Final report

The Economic Impact of Equal Opportunities in the Digital Economy

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alma economics

Contents

Executive Summary

This report estimates the potential economic gains that could be unlocked if barriers facing under-represented groups, unrelated to skills or productivity, were fully removed within the UK digital economy. To do this, we build and then utilise an economic model that allows us to estimate the impacts of improving the "allocation of talent" – that is, enabling people to work in the jobs in which their potential productivity is highest, rather than being pushed into other jobs by barriers unrelated to productivity.

The UK digital economy is less diverse than the rest of the UK economy across multiple dimensions. The most underrepresented groups among those we examine are women and older workers. The proportion of the female workforce who work in the digital economy is 39% lower than the proportion of the male workforce who do so (7% versus 11%). The proportion of workers aged 50-69 who work in the digital economy is 35% lower than for workers aged under 35 (9% versus 14%).

We estimate that the potential gains to the digital economy from fully addressing the under-representation of women would amount to £16 billion per annum (6% of digital economy Gross Value Added (GVA) based on 2024 GVA estimates). Fully removing the barriers preventing proportionate representation of those aged 50-69 could generate gains of £15 billion per annum (7%). Addressing under-representation of other groups, such as people from lower socioeconomic backgrounds (£5 billion per annum), black ethnic backgrounds (£1 billion per annum), or disabled people (£3 billion per annum), could also yield substantial gains for the digital economy. These gains cannot be summed - this would result in double-counting, since the groups in question are overlapping.

The economy as a whole also benefits through a better allocation of talent across sectors. Fully addressing the under-representation of women in the digital economy could deliver an increase in total GDP of around £4 billion per annum (based on 2024 GDP estimates), while addressing under-representation of those aged 50-69 could deliver a £7 billion per annum. These benefits are smaller than the benefits specifically to the digital economy, since additional workers and output in the digital economy would mean fewer workers and output in other sectors. However, there is still a substantial net benefit for the economy as a whole, arising from the improved match between workers' skills and the sector they are in.

At the individual level, gains per person are also substantial. These gains measure how much better off members of an underrepresented group would be, *on average*, if the barriers that currently limit access to digital jobs were removed. All gains are expressed as a cash-equivalent £ per person per year. The gains can reflect higher pay, but they would also incorporate non-pay factors that people value (working conditions, flexibility, culture, or non-pay benefits). Women in the digital economy could see gains worth around £7k/year on average from reduced barriers, while workers aged 50-69 could gain £15k/year on average. There are **other groups** who could gain significantly on an individual basis, even though, because there are fewer of them, they would not affect the aggregate picture as much. These include black workers (gain of £4k/year) and disabled workers (gain of £6k/year). These figures all include those already working in digital jobs, who are currently doing so despite the barriers, but would benefit once barriers are removed. If we focus just on those workers who would switch into the digital economy as a result of reduced barriers, the gains are also substantial: around £3k per year for women, and £7k per year for those aged 50-69.

Supplementary Information

The modelling results are *not* forecasts of what could happen under any specific policy approach aimed at increasing representation. Instead, they are estimates of the potential scale of the prize: the economic gains that *could* be unlocked in the hypothetical scenario in which barriers to representation – whatever they are – were fully removed. The model is agnostic about whether this scenario is achievable in practice or what it would cost to achieve it. In addition, the model merely infers the magnitude of the barriers, whatever they are, based on the degree of under-representation. It is agnostic about what the barriers to representation are, or what policies might address them. These are crucial questions in their own right and the subject of other research. Finally, the results should be taken as "upper bounds," in that partial but incomplete barrier removal would result in smaller gains (although still gains).

We estimate the potential gains from addressing under-representation using a model of individuals' sectoral choices in the presence of group-specific barriers. The model links the set of people who choose to work in the UK digital economy and the rest of the economy to output in both the digital economy and the economy as a whole. It therefore captures the fact that, when workers are better able to choose roles that suit their skills best – rather than being influenced by other barriers that distort these choices – they are able to be more productive. This raises output and makes them better off as individuals.

Other under-represented groups included in our analysis were disabled workers, those from low socio-economic status, women with dependent children, and black workers. The modelling framework allows for groups to be defined by intersections of characteristics very flexibly, although only certain such analyses were feasible given data availability and sample sizes. In particular, we produced an analysis by seniority level for women and by region for women and disabled workers. Analysis for LGBTQ+ individuals was considered but excluded due to data limitations. Modelling results (i.e., the potential gains from addressing under-representation) cannot be added up across the different groups considered, since they are not mutually exclusive. For example, one cannot add up the gains from addressing under-representation of women and of disabled workers, since these groups overlap.

The modelling requires assumptions about productivity. We generally make the simple and transparent assumption that, in the absence of barriers, the distribution of productivity would be the same across all groups (but that, within any group, different individuals will have different aptitudes for digital sector work and other work). Hence, we ***do not*** in general assume that under-represented groups are more productive, or more productive in the digital economy, than other groups. The exception to this is for analysis by age, given its relationship to experience, which we know can be a fundamental driver of higher productivity. We assume that, in the absence of barriers specific to the digital sector, older workers would have the same productivity advantage over younger workers as the advantage we see they have (based on relative earnings levels) in other parts of the economy.

The modelling accounts for potential displacement effects. As barriers fall and more workers from under-represented groups enter the digital economy, the sector may not expand one-for-one, meaning that other workers may be displaced. The extent to which this may happen is uncertain. It depends on an economic parameter known as the labour demand elasticity – essentially, this determines how easily additional labour is absorbed into the digital sector. We therefore anchor the magnitude of displacement to empirical evidence on the labour demand elasticity, on which there has been much previous work. We also show the sensitivity of results to a plausible range of assumptions about displacement.

We estimate the gains from addressing under-representation at both an aggregate level (i.e., output gains in the digital sector and in the economy as a whole) and per person within the under-represented groups. It is important to consider the gains from both points of view. Aggregated gains are, all else equal, higher when addressing under-representation among larger groups (e.g., women). Smaller groups tend to have smaller impacts on the whole digital sector or economy, but the individual benefits of reduced barriers and hence increased access to the digital sector can still be substantial.

At an aggregate level, we model impacts on output within the digital sector and the economy as a whole. Attracting additional talent to the digital economy would draw workers out of non-digital sectors, reducing output in those sectors. This means that gains to digital economy output will exceed the net gain to the economy as a whole, because the expansion of the digital sector is partly offset by contraction in other sectors. However, the output gained in the digital sector would exceed the output lost in other sectors – in other words, there are still benefits to the economy as a whole, even though these are smaller than the benefits to the digital sector specifically. This is because overall output is highest when people work in the sector where they are most productive, i.e., where jobs best match their skills. Barriers to sectoral choice unrelated to productivity prevent this. Removing barriers means better 'matches' between workers and the jobs in which they work.

1. Introduction

The Department of Science, Technology and Innovation (DSIT) has commissioned Alma Economics to conduct research into the economic costs of under-representation in the digital economy. This research aligns with DSIT's objectives to accelerate innovation, investment, and productivity while ensuring the benefits of technological growth are shared across society. This makes the sector central to the Government's growth mission, as seen in the Industrial Strategy (Department of Business and Trade, 2026).

Despite strong performance, the UK digital economy suffers from persistent under-representation across certain groups. Existing evidence, including the Alison Rose Review of Female Entrepreneurship (2019)[1], Diversity in Tech (2024)[2], and the Lovelace Report (2025)[3], has documented representation gaps and identified some of the barriers preventing greater representation. For instance, the Diversity in Tech (2024) report highlights a high level of attrition among women due to limited opportunities for career progression, poor work-life balance, and an unsupportive workplace culture. The report also points towards under-representation of workers from lower socio-economic backgrounds and disabled people. Across these groups, barriers include conscious and unconscious bias and exclusionary workplace culture, which drive poor retention and limit progression into senior roles.

Beyond restricting opportunities for the groups directly affected, under-representation can be economically harmful for wider society by reducing overall economic output. If workers who are particularly well-suited to working in the digital economy face barriers to entry that exclude them from the sector, aggregate productivity may be negatively affected. A large body of empirical work shows that skill mismatch (understood as the misalignment between what workers are best suited for and what their jobs require) carries significant productivity costs (McGowan & Andrews, 2015[4]; Vandeplas & Thum-Thysen, 2019[5]; Ferreira & Nikolowa, 2015[6]; Coraggio et al., 2025[7]). Another strand of

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[1] Rose, A. (2019). The Alison Rose Review of Female Entrepreneurship. Available at: The Rose Review of Female Entrepreneurship

[2] Tech Talent Charter (2024). Diversity in Tech Report 2024. Available at: Diversity in Tech report 2024

[3] O'Neill, D. Vallely, V. Blake, K. Iovita, I and Le Taillandier, C. (2025). Unlocking £2-3.5 billion: The Value of Keeping Women in Tech. Available at: https://www.oliverwyman.com/content/dam/oliver-wyman/v2/publications/2025/jul/value-keeping-women-in-tech-lovelace-report.pdf

[4] Adalet McGowan, M. and D. Andrews (2015), "Labour Market Mismatch and Labour Productivity: Evidence from PIAAC Data", OECD Economics Department Working Papers, No. 1209, OECD Publishing, Paris, https://doi.org/10.1787/5js1pzx1r2kb-en.

[5] Vandeplas, A. and Thum-Thysen, A. (2019). Skills Mismatch and Productivity in the EU. European Economy Discussion Paper 100. European Commission, Directorate-General for Economic and Financial Affairs. July 2019. doi:10.2765/954687

[6] Ferreira, D. and Nikolowa, R. (2015). Misallocation of Talent in Competitive Labor Markets. Working Paper No. 740. School of Economics and Finance, Queen Mary University of London. February 2015.

[7] Coraggio, L., Pagano, M., Scognamiglio, A. and Tåg, J. (2025). "JAQ of all trades: Job mismatch, firm productivity and managerial quality." Journal of Financial Economics, vol. 164.

literature demonstrates the economic benefits of increased diversity in the workforce for both workers and firm productivity. The OECD (2025) [8], for example, finds that increased female employment shares are associated with higher productivity. These two strands of literature are brought together by Hsieh et al (2019)[9]. They build and estimate an economic model of occupational choice, in which workers choose lines of work that will provide the highest payoffs to them, but where specific groups can face barriers to working in particular occupations. They attribute between 20-40% of growth in aggregate market output per worker in the US over the last 50 years to an improved allocation of talent, as barriers for under-represented groups have reduced - that is, improved productivity as jobs are now increasingly done by the individuals best placed to do them, rather than by people from groups who face lower barriers. In this report, we use a model whose logic is closely related to that of Hsieh et al.

Quantifying the scale of the losses from different dimensions of under-representation is an important part of DSIT's Diversity in Tech agenda and supports the work of the Women in Tech Taskforce, particularly in clarifying how under-representation may constrain growth and productivity in the digital economy. Our results provide an economic framing that complements existing evidence of representation gaps and barriers, and will guide broader policy discussions with industry and other stakeholders around how to secure more inclusive workplaces.

For the purposes of this research, we adopt the digital economy definition developed by DSIT in the Defining and Measuring the Digital Economy Phase 2 report (2025)[10]. The definition encompasses both enterprises primarily engaged in producing digital goods and services, and those that are highly digitally intensive in their operations.

[8] OECD (2025). The Global Forum on Productivity at 10. Available at: The Global Forum on Productivity at 10 (EN)

[9] Hsieh, C. T., Hurst, E., Jones, C. I., & Klenow, P. J. (2019). The allocation of talent and us economic growth. Econometrica, 87(5), 1439-1474.

[10] Department for Science, Innovation and Technology (2025). Defining and measuring the UK digital economy Phase 2: Report. Available at: https://www.gov.uk/government/publications/defining-and-measuring-the-uk-digital-economy/defining-and-measuring-the-uk-digital-economy-phase-2-report#background-and-purpose

2. Economic Modelling of the Cost of Under-representation in the Digital Economy

We use a model that is designed to estimate the economic gains from increased representation within the digital sector. The central concept is one of improved “talent allocation:” that is, people being better able to work in the jobs in which they are most productive, rather than having sectoral choice determined by barriers.

It was beyond the scope of this report to identify the drivers of under-representation in the digital economy or to assess how feasible, or costly, it would be to address these. Rather, we are inferring the magnitude of barriers (whatever they may be) based on the level of under-representation observed in the data. This allows us to estimate the benefits of reducing them, and hence increasing representation.

We model individuals’ sectoral choices in the presence of group-specific barriers. To do this, we use the logic of influential recent work by Hsieh et al. (2019)[11], who took the classic Roy (1951)[12] model of job choice and extended it to allow for group- and sector- (or occupation-) specific barriers. The model assumes that, in the absence of barriers, individuals would sort into the sector where they are most productive. Under this assumption, if all groups have the same underlying productivity potential, we would not expect to observe systematic differences in the distribution of workers across digital versus non-digital roles. Where such differences are observed in the data, the model treats them as evidence of barriers. Note that this would include any differences in preferences across groups, which may drive differences in choices.

We abstract from any debates about whether such fundamental differences in preferences exist, or whether they might themselves result from barriers such as cultural or social norms. This is a particular example of an important general point: if one believes that certain determinants of sector choice (besides productivity) are immutable, infeasible, or too costly to address, then one will treat our estimates as upper bounds on what could be achieved. It is not within the scope of this report to analyse what the barriers are, or how or whether they can be addressed. Other research has, however, studied specific barriers. For instance, the Diversity in Tech (2024)[13] report highlights that, for disabled workers, barriers centre on disclosure challenges and a lack of supportive workplace adjustments, while for older professionals, they manifest primarily as ageist stereotyping, being overlooked for promotion, and exclusion from traditional recruitment pathways.

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[11] Hsieh, C. T., Hurst, E., Jones, C. I., & Klenow, P. J. (2019). The allocation of talent and us economic growth. Econometrica, 87(5), 1439-1474.

[12] Roy, A. D. (1951). Some thoughts on the distribution of earnings. Oxford economic papers, 3(2), 135-146.

[13] Tech Talent Charter (2024). Diversity in Tech Report 2024. Available at: Diversity in Tech report 2024

We use earnings from the Labour Force Survey as a proxy for productivity for groups that face no barriers (e.g., men), and then assume that other groups share the same underlying distribution of productive potential (except where noted, such as for age). Any observed gap in representation between digital and non-digital roles is, therefore, treated as evidence of a barrier unrelated to productivity. The model then estimates how much output could increase in the digital sector and the whole economy if that barrier were removed. In doing so, it accounts for the displacement of existing digital economy workers as more workers move into the sector. As explained further below, we model the extent of displacement in a way that is anchored closely to previous evidence, while explicitly showing the sensitivity of results to a plausible range of displacement assumptions.

In this section, we give a non-technical overview of the model, the key assumptions that it makes, and the evidence we use to inform those assumptions. We use the running example of men and women, but the modelling approach extends straightforwardly to more than two groups, and to groups demarcated in any way, including by intersecting characteristics (e.g., women with children). Readers seeking additional detail should refer to the annex, which contains a full, technical write-up of the modelling approach and assumptions.

Overview of modelling approach

In the model, each person has a potential level of productivity in each sector: the digital and non-digital economy. Productivity levels are estimated using earnings data as a proxy, under the assumption that pay broadly reflects productive contribution. A worker's productivity may differ by sector, meaning their skills are better suited to working in one sector than another. As a result, economic output, both at the sectoral and whole-economy level, depends on how workers are allocated across sectors.

The concept of productivity that is relevant for our purposes is output per worker, rather than output per hour worked, although the latter is a common productivity measure used in other contexts. For example, if a part-time worker in a non-digital sector might, in the absence of barriers, work in the digital sector instead, we need to know how much output they would produce if they worked in the digital sector (not how much they would produce per hour they work). In the context of our model, this essentially means that we use information about the earnings distribution, rather than the hourly wage distribution, to make inferences about the distribution of productivity. Using a measure that implicitly accounts for differences in hours worked is particularly relevant when considering the under-representation of women. Women are more likely than men to work part-time, which can, in itself, limit access to roles in the digital economy. We continue to simply refer to "productivity" for brevity, but we note that this is simply a shorthand for output per worker.

Workers are assumed to work in the sector in which they are best rewarded for their skills. Workers who do not face barriers will work in the sector in which their productivity, and hence earnings potential, is highest. For under-represented groups, however, this is not necessarily the case, because working in the digital economy means having to overcome specific barriers (unrelated to productivity) that reduce the relative payoff from doing so. This barrier could be some form of wage discrimination, or non-wage factors, such as workplace culture, non-monetary job amenities, job flexibility, etc. The model is agnostic about the sources of these barriers. It simply requires that they discourage either entry into, or retention within, the digital economy. If there were no barriers, then we would expect the proportion of each group that chooses the digital sector to be the same as the proportion of the non-barrier-facing group (e.g., men) who make that choice. The size of the representation gap is therefore used to infer the size of the barriers. In the presence of these barriers, some workers will choose to work outside of the digital sector even though productivity considerations alone would have led them to work in the digital sector. This therefore means less output, not only for the digital sector, but also for the whole economy.

Table 1. Key definitions

Description	Source
The Digital Economy encompasses both enterprises primarily engaged in producing digital goods and services, and those that are highly digitally intensive in their operations.	Defining and Measuring the Digital Economy Phase 2 report (2025)[14]
Productivity is defined as output per worker (as opposed to output per hour)	Assumptions about productivity distributions are anchored to the earnings distributions of groups assumed to face no barriers (e.g., men) in the Labour Force Survey.
Elasticity of labour demand is the % reduction in labour demanded when wages rise by 1%. It is the key parameter that governs the extent to which higher labour supplied by one individual or group will displace other workers (and reduce the wages of the remainder).	Assumptions are based on estimates from a meta-study by Lichter et al. (2015)[15].
Correlation of skills across sectors is the extent to which someone's productivity within the digital sector is associated with their productivity in other sectors. A value of 0 means that these productivities are completely independent; a value of 1 means that they move together perfectly.	Assumptions are based on evidence suggesting that skills are highly transferable across contexts, but not perfectly so, supporting moderate to high correlation values.

[14] Department for Science, Innovation and Technology (2025). Defining and measuring the UK digital economy Phase 2: Report. Available at: https://www.gov.uk/government/publications/defining-and-measuring-the-uk-digital-economy/defining-and-measuring-the-uk-digital-economy-phase-2-report#background-and-purpose

[15] Lichter, A., Peichl, A., & Siegloch, S. (2015). The own-wage elasticity of labor demand: A meta-regression analysis. European Economic Review, 80, 94-119.

Key parameters and assumptions

We use a micro-economic model of individuals' choice of sector of work and the resulting economic output within the digital sector and the whole economy. With this model, we can then simulate what would happen if group-specific barriers to working in the digital sector were reduced. The model explicitly sets out the economic assumptions required to answer this question, allowing us to anchor those assumptions to new empirical analysis or to external evidence. The annex sets out precisely how we do this. A high-level, non-technical overview is given below.

Productivity distributions

The model specifies a distribution of productivity across individuals in the digital sector and in non-digital sectors. An individual's productivity in non-digital sectors should be interpreted as their productivity in the non-digital sector to which they are best suited. Digital sector productivity should be interpreted as the individual's productive potential in a world where there are no barriers to participation in, or retention in, the digital sector.

The distribution of productivity in non-digital sectors is based on earnings distributions in those sectors from the Labour Force Survey (LFS). The distribution of productivity in the digital sector is not solely based on the digital sector earnings distribution, since this is only observed among the small minority of workers who have chosen to work in that sector (a selected subset). However, the model allows us to infer the whole distribution of underlying digital sector productivity from a combination of digital sector earnings distributions and employment shares (again from the LFS). The annex gives the precise formula through which this is achieved. These productivity distributions are obtained using data on groups that are not under-represented in the digital sector (e.g., all men in the digital and non-digital economy, respectively) since their choices have not been distorted by barriers and hence are informative about their productivity. We then generally assume that, without any barriers, the productivity distributions of other groups would be the same. Under this assumption, all under-represented workers (e.g., women) in the digital economy under the status quo must have a comparative productivity advantage in the digital sector that is large enough to offset the barrier they face. As explained below, we relax the assumption of equal productivity distributions when we compare individuals of different age groups.

Finally, we require an assumption about the degree of correlation between an individual's productivity in the digital sector and in other sectors. This assumption is informed by empirical evidence on the transferability of skills across lines of work, e.g., Gibbons et al. (2005)[16] and Sullivan (2010)[17]. This evidence suggests that skills are highly correlated across lines of work, though not perfectly transferable. We use a central estimate of 0.75 and run sensitivity analysis from 0.6 to 0.9. A higher correlation implies a

[16] Gibbons, R., Katz, L. F., Lemieux, T., & Parent, D. (2005). Comparative advantage, learning, and sectoral wage determination. Journal of labor economics, 23(4), 681-724.

[17] Sullivan, P. (2010). Empirical evidence on occupation and industry specific human capital. Labour economics, 17(3), 567-580.

closer link between a worker's productivity in the digital and non-digital economy, while a lower correlation implies greater sector-specific specialisation. If skills were perfectly correlated, there would be no aggregate gains from reallocating workers across sectors, as it would not matter in which sector a worker is employed.

Group-specific barriers in the digital economy

Barriers to working in the digital economy vary across under-represented groups. This means that groups can end up with different employment shares within the digital economy, even if their productivity distributions are identical.

The size of the barriers used for this model is based on the share of the workforce in under-represented groups who are employed in the digital economy, as observed in the LFS data. For example, in the case of women, we compute the size of the women's digital economy barrier required to equate the model's prediction of the share of the female workforce who choose to work in the digital economy and the share actually observed in the LFS.

Displacement effects

As barriers fall and more workers from under-represented groups enter the digital economy, the sector may not expand one-for-one, meaning that certain workers may be displaced. The key economic parameter that determines the extent of displacement is the elasticity of labour demand. If labour demand were perfectly elastic, the sector could fully absorb new workers, and there would be no displacement at all. At the other extreme, if labour demand is totally inelastic, firms would employ a fixed number of people irrespective of the wage level. In such a scenario, increased labour supply (e.g., via reduced barriers facing under-represented groups) cannot actually lead to higher employment overall, meaning one-for-one displacement of other workers. The way this would happen is via reduced wages across the sector – this is the only way that labour supply will be brought back down again in line with the fixed level of labour demand. The closer the elasticity is to zero, therefore, the more wages must fall to restore equilibrium, and the greater the displacement of existing workers.

The labour demand elasticity is embedded within our model, and its value is informed by existing evidence. A meta-study of published estimates spanning many years by Lichter et al. (2015)[18] finds an average labour demand elasticity of 0.5. The study shows that this elasticity has been increasing over time and is higher in labour markets that are less regulated, such as the UK's. It is also higher when the elasticity estimated is a "total output" elasticity – i.e., estimating what happens to labour demand when wages change, incorporating the fact that total output can adjust, and that this is part of what affects the level of labour demand. The total output elasticity concept is the relevant one for our purposes. Hence, we use 0.5 as the lower end of the range for our sensitivity analysis. Our central assumption is that the labour demand elasticity is 1 (meaning that a 1% rise

[18] Lichter, A., Peichl, A., & Siegloch, S. (2015). The own-wage elasticity of labor demand: A meta-regression analysis. European Economic Review, 80, 94-119.

in digital sector wages leads to a 1% reduction in labour demand). The upper end of the range for our sensitivity analysis is 1.5.

Multi-group models

For some of the analyses, we require the model to accommodate multiple under-represented groups simultaneously. This applies to underrepresentation by age, where the under-represented groups are those aged 35-49 and 50-69, and the reference group is those aged 16-34, and to the analysis comparing women with and without dependent children to men. In these cases, we calibrate two sets of barriers for each under-represented group and simulate what happens when we reduce both barriers to zero simultaneously.

Simulating the economic impacts of addressing underrepresentation

Once the model's parameters have been specified (see above), the model can be used to directly simulate the effects of reductions in group-specific barriers to working in the digital economy. We simulate a large population of 20,000 individuals, allocated across groups in proportion to their observed population shares, and assign digital economy and non-digital economy productivity levels to each person based on the productivity distribution parameters calibrated using the model and the LFS data (see "Productivity distributions" above). We then identify the sector that each person chooses based on their productivity in each sector and, for barrier-facing groups, the size of the barrier to working in the digital economy. Given how we calibrate the model's parameters, this process will replicate the real proportions of each group that chooses to work in the digital and non-digital sectors according to the LFS. Aggregate output in both the digital economy and the rest of the economy can then be calculated based on the set of workers who choose to work in each sector and their productivity. To model the potential economic impacts of increasing representation, we reduce the barriers to zero, repeat the exercise above, and compare the results.

The model is used to estimate the following economic gains from increasing representation in the digital economy.

Digital economy output

If barriers are removed, and more workers from the under-represented group flow into the digital economy, output in the sector will increase as it now has a larger workforce. The percentage change in digital economy output simulated in our model is multiplied by the digital economy Gross Value Added, which was £286 billion in 2024 (Department for Science, Innovation and Technology, 2025). Where the group analysed only represents a subset of the labour force (for example, the socioeconomic background analysis is performed separately by education level), we scale GVA by the subset's share of total earnings in the sector (e.g., the share of digital sector earnings that are earned by degree holders), based on the LFS.

Economy-wide output

Some of the increased digital sector output will come at the expense of other sectors, since workers who join the sector would otherwise have worked elsewhere. However, the net effect on the overall economy is positive, as reduced barriers lead to better matching of workers to the jobs in which they are most productive. We multiply the change in total output derived from our simulations by the UK GDP in 2024, which was about £2.9 trillion (Office for National Statistics, 2026). Again, we scale GDP by the subgroup's share of total wages in cases where our analysis applies only to a subset of the labour force.

Individual gains per worker

Workers in underrepresented groups also benefit directly from reduced barriers. This gain may arise through higher wages or through non-wage benefits, such as lower levels of discrimination or more suitable working arrangements, depending on what the barriers represent. The model does not differentiate between the sources of these barriers, but it can be used to infer their size (based on the degree of under-representation), and hence the value to workers of reducing them. These benefits apply both to members of the under-represented group who were working in the digital sector despite the barriers – who would now be even better off – and to those who would "switch" into the digital sector as a result of barriers being removed. We differentiate between those two groups of people when reporting our results.

The results can be compared across groups to identify where the cost of under-representation in the digital economy is largest. However, the results cannot be summed across groups due to overlapping inequalities. For example, women will be represented among disabled people and those from lower socio-economic groups.

3. Data and Definitions

The Labour Force Survey

The Labour Force Survey (LFS) is the UK's largest household survey, conducted quarterly by the Office for National Statistics (ONS) since 1992. Its primary purpose is to provide official measures of employment, unemployment, and economic inactivity. Key variables include economic activity status (employed, unemployed, inactive), sector, occupation, various demographic characteristics, qualification levels, and earnings. The LFS is the natural source of broadly representative, large-scale data on the characteristics of the digital sector workforce and the wider workforce.

We used LFS data from 2022 to 2025. We focused on data drawn from the third quarter of each year (some relevant variables – e.g., our socio-economic background measure - are only available in that quarter). The LFS captures both hourly wages and weekly earnings. This research uses weekly earnings, as they reflect both how much someone earns per hour and how many hours they work, giving a better overall measure of contribution to economic output than hourly wages alone. To ensure comparability across years, we adjusted for earnings growth using the Average Weekly Earnings tables published by the Office for National Statistics (ONS). Our analysis was limited to employed workers aged 16 to 69. The analysis does not include self-employed workers.

Defining the digital economy

There is no single definition of the UK digital economy, and we recognise that this is an evolving issue. In this research, we adopted the definition developed by DSIT in their Defining and Measuring the Digital Economy Phase 2 report (2025)[19]. This framework organises digital economic activity into tiers based on Standard Industrial Classification (SIC) codes. Tier 1 covers enterprises primarily involved in the production of digital content and/or ICT goods and services, while Tier 2 captures diversified enterprises that produce such outputs as part of a broader product or service offer, or which exhibit a higher level of digital intensity in their inputs than traditional economy enterprises. We adopted this combined definition encompassing both Tier 1 and Tier 2 because it captures a breadth of meaningful digital economic activity (see Annex B). Restricting analysis to Tier 1 alone would exclude a substantial share of digitally intensive activity. However, we ran a sensitivity analysis of the main results, restricting the definition to include only Tier 1, and the broad conclusions remain unchanged.

[19] Department for Science, Innovation and Technology (2025). Defining and measuring the UK digital economy Phase 2: Report. Available at: https://www.gov.uk/government/publications/defining-and-measuring-the-uk-digital-economy/defining-and-measuring-the-uk-digital-economy-phase-2-report#background-and-purpose

Key variables and group definitions

We used the LFS to assess the representation of a range of demographic and socioeconomic groups in the digital economy. We then selected those for which we found clear empirical evidence of under-representation as the focus of our modelling:

Sex is recorded in the LFS as a binary variable.

Disability is identified based on whether the respondent reports a health condition or disability that limits their daily activities, following the Equality Act 2010 definition.

Ethnicity is captured across nine categories, including an ‘other’ category. Approximately 90% of the working-age population in the sample identifies as white, which limits the sample sizes for smaller ethnic groups.

Dependent children are defined as children under 16, or those between 16 and 18 who are not married and in full-time education. We distinguish between women with and without dependent children.

Socioeconomic background was proxied using a retrospective report of the occupation of the main wage earner in the respondent's household when the respondent was aged 14, distinguishing between higher managerial and professional occupations and all others.

Age was used to differentiate three groups: 16-34, 35-49, and 50-69.

Seniority was proxied by distinguishing between employment in higher managerial and professional occupations and all other occupations. Hence, this focuses not on age but on a proxy for the seniority of one’s position.

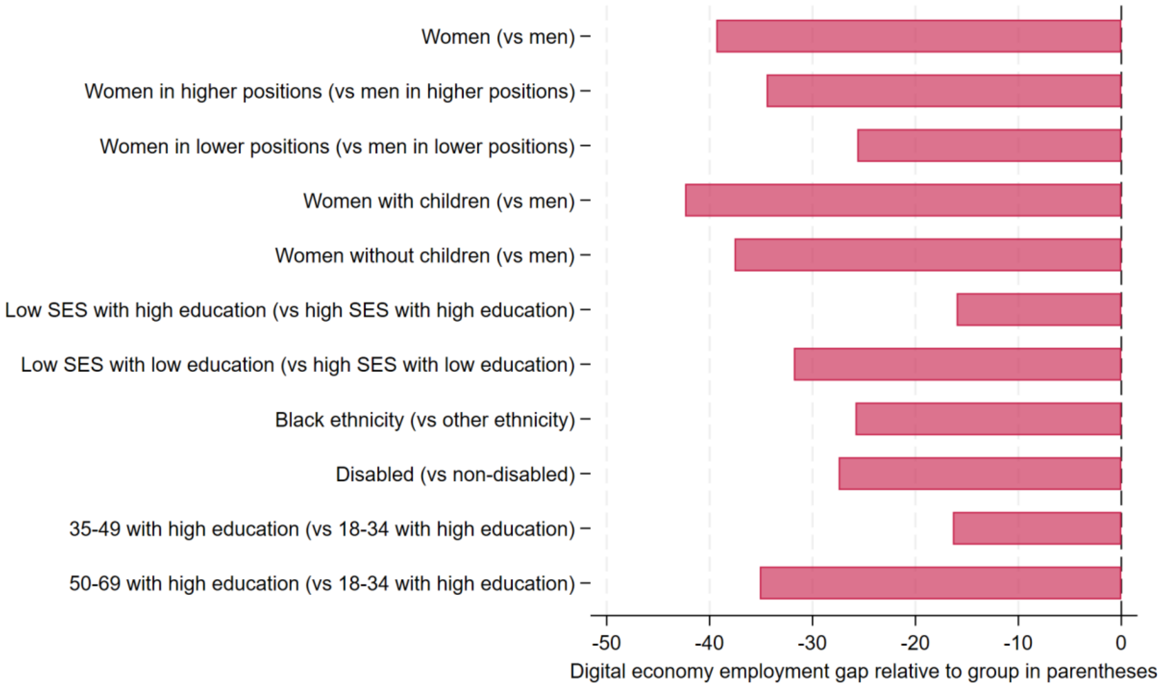
Region refers to the region of the respondent's workplace.

We also considered neurodivergent individuals and LGBTQ+ groups; however, we did not find evidence of under-representation in the digital economy for the former and the LFS data that we were able to access did not contain a variable identifying the latter, so we ultimately did not include them in our analysis.

4. Descriptive Analysis of Under-representation

Figure 1 documents several key patterns of under-representation. These patterns inform our choice of groups to focus on in the modelling in the next section.

Figure 1. Underrepresentation of different groups in the LFS



Data source: LFS 2022–2025, Quarter 3. Notes: Bars show the gap in employment in the digital economy of an underrepresented group compared to the respective reference group. Reference groups vary across underrepresented groups and are found in parentheses. ‘Higher position’ refers to high managerial and professional roles, while ‘lower position’ refers to all other roles. ‘High education’ refers to individuals with a higher education qualification. ‘SES’ refers to socio-economic status.

This section is aimed at identifying under-represented groups using the LFS. It does so by more than just reporting headline workforce shares. The proportion of the digital workforce made up by a given group does not, by itself, indicate under-representation. Instead, we assess under-representation by comparing the likelihood that workers from different groups work in the digital economy rather than in other sectors. These comparisons provide stronger evidence base and feed directly into the modelling results that follow. Below are the main findings.

- **Women are the most under-represented group in the digital economy: 7% of female workers in the UK work in digital versus 11% of men (a 4.4ppts or 39% gap)**. Given that women are also the largest under-represented group, this will be particularly significant when we come to model the aggregate impacts on economic output of removing the barriers that lead to this under-representation. The representation gap (relative to men) is 42% for those with children and 38% for those without.

- **The gender gap is larger in senior digital roles: senior women are 34% less likely than senior men to work in the digital economy,** meaning that they are particularly under-represented in senior positions within the digital economy.
- **Socio-economic background and education are often intertwined, but socio-economic background matters even when education is held constant, especially for non-graduates.** Among non-graduates, those from lower-SES backgrounds are 32% less likely to work in digital than higher-SES non-graduates. The gap is 16% among degree-holders.
- **Older, higher-educated workers are significantly under-represented: degree-holders aged 50–69 are 35% less likely to work in digital than those with similar education aged 18–34. Those aged 35-49 are 16% less likely to be working in the digital economy than those aged 18-34.** Because older cohorts are substantially less likely to have high educational qualifications than younger ones, we segment this analysis by education level (as we did for socio-economic background). When we do this, we find that the under-representation of older workers is, in fact, driven by the highly educated group, as under-representation is significantly larger in this group.
- **Black workers are 26% less likely to work in the digital economy than other ethnic groups, despite ethnic minorities overall being well-represented.** We examined a fuller set of ethnicity breakdowns, but workers of black ethnicity were the group who were clearly under-represented within the digital economy (ethnic minority groups as a whole are actually more likely to be employed within the digital economy than the white majority).
- **Equality Act disabled workers are substantially under-represented, with a 27% lower likelihood of working in the digital economy compared to non-disabled workers.**

We also examined how patterns of representation within the digital sector differ across regions. Patterns of representation were generally quite similar across the UK. London and the Southeast are the regions that stood out most, in particular in exhibiting the largest absolute gap in employment in the digital economy by sex (see Annex C). In the modelling presented in the next section, we examine results by sex and disability specifically for London and the Southeast, as these groups had large enough sample sizes to support analysis specifically within those regions.

5. Main Results

In this section, we present the potential economic gains from addressing under-representation in the digital economy. We start with the aggregate gains, which reflect both the digital economy and the economy-wide increase in output that could result from reduced under-representation. Key considerations for interpreting the results include:

- **Scale depends on both group size and the representation gap.** A modest gap in a large group can produce substantial aggregate effects, while a larger gap in a smaller group may yield more limited economy-wide effects – even while having a large per-person impact among those in the under-represented group.
- **Groups are analysed separately and should not be added together.** Identities overlap; for example, a worker may be both a woman and have a disability. Adding figures across groups would double-count the benefits from reducing under-representation.
- **These are illustrative estimates of the benefits of expanding the labour supply to the digital economy; they are not forecasts of the impact of any particular policy measures.** The estimates reflect a hypothetical scenario in which all barriers are removed. They are intended to show the scale of potential gains rather than to predict the outcome of any specific policy, or to make any judgements about how easy or costly it would be to achieve such gains.
- **The economy-wide gains will be smaller than the digital economy gains.** This is because attracting workers into the digital economy draws them out of other sectors, reducing output in the non-digital economy. The net gain to the whole economy reflects the gains from improving the allocation of workers to jobs, meaning that workers can use their skills in the best way possible.

We also show the benefits per person to individual workers in the under-represented group. Individual gains measure the gains to individual workers, on average, if the barriers currently limiting their access to digital jobs were removed. Important considerations for interpreting these numbers include:

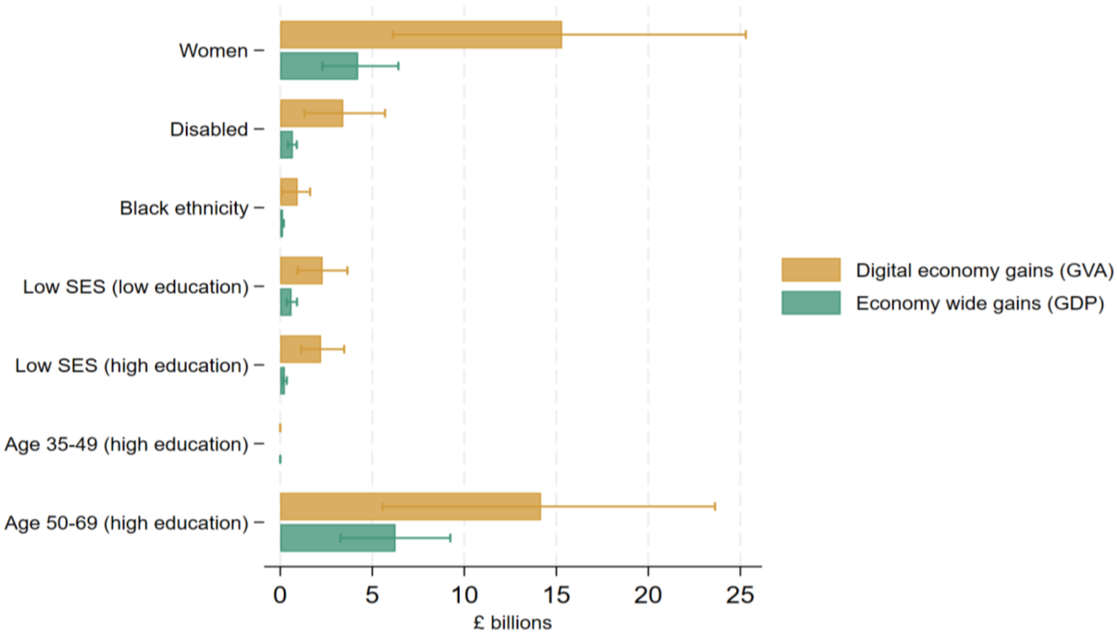
- **The gains may capture more than pay.** Gains can reflect higher earnings, but also anything else that workers value and that might previously have been part of the “barrier” preventing greater digital representation, e.g., non-pay benefits, working conditions, culture or flexibility. All gains are expressed as a cash-equivalent pounds per person per year, but it is not only £1 of pure cash that could deliver a gain worth £1.
- **Gains are in net terms,** meaning they account for reductions in wages across the digital sector that occur when digital labour supply increases. These wage reductions are part and parcel of what happens when there is displacement of other workers (see Chapter 2): if digital labour is more plentiful, its price (the wage) falls, and this causes some digital workers to choose other sectors instead.

- **Results are reported for two groups of people:**
  - Switchers: workers who would move into digital jobs if barriers were reduced; and
  - All under-represented workers in digital jobs: workers currently in the digital economy, despite the barriers they face, as well as those who would switch into the digital economy. The former group also benefit from barrier removal and, indeed, stands to see larger absolute gains due to their relatively high productivity levels in the digital economy.

Aggregate economic effects

The first set of results presents the potential output gains for i) the digital economy and ii) the whole economy from addressing digital sector under-representation, for each group analysed (Figure 2). Importantly, as these are aggregate output gains, their magnitude is inherently shaped by the relative sizes of each group (we turn to the benefits per person in the next section). These gains were calculated by using the model to simulate output in the digital economy and output in the whole economy before and after removing the barriers to working in the digital economy. We took the percentage changes in output simulated by the model and multiplied them by official estimates of the level of Gross Value Added for the digital economy and Gross Domestic Product for the whole economy.

Figure 2. Aggregate annual economic gains from addressing under-representation in the Digital Economy



Data source: LFS 2022–2025, Quarter 3. Notes: Bars show central estimates and lines show the sensitivity range reflecting modelling assumptions around the transferability of skills (correlation between digital and non-digital log-productivity of 0.6–0.9) and labour demand elasticity (0.5–1.5). The age analysis is restricted to those with higher education and is run as a single model, with those aged 35–49 and 50–69 as underrepresented groups and those aged 16–34 as the reference group. Productivity differences by age group are calibrated based on wages of degree holders in the non-digital economy. For all other groups, separate models are run assuming the same productivity distribution for the underrepresented and reference groups. The reference group for black ethnicity includes all other ethnicities. 'High education' refers to individuals with a higher education qualification. 'SES' refers to socioeconomic status. GDP and GVA figures use 2024 estimates and are scaled according to the subgroup's share of total wages for the socio-economic status analysis.

Figure 2 presents our modelled results of potential output gains from removing barriers facing the following under-represented groups in the digital economy: women, disabled workers, those of black ethnicity, those from lower socio-economic backgrounds (separately by whether they have a degree-level qualification), and older workers (specifically for those with higher education qualifications, since this is the group of older workers for whom under-representation is most pronounced). Note that the potential output gains cannot be added together across these groups as they are not mutually exclusive.

The lines in Figure 2 reflect the sensitivity of the results to a range of plausible modelling assumptions around the extent of correlation of skills across sectors and the magnitude of displacement that occurs when new workers enter the digital sector (see Section 2). The figure shows that these are important assumptions in shaping the potential gains from addressing under-representation. However, the gains remain substantial, and the relative results across different groups do not change substantially.

The largest potential output gains would flow from addressing the under-representation of women in the digital sector. Recall that this is a statement about the size of the gains if all barriers were successfully removed; this says nothing about the feasibility of doing this, or the costs of doing so, which are crucial but separate questions from the ones addressed in this report. The main reasons why the potential aggregate gains are largest in this case are two-fold: women are the most under-represented group in the digital economy (see previous section), and women are also the largest under-represented group, at around half of the whole labour force. Under our central modelling assumptions, fully addressing the barriers preventing proportionate representation of women in the digital sector would increase the UK's digital sector output by 6%, or £16 billion per year. This accounts for the fact that there would be displacement of other workers, which reduces the net increase in digital sector employment from 26% to 8%.

The economy-wide gains are lower than the digital economy gains: we estimate that total GDP would rise by £4 billion if all barriers to women working in the digital economy were successfully removed. This is because the women who would work in the digital sector if barriers were reduced or removed are currently working in other sectors. Hence, although the digital sector gains output if they switch, other sectors will lose output. However, this is not a "zero-sum" phenomenon: the output gained by the digital sector is larger than the output lost by other sectors. The reason for this is an improved matching of workers to roles that suit their skills. Once barriers are removed, people's choice of sector more closely reflects their productivity, and, hence, potential earnings in each sector – rather than being distorted by non-productivity related factors. Essentially, the women who would switch into the digital sector once sector-specific barriers are removed are women who would be more productive in the digital sector than they would have been in another sector. Consequently, overall output increases.

Large potential output gains also arise from addressing the under-representation of older workers (£15 billion, or 7%, to the digital economy and £7 billion to the whole economy). This is largely because they are both significantly under-represented and a sizeable group. It is also because we assume that, in the absence of barriers, older workers' potential productivity would be higher than that of younger workers (in line with the age-earnings relationship we observe in non-digital jobs), due to the returns to experience. All the output gains are driven by the 50-69 group, although we also model the impact of removing any barriers facing the 35-49 group. Essentially, because the 35-49 group are only slightly under-represented, the direct impact on them of removing barriers is small. Meanwhile, the much larger influx of 50–69-year-old workers into the digital sector would displace some younger workers, meaning no net positive impact on the employment of 35–49-year-olds in the digital economy once displacement is accounted for. These effects are modelled only on the set of workers with higher education qualifications who drive most of the under-representation of older workers. Once again, this report is agnostic about the feasibility or cost of reducing any barriers. We are simply addressing the question of what the potential output gains would be if these barriers *could* be removed.

The potential output gains from addressing barriers faced by other under-represented groups are smaller, yet far from negligible, ranging from an estimated £1 billion boost to the digital economy through eliminating the under-representation of black workers to approximately £3 billion for disabled workers. These figures do not directly capture the magnitude of benefits accruing to the individuals themselves. A complementary question, therefore, concerns the scale of gains experienced by the individuals within these groups—an issue we turn to in the following section.

Individual-level gains

We now examine the potential per-person gains to individuals from addressing under-representation in the digital economy (Figure 3). These results generally vary less across groups than the aggregate results in the previous section because the previous results were also affected by group size, whereas the gains per person are not.

We show estimated gains to individuals in pounds (GBP) per year. It is important to bear in mind that the gains do not necessarily have to come in the form of "cash" or higher wages, although they could well come in that form. Barrier sizes are inferred from the degree to which each group is under-represented in the digital economy relative to what their potential productivity would predict. The barriers could be in the form of actual wage discrimination, but they could also represent anything else that workers value equivalently and which can, therefore, distort their sector choice (e.g., workplace culture).

Within each under-represented group, we show gains separately for two sets of workers. First, we show the average gains for those individuals who are not working in the digital sector currently but who we simulate *would* work in the digital sector once barriers are eliminated. We call these people the "switchers." They are the group that drives the increases in output modelled in the previous section.

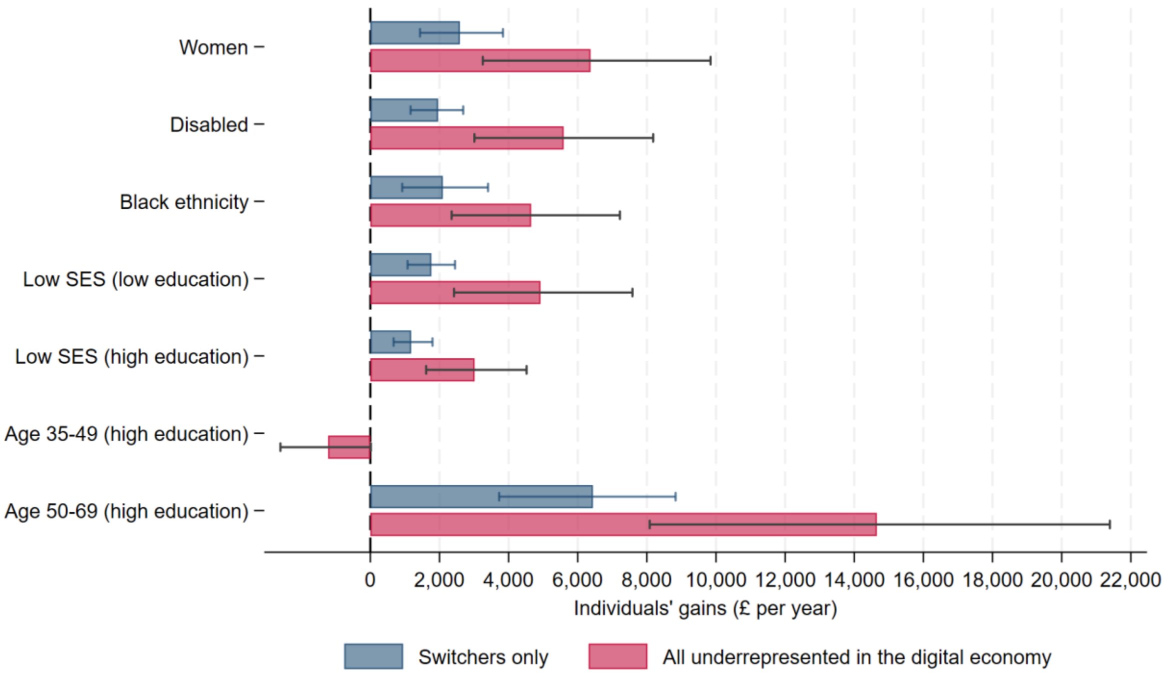
Second, we also show the potential average gains among all individuals in the under-represented group who work in the digital economy (i.e., including those who are working there already, despite the barriers). The reasoning for this is that, if the barriers impact all members of a group, then their removal presumably benefits those members of the group who were working in the digital sector despite them (e.g., via lower wage penalties, a more inclusive workplace culture, etc). In fact, we would expect the benefits to be larger in absolute terms for the second group. The "barrier" represented a kind of cost to working in the digital sector. For workers already in the digital sector, removing that benefits them in full. Switchers, by contrast, previously found non-digital work more attractive (otherwise they would already have been in the digital sector). Therefore, part of the barrier reduction simply brings them to the point where they are indifferent between what they were already doing (working in the non-digital sector) and switching to the digital sector. It is only the remaining reduction in the barrier, over and above that, which unlocks the extra benefits for them of working in the digital sector compared to working somewhere else.

In addition, we model the barriers as acting to reduce payoffs proportionally (i.e., by more, in absolute terms, for those who would earn more in the digital sector). Those people in under-represented groups already working in the digital sector tend, on average, to have higher digital productivity than switchers (since this helps explain why they were already working in the digital sector, despite the barriers), meaning they can gain more in absolute terms when barriers are removed. We acknowledge, however, that whether barriers are best thought of as proportional may depend on exactly what the barriers are, which is not something in the scope of this report.

Individual-level gains for switchers into the digital economy are substantial. For women, the average gain is £3k per year. For those aged 50–69, switcher gains are £7k per year, reflecting both the relatively large barrier they face and their higher average wages. Gains are smaller but still notable for other groups switching into the digital economy: around £2k per year for disabled workers, black workers, and those from lower socio-economic backgrounds without higher degrees. For workers from lower socio-economic backgrounds with higher degrees, the gains are £1k per year.

Considering all under-represented workers already in the digital economy (not just switchers), women in the digital economy gain £7k per year on average, disabled workers £6k, black workers £4k, workers from lower socio-economic backgrounds with higher degrees £3k and without £5k, and those aged 50–69 £15k per year. For those aged 35-49, the relatively small gain from removing their barrier is actually outweighed by the displacement and reduced wage effects from the influx of older workers entering the digital economy, as explained above.

Figure 3. Gains to individuals from addressing under-representation in the Digital Economy



Data source: LFS 2022–2025, Quarter 3. Notes: Individual gains are the sum of wage and non-wage benefits. Bars show central estimates and lines show the sensitivity range reflecting modelling assumptions around the transferability of skills (correlation between digital and non-digital log-productivity of 0.6–0.9) and labour demand elasticity (0.5–1.5). The age analysis is restricted to those with higher education and is run as a single model, with those aged 35–49 and 50–69 as underrepresented groups and those aged 16–34 as the reference group. Productivity differences by age group are calibrated based on wages of degree holders in the non-digital economy. For all other groups, separate models are run assuming the same productivity distribution for the underrepresented and reference groups. The reference group for black ethnicity includes all other ethnicities. 'High education' refers to individuals with a higher education qualification. 'SES' refers to socioeconomic status. Estimates for all under-represented groups in the digital economy reflect average gains for those in the under-represented group working in the digital economy following barrier removal. Switchers are those who move into the digital economy as a result of barrier removal.

6. Analysis by Region, Seniority, and Motherhood

Barriers are not constant across individuals within an under-represented group. Descriptive analysis indicates that under-representation of women and disabled workers is more pronounced in London and the Southeast compared to the rest of the country. As a result, these are the two regions focused on in the analysis presented here.

Existing research also points towards a "leaky pipeline" for women in tech, with particular representation gaps at more senior levels, as many women leave the sector due to a lack of advancement opportunities (O'Neill et al., 2025)[20]. Indeed, the data show that representation issues are more pronounced in higher-level positions of the digital economy (see section 4). Finally, a broader literature on gender inequality in the labour market further stresses the role of motherhood as a driver of diverging career trajectories (Kleven et al., 2024)[21]. We therefore estimate our main results separately for women in higher and lower positions and by region for both women and disabled workers. In addition, we run a multi-group model in which we compare women with dependent children and women without dependent children to men.

Aggregate economic effects

Results in Figure 4 indicate the following aggregate gains from reducing under-representation:

- Reducing under-representation among **women without dependent children** generates the largest gains (£10 billion per annum or 6%, to the digital economy; £3 billion per annum to the wider economy). Despite women with dependent children facing greater under-representation, the larger number of women without dependent children drives higher aggregate gains.
- Reducing under-representation among **women in higher positions** yields gains of £6 billion (3%) to the digital economy and £1 billion to the wider economy. Under-representation is more pronounced at senior levels – consistent with attrition patterns documented in DCMS labour force analysis (2022)[22] – and productivity is also higher, both of which amplify the gains.

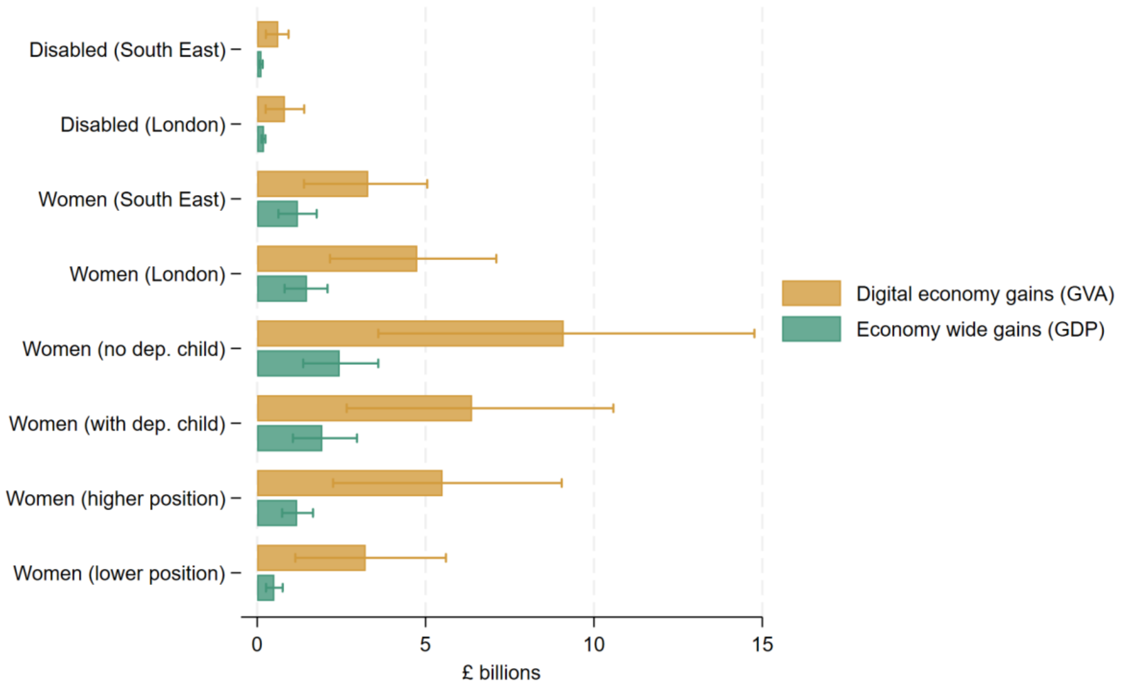
[20] O'Neill, D. Vallely, V. Blake, K. Iovita, I and Le Taillandier, C. (2025). Unlocking £2-3.5 billion: The Value of Keeping Women in Tech. Available at: https://www.oliverwyman.com/content/dam/oliver-wyman/v2/publications/2025/jul/value-keeping-women-in-tech-lovelace-report.pdf

[21] Kleven, H., Landais, C., Posch, J., Steinhauer, A., & Zweimüller, J. (2024). Do family policies reduce gender inequality? Evidence from 60 years of policy experimentation. American Economic Journal: Economic Policy, 16(2), 110-149.

[22] DCMS (2022). Sector Economic Estimates: Employment Apr 2021–Mar 2022.

For both women and disabled workers, gains from addressing under-representation are **larger in London than in the Southeast**. However, both are smaller than the national figures in Figure 2, as one would expect, because we are now looking at only a portion of the UK economy.

Figure 4. Aggregate Annual Economic Gains from addressing under-representation in the Digital Economy



Data source: LFS 2022–2025, Quarter 3. Notes: Bars show central estimates and lines show the sensitivity range reflecting modelling assumptions around the transferability of skills (correlation between digital and non-digital log-productivity of 0.6–0.9) and labour demand elasticity (0.5–1.5). The analysis by motherhood is run as a single model, with women with and without dependent children as under-represented groups and men as the reference group. For all other groups, separate models are run. In the regional analysis, the reference group consists of men and non-disabled workers within the same region. Higher positions include higher managerial and professional occupations. GDP and GVA figures use 2024 estimates and are scaled according to the subgroup's share of total wages for the regional and position level analysis.

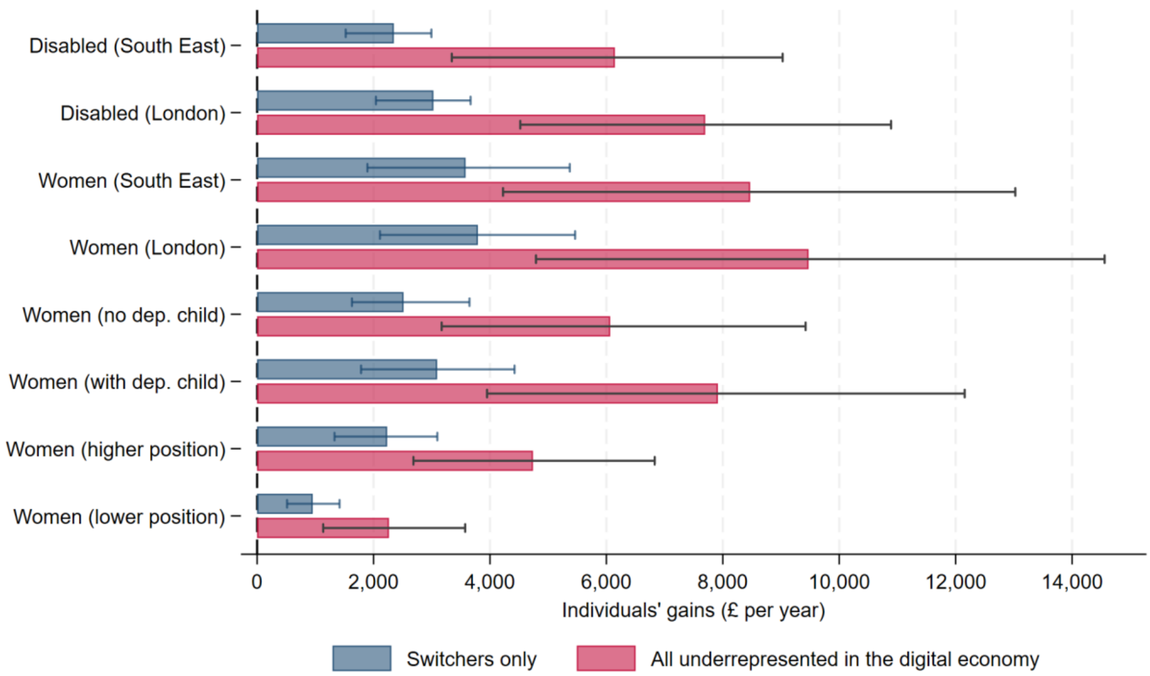
Individual-level gains

The individual-level picture more closely reflects variation in the magnitudes of barriers within groups than the aggregate picture (which also depends on the sizes of the groups):

- **Regional variation:** Women and disabled workers in London and the Southeast are more under-represented in the digital sector than elsewhere in the country. For switchers, this translates into gains of £4k/year (7-8%) for women and £3k/year (5-6%) for disabled workers in both regions. Expanding the analysis to all group members in the digital economy, gains are £10k/year (12%) for women and £8k/year (11%) for disabled workers in London and £9k/year (14%) for women and £6k/year (10%) for disabled workers in the Southeast.

- **Dependent children:** Gains for those switching into the digital economy are slightly higher for women with dependent children, but amount to roughly £3k/year (6-7%) for both groups of women. For all under-represented women in the digital economy, gains are higher for those with dependent children (£8k/year, 12%) than without (£6k/year, 10%), reflecting the greater barriers faced by mothers.
- **Seniority:** Gains for women switching into the digital economy are £2k/year (5%) in higher positions and £1k/year (3%) for those in lower positions. For all underrepresented women in the digital economy, gains are £5k/year (8%) for women in higher positions and £2k/year (5%) for those in lower positions. It is worth noting that this comparison assesses women's representation in senior roles within the digital economy relative to the broader economy and therefore does not capture the fact that women are already under-represented in senior positions across the economy as a whole.

Figure 5. Gains to individuals from addressing under-representation in the Digital Economy



Data source: LFS 2022–2025, Quarter 3. Notes: Individual gains are the sum of wage and non-wage benefits. Bars show central estimates and lines show the sensitivity range reflecting modelling assumptions around the transferability of skills (correlation between digital and non-digital log-productivity of 0.6–0.9) and labour demand elasticity (0.5–1.5). The analysis by motherhood is run as a single model, with women with and without dependent children as under-represented groups and men as the reference group. For all other groups, separate models are run. In the regional analysis, the reference group consists of men and non-disabled workers within the same region. Higher positions include higher managerial and professional occupations. Estimates for all under-represented in the digital economy reflect average gains for those in the under-represented group working in the digital economy following barrier removal. Switchers are those who move into the digital economy as a result of barrier removal.

7. Conclusion

As set out in this report, the potential economic gains from fully addressing under-representation are significant.

We estimate that the potential gains to the digital economy from fully addressing the under-representation of women would amount to £16 billion per annum (6% of digital economy Gross Value Added (GVA) based on 2024 GVA estimates). Fully removing the barriers preventing proportionate representation of those aged 50-69 could generate gains of £15 billion per annum (7%). Addressing under-representation of other groups, such as people from lower socioeconomic backgrounds (£5 billion per annum), black ethnic backgrounds (£1 billion per annum), or disabled people (£3 billion per annum), could also yield substantial gains for the digital economy.

The economy as a whole also benefits through a better allocation of talent across sectors. Fully addressing the under-representation of women in the digital economy could deliver an increase in total GDP of around £4 billion per annum (based on 2024 GDP estimates), while addressing under-representation of those aged 50-69 could deliver a £7 billion per annum. These benefits are smaller than the benefits specifically to the digital economy, since additional workers and output in the digital economy would mean fewer workers and output in other sectors. However, there is still a substantial net benefit for the economy as a whole, arising from the improved match between workers' skills and the sector they are in.

At the individual level, gains per person are also substantial. These gains measure how much better off members of an underrepresented group would be, *on average*, if the barriers that currently limit access to digital jobs were removed. All gains are expressed as a cash-equivalent £ per person per year. The gains can reflect higher pay, but they would also incorporate non-pay factors that people value (working conditions, flexibility, culture, or non-pay benefits). Women in the digital economy could see gains worth around £7k/year on average from reduced barriers, while workers aged 50-69 could gain £15k/year on average. There are **other groups** who could gain significantly on an individual basis, even though, because there are fewer of them, they would not affect the aggregate picture as much. These include black workers (gain of £4k/year) and disabled workers (gain of £6k/year). These figures all include those already working in digital jobs, who are currently doing so despite the barriers, but would benefit once barriers are removed. If we focus just on those workers who would switch into the digital economy as a result of reduced barriers, the gains are also substantial: around £3k per year for women, and £7k per year for those aged 50-69.

This report documents that various demographic groups are more under-represented in the digital economy than in the rest of the economy. The purpose of the modelling we undertook was to estimate the economic costs of under-representation, or, conversely, the potential benefits of addressing under-representation in the digital economy – both in aggregate and for the groups concerned. Our approach uses an occupational choice model to quantify the losses that arise when barriers prevent workers from sorting into the jobs that best suit their abilities.

Our results are best understood as an illustration of the potential scale of opportunity rather than a prediction of what any specific policy will deliver. The figures are based on the hypothetical scenario where barriers can be removed entirely. Partial progress would yield smaller gains. Our results should therefore be taken as an illustrative upper bound on the potential gains. Importantly, the purpose of the analysis was *not* to identify the causes of under-representation – i.e., the sources of the barriers - nor to assess the feasibility or costs of addressing them. These are big and important questions in their own right and crucial ones for wider policy development and appraisal of policy options. Instead, our report focuses on another part of the jigsaw – understanding the potential benefits that could be unlocked if policy to address under-representation were successful.

Our findings underline the point that a more representative workforce can also be a more productive one. Unlocking the potential of under-represented groups can benefit not only those individuals but society at large. Indeed, there are billions of pounds potentially at stake – not only for the digital sector, but for the UK economy as a whole.

Annex A: Technical Model Description

Introduction

This annex outlines how we quantified the economic effects of increased representation in the digital economy. We used an economic model of individuals' sectoral choices in the presence of group-specific barriers in order to infer the economic costs associated with those barriers and the gains from reducing them. The framework builds on the logic of Hsieh et al. (2019)[23], who extend the classic Roy model (1951)[24] of occupational sorting to allow for group- and occupation-specific distortions.

The economic model

We provide an overview of the modelling approach using the running example of men and women. However, this extends straightforwardly to more than two groups, and to groups demarcated in any way, including by intersecting characteristics (e.g., women with children), as long as the assumption holds that underlying productivity does not differ between groups. The intuition for how the model works is as follows. Each person has a potential level of productivity in each sector: the digital economy and the non-digital economy. Someone's productivity may be different in different sectors, meaning their skills are better suited to working in one sector than another. As a result, economic output, both at the sectoral and whole-economy level, depends on how workers are allocated across sectors. For groups that do not face barriers to working in the digital economy, their sector choice is driven solely by productivity in each sector, since this determines the wage they can earn. For under-represented groups, however, working in the digital economy may involve an additional barrier that reduces the relative payoff from working in the digital economy. This barrier could be some form of wage discrimination, or non-wage factors, such as workplace culture, non-monetary job amenities, flexibility, etc. The model is agnostic about the sources of these barriers. It simply requires that they discourage either entry into, or retention within, the digital economy. This means that the sizes of the barriers can be inferred from observed sectoral choices.

In the model, people choose to work in the digital economy if the payoff (which need not be only monetary) from doing so exceeds that available elsewhere. For under-represented groups, this requires that any productivity advantage in the digital economy is large enough to offset the digital economy barrier. As a result, some individuals whose skills would be best suited to the digital economy do not work in the sector – a misallocation of talent, which reduces output and productivity.

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[23] Hsieh, C. T., Hurst, E., Jones, C. I., & Klenow, P. J. (2019). The allocation of talent and us economic growth. Econometrica, 87(5), 1439-1474.

[24] Roy, A. D. (1951). Some thoughts on the distribution of earnings. Oxford economic papers, 3(2), 135-146.

Below, we explain the components of the model.

Productivity

The economy consists of two sectors, s ∈ {D, N}, where D denotes the digital sector, and N denotes the non-digital sector. Individuals belong to mutually exclusive and exhaustive demographic groups g, for example, men (M) and women (W). Each individual *i* has sector-specific log productivity θ_{is} in sector s. We assume the underlying productivity distribution to be the same across the groups g. Productivity is assumed to be log-normally distributed within each sector:

$$\theta_{is} \sim N(\mu_s, \sigma_s^2), \qquad s \in \{D, N\}$$

where θ_{is} is the log of productivity and the parameters μ_s, σ_s^2 denote the mean and variance of log productivity in sector s. An individual's productivity may be correlated across sectors:

$$\rho = Corr(\theta_{iD}, \theta_{iN}) \neq 0$$

A positive ρ implies that individuals who are highly productive in the digital economy also tend to be relatively productive in other sectors. However, because p <1 (productivity in the digital economy and other sectors is not perfectly correlated), relative productivity levels across sectors can differ between individuals. This means that some people have a comparative advantage in the digital economy, while others have a comparative advantage in other sectors.

Group-specific barriers

Group- and sector-specific barriers are represented by τ_{gs}, which reduces the net return to working in sector *s* for group *g*. These barrier parameters are agnostic over the source of the barriers (and how costly or feasible it would be to reduce them), since the focus of this project is to quantify the costs of those barriers, whatever they are. The barriers may represent wage discrimination, unequal access to networks, information frictions, cultural barriers, or any factors besides productivity affecting sector entry or retention. Our focus is on under-represented groups and on barriers specific to the digital economy, so we impose the normalisation that barriers outside the digital economy, and for the "reference" group that is not under-represented (e.g., men), are zero:

$$\tau_{gN} = 0 \quad \forall g, \qquad \tau_{MD} = 0.$$

The barrier parameter remaining, and the one of interest, is τ_{WD} , which represents the barrier faced by women in the digital economy.

Sector choice

In the absence of any barriers, the wage that individual *i* can earn in each sector is given by:

$$\ln w_{is} = \theta_{is} + \ln W_s.$$

This depends on their underlying individual-level productivity parameter in that sector and a sector-wide wage shifter, W_s.

The sector-wide wage shifter allows for general equilibrium wage effects when labour supply changes (this is to model “displacement” and the size of the wage adjustment is determined by the interaction with labour demand – see below). It does not matter for our purposes what absolute value this wage shifter takes, so we simply normalise it to 1 at baseline. However, in our counterfactual scenarios with reduced barriers, its value can change when labour supply changes, which can cause displacement (i.e., wage reductions that cause other workers to leave the sector).

In the absence of barriers, workers would choose their sector by comparing the wages they could earn in each sector, as given by the expression above. In practice, however, under-represented groups have an additional barrier distorting their choice. The indirect utility from working in sector *s* is therefore:

$$U_{isg} = \theta_{is} + \ln W_s - \tau_{gs}.$$

Based on this, we can derive the sorting condition under which individual *i* chooses to work in the digital economy. Men will choose to work in the digital economy if the utility they derive from working in the digital economy exceeds the utility of working in other sectors. As the model assumes men face no barrier to working in the digital economy, this is the case if:

$$\theta_{iD} - \theta_{iN} \geq -\ln\left(\frac{W_D}{W_N}\right)$$

Accounting for the digital economy barrier, women work in the digital economy if:

$$\theta_{iD} - \theta_{iN} \geq \tau_{WD} - \ln\left(\frac{W_D}{W_N}\right)$$

Output

Sectoral output aggregates effective productivity across workers:

$$Y_s = \Sigma_{\{i \in s\}}\, exp(\theta_{is}).$$

Aggregate output equals the sum of output across the two sectors:

$$Y = Y_D + Y_N.$$

Displacement (i.e., finite labour demand elasticity)

To allow for displacement effects in the digital economy, we allow for a finite labour demand elasticity. We will do this by writing the inverse labour demand function, which says that digital economy wages respond to labour supply:

$$\ln W_D = \alpha - \eta \ln L_D$$

where $L_D = \Sigma_{\{i \in D\}}\, exp(\theta_{iD})$ denotes the effective labour supply in the digital economy, and $\eta \geq 0$ is the inverse labour demand elasticity. Higher η implies stronger wage declines when the digital economy labour supply increases. As described above, W_D acts as a sector-wide wage shifter. We normalise it to 1 at baseline, implying:

$$\alpha = \eta \ln L_D^0.$$

When the labour demand elasticity is finite, the inverse labour demand elasticity is positive (i.e., $\eta > 0$). This means that increased entry into the digital economy reduces digital economy wages according to the inverse labour demand equation. This may mean that some other workers (those for whom the choice between the digital economy and other sectors was most marginal) may leave the digital economy (i.e., be displaced). The way that we simulate these effects to find the new equilibrium between labour demand and supply is described below.

Calibration of the model parameters

The model is calibrated largely using Labour Force Survey (LFS) data, supplemented by evidence from external literature to provide plausible values of the two remaining parameters.

Productivity in the non-digital economy sector

Non-tech log-productivity is assumed to be normally distributed.

$$\theta_{iN} \sim N(\mu_N, \sigma_N^2).$$

To estimate the mean and variance of log productivity, we take the group that does not face barriers (men in our running example), since, for them, the earnings distribution should be directly informative about the distribution of individual productivity.

The parameters are therefore calibrated directly from the distribution of male wages outside of the digital economy using the LFS:

$$\mu_N = E[\ln w \mid g = M, s = N],\ \sigma_N^2 = Var(\ln w \mid g = M, s = N).$$

The literature suggests skills are transferable across lines of work but not perfectly so (e.g., Gibbons et al, 2005[25]; Sullivan, 2010[26]). As there is no estimate in the literature of the transferability of skills across sectors, we have based this on assumptions and have conducted sensitivity analysis.

Digital sector productivity

Digital sector productivity is also assumed to be log-normally distributed:

$$\theta_{iD} \sim N(\mu_D, \sigma_D^2).$$

However, more care needs to be taken to accurately calibrate the mean and variance of digital economy productivity from the LFS. This is because only a minority of individuals choose to work in the digital economy, so observed wages in the sector are not representative of the distribution of digital economy productivity across the population (instead, they are the wages of a select subset of people who have chosen to work in the

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[25] Gibbons, R., Katz, L. F., Lemieux, T., & Parent, D. (2005). Comparative advantage, learning, and sectoral wage determination. Journal of labor economics, 23(4), 681-724.

[26] Sullivan, P. (2010). Empirical evidence on occupation and industry specific human capital. Labour economics, 17(3), 567-580.

digital economy). However, the structure of our economic model provides a ready-made framework for inferring digital economy productivity parameters from the LFS data. Specifically, we have two unknown parameters (the mean and variance of log-productivity in the digital economy), which means we can solve for them using two equations in which there are no other unknowns (i.e., no other terms that we cannot either calculate from LFS data or have already calibrated). The model gives us those two equations.

First, the model says that the proportion of men who choose to work in the digital economy (something we observe in the LFS) is the proportion of men for whom digital economy productivity exceeds productivity outside the digital economy. Given that digital economy and non-digital economy log-productivity are joint-normally distributed, it can be shown that this proportion is in turn given by

$$p_M = \Phi\left(\frac{(\mu_D - \mu_N)}{\sqrt{\sigma_D^2 + \sigma_N^2 - 2\rho\sigma_D\sigma_N}}\right)$$

where the left-hand side is the male digital economy employment share (from the LFS), and the right-hand side contains the CDF of a standard normal distribution evaluated at the value inside the parentheses. The only two unknown terms on the right-hand side are the digital economy productivity parameters.

It can similarly be shown that the model-implied mean log wage among men who choose to work in the digital economy (something we observe in the LFS) is given by:

$$m_{D(\mu_D)}^{model} = E[\theta_D \,|\theta_D - \theta_N \geq 0]$$
$$= \mu_D + (\sigma_D^2 - \rho\sigma_T\sigma_N) \,/\, \sqrt{}(\sigma_D^2 + \sigma_N^2 - 2\rho\sigma_D\sigma_N) \cdot \varphi(z)/\Phi(z)$$

where

$$z = \frac{(\mu_D - \mu_N)}{\sqrt{\sigma_D^2 + \sigma_N^2 - 2\rho\sigma_D\sigma_N}} = \Phi^{-1}(p_M)$$

and the final term captures the selection effect. As only individuals whose productivity exceeds the cut-off threshold choose the digital economy, the observed average productivity in the digital economy will be above the unconditional mean μ_D. This final product in the final term is the inverse Mills ratio evaluated at z, where $\varphi(\cdot)$and $\Phi(\cdot)$ are the standard normal PDF and CDF, respectively.

We are left with two equations in our two unknown digital economy productivity parameters. This means we can solve for the values of those parameters. In practice, this is done using a simple iterative loop until convergence.

Barriers

Next, we assume that barrier-facing groups share the same underlying productivity distribution as the non-barrier-facing group. Under this assumption, differences in sectoral allocation across groups arise solely from barriers to entry τ_{WD}. Setting W_D = 1 at baseline, the condition for women to choose to work in the digital economy simplifies to saying that their digital economy productivity advantage must exceed the digital economy barrier they face:

$$\Delta\theta_i \equiv \theta_{iD} - \theta_{iN} \geq \tau_{WD}$$

Given this choice condition and the joint log normality of the productivity parameters, the model's equations can be rearranged to show that the barrier equals:

$$\tau_{WD} = \mu_\Delta - \sigma_\Delta \Phi^{-1}(p_W)$$

where μ_Δ is the difference between the mean of digital economy and non-digital economy productivity, and σ_Δ represents the difference between the digital economy and non-digital economy standard deviations of productivity. By replacing p_W with its counterpart from the LFS (the proportion of women who work in the digital economy), we can directly derive an estimate of the size of the digital economy barrier.

Labour demand and displacement

To allow for displacement effects, when we simulate counterfactual scenarios with reduced barriers, digital economy wages are permitted to adjust endogenously as the digital economy labour supply changes. The inverse labour demand function is:

$$\ln W_D = \alpha - \eta \ln L_D$$

where L_D denotes effective digital economy employment, and $\eta \geq 0$ governs the responsiveness of digital economy wages to changes in employment. When $\eta = 0$, labour demand is perfectly elastic and digital economy wages do not respond to changes in employment. When $\eta > 0$, increases in digital economy labour supply reduce W_D, which can cause some individuals near the margin to reallocate out of the digital economy because their digital economy payoff no longer exceeds their outside option. The parameter η is the inverse of labour demand elasticity and is calibrated using an externally sourced labour demand elasticity from the literature.

A meta-study of published estimates spanning many years by Lichter et al. (2015)[27] finds an average labour demand elasticity of 0.5. It shows that this elasticity has been increasing over time and is higher in labour markets that are less regulated, such as the UK's. It is also higher when the elasticity estimated is a "total output" elasticity – i.e., estimating what happens to labour demand when wages change, incorporating the fact that total output can adjust and that this is part of what affects the level of labour demand. The total output elasticity concept is the relevant one for our purposes. Hence, we use 0.5 as the lower end of the range for our sensitivity analysis. Our central assumption is that the labour demand elasticity is 1 (meaning that a 1% rise in digital sector wages leads to a 1% reduction in labour demand). The upper end of the range for our sensitivity analysis is 1.5.

Simulation and counterfactuals

Once the model is specified and all its parameters are calibrated, we create a synthetic population using those parameters, drawing from the joint distribution of digital and non-digital economy productivity and assigning under-represented groups the barrier that we have calibrated. By construction, when we simulate the choices of this synthetic

[27] Lichter, A., Peichl, A., & Siegloch, S. (2015). The own-wage elasticity of labor demand: A meta-regression analysis. European Economic Review, 80, 94-119.

population, the proportion of each group who choose to work in the digital economy will reproduce the baseline LFS proportions (subject to random simulation error, which was minimised by simulating a large population, e.g., 10,000 men and women). We then change the value of the group-specific barriers and recompute the choices of all individuals in the model. When we allow for displacement, a final iterative step involves allowing the sector-wide digital economy wage shifter to change according to the inverse labour demand function, recomputing choices, and then recomputing the wage shifter in an iterative loop until convergence, indicating equilibrium between labour supply and demand.

With the simulation complete, digital (and non-digital) economy output can be computed and compared to its baseline level. The percentage effect on output is applied to estimates of the total baseline GVA of the digital economy. At the individual level, the gains (including both wage and non-wage gains arising from reduced barriers) were also computed.

Annex B: Digital Economy classification using SIC codes

Table 2 shows a summary of the SIC codes used for defining the digital economy. 'Tier 1' refers to activity that is digital by definition, i.e., where enterprises primarily produce digital content, ICT goods, or ICT services. 'Tier 2' refers to activity that is digital by use, where more diversified enterprises include digital outputs and rely more heavily on digital inputs as part of a broader, non-digital core offering.

Table 2. Digital economy SIC codes

SIC Code(s)	SIC Description	Tier
18.20	Reproduction of recorded media	1
26.1 - 26.4	Manufacture of computer, electronic, and communication equipment	1
58.14 & 58.2	Publishing of journals, periodicals, and software	1
59	Motion picture, video, and television programme production, sound recording and music publishing activities	1
60	Programming and broadcasting activities	1
61	Telecommunications	1
62	Computer programming, consultancy, and related activities	1
63.11 - 63.91	Information service activities	1
95.11	Repair of computers and peripheral equipment	1
66	Activities auxiliary to financial services and insurance activities	2
69	Legal and accounting activities	2
92	Gambling and betting activities	2

Annex C: Digital Economy employment gap by sex and region

Table 3. Digital economy employment gap by sex and region

Region	Absolute gap
London	-8%
South East	-7%
Wales	-4%
East Midlands	-4%
East of England	-4%
Yorkshire and Humberside	-4%
North West	-4%
West Midlands	-4%
South West	-3%
North East	-3%
Scotland	-3%
Northern Ireland	-2%

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