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ABSTRACT

Technological Change and the Upskilling of European Workers

Using the second wave of the European Skills and Jobs survey, this paper measures the relationship between technological change that automates or augments workers' job tasks and their participation in work-related training. We find that 58 per cent of European employees experienced no change in the need to learn new technologies in their jobs during the 2020-21 period. Of those exposed to new digital technology, 14 per cent did not experience any change in job tasks, 10 per cent reported that new tasks had been created while 5 per cent only saw some of their tasks being displaced by new technology. The remaining 13 per cent simultaneously experienced both task displacement and task creation. Our analysis shows that employees in jobs impacted by new digital technologies are more likely to have to react to unpredictable situations, thus demonstrating a positive link between technologically driven task disruption and job complexity. We show a strong linear relationship between technologically driven job task disruption and the need for job-related training, with training requirements increasing the greater the impact of new technologies on task content.

JEL Classification: J24, O31, O33

Keywords: technological change, digitalisation, tasks, automation, training, upskilling, complexity

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1.0 Introduction

The literature on the impact of technological change on labour markets has been expanding rapidly over recent years, however, despite this expansion relatively little is known on the impact of technologies on the task content of jobs and the associated implications for employer-based training. Understanding the extent to which technology will alter the composition of jobs and the likely associated costs for employers in assisting workers to adjust to technologically driven job disruption is a important question for policymakers. In this paper, we use data from the second wave of the European Skills and Jobs Survey (ESJS2) for 29 European countries to address these issues and we find that 57 per cent of employees report that they have experienced no change in the use of new technologies within their main jobs. Of the 43 per cent of workers experiencing some technological change, 15 per cent reported no impact on job composition, 5 per cent reported task displacement only, 10 per cent task creation only and 13 per cent both task displacement and task creation. Within countries we find that technological task displacement and task creation are highly correlated with each other. Our model results indicate a strong relationship between technologically driven job task disruption and the need for job related training. The remainder of the paper is structured as follows. Section 2 reviews the literature linking technology and work based learning, Section 3 provides an overview of the data and methods, section 4 details the results from the analysis while section 5 provides a summary and conclusions.

2.0 Literature on the impacts of Technological Change on Job Composition

Clearly, the greater the impacts of technological change the greater the requirement for work-based learning will be. A good deal of the relevant literature liking work based learning and technological change has focused on the potential impacts of diffusion of Artificial Intelligence within the workplace on job composition. Turning first to studies conducted by policy organisations, the OECD (2023) conducted a survey of employers and employees in Finance and Manufacturing firms in early 2022 (Employers N: 2,053; Workers N: 5,334) in Austria, Canada, France, Germany, Ireland, UK and US. The OECD (2023) study found that over two thirds of employers in Manufacturing and Finance indicated had used AI to automat tasks previously carried out by employees. Workers in both sectors were generally positive with regard to the productivity enhancing potential impacts of AI, however, there was also concern regarding potential displacement effects with between 15 and 20 per cent of workers, in both sectors, worried about AI related job loss in the next ten years (OECD, 2023). Over 50 per cent of employees surveyed who use AI stated that their employer had provided training on the new technology. The study found that training is playing an important role in adapting to AI's integration in the workplace. Employers tend to opt for training current employees, or outsourcing, over hiring and firing to overcome AI related skill gaps (OECD, 2023).

The ILO also published a report in 2023 on the potential global impacts of job quantity and quality arising from generative AI (specifically generative pre-trained transformers[1]) (ILO, 2023). While earlier research suggests that low-skill, repetitive and routine jobs are at most risk of automation (Frey and Osborne, 2013, 2017), this research argues that the ability of GPTs to perform cognitive tasks (analysing text, drafting documents and messages, or searching through private repositories and the web for additional information) will result in the new wave of automation affecting a different group of workers – 'knowledge workers'. According to the study the broad occupation of clerical work is highly exposed to AI, with 24 per cent of clerical tasks considered highly

[1] GPT models generally refer to intelligent interactive voice assistants.

exposed and an additional 58 percent with medium-level exposure (ILO, 2023). For the remaining occupational groups, the greatest share of highly exposed tasks oscillates between 1 and 4 per cent, and medium exposed tasks do not exceed 25 per cent. As a result, the most important impact of GPT is likely to be of augmentation of existing jobs with a new blend of tasks – automating some tasks within an occupation while leaving time for other duties – as opposed to fully automating occupations.

The bulk of the academic literature has focused on the overall employment impacts of automation and technological change. Frey and Osborne (2013, 2017) is often cited, with these studies predicting that close to a half of all jobs in advanced economies are susceptible to replacement by machine learning. Nevertheless, subsequent studies that account for task heterogeneity within occupations have shown that the share of all jobs that are considered to be at high risk of automation is between is 9-14% within the labour markets studied (Pouliakas, 2018; Nedelkoska and Quintini, 2018; Arntz et al., 2017). This is still very high, but much lower than what was initially predicted. Much of the recent literature has focused on the potential impacts of technology on the composition of job tasks.

With respect to impacts on job composition, Acemoglu and Restrepo (2018) show that around half of employment growth in the US over the 1980- 2015 period occurred in occupations where the tasks performed by employees changed. McGuinness et. al. (2023) find evidence of a reinstatement effect arising from new technologies, whereby skills displacing technological change (defined as technological change with potential to make skills outdated) was found to improve the task content and skill requirements of jobs. They also found that high skilled occupations had a higher incidence of being impacted by technological change. Similarly, Acemoglu & Restrepo (2018) also point out that the job displacement effect of automation is counterbalanced by productivity enhancing impacts that will increase the demand for labour in non-automated tasks. In particular, increased automation will see the creation of new labour-intensive tasks within jobs that will serve to rebalance labour share of the productive process relative to capital.

Which specific tasks could be affected by the diffusion of AI? Frey and Osborne (2023) provide a succinct outline of the current capabilities of generative AI in order to highlight which tasks may be affected in the future. They pose that the current iteration of generative AI will be transformative rather than displacing, particularly in occupations with content creation tasks (e.g. writers, journalists).[2] The authors assert that generative AI may also lower the skill barriers to entry in such fields, incurring an influx of labour which could reduce wages.

Huang et. al. (2019) use O*NET data (US, 2006-2016) to document the increasing importance of "feeling tasks" (i.e. tasks that require social and emotional intelligence as opposed to technical or mechanical skills). They demonstrate the growing emphasis on transversal and social skills (relative to thinking/technical skills) in occupations such as finance and management. Huang et. al. (2019) suggest that as increasingly more analytical and thinking tasks are undertaken by AI, this will result in an increased emphasis of empathetic and emotional tasks. Alekseeva, et. al (2021) using Burning Glass (job vacancy) data to point out an increase in AI skills demand across occupations in the US between 2010 and 2019. They find that demand for AI skills is concentrated in

[2] The authors acknowledge the intrinsic limitations associated with the current iteration of generative AI (LLM) models, in that they 1) cannot generate original material organically, requiring precedent (data) to function and 2) have the propensity to 'hallucinate' (fabricate material). These limitations could hinder the diffusion and application of generative AI across all occupations requiring the creation of content.

the ICT sector, but is also prevalent in finance, manufacturing, architecture, engineering, science and management. Larger and more capitalised firms also exhibit higher demand than smaller firms. The authors also estimate a 20% wage premium on AI-related occupations.

A recent paper by Autor (2024), suggests that as AI provides information and rules that supports decision making, it will enable workers equipped with basic skills to perform higher level tasks that have been exclusively carried out by highly skilled workers. Some empirical evidence supporting this has been provided by a working paper from Brynjolfsson *et al.* (2023), demonstrating this dynamic in the area of customer support and Noy *et al*. (2023) in the area of writing tasks. Autor (2024) argues that this process can help restore the middle class within the US labour market that was previously hollowed out as a consequence of globalisation and automation. In the more skilled areas of the labour market, Autor (2024) argues that AI is merely a tool, similar to a calculator or a chainsaw, that will quicken job tasks that were previously time consuming, thus allowing workers to spend greater time on higher value-added tasks. Another key point from the Autor (2024) paper, is that there is a need for more realistic expectations regarding the impacts of new technologies on human capital; AI will allow individuals with good foundational skills in a particular occupation to "level up" to a higher level of expertise, however, it will not make everyone experts as AI tools with have relatively marginal impacts on the skill levels of workers who do not possess foundational occupational skills. The analysis again suggests that the job displacement impacts of AI are likely to be more limited as suggested by some, due to the inability of AI to respond to unpredictable changes in the external environment that require workers to interact their existing expertise with critical and creative thinking. Furthermore, technological change has historically created a demand for new occupations, or increased the demand within existing occupations, and this is likely to continue as AI capacity develops.

Finally, Acemoglu and Restrepo (2020) make the point that the direction of AI development, and its subsequent impact on task composition and labour demand, is largely a strategic choice. The authors argue that recent AI developments have been focused on automation, with much less emphasis directed on task creation that will enhance labour productivity. Acemoglu and Restrepo (2020) point to a clear role for policy in attempting to ensure that the future direction of AI is skewed towards improving labour productivity and maximising the value to workplace learning, rather than task replacement.

3.0 Data and Methods

The data used in this study comes from the second wave of the European Skills and Jobs Survey (ESJS2), The ESJS2 is managed by the European Commission's agency for vocational education, CEDEFOP, and collects data from all EU member states. The first wave of the survey was carried out in 2014 and the second wave, used here, in 2021. The ESJS is an employee survey, with both waves collecting core information of factors such as socio-economic and job characteristics, job skill requirements, skill mismatches, training and labour market outcomes. The second wave of the survey is particularly focused on the impact of new digital technologies and technological change on the future of work. In this paper we focus particularly on the questions related to (a) the adoption of new technologies in the current job (b) the impact of technological adoption of task composition and (c) work based training. The key goals of the study are to uncover the relationships between these three aspects of the survey.

A key feature of our study is that we separate out workers into the following five categories, which are also described in Table 1.

1. Workers who have not seen any change in the use of new technologies, digital or computerised, within their main job.
2. Worker who have experienced new technologies, digital or computerised, within their main job and have not experienced any change in job tasks as a consequence of these new technologies.
3. Worker who have experienced new technologies, digital or computerised, within their main job and have only experienced task displacement as a consequence of these new technologies.
4. Worker who have experienced new technologies, digital or computerised, within their main job and have only experienced task creation as a consequence of these new technologies.
5. Worker who have experienced new technologies, digital or computerised, within their main job and have experienced both task displacement and task creation as a consequence of these new technologies.

Table 1: Definitions of Technological Change Categories

Technological Change Category	*There has been a change in the use of technology used at work for the main job (digital or machines).*	*You now do not do some tasks you did before.*	*You now do some different or new tasks.*
1. No Technological Change	NO	NO	NO
2. Technological Change, No Task Changes	YES	NO	NO
3. Displacement Only	YES	YES	NO
4. Creation Only	YES	NO	YES
5. Displacement & Creation	YES	YES	YES

Technological change categories are derived from variables *D_CHTECH, D_CHJOBNEW* and *D_CHJOBDISP.*

We begin by identifying the job characteristics of workers in categories 2, 3, 4 and 5 relative to the references category 1, i.e. workers who have not seen any change in the use if new technologies in their job, using equation 1. TaskΔ is a binary variable indicating the degree to which a worker's tasks have been changed as a result of new technologies, X1 is a vector of individual and job characteristics, X2 are sectoral and country level fixed effects while ε_i denotes the error term.

$$Task\Delta_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i \quad (1)$$

A key objective of the paper is to assess the extent to which training costs will vary depending on the extent to which new technologies result in changes in task composition. In order to assess this we estimate equation 2, whereby Train indicates the extent to which workers were in receipt of job related training in the 12 months prior to the survey, TaskΔ is a binary variable indicating the degree to which a worker's tasks have been changed as a result of new technologies, X1 is a vector of individual and job characteristics, X2 are sectoral and country level fixed effects while ε_i denotes the error term.

$$Train_i = \beta_0 + \beta_1 Task\Delta_i + \beta_2 X_{1i} + \beta_3 X_{2i} \varepsilon_i \quad (2)$$

However, we need to be wary that the results from Equation 2 are not impacted by selection bias, whereby the treatment variable training is non-randomly correlated with another right-hand side covariate that will also influence the outcome variable. For example, employers may disproportionately implement new technologies in posts staffed by more educated employees, who are also more likely to be selected for training. In such circumstances, the coefficient task composition may also be incorporating some of the influences of educational attainment on the probability of training and will be biased. To account for this, we also estimate the relationship between training and task content using Propensity Score Matching (PSM). The propensity score is defined as the conditional probability of receiving a treatment given certain determining characteristics (Equation 3): D indicates exposure to the treatment and X is a vector of determining characteristics. For the probit and PSM models, the treatment group will be employees in each of the 4 technological change and task composition categories , and the control group will be those workers who have not experienced any new technologies in their main job. In the second stage of the PSM estimation procedure, individuals in the treatment group (experiencing technological change) are "matched" with counterparts in the control group (that have experienced no new technologies) that have similar propensity scores of being subject to the treatment effect and their actual outcomes (job related training) are compared.

$$P(X) = \Pr(D = 1|X) = E(D|X) \quad (3)$$

4.0 Results

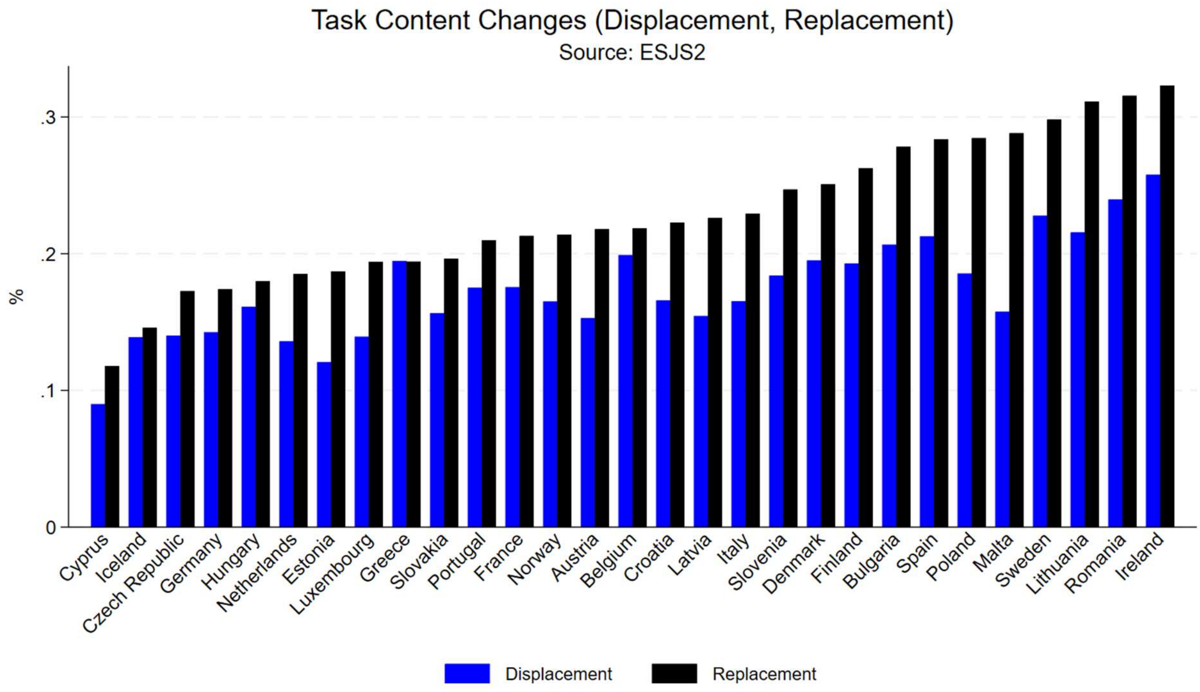
We begin by assessing the extent to which workers who are experiencing technological change within their main jobs varies across the European countries (Table 2). that 57 per cent of employees report that they have experienced no change in the use of new technologies within their main jobs, with the percentage varying from under 50 per cent in Finland, Norway and Sweden and over 65 per cent Germany. An average of 15 per cent reported new technologies resulting in no impact on task composition, with country level less than 10 per cent in France and Poland. The average incidence of technological driven task displacement only stood at 5 per cent, with country level rates varying from approximately 3.5 per cent in Romania, the Netherlands and Estonia to over 7.5 per cent in Greece and Ireland. The relatively low percentages of jobs experiencing task displacement as a consequence of technological change places serios question marks over previous studies predicting large scale job destruction arising from new technologies. An average of 10 per cent of European employees report experiencing new technologies resulting in task creation only, with the incidences running from below 8 per cent in Cyprus, Belgium and Hungary to almos7 17 per cent in Malta. Finally, where technological change is present within a workers main job it is most likely to result in both task creation and task displacement, with an average of 13 per off European workers reporting this outcome. Rates of technologically driven combined task displacement and task creation rates from 5 per cent of employees in Cyprus to 22 per cent in Ireland.

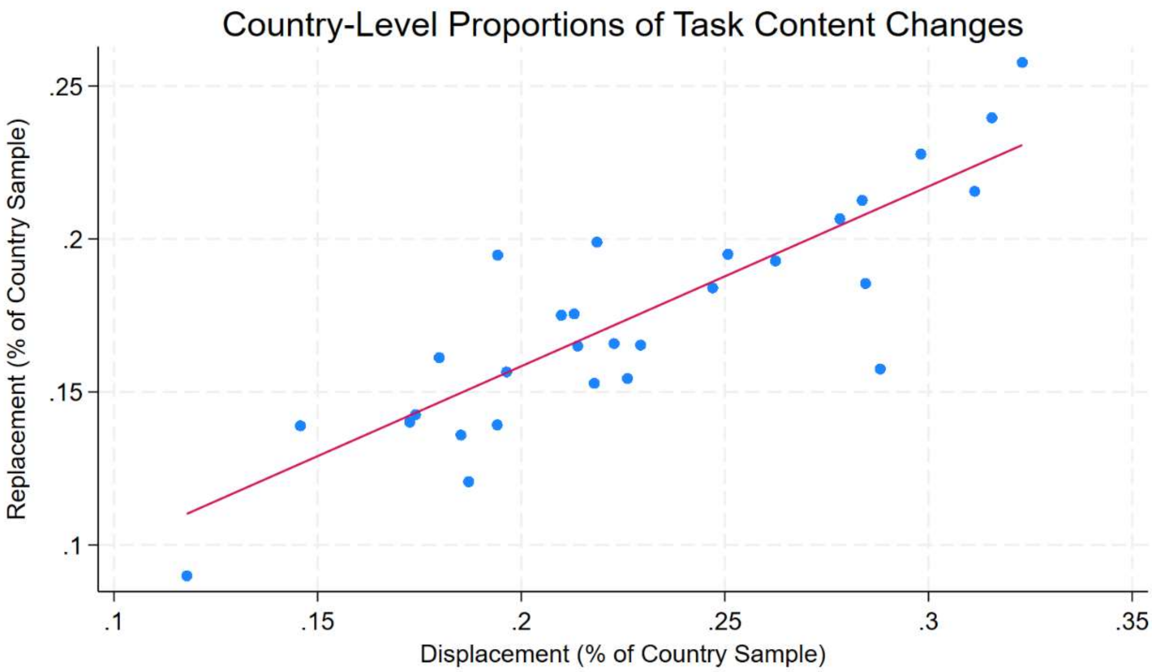
In Figure 1 we plot the incidences of task creation (either in isolation or in combination with task displacement) and task displacement (either in isolation or in combination with task creation) for each European country ranked by rates of task creation. There is no clear pattern emerging regarding geographical location and the incidence of technologically driven task replacement, eastern and central European countries are amongst those with the lowest rate of task replacement, whilst central, eastern and peripheral European countries have some of the highest incidences. It is also clear from Figure 1 that rates of task creation within countries tend to be also correlated with rates of technologically driven task displacement, for instance, Cyprus and Iceland have some of the lowest incidences of both task displacement and creation, while Ireland and Romania have some of the highest rates of both forms of taj disruption. This relationship is confirmed in Figure 2, where we plot country level rates of technologically driven task displacement and task creation and the chart provides strong descriptive evidence to support that levels of technological task disruption are both highly dispersed internationally and tend that rates of task creation and task disruption are positively correlated with each other at county level.

Table2: Country-Level Proportions of Respondents Reporting Technological Change and Task Content Changes (% of Total Country Sample)

Country	No Technological Change	Technological Change, No Task Changes	Displacement Only	Replacement Only	Displacement & Replacement
Austria	60.90%	12.90%	4.40%	10.90%	10.90%
Belgium	58.00%	14.30%	5.60%	7.60%	14.30%
Bulgaria	56.00%	11.40%	4.60%	11.60%	16.00%
Croatia	59.60%	13.40%	4.50%	10.10%	12.10%
Cyprus	64.40%	19.80%	3.80%	6.70%	5.10%
Czechia	61.00%	16.70%	4.80%	8.10%	9.20%
Denmark	48.40%	19.10%	6.90%	12.10%	12.60%
Estonia	61.70%	15.30%	3.60%	10.00%	8.30%
Finland	43.80%	22.60%	6.50%	13.50%	12.60%
France	64.90%	9.30%	4.50%	8.30%	13.00%
Germany	67.40%	11.40%	3.70%	6.90%	10.50%
Greece	55.50%	16.90%	8.00%	8.00%	11.40%
Hungary	59.90%	16.60%	5.50%	7.30%	10.60%
Iceland	51.40%	25.80%	7.60%	8.10%	6.30%
Ireland	54.00%	9.30%	4.20%	10.60%	21.60%
Italy	58.40%	14.20%	4.40%	10.70%	12.20%
Latvia	61.90%	11.80%	3.80%	10.70%	11.70%
Lithuania	52.20%	12.10%	4.00%	13.10%	17.50%
Luxembourg	58.40%	17.80%	4.10%	9.70%	9.70%
Malta	51.70%	15.00%	4.10%	16.70%	11.70%
Netherlands	61.20%	16.80%	3.50%	8.40%	10.10%
Norway	47.90%	24.00%	6.10%	10.90%	10.40%
Poland	59.10%	9.50%	2.90%	12.70%	15.60%
Portugal	58.00%	14.70%	6.30%	9.80%	11.20%
Romania	54.90%	10.00%	3.40%	10.90%	20.60%
Slovakia	59.70%	15.50%	4.70%	8.50%	10.90%
Slovenia	57.00%	14.20%	4.00%	10.40%	14.30%
Spain	54.70%	12.40%	4.50%	11.60%	16.80%
Sweden	48.50%	16.30%	5.10%	12.00%	17.70%

Figures in these two graphs are for non-exclusive technological change categories (e.g. 'Displacement' refers to workers experiencing displacement, regardless of whether they experience replacement). They are also unweighted.


Task Content Changes (Displacement, Replacement)
Source: ESJS2
%
0
.1
.2
.3
Cyprus
Iceland
Czech Republic
Germany
Hungary
Netherlands
Estonia
Luxembourg
Greece
Slovakia
Portugal
France
Norway
Austria
Belgium
Croatia
Latvia
Italy
Slovenia
Denmark
Finland
Bulgaria
Spain
Poland
Malta
Sweden
Lithuania
Romania
Ireland
Displacement
Replacement


Country-Level Proportions of Task Content Changes
Replacement (% of Country Sample)
.1
.15
.2
.25
.1
.15
.2
.25
.3
.35
Displacement (% of Country Sample)

It is of importance for us to understand the characteristics of workers whose jobs are impacted by technological disruption as this will determine their ability to adjust to change and help inform policy aimed at helping employers and workers adopt to technological change (Table 3). The key characteristics considered are gender, tenure, educational attainment and hours worked, we also consider whether or not the job contained repetitive tasks and, as an indicator of job complexity, the extent to which workers must react to situations that could not be predicted[3]. With respect to gender, relative to the sample mean, females (males) appear to be under-represented (over-represented) in jobs where new technologies have lead to task displacement only or task displacement combined with task creation. With respect to levels of schooling, again relative to the sample mean, workers with higher levels of education are over-represented in jobs impacted by technological change. Workers with the lowest level of educational attainment, these are under-represented to varying degrees in jobs that have been effected by technological change. There are no consistent patterns with respect to tenure, however, part-time employees are generally somewhat less likely to be employed in jobs that have incorporated new technologies.

With respect to our measures of task content, contrary to the predictions of previous research, we find no evidence that workers who experienced technologically driven task displacement were more likely to be in repetitive posts. We find that workers in jobs that have experienced technological change are less likely to undertake repetitive tasks relative to the sample average or compared to workers where no new technologies have been implemented. Finally, with regard to our measure of job complexity, our descriptive analysis suggests that employees in jobs impacted by new technologies are more likely to routinely have to react to unpredictable situations relative to both the sample mean and workers in jobs not affected by technological change.

However, it is difficult to assess from the descriptive statistics the extent to which the apparent differences are statistically significant, therefore we next assess the characteristics of our four technologically impacted treatment groups, relative to workers in jobs not influenced by technology, be estimating equation 1 (Table 4). We estimate probit models and marginal effects are reported. The results from our models confirm the conclusions of our descriptive analysis. In terms of gender, females were between one and 4 percentage points less likely to be employed in jobs impacted by technological change, with the marginal effects highest for jobs experiencing both task displacement and task creation. Employees with third level qualifications were also more likely to be in jobs impacted by technology, however, this was particularly the case for those employees in jobs where tasks content was not changed following the introduction of new technologies. Workers on part-time hours and those with lower tenure were generally less likely to be employed in jobs impacted by technological change. Consistent with our descriptives, workers in three of the four categories impacted by new technologies were between 1 and 3 percentage points less likely to undertake repetitive tasks; however, employees in jobs were technological change resulted in both task displacement and task creation were no less likely to undertake repetitive tasks compared to the reference category. Finally, relating to job complexity, workers impacted by new technologies were much more likely to have to respond to unpredictable situations with the marginal effect, at approximately 7 percentage points, highest in jobs where new technologies result in both task displacement and task replacement.

[3] Based on the variable B_RTPLAN: How often does your job involve reacting to situations that could not be predicted (1=always or very often and 0 otherwise).

Table 3: Summary Statistics by Technological Change Category

Variable	No Technological Change	Technological Change (No Task Changes)	Technological Change (Displacement Only)	Technological Change (Replacement Only)	Technological Change (Displacement & Replacement)	Total Sample
Training	0.514 (0.500)	0.744 (0.436)	0.810 (0.392)	0.842 (0.364)	0.878 (0.327)	0.641 (0.480)
Female	0.521 (0.500)	0.506 (0.500)	0.424 (0.494)	0.503 (0.500)	0.446 (0.497)	0.503 (0.500)
Repetitive	0.271 (0.445)	0.204 (0.403)	0.218 (0.413)	0.229 (0.420)	0.264 (0.441)	0.254 (0.435)
Uncertain	0.252 (0.434)	0.296 (0.457)	0.302 (0.459)	0.317 (0.465)	0.349 (0.477)	0.280 (0.449)
Employment Duration (Years)	10.411 (9.408)	9.924 (9.633)	10.024 (9.384)	9.439 (9.432)	8.893 (8.714)	10.027 (9.370)
Part Time	0.222 (0.416)	0.188 (0.391)	0.187 (0.390)	0.182 (0.386)	0.207 (0.405)	0.210 (0.407)
Highest Level of Education						
Low	3,089 (11.6%)	355 (5.4%)	145 (6.7%)	237 (5.1%)	480 (8.0%)	4,306 (9.3%)
Medium	10,980 (41.2%)	1,842 (28.0%)	630 (29.1%)	1,376 (29.5%)	1,773 (29.5%)	16,601 (36.0%)
High	12,537 (47.0%)	4,363 (66.4%)	1,387 (64.0%)	3,035 (65.1%)	3,757 (62.5%)	25,079 (54.4%)
Don't Know/No Answer	61 (0.2%)	13 (0.2%)	4 (0.2%)	14 (0.3%)	5 (0.1%)	97 (0.2%)
N	26,667 (57.9%)	6,573 (14.3%)	2,166 (4.7%)	4,662 (10.1%)	6,015 (13.1%)	46,083 (100.0%)

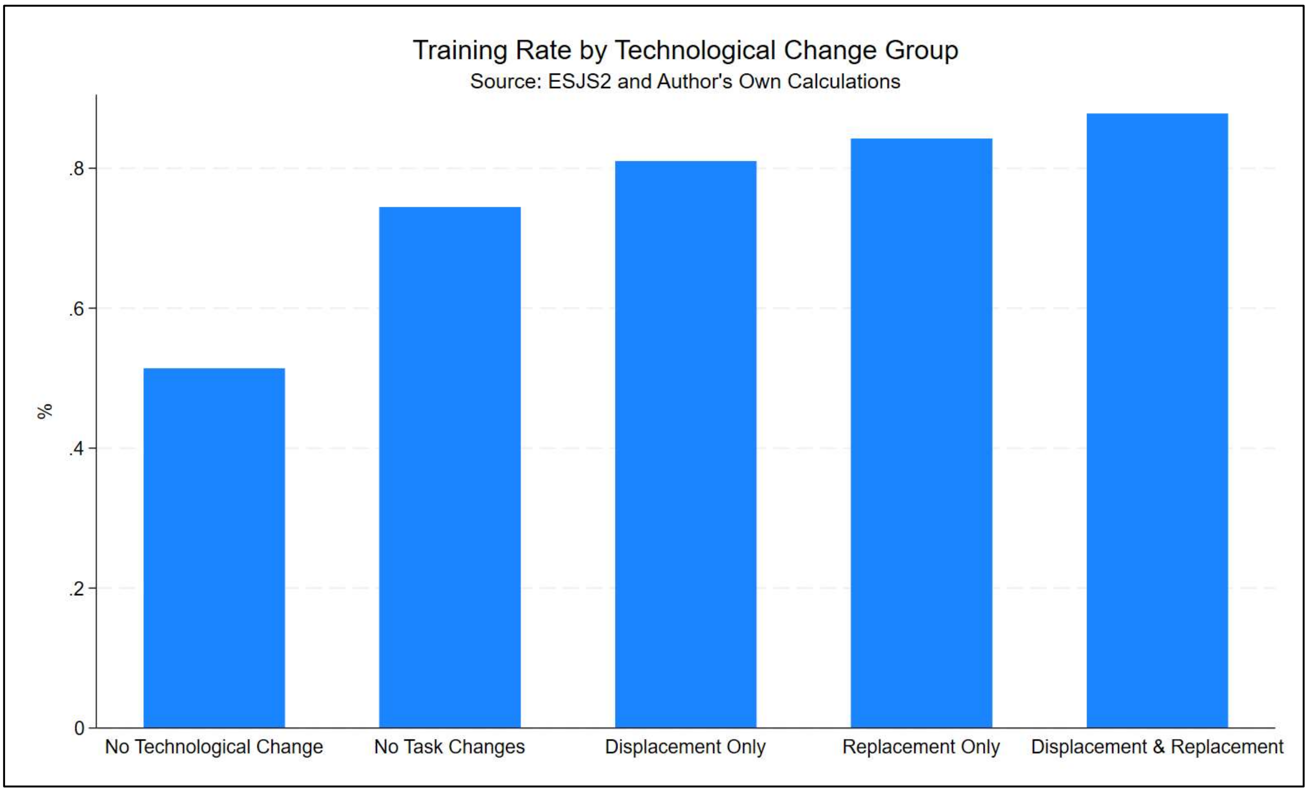
Table 4: Determinants of Technological Change (Probit Estimates, dY/dX)

VARIABLES	Technological Change (No Task Content Changes)	Technological Change (Displacement Only)	Technological Change (Replacement Only)	Technological Change (Displacement & Replacement)
Female	-0.0128**	-0.0249***	-0.0119*	-0.0424***
	(0.00535)	(0.00376)	(0.00690)	(0.00467)
Repetitive	-0.0304***	-0.00826**	-0.0102**	0.00349
	(0.00571)	(0.00360)	(0.00471)	(0.00601)
Uncertain	0.0327***	0.0181***	0.0345***	0.0672***
	(0.00488)	(0.00351)	(0.00405)	(0.00516)
Employment Duration (Years)	-0.00118***	-0.000400**	-0.00173***	-0.00252***
	(0.000260)	(0.000186)	(0.000224)	(0.000322)
Part Time	-0.0222***	-0.00583	-0.0252***	-0.00544
	(0.00688)	(0.00513)	(0.00576)	(0.00931)
Education				
Low (ISCED 0-2)	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Medium (ISCED 3-4)	0.0347***	0.0116**	0.0371***	0.00334
	(0.00919)	(0.00501)	(0.00760)	(0.00888)
High (ISCED 5-8)	0.121***	0.0470***	0.0989***	0.0768***
	(0.0101)	(0.00530)	(0.00684)	(0.00965)
Observations	32,790	28,403	30,891	32,217

Standard errors (clustered at the country level) in parentheses. Marginal effects for industry and country not reported for brevity.

We next address a core question of our study i.e. the extent to which training requirements increase as a consequence of new technological adoption. Our key training measure here is measured by the question "in the last 12 months have you participated in any education or training activities to learn new job-related skills"[4]. Across the entire sample, approximately 64 per cent of employee's report undertaking some job-related training in the previous 12 months, however, this varies substantially with the technological job penetration. Just 51 per cent of workers in jobs not impacted by new technology were in receipt of job-related training, increasing to 74 per cent for jobs where new technologies were adopted but there was no impact on job tasks (Figure 3). The incidence of job related training increases further among employees in jobs were task were disrupted as a consequence of new technologies, rising to 81 per cent where tasks are displaced only, 84 per cent where tasks are created only and 88 in jobs where new technologies have both displaced and created tasks.

[4] Variable E_TRAIND in the ESJS2 data.



The results from our initial probit model are reported in Table 5 and, again, confirm the results of our descriptive analysis of job-related training. In our models for training, we must be cautious of uboserved factor that might potentially bias our result, for instance, it might be that new technologies are more (less) likely to be introduced into jobs undertaken by workers who are more (less) able to adapt to technologies and who are also more (less) likely to receive training. To account for such influences, we introduce additional controls into our model that will capture the extent to which employees have skill sets that are complementary to new technologies. We add the following three additional controls to our specification (1) Digital Intensity[5] (2) Tech Savvy[6] and (3) an ICT skill gap[7] The results from a pooled model containing full controls indicate that, relative to workers in jobs not impacted by new technologies, employees in jobs with new technologies and no task disruption were 14 percentage points more likely to receive job related training. The marginal effects increase with the extent of technological task disruption to 20 percentage points for task displacement only and 23 percentage points for task creation only. Employees in jobs were new technologies resulted in both task displacement and task creation were over 26 percentage points more likely to have undertaken job-related training in the previous 12 months, relative to employees in jobs not impacted by new technologies. In terms

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[5] We derive this from the question: "*Did you use any of the computing devices from the previous question to do the following activities as part of your main job in the last month?*" (Q37). We construct a simple index variable using the eight digital tasks captured in the question, weighting each task based on its technical complexity. For the first three tasks (i.e. web browsing, word processing and presentations), we assign a weight of one. For the second three tasks (i.e. using spreadsheets, using advanced formulae in spreadsheets and working with occupation-specific software), we assign a weight of two. For the last two, more advanced tasks (i.e. managing databases and writing code), we assign a weight of three. For each respondent, we simply aggregate the total value of each task, dependent on the respondent stating that they carried out such tasks in their daily work, giving us the $Digital\ Intensity$ value.

[6] This is a binary variable denoting whether respondents reported that *their friends* would say that they were technologically savvy (Q76).

[7] This is derived from the question "*To what extent do you need to further develop your computer/IT skills to do your main job even better?*" (Q61). We code this variable as a binary, where respondents who responded "Great extent" or "Moderate extent" were assigned a one, and those who responded "Small extent" or "Not at all" were assigned a zero.

of the other control variables, our three controls for worker technological complementary are all positive and significant. Training is also more likely to be allocated workers who are full time, with lower tenure and with third level qualifications. As a further robustness test we re-estimated the models on a sub-sample of data collected through CAWI with additional controls for technological complementarity, such as levels of satisfaction with technologies used in the workplace[8]e and a measure of employees use of technology in the workplace post Covid[9]. The results of this model, with more extensive controls for technological complementarity are presented in the appendix (Table A1) and are wholly consistent with our main results presented in Table 5.

In Tables 6 and 7 were undertake robustness checks that confirm our results. It Table 6 we re-estimate our probit models where the characteristics of each treatment group are estimated against a sample containing only observations of the control group of employees in jobs not impacted by new technologies. We do this to ensure that we have a set of multivariate estimates that fully align with our propensity score matching estimation approach (Table 7). The results of Table 7 closely align with those estimated using the pooled sample in Table 6. The results from our PSM models, using two different matching algorithms, are presented in Table 7 and fully align with our parametric estimates and confirm that our initial results were unaffected by sample selection bias. At the bottom of Table 7 we provide diagnostics that confirm that the matching estimators pass all balancing tests, specifically our post balancing pseudo R2 statistics are effectively zero, the Rubin's B statistics are below 25 and the Rubins R statistics all fall within the required range (0.5 and 2)

[8] This is derived from the question "*On a scale from 0 to 10, where 0 is completely dissatisfied, 5 moderately satisfied and 10 is completely satisfied, how satisfied are you with the following aspects of your job? – Digital or computer technologies you use.*" (Q64). Where respondents answered between seven and ten, they were coded as being "Satisfied", with values of zero to three corresponding to being "Unsatisfied" and four to six being "Moderately satisfied".

[9] This is derived from the question "*Compared with the situation before the Covid-19 pandemic, do you now experience any of the following situations in your main job? – You more often use digital technologies to perform some of your work tasks*" (Q78).

Table 5: Marginal Effects of Probit Models Predicting Likelihood of Training

Variables	(1) Training	(2) Training
Technological Change		
No Technological Change	*Ref.*	*Ref.*
Technological Change (No Task Changes)	0.231***	0.136***
	(0.0124)	(0.008)
Technological Change (Displacement Only)	0.296***	0.197***
	(0.0151)	(0.013)
Technological Change (Replacement Only)	0.328***	0.228***
	(0.0119)	(0.007)
Technological Change (Displacement & Replacement)	0.364***	0.256***
	(0.0136)	(0.009)
Female		-0.003
		(0.006)
Repetitive		-0.002
		(0.006)
Uncertain		0.047***
		(0.007)
Skill Gap		0.033***
		(0.006)
Tech-Savvy		0.025***
		(0.006)
Digital Intensity		0.015***
		(0.001)
Employment Duration (Years)		-0.001***
		(0.000)
Part Time		-0.026***
		(0.008)
Education		
Low (ISCED 0-2)		*Ref.*
Medium (ISCED 3-4)		-0.018*
		(0.011)
High (ISCED 5-8)		0.044***
		(0.015)
Country Included	NO	YES
Industry Included	NO	YES
Observations	45,986	40,605
Pseudo R-Squared	0.09	0.13

Standard errors (clustered at the country level) in parentheses. Marginal effects for industry and country not reported for brevity.

Table 6: Marginal Effects of Probit Models Predicting Likelihood of Training (Separate)

Variables	(1) Training	(2) Training	(3) Training	(4) Training
Technological Change	0.140***			
	(0.00874)			
Task Displacement		0.216***		
		(0.0166)		
Task Replacement			0.248***	
			(0.00865)	
Task Displacement + Replacement				0.273***
				(0.0107)
Female	-0.000241	-0.00696	-0.00333	-0.00474
	(0.00686)	(0.00759)	(0.00673)	(0.00595)
Repetitive	-0.0113	-0.0122	-0.00977	-0.00535
	(0.00736)	(0.00750)	(0.00736)	(0.00735)
Uncertain	0.0620***	0.0655***	0.0616***	0.0563***
	(0.00838)	(0.0101)	(0.00910)	(0.00831)
Skill Gap	0.0348***	0.0365***	0.0353***	0.0342***
	(0.00803)	(0.00843)	(0.00819)	(0.00807)
Tech-Savvy	0.0373***	0.0243***	0.0264***	0.0227***
	(0.00732)	(0.00649)	(0.00767)	(0.00676)
Digital Intensity	0.0157***	0.0174***	0.0162***	0.0173***
	(0.00124)	(0.00128)	(0.00124)	(0.00106)
Employment Duration (Years)	-0.00111***	-0.00157***	-0.00141***	-0.00123***
	(0.000322)	(0.000395)	(0.000372)	(0.000372)
Part Time	-0.0341***	-0.0221**	-0.0315***	-0.0192**
	(0.00931)	(0.00987)	(0.00930)	(0.00920)
Education				
Low (ISCED 0-2)	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Medium (ISCED 3-4)	-0.00737	-0.0192	-0.0159	-0.0216**
	(0.0134)	(0.0118)	(0.0120)	(0.0103)
High (ISCED 5-8)	0.0689***	0.0578***	0.0537***	0.0440***
	(0.0180)	(0.0172)	(0.0158)	(0.0148)
Country Included	YES	YES	YES	YES
Sector Included	YES	YES	YES	YES
Pseudo R-Squared	0.08	0.08	0.10	0.12
Observations	28,250	23,973	26,365	27,675

Standard errors (clustered at the country level) in parentheses. Marginal effects for industry and country not reported for brevity.

Table 7: ATEs (Propensity Score Matching Estimates)

Table 7: ATTs (Propensity Score Matching Estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Training (No Caliper)				Training (Caliper = 0.01)			
Technological Change	0.133***				0.133***			
	(0.010)				(0.010)			
Displacement Only		0.198***				0.198***		
		(0.015)				(0.015)		
Replacement Only			0.201***				0.210***	
			(0.011)				(0.011)	
Displacement & Replacement				0.229***				0.232***
				(0.011)				(0.011)
Caliper	--	--	--	--	0.01	0.01	0.01	0.01
Nearest Neighbour Min.	1	1	1	1	1	1	1	1
Observations (On Support)	28,227	23,959	26,342	27,637	28,208	23,954	26,312	27,536
Postestimation								
Pseudo R-Squared (Pre)	0.066***	0.089***	0.097***	0.203***	0.066***	0.089***	0.097***	0.203***
Pseudo R-Squared (Post)	0.002	0.004	0.003	0.006	0.002	0.004	0.003	0.005
Rubin's B (R)	9.1 (1.02)	15.0 (1.01)	13.9 (1.07)	18.2 (0.96)	9.1 (1.02)	15.1 (1.00)	13.7 (1.07)	16.1 (0.98)

Standard errors in parentheses.

Robust standard errors in parentheses. Calipers are specified as 25% of the standard deviation of propensity scores. Unmatched observations are dropped from caliper estimations and calipers are re-estimated until all observations are matched.

While the PSM approach does not correct for unobserved heterogeneity, it does allow us to implement post-estimation checks to measure the degree to which the PSM estimates on the impact of technological change on training are robust to the influence of unobserved heterogeneity. Becker and Caliendo (2007) outline a sensitivity check which allows the researcher to determine how strongly unobserved effects must influence the selection process to undermine the propensity score matching results. This can be implemented using their *mhbounds* Stata command.[10] The results from the tests (Table 8) indicate that the estimated impacts of technologically driven task change on training, are highly robust and would remain statistically reliable even in the presence of an unobserved variable that would cause the odds ratio of treatment assignment to increase by a factor of between 2 and 4.5. We also carried out the sensitivity tests on the PSM estimates generate using a Caliper and get approximately the same results[11].

[10] See Becker and Caliendo (2007) for a detailed exposition of this sensitivity check.

[11] Results available from the authors.

Table 8: Mhbounds Estimates (No Caliper)

	Technological Change		Displacement		Replacement		Displacement + Replacement	
Γ	p_mh+	p_mh-	p_mh+	p_mh-	p_mh+	p_mh-	p_mh+	p_mh-
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1.5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	**0.22**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2.5	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	**0.14**	0.00	0.04	0.00	0.00	0.00
3.5	0.00	0.00	0.00	0.00	**0.15**	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00
4.5	0.00	0.00	0.00	0.00	0.00	0.00	**0.30**	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
5.5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6.5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7.5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

5.0 Summary and Conclusions

Understanding the extent to which technology will alter the composition of jobs and the likely associated costs for employers in assisting workers to adjust to technologically driven job disruption is a important question for policymakers. In this paper, we use data from the second wave of the European Skills and Jobs Survey (ESJS2) for 29 European countries to address these issues among employees in Europe. In terms of technological job penetration, our results indicate that 57 per cent of European employees have experienced no change in the use of new technologies within their main jobs. Of the 43 per cent of workers experiencing some technological change, 15 per cent reported no impact on job composition, 5 per cent reported task displacement only, 10 per cent task creation only. The relatively low percentages of jobs experiencing task displacement only as a result of new technologies places serious question marks over previous studies predicting large scale job destruction arising from technological change. Where technological change is present within a worker's main job it is most likely to result in both task creation and task displacement, with an average of 13 per off European workers reporting this outcome.

We find that there are no clear patterns emerging regarding geographical location and the incidence of technologically driven task replacement. Eastern and central European countries are amongst those with the lowest rate of task replacement, whilst central, eastern and peripheral European countries have some of the highest incidences. Rates of task creation within countries tend to be correlated with rates of technologically driven task displacement, for instance, Cyprus and Iceland have some of the lowest incidences of both task displacement and creation, while Ireland and Romania have some of the highest rates of both forms of taj disruption. We provide strong descriptive evidence to support the view that rates of task creation and task disruption are positively correlated with each other at county level.

Relative to the sample mean, workers with higher levels of education are over-represented in jobs impacted by technological change. Contrary to the predictions of previous research, we find no evidence that workers who experienced technologically driven task displacement were more likely to be in jobs with high levels of repetitive tasks. Our analysis shows that employees in jobs impacted by new technologies are more likely to routinely have to react to unpredictable situations, thus demonstrating a positive link between technologically driven task disruption and job complexity.

The results from our models indicate that, relative to workers in jobs not impacted by new technologies, employees in jobs with new technologies and no task disruption were 18 percentage points more likely to receive job related training. The marginal effects, with respect to job-related training, increase substantially with the extent of technological task disruption. Employees in jobs were new technologies displaced task only were 26 percentage points more likely to have undertaken training, with the probability of training for employees in jobs where new technologies have created tasks only 28 per cent higher than those in jobs. Employees in jobs were new technologies resulted in both task displacement and task creation were over 30 percentage points more likely to have undertaken job-related training in the previous 12 months, relative to employees in jobs not impacted by new technologies. Our robustness checks confirm that our results are robust to the impacts of sample selection bias and potential unobserved heterogeneity.

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Table 1A: Marginal Effects of Probit Models Predicting Likelihood of Training (CAWI)

Variables	(1) Training	(2) Training
<u>Technological Change</u>		
No Technological Change	*Ref.*	*Ref.*
Technological Change (No Task Changes)	0.231***	0.135***
	(0.014)	(0.009)
Technological Change (Displacement Only)	0.330***	0.216***
	(0.016)	(0.014)
Technological Change (Replacement Only)	0.348***	0.231***
	(0.014)	(0.009)
Technological Change (Displacement & Replacement)	0.395***	0.260***
	(0.016)	(0.010)
Female		-0.018**
		(0.007)
Repetitive		-0.002
		(0.007)
Uncertain		0.049***
		(0.008)
Skill Gap		0.031***
		(0.009)
<u>Digital Satisfaction</u>		
Unsatisfied		*Ref.*
Moderately Satisfied		-0.004
		(0.009)
Satisfied		0.016
		(0.013)
Tech Use Post-COVID		0.110***
		(0.005)
Tech-Savvy		0.008
		(0.006)
Digital Intensity		0.012***
		(0.001)
Employment Duration (Years)		-0.002***
		(0.000)
Part Time		-0.014
		(0.010)
<u>Education</u>		
Low (ISCED 0-2)		*Ref.*
Medium (ISCED 3-4)		-0.028**
		(0.012)
High (ISCED 5-8)		0.015
		(0.015)

Country Included	NO	YES
Industry Included	NO	YES
Observations	30,667	27,175
Pseudo R-Squared	0.10	0.15