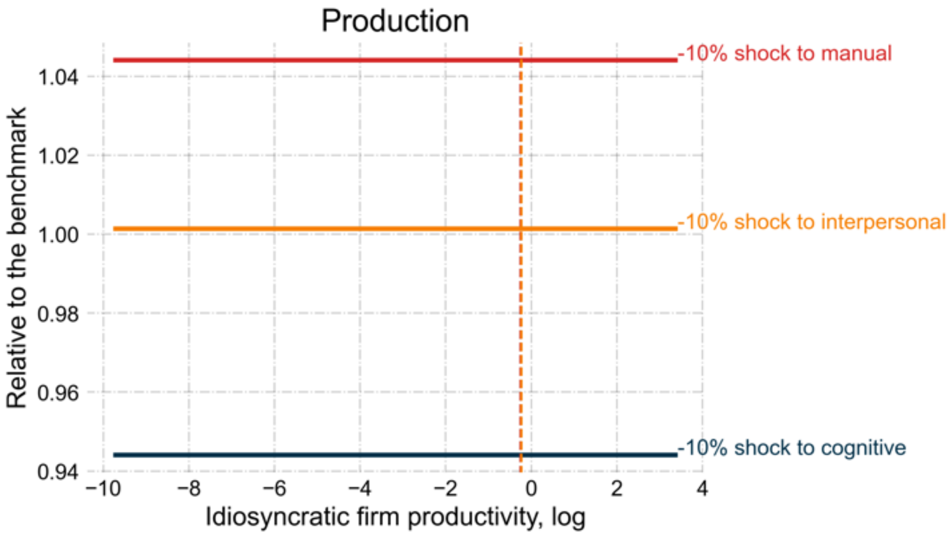


(a) Production Sector

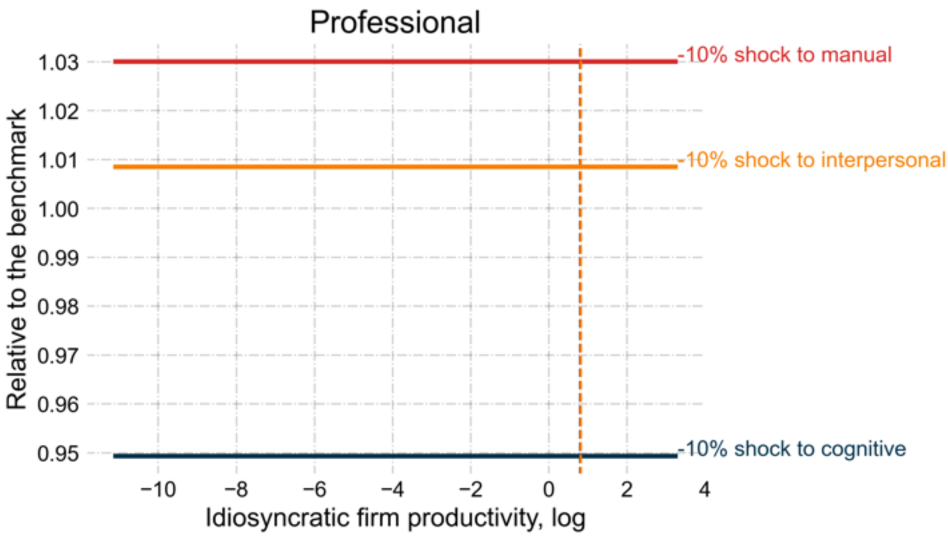


(b) Prof. Services

Figure A2: Employment-Output Distribution across Firms



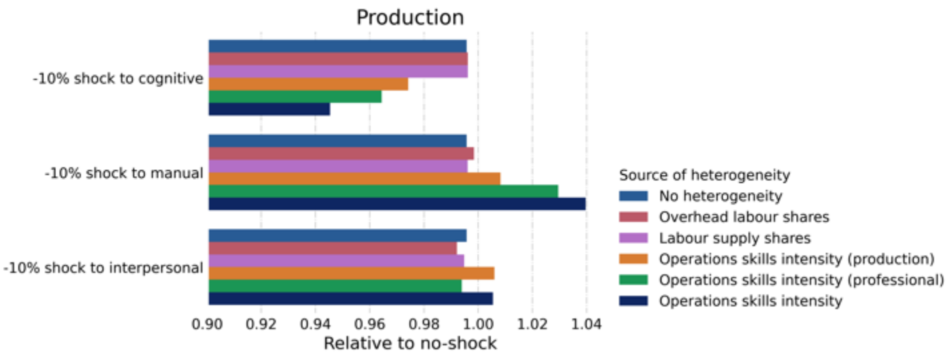
(a) Production Sector



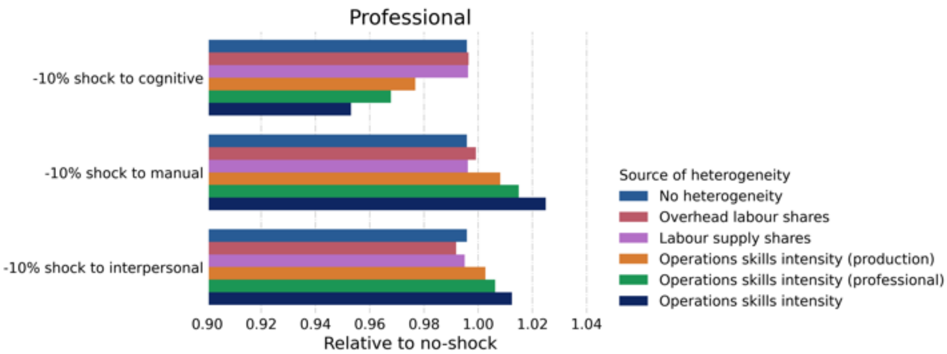
(b) Professional Services Sector

Figure A1: Output per unit of production labour: distribution across firm types

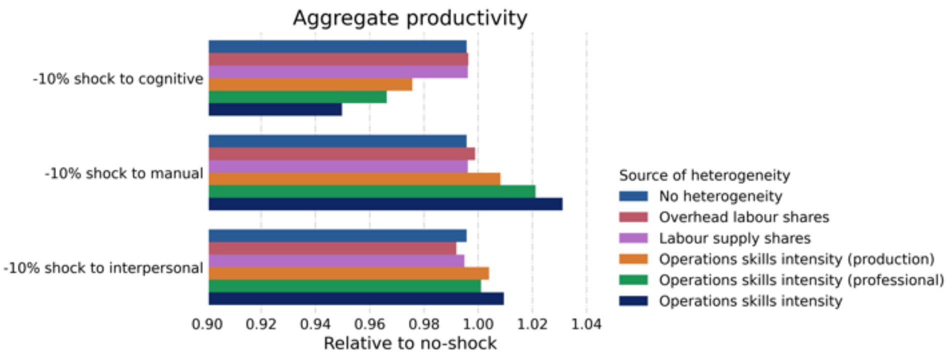
Output per unit of production labour (as opposed to labour productivity defined as output per unit of overall labour, the sum of production and overhead labour) for each idiosyncratic firm technology, s, in different economies relative to the benchmark economy. The dashed vertical lines represent the (sector-specific) idiosyncratic threshold s^* below which firms exit the market.



(a) Production Sector Labour Productivity



(b) Professional Services Labour Productivity



(c) Aggregated Labour Productivity

Figure A3: Effect Heterogeneity by Skills Shock

D Skills grouping

Below are our manually constructed groupings of the skills found in ONS Employer Skills Survey.

Table A7: Employee Skills - Part 1 of 4

Skill	**ONS Survey Grouping**	**Our Grouping**
Instructing, teaching or training people	Soft / people	Interpersonal
Sales skills	Soft / people	Interpersonal
Customer handling skills	Soft / people	Interpersonal
Persuading or influencing others	Soft / people	Interpersonal
Team working	Soft / people	Interpersonal
Managing or motivating other staff	Soft / people	Interpersonal
Ability to manage own time and prioritise own tasks	Soft / people	Dropped from data
Setting objectives for others and planning human, financial and other resources	Soft / people	Dropped from data
Managing their own feelings, or handling the feelings of others	Soft / people	Dropped from data
Making speeches or presentations	Soft / people	Interpersonal
Interviewing	Soft / people	Interpersonal
Counselling, advising or caring for customers or clients	Soft / people	Interpersonal
Physical strength (for example, to carry, push or pull heavy objects)	Technical / practical	Manual

Table A8: Employee Skills - Part 2 of 4

Skill	**ONS Survey Grouping**	**Our Grouping**
Physical stamina (to work for long periods on physical activities)	Technical / practical	Manual
Skill or accuracy in using hands (for example, to mend, repair, assemble, construct or adjust things)	Technical / practical	Manual
Knowledge of particular products or services	Technical / practical	Cognitive
Specialist knowledge or understanding	Technical / practical	Cognitive
Reading and understanding instructions, guidelines, manuals or reports	Technical / practical	Cognitive
Writing instructions, guidelines, manuals or reports	Technical / practical	Cognitive
Number skills	Technical / practical	Cognitive
Measuring, calculating or estimating	Technical / practical	Cognitive
Spotting problems or faults	Technical / practical	Cognitive
Thinking of solutions to problems	Technical / practical	Cognitive
Analysing complex problems in detail	Technical / practical	Cognitive
Checking things to ensure there are no errors	Technical / practical	Cognitive
Following instructions precisely	Technical / practical	Cognitive

Table A9: Employee Skills - Part 3 of 4

Skill	**ONS Survey Grouping**	**Our Grouping**
Adapting to new equipment or materials	Technical / practical	Cognitive
Using or operating tools or equipment	Technical / practical	Manual
Computer literacy	IT	Cognitive
Using a computer for word processing, email etc	IT	Cognitive
Using computer applications for carrying out specialised tasks	IT	Cognitive
Writing computer software	IT	Cognitive
Designing, building, repairing computer hardware	IT	Cognitive
Building or repairing electronic equipment	Technical / practical	Cognitive
Knowledge of how different materials behave	Technical / practical	Cognitive
Knowledge of production processes	Technical / practical	Cognitive
Technical drawing	Technical / practical	Cognitive
Understanding diagrams, drawings or blueprints	Technical / practical	Cognitive
Artistic or creative skills	Technical / practical	Dropped from data

Table A10: Employee Skills - Part 4 of 4

Skill	ONS Survey Grouping	Our Grouping
Design skills	Technical / practical	Cognitive
Foreign language skills	Technical / practical	Cognitive
Driving or operating vehicles	Technical / practical	Manual
Knowledge of safety issues	Technical / practical	Cognitive
Knowledge of relevant law or regulations	Technical / practical	Cognitive
Keeping records	Technical / practical	Cognitive
Researching facts or information	Technical / practical	Cognitive
Using statistics	Technical / practical	Cognitive
Organising time or activities	Technical / practical	Dropped from data
Being able to work at speed	Technical / practical	Dropped from data
Working accurately under pressure	Technical / practical	Dropped from data
Manual skills	Technical / practical	Manual
Observing, inspecting, detecting	Technical / practical	Cognitive
Knowledge of organisation and planning	Technical / practical	Cognitive
Performing or entertaining	Technical / practical	Dropped from data

Table A11: Applicant Skills - Part 1 of 4

Skill	**ONS Survey Grouping**	**Our Grouping**
Instructing, teaching or training people	Soft / people	Interpersonal
Sales skills	Soft / people	Interpersonal
Customer handling skills	Soft / people	Interpersonal
Persuading or influencing others	Soft / people	Interpersonal
Team working	Soft / people	Interpersonal
Managing or motivating other staff	Soft / people	Interpersonal
Ability to manage own time and prioritise own tasks	Soft / people	Dropped from data
Setting objectives for others and planning human, financial and other resources	Soft / people	Dropped from data
Managing their own feelings, or handling the feelings of others	Soft / people	Dropped from data
Making speeches or presentations	Soft / people	Interpersonal
Interviewing	Soft / people	Interpersonal
Counselling, advising or caring for customers or clients	Soft / people	Interpersonal
Physical strength (for example, to carry, push or pull heavy objects)	Technical / practical	Manual

Table A12: Applicant Skills - Part 2 of 4

Skill	**ONS Survey Grouping**	**Our Grouping**
Physical stamina (to work for long periods on physical activities)	Technical / practical	Manual
Skill or accuracy in using hands (for example, to mend, repair, assemble, construct or adjust things)	Technical / practical	Manual
Knowledge of particular products or services	Technical / practical	Cognitive
Specialist knowledge or understanding	Technical / practical	Cognitive
Reading and understanding instructions, guidelines, manuals or reports	Technical / practical	Cognitive
Writing instructions, guidelines, manuals or reports	Technical / practical	Cognitive
Number skills	Technical / practical	Cognitive
Measuring, calculating or estimating	Technical / practical	Cognitive
Spotting problems or faults	Technical / practical	Cognitive
Thinking of solutions to problems	Technical / practical	Cognitive
Analysing complex problems in detail	Technical / practical	Cognitive
Checking things to ensure there are no errors	Technical / practical	Cognitive
Following instructions precisely	Technical / practical	Cognitive

Table A13: Applicant Skills - Part 3 of 4

Skill	**ONS Survey Grouping**	**Our Grouping**
Adapting to new equipment or materials	Technical / practical	Cognitive
Using or operating tools or equipment	Technical / practical	Manual
Computer literacy	IT	Cognitive
Using a computer for word processing, email etc	IT	Cognitive
Using computer applications for carrying out specialised tasks	IT	Cognitive
Writing computer software	IT	Cognitive
Designing, building, repairing computer hardware	IT	Cognitive
Building or repairing electronic equipment	Technical / practical	Cognitive
Knowledge of how different materials behave	Technical / practical	Cognitive
Knowledge of production processes	Technical / practical	Cognitive
Technical drawing	Technical / practical	Cognitive
Understanding diagrams, drawings or blueprints	Technical / practical	Cognitive
Artistic or creative skills	Technical / practical	Dropped from data

Table A14: Applicant Skills - Part 4 of 4

Skill	**ONS Survey Grouping**	**Our Grouping**
Design skills	Technical / practical	Cognitive
Foreign language skills	Technical / practical	Cognitive
Driving or operating vehicles	Technical / practical	Manual
Knowledge of safety issues	Technical / practical	Cognitive
Knowledge of relevant law or regulations	Technical / practical	Cognitive
Keeping records	Technical / practical	Cognitive
Researching facts or information	Technical / practical	Cognitive
Using statistics	Technical / practical	Cognitive
Organising time or activities	Technical / practical	Dropped from data
Being able to work at speed	Technical / practical	Dropped from data
Working accurately under pressure	Technical / practical	Dropped from data
Manual skills	Technical / practical	Manual
Observing, inspecting, detecting	Technical / practical	Cognitive
Knowledge of organisation and planning	Technical / practical	Cognitive
Performing or entertaining	Technical / practical	Dropped from data