Working in the *wrong job* or in the *wrong industry?*

Graduate mismatch in turbulent times

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Abstract

Skill mismatch is a characteristic common to most knowledge-based (education intensive) economies that generates significant costs at the individual and aggregate level, especially for graduate workers. It is unknown however whether (and how) talent misallocation changes in response to unexpected shocks.

Using UK individual-level data between 2017 and 2020, we address these issues through two different lenses: by identifying graduates that are employed in non-graduate occupations or overqualified (in the wrong job) and graduates earning the lowest premium in their sector (in the wrong industry). Our approach allows us to capture different dimensions of graduate misallocation and help explain wage differences across jobs and geographical areas.

Our results show that graduate mismatch based on occupation declines steadily from 2018, whilst industry-specific mismatch is generally lower but more volatile over time. However, the gap between the two measures narrows over time. Using a pseudo-panel regression approach, we estimate that mismatched graduates earn between 8% and 19% less than workers with similar qualifications who are not mismatched: one third of the wage penalty is due to graduates being in the wrong job, two thirds to graduates in the wrong job and the wrong industry. Our work therefore emphasizes the role of the sector of activity, along with that of occupation, when designing policies that target improved labour market efficiency.

1. Introduction

Economic growth and prosperity require an appropriate supply of skills and their efficient allocation across different jobs and tasks. While having a highly educated workforce is a prerequisite for achieving sustained rates of income growth (Romer 1989, Barro 2001, Mason et al. 2012), reaping the full benefits requires those skilled workers to be allocated appropriately. Evidence of substantial and persistent skill mismatch across several developed countries (Green and Henseke 2016, Flisi et al. 2017) signals the widespread inability of current labour markets to achieve an efficient skill allocation. This warrants an in-depth investigation, especially due to challenges raised by rapid technological change (automation, etc.), greater uncertainty and more volatile markets, in the face of recent recessions, war and health crises.

The literature on skills mismatch provides extensive evidence on the costs associated with the misallocation of workers. At the individual level, these include income foregone for those who are over-skilled for the job they hold (overqualified), as well as lower levels of wellbeing and job satisfaction (Hartog 2000, Green and Henseke 2016, Zhu and Chen 2016). At an aggregate level, there is an issue of lost productivity as human capital goes to waste, and concerns around the efficiency of public resource allocation for education that is underutilised. This is particularly relevant for graduates who represent the highly skilled segment of the labour force, hence their misallocation can result in important productivity losses. This paper examines graduates' skill mismatch in the UK during a time of considerable uncertainty and change following the Brexit decision in mid-2016 and the start of the COVID-19 pandemic in mid-2020. Our main question is whether the mismatch is stable over time or whether it responds to exogenous shocks.

We explore the extent of skill mismatch using two approaches. We first construct a statistical measure of mismatch, based on the average qualification within each occupation. Graduates are classified as mismatched (overqualified) if their level of education is above the benchmark. However, because of graduate heterogeneity, differences in education do not always capture true differences in skills, thus workers can be overeducated but not over-skilled (Green and McIntosh 2007, Pecoraro 2016). We therefore construct a second measure using an alternative, inferential methodology, adapting previous work by Liu et al. (2011). This evaluates the quality of the labour market match within industries rather than occupations, using information on average wages by degree subject and industry of main employment. Based on the assumption that more skilled graduates earn higher wages, this measure can potentially account for both observable and unobservable skills; in addition, it allows us to evaluate different types of graduate misallocation, those in the *wrong job* and those in the *wrong industry.* Our second method of calculation, while still qualification based goes some way in capturing wider elements of skill by adopting *a field of education* mismatch approach (Stoevska, 2018).

Comparing the extent of the mismatch using two different measures provides a robustness test rarely seen in the existing literature. It also allows us to address a second and crucial question of whether graduates in the *wrong job* are more (or less) penalized in terms of hourly earnings compared to graduates working in the *wrong industry*. The mismatch literature typically finds that overqualified workers earn less than those properly matched, that is workers with a qualification matching that one required for performing the job efficiently (Freeman 1976, Hartog 2000, Dolton and Silles, 2001, Green and Henseke, 2016, Vecchi et al. 2021). However, how the wage penalty differs for different types of mismatch remains largely unknown. If wage differentials reflect differences in workers' abilities (and productivity), they act as good proxies for the economic cost of misallocated skills. Such costs can vary along different dimensions: occupational mismatch, industry mismatch or both. Indeed, we expect that working in *the wrong job* within the *wrong industry* will be correlated with higher wage penalties and higher productivity losses.

A final question we address is whether there are regional variations in the extent of the mismatch and whether they can be related to the persistent productivity differentials across UK regions (Webber et al. 2009). Concerns about reducing regional productivity differentials have become a primary objective for the UK government, as it seeks to reduce regional inequalities. To our knowledge, few studies so far have considered the role of the skill mismatch in regional development. However, the incidence of high levels of skill mismatch in certain regions can reveal the presence of insufficient opportunities for graduates, a situation that can contribute to a low-wage and low productivity trap. Recent analysis by Evans et al. (2024) estimates that regional skills inequalities is costing the UK in productivity terms, suggesting that the UK would require 4.1 million more graduates to reduce regional skills inequality to a level comparable to other European nations. Hence, our analysis intends to provide a better understanding of regional job opportunities and of widening disparities in regional income.

Using the UK Quarterly Labour Force Survey (QLFS) and the Annual Population Survey (APS) over the 2017-2020 period, we find that on average 60% of graduates are misallocated in the UK, with 22% working in the wrong job, 21% working in the wrong industry and 16% mismatched along both dimensions. Over time, we find that the statistical (occupation-based) measure of skill mismatch declines from 2018. The inferential (industry-based) measure predicts lower levels of mismatch but is more volatile over time. During the latter part of the period, the gap between our two measures narrows as industry mismatch increases. Skills misallocations are associated with negative productivity outcomes, captured in our analysis by lower hourly earnings of mismatched graduates, compared to those that are matched either in terms of occupation or industry (or both). Our findings show that this wage penalty is substantially lower for graduates in the wrong industry (below 10%), compared to graduates in the wrong job (19%-38%) and to those who are mismatched along both dimensions (28%-45%). From a regional perspective, while the occupational mismatch has mainly decreased throughout the period, the industry measure shows an increase in several areas, particularly in Scotland, the North-East, and Wales. Compared to the rest of the country, the industry structure of these regions includes a lower proportion of employment in some key sectors for graduates' employment, such as information and communications, finance and insurance, professional, scientific and technical activities. This is likely to be at the root of the higher incidence of skill mismatch in these areas.

This article makes several important contributions to the skill mismatch and overeducation literature. Our analysis is the first to compare two measures of mismatch that account for different dimensions of the phenomenon: considering both differences between the workers' educational endowments and the requirements within occupations and the importance of workers' skills matching the needs of industries. We contribute to the understanding of how talent misallocation and graduate skill mismatch may translate into poor productivity outcomes. Our results indicate that understanding the common traits and main differences between the two types of mismatch (mismatched across both dimensions) helps identify the categories of workers that should be prioritized by policy interventions: these employees suffer the most from the lowest earnings and contribute the most to lower productivity performance of certain industries and regions.

The paper is organized as follows; in section 2 we present a background discussion and set up our research objectives. Section 3 presents our methodology for the estimation of the skill mismatch. This is followed by the presentation of the data sources and a descriptive analysis. In section 4 we discuss the empirical strategy and present our results for the estimation of the relationship between productivity and the skill mismatch, where productivity is measured by hourly earnings. Section 5 presents the analysis at the regional level while section 6 concludes the paper.

1. Background

Skill mismatch traditionally represents a misallocation of resources as the skills supplied by the labour force do not match those required for the job. While skill mismatches have important consequences for all types of workers (see, for example, Quintini 2011), they are of particular importance for graduates, as they imply that the most talented part of the workforce is misallocated. This limits its effectiveness to contribute to economic growth and indicates that a portion of resources invested by the public sector in education is wasted. Graduates represent a crucial supply of high skills that are necessary for productivity growth (Mason et al. 2020), innovation (Toner 2011) and absorptive capacity (Cohen and Levinthal, 1989, 1990). A misallocation of these resources may have a negative impact on a country's overall economic performance by reducing returns to innovation (Igna and Venturini, 2019) and resulting in substantial wage penalties for mismatched graduates. At the microeconomic level, this penalty (the difference in earnings between a matched and a mismatched worker) has been consistently documented in the literature (Verdugo and Verdugo 1989, Alba-Ramirez 1993, Dolton and Vignole 2000 Hartog 2000, Bauer 2002, Leuven and Oosterbeek 2011, among others). Skill mismatch weakens the relationship between investment in education, productivity and wages (Becker 1964, Mincer 1974), resulting in lower job satisfaction (Allen and van der Velden 2001), increased presenteeism and other counterproductive behaviors in the workplace (Tzang and Levin 1985).

A major issue frequently highlighted in the literature relates to the measurement of skill mismatch and the difficulty in discriminating between the level of education, which can be easily measured, and the skill level of graduates, which includes a wide range of abilities that are difficult to capture. With the rise in the enrolment rate in higher education systems, this gap has increased over time (Chevalier and Lindley 2009), increasing the risk of inflating *measured* skill mismatch. In these circumstances, graduates who have not fully developed graduate-level skills may appear to be overeducated, while their abilities may be suitable for their occupation. Attempts to address this issue and to distinguish between observed and unobserved skills have relied on either self-reported measures of the job match quality (Chevalier 2003, Chevalier and Lindley 2009, and Green and Zhu 2010, Meroni and Vera-Toscano 2017) or by referring to the skill content of occupations, under the assumption that this reveals the skills of graduates (Vecchi et al. 2021). Both methods result in a lower incidence of the *true* skill mismatch when graduate workers with low level skills are netted out.

The literature has not only focused on the size of the skill mismatch but also its changes over time, to address the question of whether this is a temporary phenomenon or something that persists over time. While the hypothesis of a temporary skill mismatch in the transition from university to labour market has often been rejected (Duncan and Hoffman 1981, Hartog and Oosterbeek 1988, Tsang and Levin 1985, Baert et al. 2013, Meroni and Vera-Toscano 2016), there is less consensus on the cyclical variation of the mismatch. In fact, there are several views on what may happen to the skill mismatch during recessions. According to Brunello and Wruuck (2018), periods of recession can lead to the destruction of low-quality jobs and a decline in the skill mismatch. Along similar lines, Kahn and Hershbein (2018) argue that during recessions firms can adopt upskilling policies and the ensuing demand for skilled workers can promote an improvement in skill match. In the UK, Bicakova et al. (2023) find that graduates who start college during poor economic times earn on average higher wages than those who graduate in good times. This result is explained by an increasing effort of graduates both during their studies and in their employment. However, good jobs may be scarce during recessions (Reder 1955, Okun et al 1973, McLaughlin and Bils 2001), leading to an increase in the mismatch as graduates entering the labour market have to settle on lower quality jobs. Outside the UK, graduating in bad times has been found to lead to persistent lower wages (see Oreopulos et al. 2012 for North America) and to higher levels of skill mismatch (see Liu et al. 2016 for Norway).

Graduates' overqualification status and skill heterogeneity impact on their average earnings. As discussed above, the literature consistently shows that graduates who are overqualified suffer a wage penalty, which can be substantial, ranging between 30% and 40%, depending on the estimation methods and mismatch measures (Sloane and McGuinness 2009, Vecchi et al. 2021). Differentiating between skill mismatch and skill underdevelopment has important implications for the size of the earning penalty, although results are not always consistent. In Chevalier and Lindley (2009) the wage difference is larger for graduates who are genuinely overeducated than for those who appear to be overeducated (0.23 vs 0.07 log points). However, the group of genuinely overeducated workers include graduates of different skill types, therefore this classification does not allow us to distinguish between true overqualification and skill underdevelopment. In Vecchi et al. (2021), the distinction is between pure mismatch and those graduates who are under-skilled. In this case, the wage penalty is substantially larger for the latter than the former group of graduates (38% vs 20%). A further development of this analysis (Vecchi et al. 2023) accounts for the mismatch between field of study and field required for the job (horizontal mismatch). Considering both horizontal and vertical mismatch, the authors distinguish 6 skill types, finding penalties ranging from 2% to 41%, depending on the distance between jobs' skill requirements and workers' skill endowment. If we consider wages as a measure of productivity, these results show that there is an additional (and larger) effect, deriving from skill deficiencies among graduates (Mason et al. 2020, Augar et al. 2019).

An issue that has been often overlooked in the extant literature is how the skill mismatch varies across regions and whether it contributes to productivity differentials. Regional productivity differentials in the UK are large (Webber et al. 2009)[1] and reducing such differentials have been the focus of the Government's levelling up agenda. Skills are one of the key factors that can drive productivity differentials across regions (HM Treasury 2001, Webber et al. 2009). If a region is unable to attract highly skilled workers, its productivity performance is likely to be compromised. In terms of skills mismatch, a high proportion of mismatch graduates in certain regions may reveal lack of graduates' opportunities and can contribute to a 'brain drain' as graduates move into regions with better prospects. This will reinforce existing inequalities. Despite the importance of skills in nurturing productivity differentials, only few studies have analysed the possible role of skill mismatch. Lenton (2012) shows a high proportion of male overeducated workers in Grater London, followed by the North-West, Wales and the West Midlands. London has the highest returns for the correct level of education but also the highest penalty for overeducation. These results are important as they are among the few with a regional perspective. However, focusing only on male workers means that approximately half of the labour force is excluded from the analysis. Work conducted by the ONS, considers both male and female workers and confirms the higher incidence of overeducation in London (Savic et al. 2019); however, a more recent evaluation of the skill mismatch at the regional level among graduates, and the impact on their earnings is a clear gap in existing literature.

3. Methodology: measuring the skill mismatch

Occupational-based measure of skill mismatch (statistical measure)

Our first measure of mismatch is based on an established methodology routinely used by various statistical offices and international institutions, such as the UK Office of National Statistics (ONS) and the International Labor Organization (ILO). This measure involves first, the calculation of the observed average educational level per occupational group at the level of 3-digit Standard Occupational Classification. Second, a worker is classified as matched (i.e, appropriately qualified) if their qualification falls in the range of +/- one standard deviation around the occupation mean. If workers

[1] Other key drivers include investment, innovation, enterprise and competition (Webber et al. 2009).

have a qualification above the upper threshold, they are considered over-qualified; if they have a qualification level below the lower threshold they are considered under-qualified.

The implicit assumption behind this method, (usually termed the realized matches or the statistical method; Hartog 2000, Lenton 2012), is that the current educational levels in the occupation are representative of the level of qualification required. By construction, the average educational requirement increases across all occupations if participation in education, and the average level of educational attainment in the population, increases over time – as has been the case in the UK over the past three decades. The effect on the degree of matching across the whole economy is therefore dependent on the age composition of each occupational group and the distribution of older and younger workers across occupations. To mitigate a potential age composition bias, we construct estimates of required education for two age groups separately *(i)* 16 to 35 years, and *(ii)* 36 to 64 years.

An advantage of the occupational mismatch measure is that it is straightforward to calculate, requiring only the occupational status and educational attainment of each worker. It also useful for comparison across different studies and countries as it has been used in several applications (Martins 2004, Flisi et al. 2017, Biagi et al. 2020). One limitation is that is based solely on qualifications, which may not reflect all skills required to successfully perform tasks, and it does account for different fields of study. Hence, it is difficult to evaluate whether a specific qualification is appropriate for the related field of work. For example, a degree in history may not be particularly helpful for a job in the healthcare sector (i.e. horizontally mismatched workers), and thus some of the costs associated with mismatch may still hold even if the individual is not classified as overqualified.

Industry-rank measure of skill mismatch (inferential measure)

Our second measure of skill mismatch builds upon the methodology developed by Liu et al. (2016). This method exploits cross-industry (exogenous) variation in worker allocation, and hence in the quality of the labour market matches, by inferring the skill requirement of each industry from the wage premium rewarded to different groups of workers. Since the field of education captures the different set of (certified) worker abilities, one can look at which industries pay higher (and lower) graduate wages in each field and identify those that are more likely to offer good (or bad) matches for particular degree fields.

Construction of the Industry measure begins with the estimation of the wages premium for each graduate (*i*) and each industry (*j*) and year (t):

$$\ln\left(hpay_{i,j,t}\right) = \sum_{f=1}^{17} \omega^f Field_{i,j}^f + \omega^p Part-time_{i,j} + \sum_{r=1}^{4} \omega^r Region_{i,j}^r + \varepsilon_{i,j} \quad (1)$$

Where the dependent variable is the log of hourly pay, f is the degree field (f=1, …17); j is the industry (j=1,..,7), and r denotes macro regions of the UK (r=1,..4). The specification also accounts for the type of job, i.e., whether full-time or part-time. In equation (1), *Field* represents a set of dummy variables identifying the subject area of degree held by each worker, with $\omega^f s$ reflecting the associated wage premiums. After estimation, industries are ranked in each year from the highest to the lowest wage premium. The rank, denoted by R_i^f gives us a measure of the quality of the match. A graduate with a degree field '*f*' is considered as mismatched if he/she is employed in one of the industries that pays the three lowest wage premiums (see Liu et al. 2016):

$$Mismatch_i^f = 1(R_i^f \leq 3). \quad (2)$$

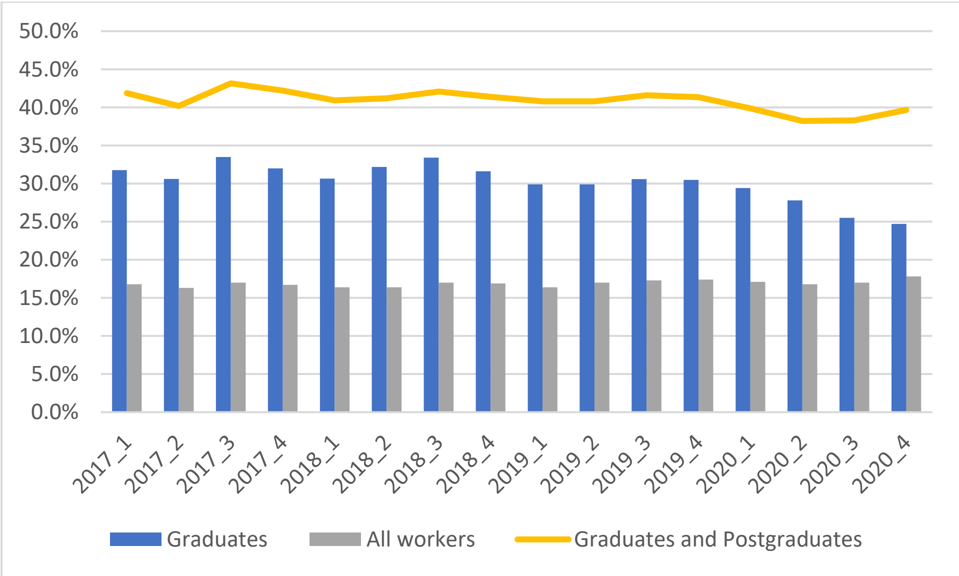
As the two measures of mismatch are quite different, we expect that they will capture different graduates, hence we expect the correlation between the two measures to be fairly low. Our analysis will also look at the cross-section between the two measures to identify graduates that are mismatched under both dimensions.

4. Data and descriptive analysis

This paper utilizes two related data sources: the Quarterly Labour Force survey (LFS) which offers timely and representative analyses of the UK labour market for the period the 2017-2020 period; and the Annual Population Survey (APS) which draws from the same survey as the LFS but contains additional regional boosts to the data to increase the sample size, enabling finer disaggregation when exploring specific variables. Both datasets are produced by the Office for National Statistics (ONS) and are the source of official labour market estimates. Using both datasets ensure consistency in definitions, while providing greater granularity either in time or in sample size depending on which we use.

Measures of mismatch based on occupations are derived at the quarterly and annual level, using QLFS and APS, respectively. Figure 1 shows the variation of the skill mismatch over the 2017-2020 period, considering all workers and the subgroups of graduates (first degree only) and graduates plus postgraduates, separately. In related studies, measures of skill mismatch generally exclude postgraduates. However, as we focus on graduate mismatch, it is important to consider workers across the educational attainment distribution to gain a complete overview on the issue under investigation. Moreover, postgraduates are a category of workers expected to provide a sizeable contribution to productivity growth in digitizing economies (Stanton, 2023). While the overall figures show persistence in the proportion of mismatch, skill mismatch for graduates shows a clear decline, starting in 2018 Q4 and continuing throughout the period (from 32% to 25%). When postgraduates are included, the proportion of skill mismatch is 10 percentage points higher on average, following a similar but more muted trend (from 42 to 40%). This suggests that for postgraduate qualifications the finding of a '*proper*' job is harder and long lasting, and hence these workers are less likely to be affected by short-run changes in labor demand than first degree graduates. In addition, the benchmark (i.e., the level of education required) remains the same whether postgraduates are included or not. Their inclusion therefore increases the number of graduates in the ratio, naturally resulting an increase in the extent of the mismatch.

Figure 1: Occupational skill mismatch total and graduates (2017-2020)



Source: Quarterly Labour Force Survey, 2017 Q1 – 2020 Q4

The estimation of the wage premia and the industry ranking for the construction of our second mismatch indicator necessitated the use of the APS due to the data requirements as we need to allocated 17-degree subjects across 7 industries. This indicator allows us to identify which industry provides a good match for each degree in each year, hence deriving the mismatch criteria used to classify graduates into matched/mismatched groups. Information on the 17-degree fields can be found in Appendix table A.1. Industries included in the analysis are: (1) Agriculture, Energy and Construction, (2) Manufacturing, (3) Distribution and Hotels, (4) Transport and Communications, (5) Banking and Finance, (6) Public Services, (7) Other services.

Figure 2 presents predicted values of the wage premia derived from the regressions underlying our inferential procedure (Eqn1), for a sample (6 out 17) of degree subjects over the full set of industries (7). The upper panel presents results for Medicine and Medical Related Studies, Biological Science and Physical and Environmental Science. The lower panel reports similar estimates for Social Sciences, Business and Finance and Media Studies. Estimates for the remaining degrees (included in Appendix Table A.1), are available from the authors on request.

For each degree field, we observe large variations both across industries and over time. The lowest premia are mostly observed in Distribution and Hotels (G, J), Other Services (R-U) and Public Administration, Defense and Education (O, P, Q), irrespective of the degree subject, while premia are particularly high in the Finance sector (K-M), albeit with large variation according to the degree subject. Graduates in Biological Sciences employed in the Transport and Information and Communication industry (H, I) earn a relatively high wage in almost all years, while for Social Sciences we observe greater variation over time, suggesting there are winners and losers amongst social science graduates.

Measurement of skill mismatch is typically affected by selectivity issues, as workers with better (worse) abilities self-select into industries requiring more (less) advanced skills and paying better wages. This may potentially exacerbate the mismatch based on industry data if it generates an imbalance in wage premia for the same field across sectors. However, Figure 2 shows that the ranking of industries paying lower wage premia is stable across fields of degree (i.e., it is unrelated to field of education and certified abilities of the workers) implying the selection of low-skilled workers into low-skilled production is unlikely to affect their status of (mis)matched as arising from our inferential method[2].

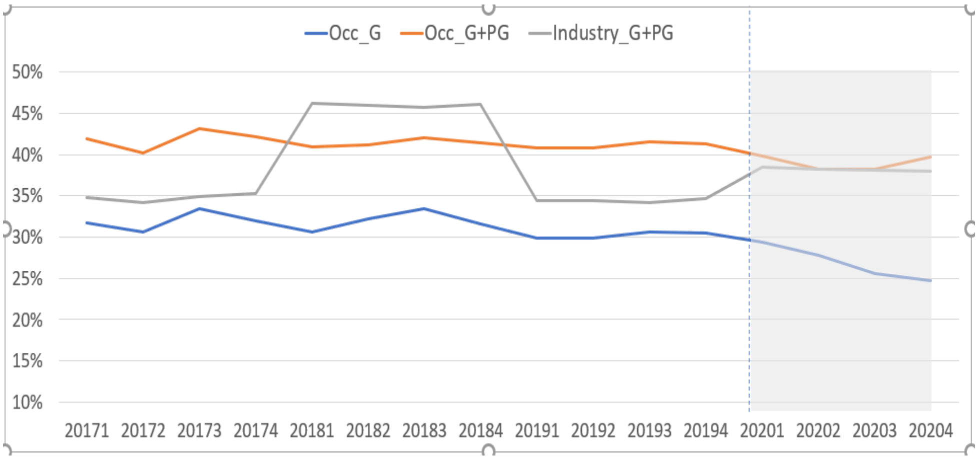
Figure 3 compares the evolution of occupational mismatch (both with and without postgraduates included) over time, relative to the industry-rank based indicator. The latter measure is more volatile and sits below the corresponding occupational based measure, except for 2017Q4 – 2018Q4, when the proportion of graduates in the *wrong industry* reaches approximately 46%, substantially above the occupational mismatch measure for graduates and postgraduates. This large increase is thought to be driven by the introduction of a wage freeze in the public sector during the period of austerity, and by the large proportion of graduates employed in this sector. During 2017-2020, approximately 31% of graduates were employed in Government services (Romiti et al. 2021). The shaded area in Figure 4 illustrates the first lockdown period (from April 2020). Overall, the occupational skill mismatch continues the slight downward trend, which began at the end of 2018. The industry mismatch measure starts to increase just before the Covid19-pandemic and then plateaus in 2020 at approximately 37%, when the two measures of mismatch converge.

[2] The methodology employed for our inferential measure of skill mismatch was originally developed for panel data sets, tracking different cohorts of graduates over time (Liu et al. 2016). Due to data limitations, the construction of rank indicator of skill mismatch relies here on repeated cross-sections, i.e., tracking different samples of workers over time. However, our data offers the possibility to exploit variation in geographical distribution of production to infer differences in regional job opportunities (and risk of mismatch) for graduates/skill gaps, which is a novel contribution to the literature.

Figure 2: Industry wage premia over time, 2017 -2021

Notes: A,E,F: Agriculture, energy and construction; C: Manufacturing; G,J: Distribution, Hotels; H,I: Transport and Storage, Information and Communication; Accommodation and Food; K,L,M,N: Banking, Finance, Real Estate, Professional, Scientific and Technical Activities, Administrative Support; O,P,Q: Public Administration and Defense, Education, Human Health and Social Work; R,S,T,U: Other Services

Figure 3: Quarterly mismatch measures, 2017-2020



Notes: data source is Quarterly LFS. Occ_G = occupational mismatch measure for graduates only (first degree). Occ_G+PG= occupational mismatch measure including postgraduates. Industry_G+PG = industry mismatch measure. The latter always includes postgraduates.

The correlation between the occupational mismatch and industry mismatch indicators is statistically significant but low (8.4%). This indicates that the two measures are capturing different dimensions of graduate mismatch, i.e., graduates in the *wrong* type of job are likely to differ from graduates in the *wrong* industry. Table 1 presents the proportion of graduates who are matched both in terms of occupation and industry (first row), next to those who are mismatched according to each indicator considered in isolation (second and third row), and finally those who are mismatch along both dimensions. Our average figures over the 2017-2020 period show that 40% of graduates in the UK are employed in graduate jobs and in industries that pay a high premium for their degree subject, while the remaining 60% suffer from a type of mismatch. More specifically, 22% of graduate workers are in non-graduate jobs (but in the right industry) and 21% are in the wrong industry, while being employed in graduate jobs. From Table 1, we also see that 16% of workers are mismatched according to both measures. We expect these graduates to suffer the most from their mismatch status, suggesting that they would benefit most from policy interventions designed to support them into matched employment.

Table 1: Competing measures of mismatch (average over the 4 years)

Type of mismatch	Proportion of all graduates
Matched according to both measures	40%
Mismatched by occupational measure	22%
Mismatch by industry-ranking measure	21%
Mismatch by both measures	16%
Total	**100%**

While the discussion in this section highlights the scale of mismatch, the figures are not enough to understand the extent to which mismatched workers experience any adverse labour market outcomes nor do we have a sense of the likely productivity affect. We go on to consider these issues in the following section.

3. Modelling the relationship between productivity and the skills mismatch

The estimation of the relationship between skill mismatch and productivity generally follows the Mincer equation (Mincer 1974), where hourly wages are expressed as a function of the mismatch status and a set of individuals' characteristics. This approach follows the neoclassical assumption that wages equal marginal productivity. When panel data are available, fixed effects can be added to the specification to control for unobserved factors, such as abilities, that are likely to cause endogeneity issues in a cross-section analysis. In our case, we are dealing with repeated cross-sections, hence we estimate the productivity effect of skill mismatch based on the construction of a pseudo panel (Oreopoulos et al. 2012, Schwandt and Wachter 2019). Following Liu et al. (2016), we use cell observations obtained by collapsing the individual data at the level of field of study (*f*), region of residence (*r*), industry (*j*) and year (*t*). Our cell-level model is based on the following specification, estimated over the 2017-2020 period:

$$(3) \qquad \overline{w}_{f,j,r,t} = \alpha + \beta_i \overline{Mismatch}_{f,j,r,t} + \delta_t + \gamma_r + \theta_f + \vartheta_j + u_{f,j,r,t}$$

where the dependent variable is the cell average log of hourly earnings for graduates with the same field of study, working within the same industry and residing in the same region. On the right-hand side, we have skill mismatch measures (described above) also collapsed by the field of study, industry, region and year, time dummies, and fixed effects for the region of residence (γ_r), field of study (θ_f) and industry (ϑ_j). Regions refers to the 13 UK regions (variable GOVTOF in the LFS/APS) while we account for 17 field of study and 7 industries, as detailed in section 4 and Appendix table A.1.

The coefficient β provides an estimate of wage penalty associated with mismatch. In cross-sectional estimates using worker-level data, the mismatch indicator is defined as a dummy variable and so β would represent the wage difference between matched and mismatch graduates. In our case, the mismatch variable is computed as the share of mismatch workers within each cell. Therefore, β represents the (log) difference in wages resulting from a percentage point change in the proportion of mismatch worker within each cell or, equivalently, represents the wage gap between groups (cells) with one-percent difference in the proportion of mismatch workers. A negative value for β would imply that a wage penalty is associated with the mismatch status compared to similar workers employed in job positions requiring their level of skills (perfectly matched workers).

4. Skill mismatch and productivity: econometric results

Results from the estimation of equation 3 are presented in Table 2. Coefficient estimates in the first two columns refer to regressions using the occupational measure of mismatch (graduates in the *wrong job*), while columns (3) and (4) report results for the industry measure of mismatch (graduates in the *wrong industry*). To gain insights on consistency of estimates we compare our cell fixed effect regression with the results yielded by a pooled OLS regression. Our Pooled OLS estimates include controls for year, region, degree subject and industry (columns (1) and (3)). Our FE regressions include fixed effects for unobservable cell characteristics and fixed effects for common time shocks (columns (2) and (4)).

Table 2: Graduate skill mismatch and wage penalty – cell regression

	(1)	(2)	(3)	(4)
	Occupational measure (wrong job)		Industry measure (wrong industry)	
VARIABLES	Pooled OLS	FE estimator	Pooled OLS	FE estimator
Mismatch measure	-0.375***	-0.189***	-0.065***	-0.082***
	(0.024)	(0.036)	(0.007)	(0.018)
Constant	3.125***	2.963***	2.740***	2.575***
	(0.019)	(0.019)	(0.052)	(0.063)
Observations	5,560	5,560	5,551	5,551
R-squared	0.539	0.025	0.523	0.033
Year FE	YES	YES	YES	YES
Region FE	YES		YES	
Subject FE	YES		YES	
Industry FE	YES		YES	
Cell FE		YES		YES
Groups		1,523		1,522

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2 shows that there is a significant wage penalty for mismatched graduates, even though it differs across estimation methods and mismatch measures. Working in the wrong job is associated with a penalty of 37.5% (column (1)), an outcome that is largely consistent with existing studies.[3] However, the size of the penalty nearly halves when using a FE estimator, suggesting that the impact of the mismatch is reduced when accounting for unobservable characteristics of the workers belonging to the same group (cell). Under the reasonable assumption that skills do not change substantially in the short run (four years in our analysis), and that these are captured by the deterministic components of the model, FE regressions yield more reliable estimates of the wage penalty associated with the mismatch status. These results are consistent with related work by Vecchi et al. (2021), where distinguishing between true skill mismatch and under-skilled graduates, halves the size of the wage penalty related to the mismatch status.

Results based on the industry measure of mismatch provides slightly different insights (Table 2 columns (3) and (4)). The wage penalty is approximately 8%, which is substantially lower than that estimated for the occupational measure. This may reflect the lower variation in the mismatch status within sectors. In addition, graduates working in the wrong industry could still be employed in graduate occupations, which typically command higher wages, hence resulting in a lower penalty. As argued above, the industry measure of mismatch allows us to identify the wage penalty of graduates, accounting for their skill level. Consistent with this explanation, results based on the industry mismatch indicator are not significantly different across the Pooled-OLS and FE regressions.

As a robustness check, we investigate how a different data aggregation might affect our results. We construct a second cell-based model that aggregates variables over cohort of graduates, with the same degree, working in the same industry and in the same year, but removing the regional dimension. Each cohort is identified as workers within a 10-year interval. Results presented in Table 3 show that, for the occupational mismatch measure, the size of the penalty is consistent across the two estimators (columns 1 and 2), suggesting the mismatch status may be persistent, supporting related evidence in Meroni and Vera-Toscano (2016). Consistent with the results reported in Table 2, the wage penalty associated with industry mismatch is lower, and although it doubles when controlling for unobserved ability (column 4), the estimates confirm that working in the wrong job leads to worse labour market outcomes compared to working in the wrong sector.

[3] For example, in McGuinness and Sloane (2011), the wage penalty ranges between 37% and 40% depending on the estimation method used; in a cross-sectional analysis for the year 2017, Vecchi et al. (2021) estimates for the wage penalty range between 22% and 35%.

Table 3: Graduate skill mismatch and wages – Cell-based model based on cohorts of graduates

	(1)	(2)	(3)	(4)
	Occupational measure (wrong job)		Industry measure (wrong industry)	
VARIABLES	Pooled OLS	FE estimator	Pooled OLS	FE estimator
Mismatch measure	-0.284***	-0.261***	-0.066***	-0.120***
	(0.048)	(0.082)	(0.010)	(0.030)
Constant	2.834***	3.061***	2.740***	2.966***
	(0.035)	(0.048)	(0.029)	(0.017)
Observations	2,517	2,517	2,517	2,517
R-squared	0.688	0.016	0.684	0.016
Year FE	YES	YE	YES	YES
Region FE	YES		YES	
Subject FE	YES		YES	
Industry FE	YES		YES	
Number of id	679	679	679	679

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

One caveat for the estimates presented in Table 2 is that there is an overlap between the two measures, since those graduates included in the occupational mismatch indicator can potentially be included in the wrong industry mismatch measure, confounding the effect of the two types of mismatches. Indeed, Table 1 shows that there is a substantial proportion of graduates who are mismatched along both dimensions, i.e. they are employed in the wrong job within the wrong industry. We therefore re-estimate equation (3) using the distribution of graduates presented in Table 1, hence accounting for three types of mismatched workers. Results in Table 4 reveal that the wage penalty is mainly associated with working in the wrong job rather than in the wrong industry. Indeed, the penalty associated with the pure industry mismatch is not statistically significant. However, although graduates employed in a graduate job within the wrong industry do not appear to be penalised in terms of wages, the size of the pure industry mismatch, estimated at 21% of all graduates, indicates the presence of a sizeable misallocation of resources which might affect aggregate productivity. The size of the penalty increases when graduates are employed in the wrong job within the wrong industry. This category of worker suffers the most from their mismatch status. Under the assumption that the inferential (industry) mismatch measure captures different in abilities, this group of workers is unlikely to have developed graduate-level skills and are therefore likely to be under-skilled rather than mismatched.

Table 4: Graduate skill mismatch and wages: accounting for different mismatch status

VARIABLES	(1) Pooled OLS	(2) FE estimator
Mismatch – occupation only	-0.277***	-0.154***
	(0.037)	(0.049)
Mismatch – industry only	0.019	-0.043
	(0.018)	(0.034)
Mismatch – occupation & industry	-0.452***	-0.283***
	(0.023)	(0.039)
Constant	3.070***	2.984***
	(0.024)	(0.024)
Observations	5,560	5,560
R-squared	0.544	0.031
Year FE	YES	YES
Region FE	YES	
Field of study FE	YES	
Industry FE	YES	
Number of Groups		1,523

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. Skill mismatch at the regional level

As a final contribution, we explore regional differences in skill mismatch and whether these relate to productivity differences across regions. Table 5 shows the average growth of value added per hour worked across the 12 UK regions. The table shows that productivity differences are substantial. London and the South-East lead in terms of productivity performance, followed by Scotland and the East of England. If the skill mismatch is negatively related to productivity, we would expect: (1) regions with the highest level of mismatch to be characterized by lower productivity growth; (2) higher wage penalties in low productivity areas.

Estimates of the skill mismatch for 13 Government office regions of the UK are presented in Figure 4. The figure reports changes in the skill mismatch between 2017 and 2020, together with the average level over the period, in each region. The (right hand side) blue bars represent changes in the proportion of graduates in the wrong job (occupational mismatch) and the orange bars show the changes in the proportion of graduates in the wrong industry (industry mismatch). The same colour scheme is used for the dots in the figure, representing average mismatch levels.

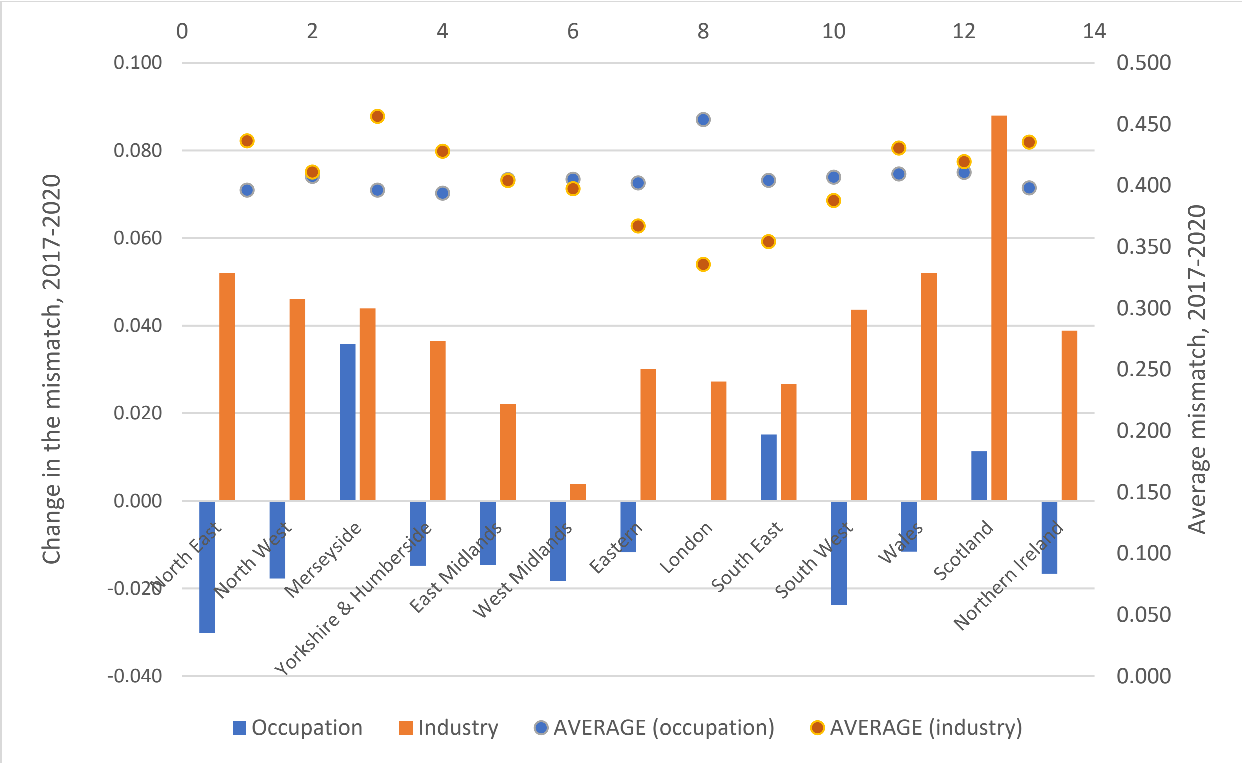
Table 5: Output per hour worked, 2017 – 2020. UK = 100

	2017	2018	2019	2020	Avg. 2017-2020
Northeast	86.1	84.2	86.7	85.4	85.6
Northwest	91.7	90.2	88.8	90.2	90.2
Yorkshire and the Humber	85.7	83.5	85.1	85.0	84.8
East Midlands	83.8	86.4	85.7	86.6	85.6
West Midlands	88.2	88.4	87.4	86.9	87.7
East of England	94.7	93.6	94.1	93.1	93.9
London	133.8	134.0	133.8	133.1	133.7
Southeast	107.4	109.9	108.6	111.1	109.3
Southwest	92.0	90.5	90.9	89.7	90.8
Wales	83.2	82.2	85.1	83.4	83.5
Scotland	96.6	97.8	98.2	96.7	97.3
Northern Ireland	82.1	82.4	82.3	84.2	82.7

Data source: regional productivity estimates, ONS.

Figure 4 shows that London has the highest level of graduate mismatch when considering the occupational measure, consistent with results reported in Savic et al. (2019). It also has the lowest incidence of industry mismatch. Figure 4 also reveals that the level of mismatch within occupations had declined in most regions between 2017 and 2020, apart from Merseyside, the Southeast and Scotland. For the industry mismatch, it has increased in all regions except for the West Midlands. The highest incidence is in Scotland (approx. 9% increase) followed by the Northeast of England, the Southwest and Wales, all reporting a 5% increase in the industry mismatch measure.

Figure 4: Skill mismatch at the regional level, 2017-2020



Notes: bars identify changes in the skill mismatch between 2017-2020 (left axis). Dots represent average levels of mismatch over the same period (right axis).

To address the question of whether we observe higher wage penalties in low productivity areas we extend equation (3) by interacting the two mismatch measures with regional dummies:

$$(4) \qquad \overline{w_{f,J,r,t}} = \alpha + \beta_i \overline{Mismatch}_{f,j,r,t} + \delta_t + \gamma_r + \gamma_r * \overline{Mismatch}_{f,j,r,t} + \theta_f + \vartheta_j + u_{f,j,r,t}$$

Table 5 reports coefficient estimates only for those regions where the mismatch coefficient is statistically significant. The full set of results can be found in Appendix table A.2. These estimates are obtained with a pooled OLS regression and hence, for the reasons discussed above, can be considered as the upper bound of the wage penalty.

Table 6 shows that the association between mismatch status and earnings is relatively robust, since our findings are broadly consistent with earlier estimates, although the size of the wage penalty associated with the occupation mismatch is larger when accounting for regional differences. In the Northeast, our benchmark, the wage penalty is estimated at -0.454, suggesting that in this region graduates in non-graduate jobs earn nearly 50% less than those appropriately matched. Only in 4 regions (East Midlands, East, Southeast and Southwest) do we find that wage penalties are significantly lower, although the size of the difference is not substantial. As expected, and consistent with previous estimates, the industry mismatch measure is associated with substantially lower wage penalties: – 5.3% in the Northeast and slightly higher penalties in London and the Southeast. As previously discussed, even when accounting for regional differences we find that the skill mismatch penalty is evident with the occupational measure, i.e. graduates in the wrong job, compared to those employed in the wrong industry.

Table 6: Skill mismatch and wages - differences across regions

VARIABLES	(1) Graduates in the wrong job	(2) Graduates in the wrong industry
Mismatch (benchmark- Northeast)	-0.454***	-0.053***
	(0.051)	(0.017)
Mismatch EM	0.030**	-0.003
	(0.014)	(0.005)
Mismatch EST	0.027***	-0.004
	(0.008)	(0.003)
Mismatch LDN	0.010	-0.007***
	(0.008)	(0.002)
Mismatch SE	0.034***	-0.007***
	(0.008)	(0.002)
Mismatch SW	0.012**	-0.005
	(0.006)	(0.003)
Constant	3.157***	2.991***
	(0.028)	(0.018)
Observations	5,560	5,560
R-squared	0.542	0.521
Year FE	YES	YES
Region FE	YES	YES
Subject FE	YES	YES
Industry FE	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Considering wages as a measure of productivity, our results do not support the presence of large productivity differences across regions due to skill mismatched, as the wage penalties are similar throughout the country. Understanding the relationship between skills mismatch and output per worker is particularly challenging. McGowan and Andrews (2015), in a study of OECD countries, find that overqualification and over skilled are positively associated with firm productivity. However, at the aggregate level, this misallocation constrains the growth of relatively more productive firms that could use skilled workers more efficiently. In our case, London, with the highest proportion of overqualified graduates, performs better than any other UK region. However, if some of those skills were more efficiently allocated throughout the country, they could promote a more equal productivity performance. Testing this assumption is beyond the scope of the study but we believe it is an important development for future research.

6. Conclusions and future directions

Having the right workers in the right jobs is an important step in ensuring labour markets are equipped for productivity growth, particularly in the face of turbulent economic times. Our analysis provides new evidence of skill mismatches through two different lenses, measuring the proportion of graduates working in the wrong jobs and in the wrong industries. To our knowledge, this is the first UK-based analysis where graduate outcomes in terms of job match quality is evaluated both at the occupation and at the industry level. A first important finding is that, over the 2017-2020 period, 40% of graduates are matched across both dimensions of industry and job, while the remaining 60% are in some form of mismatched employment, either employed in the wrong job or the wrong industry. This means that a sizeable proportion of graduates' skills is misallocated; in addition, 16% of graduates are mismatched along both dimensions, indicating that part of the supposedly high-skilled labour force is employment in low-paying non-graduate jobs, potentially suffering the most from the mismatch status, and contributing the least to the country's productivity performance.

Our results show that over the short time period of 2017-2020 at the aggregate level there has been little impact on the proportion of mismatched graduates. This suggests that the skill mismatch is both structural and pervasive. In terms of wages, we provide estimates of the average wage penalty for overqualification, using a pseudo panel approach, which allows us to account for unobserved factors when working with repeated cross-sections. By removing the noise of individual-level data and potentially accounting for unobserved abilities, this method should provide a less biased estimate of the relationship between skill mismatch and wages. Indeed, when fixed effects are included in the estimation, the wage penalty related to the occupational mismatch is much reduced, suggesting that part of the penalty is due to unobservable characteristics rather than the mismatch status. Estimates of the penalty for working in the wrong industry are more consistent across different estimators, confirming our initial assumption that this measure can better account for graduates' unobserved skills. The size of the penalty is lower compared to that associated to the occupational mismatch, 8% vs 19%, indicating that working in the wrong job is more punishing than working in the wrong industry. Being mismatched at the occupation and at the sectoral level leads to the highest wage penalty (28% - 45%) as expected.

Looking at the regional dimension, we find some unexpected results. The common assumption is that high levels of skills mismatch are positively correlated with low productivity performance. However, while the mismatch of skills within occupations is particularly large in (Greater) London, confirming existing results (Lenton 2012, Savic et al. 2019), London outperforms all other UK regions in terms of productivity performance. In addition, while cross-regional productivity differences are large, we do not find substantial differences in the size of the wage penalty across regions, for either type of mismatch. This may suggest that the skill mismatch is not a contributing factor to the observed regional inequalities. However, we believe that the relation between skill mismatch and productivity is much more complex than usually assumed and that evaluating differences in productivity using wage differentials provides potentially distorted results (McGowan and Andrews 2015). We consider a better understanding of these trends an important development for future research, particularly to assist the design of policies to reduce inequalities.

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Appendix

Table A.1:

Degree classification used in the industry-rank measure of skill mismatch.

1	Medicine and Medical related studies
2	Biological Sciences
3	Agricultural Sciences
4	Physical/Environmental Science
5	Math and Computer Science
6	Engineering
7	Technology
8	Architecture
9	Social Sciences
10	Business & Finance degree
11	Media and Information studies
12	Linguistic, English
13	Other Languages
14	Humanities
15	Education
16	Arts
17	Law

Table A.2 Skill mismatch and wages at the regional level. Full set of results.

VARIABLES	(1) lhourpay	(2) lhourpay
	Occupational mismatch	Industry mismatch
Mismatch (benchmark- Northeast)	-0.454***	-0.053***
	(0.051)	(0.017)
Mismatch _EM	0.030**	-0.003
	(0.014)	(0.005)
Mismatch _EST	0.027***	-0.004
	(0.008)	(0.003)
Mismatch _LDN	0.010	-0.007***
	(0.008)	(0.002)
Mismatch _MSY	0.031	0.003
	(0.019)	(0.006)
Mismatch _NI	0.007	-0.000
	(0.007)	(0.004)
Mismatch _NW	0.015	-0.008
	(0.027)	(0.009)
Mismatch _SCO	-0.003	-0.001
	(0.004)	(0.002)
Mismatch _SE	0.034***	-0.007***
	(0.008)	(0.002)
Mismatch _SW	0.012**	-0.005
	(0.006)	(0.003)
Mismatch _WAL	-0.002	0.002
	(0.006)	(0.002)
Mismatch _WM	0.010	-0.001
	(0.018)	(0.004)
Mismatch _YH	0.026*	0.006
	(0.013)	(0.008)
Constant	3.157***	2.991***
	(0.028)	(0.018)
Observations	5,560	5,560
R-squared	0.542	0.521
Year FE	YES	YES
Region FE	YES	YES
Subject FE	YES	YES
Industry FE	YES	YES

Notes: standard errors in brackets.