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Exposure to Artificial Intelligence and Occupational Mobility:

A Cross-Country Analysis

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ABSTRACT: We document historical patterns of workers' transitions across occupations and over the life-cycle for different levels of exposure and complementarity to Artificial Intelligence (AI) in Brazil and the UK. In both countries, college-educated workers frequently move from high-exposure, low-complementarity occupations (those more likely to be negatively affected by AI) to high-exposure, high-complementarity ones (those more likely to be positively affected by AI). This transition is especially common for young college-educated workers and is associated with an increase in average salaries. Young highly educated workers thus represent the demographic group for which AI-driven structural change could most expand opportunities for career progression but also highly disrupt entry into the labor market by removing stepping-stone jobs. These patterns of "upward" labor market transitions for college-educated workers look broadly alike in the UK and Brazil, suggesting that the impact of AI adoption on the highly educated labor force could be similar across advanced economies and emerging markets. Meanwhile, non-college workers in Brazil face markedly higher chances of moving from better-paid high-exposure and low-complementarity occupations to low-exposure ones, suggesting a higher risk of income loss if AI were to reduce labor demand for the former type of jobs.

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Exposure to Artificial Intelligence and Occupational Mobility: A Cross-Country Analysis

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Abstract

We document historical patterns of workers' transitions across occupations and over the life-cycle for different levels of exposure and complementarity to Artificial Intelligence (AI) in Brazil and the UK. In both countries, college-educated workers frequently move from high-exposure, low-complementarity occupations (those more likely to be negatively affected by AI) to high-exposure, high-complementarity ones (those more likely to be positively affected by AI). This transition is especially common for young college-educated workers and is associated with an increase in average salaries. Young highly educated workers thus represent the demographic group for which AI-driven structural change could most expand opportunities for career progression but also highly disrupt entry into the labor market by removing stepping-stone jobs. These patterns of "upward" labor market transitions for college-educated workers look broadly alike in the UK and Brazil, suggesting that the impact of AI adoption on the highly educated labor force could be similar across advanced economies and emerging markets. Meanwhile, non-college workers in Brazil face markedly higher chances of moving from better-paid high-exposure and low-complementarity occupations to low-exposure ones, suggesting a higher risk of income loss if AI were to reduce labor demand for the former type of jobs.

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1 Introduction

The adoption of artificial intelligence (AI) promises to bring about a wave of structural transformation that could reshape both the economy and society. As industries increasingly integrate AI technologies, the repercussions of this shift are expected to be most acutely felt in the labor market. Here, AI has the potential to both augment the productivity of certain workers and compete directly with others. This dual potential points to a period of significant disruption and adaptation in the workforce, possibly challenging traditional notions of employment, skill requirements, and job security. Several studies have sought to categorize the likely impact of AI on different occupations, offering a snapshot of labor market opportunities and risks based on countries' current economic structures. This paper attempts to move beyond these "static" approaches to capture the dynamic nature of occupational shifts and the resilience of the workforce to technological change.

Although the nature of AI's integration into different industries and occupations remains highly uncertain, recent studies by Webb (2020), Felten et al. (2021), Felten et al. (2023), Eloundou et al. (2023), Gmyrek et al. (2023) and contributions from Pizzinelli et al. (2023) and Cazzaniga et al. (2024) have laid the conceptual framework for this analysis by developing measures of the exposure of individual occupations to AI, considering the interplay between AI capabilities and human skills as well as the social context of each job. This stream of works offers a lens for a first-order view of the expected impact of AI based on a country's economic composition. Meanwhile, Acemoglu et al. (2022) and Bonfiglioli et al. (2023) provide empirical evidence of the early impact of AI adoption on the US labor market, stressing its heterogeneity across occupations and workers' skills. Both approaches provide valuable insights. However, neither of them considers workers' ability to adjust to structural change that takes place throughout their careers, and to transition away from the hardest-hit occupations by moving to those experiencing growing demand and soaring wages.

This paper therefore aims to provide preliminary insights on the ability of workers to transition across occupations that are expected to be positively and negatively affected by AI, appraising the potential impact of this technological change on their career trajectories and lifetime earnings. Using labor force microdata from two very different countries, the UK and Brazil, this study documents historical patterns of workers' occupational transitions, offering a first view of potential labor market dynamics in the face of AI. Drawing upon

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the occupational frameworks proposed by Felten et al. (2021) and Pizzinelli et al. (2023), we categorize occupations into three distinct groups based on their exposure to AI and the complementary nature of AI to human labor: i) occupations where AI is poised to enhance workers' productivity (high-exposure and high-complementarity or HEHC), ii) roles where AI is likely to substitute for human labor in performing key tasks (high-exposure and low-complementarity or HELC), and iii) occupations expected to witness minimal impact from AI (low-exposure or LE). This classification enables a nuanced but intuitive analysis of how frequently workers change between these job categories, the demographic profiles most susceptible to or benefiting from such transitions, and the associated implications for earnings.

As AI still has to be adopted on a large scale, its long-run repercussions on workers' labor market outcomes cannot yet be observed. Although historical transition patterns may not necessarily hold once a new technology spreads in the economy, they are informative of possible future developments to the extent that they help identify the demographic groups and career phases where workers are more or less likely to adjust to structural change induced by AI. The analysis can thus provide tentative answers to questions that a static analysis cannot address. In particular, it can identify the demographic groups (e.g., age and education) that are more likely to fill positions in growing occupations and those that, if displaced from their current positions, are more likely to move to lower-paid occupations. Moreover, considering the life-cycle profiles of occupational transitions offers an additional lens to examine how technological change interacts with workers' entire career paths, helping answer the following questions: will AI-induced structural change create more opportunities for workers to transition into high-earning jobs or reduce those opportunities by disrupting their traditional job ladder? How easily can workers who lose their jobs move to other fields? And what will the consequences be for workers' expected lifetime earnings?

The comparison between Brazil and the UK makes the analysis richer, as the significant differences in their labor markets capture the general features of emerging markets and advanced economies, respectively. The UK is characterized by an older labor force, where a larger share of workers holds a college degree and is employed in cognitive-intensive jobs. Brazil is comprised of a younger population with a lower average level of education and a high rate of economic informality, but where college-educated workers command a high wage premium. Moreover, the labor market in Brazil is characterized by greater dynamism, with higher rates of transition across employment, unemployment, and inactivity, suggesting a higher degree of idiosyncratic risk. The composition of employment in the two countries also differs. As shown in Pizzinelli et al. (2023), the UK has a higher share of employment in both HEHC (35 percent) and HELC (30 percent) occupations compared to Brazil (19 and 21 percent, respectively).

This study's first main finding is that college-educated workers exhibit remarkably similar patterns of transitions across the three occupation groups we consider (HEHC, HELC, and LE) in Brazil and the UK. Transition probabilities out of lower-paid LE jobs are higher than those out of higher-paying HELC and HEHC ones, implying a tendency for college-educated workers to make "upward" moves during their careers. A particularly encouraging observation is that among workers in HELC occupations, which are those facing an elevated risk from AI, there exists a significant amount of transitions toward HEHC jobs, which are those more likely to benefit from AI adoption. These transitions are also associated with wage increases. These historical patterns suggest that a substantial fraction of college-educated workers may be able to move from AI-vulnerable occupations to those where AI is more likely to boost productivity and earnings. Examining the life-cycle profile of employment of college-educated individuals reveals a tendency to move from HELC to HEHC occupations over their careers, and in particular in their 20s and 30s. This pattern underscores the potential risk of younger workers' entry into the labor market being disrupted if the availability of HELC jobs, which serve as a stepping stone, were to decline.

Workers without a university education exhibit distinct career transition patterns across the major occupation groups compared to those with a college degree. In general, non-college-educated workers face a considerably higher risk of experiencing downward mobility into LE occupations, a trend that is relatively independent of their current occupation of employment. These disparities in job transition patterns between college-educated and non-college-educated workers are particularly pronounced in Brazil, but are present in the UK as well. Furthermore, the life-cycle trajectory of earnings reveals a stark disparity: differently from the UK, in Brazil, workers without a college education realize virtually no wage growth through their careers. Nonetheless, it holds in both countries that returns from work experience are lowest for non-college-educated individuals employed in low-exposure jobs.

To further assess the impact of AI on workers' lifetime earnings, we conduct a simple partial-equilibrium counterfactual exercise where we compute the expected salary at different ages for a cohort of workers just entering the labor market under different AI adoption scenarios. This involves analyzing the distribution of workers across various occupations and earnings throughout their careers. While being illustrative in nature, the exercise points to the wide range of potential outcomes and the heterogeneity in the impact both across and within countries. For instance, the displacement of workers from HELC jobs to unemployment would have a more negative effect on average lifetime earnings in Brazil than in the UK (regardless of education level), as the relative wage of HELC jobs is higher in the former. However, in both countries, the effect of this disruption is larger for non-college workers than for the highly educated. Meanwhile, consistent with our other results, wage growth in HEHC jobs would mostly increase the lifetime earnings of highly-educated workers, and most so in the UK.

Finally, given the importance of employment informality for emerging markets, we examine whether in Brazil movements across occupation groups are associated with transitions between formality and informality. We find that occupation switches for formal workers are rarely accompanied by movements into informality when the moves take place through employment. However, when they occur via unemployment, we find that formal workers in LE jobs have a large probability of moving to informal jobs. This suggests that AI-induced job disruption is less likely to infer a "double blow" to workers by pushing them to the informal sector if they can find new opportunities without facing an unemployment spell.

This paper is related to the growing number of works discussing the impact of AI adoption on the labor market.[1] To our knowledge, this is the first attempt to tackle this question from the viewpoint of individual workers' job transitions. In particular, this approach complements well the studies that apply classifications of AI exposure to the composition of employment in one or more countries at one point in time (Pizzinelli et al., 2023; Webb, 2020; Felten et al., 2023; Eloundou et al., 2023; Briggs and Kodnani, 2023). These studies, centered on the concept of occupational taxonomies, evaluate the potential for AI to either augment human work or replace it entirely within specific job roles, taking into account societal preferences towards deploying AI in different settings. Such assessments provide valuable first-order insights, analyzing a country's vulnerability or opportunities from AI-induced labor market shifts based on its current occupational composition. Other works measure the early impact of AI on the labor market, focusing on the US. For instance, Acemoglu et al. (2022) study AI adoption and employment decisions of individual establishments, while Bonfiglioli et al. (2023) examine AI exposure at the metropolitan level. These studies find evidence of heterogeneous effects from AI adoption, with some occupations and demographic groups experiencing employment contractions while others benefit from growing opportunities. However, AI adoption so far may not be reflective of the more far-reaching

[1] A non-exhaustive list includes Alekseeva et al. (2021); Acemoglu and Restrepo (2018); Acemoglu et al. (2022); Webb (2020); Felten et al. (2023); Eloundou et al. (2023); Briggs and Kodnani (2023); Lane et al. (2023); Milanez (2023); Manca (2023); Gmyrek et al. (2023); Copestake et al. (2023); Albanesi et al. (2023); Gmyrek et al. (2024).

effects the technology might have when adopted more widely in the economy. Our paper thus considers the labor market implications of AI through a broader scope and focusing on workers' full careers as the time frame of analysis.

This paper is also related to studies that examine how structural transformation occurs through job transitions and workers' life-cycles. For instance, Cortes et al. (2020) find that automation replaced routine-intensive occupations primarily through persistent falls in the job finding rate in the aftermath of recessions. Similarly, Carrillo-Tudela et al. (2016) show that in the UK, from 1993 through 2012, worker reallocation across occupations or industries was high and procyclical, leading to wage increases, especially during economic expansions. Other works, on the other hand, note the important role of generational turnover. Adão et al. (2024) find that when new technologies require specific skills, structural change is slower and takes place through the entry in the labor market of new cohorts of workers who possess the required skills. Similarly, Dabla-Norris et al. (2023) employ the life-cycle framework to examine how routine-biased technical change affected the expected career paths and earnings of non-college female workers in the UK across different generations. Bluedorn et al. (2022) use individual-level data for 30 European countries between 1983 and 2019 to explore the extent of workers' reallocation across occupations and industries, finding a heterogeneous impact on earnings based on education, gender, and age, with large earning penalties for low-skilled and older workers transitioning to routine occupations during recessions. While these works study episodes of structural transformations that have already occurred, in this paper we use the same analytical lenses to inform the discussion over the potential impact of a technology that is yet to be widely adopted in most sectors.

The rest of the paper is structured as follows. Section 2 describes the data sources used for the analysis and the classifications of AI exposure that we take from the literature, including those developed in the companion paper Pizzinelli et al. (2023). Section 3 provides general descriptive statistics on the labor markets in Brazil and the UK and an overview of individual workers' employment dynamics. Section 4 studies workers' transitions across occupation groups by AI exposure. Section 5 studies the potential impact of AI adoption on workers' life-cycle profiles of employment and wages in each occupation group. Section 6 briefly discusses the potential link between AI exposure and informality in Brazil. Section 7 concludes.

2 Data and Methodology

This section describes the data and the construction of the variables used in the empirical analysis. We use worker-level microdata from the UK quarterly Labor Force Survey (LFS) and of the Pesquisa Nacional por Amostra de Domicílios Contínua (PNADc), which is Brazil's national labor force survey. Both surveys share a similar rolling replacement structure, where a panel of households remains in the survey for five consecutive quarters (or waves). This structure allows us to track the outcomes of a given individual over the course of a full year. For the UK LFS, we use survey data from 2010Q1 to 2019Q4, while for the PNADc we use data from 2012Q1 (when the survey is first available) through 2019Q4. We do not use data from 2020 to avoid the analysis being affected by the exceptional labor market dynamics of the COVID-19 pandemic.

The UK LFS is publicly available in a panel format where each individual is assigned the same identifier over five quarters. For the PNADc, households can be uniquely identified across quarters, but not individuals. This means that individuals must be matched across survey quarters based on demographic characteristics. We use the matching algorithm proposed by Ribas and Soares (2008), as implemented by DataZoom (2023).

For both surveys, we restrict the sample to individuals aged 16 to 64 who are employed in the reference period of the survey. The lower bound of the age interval corresponds to the age used to report the population of working age in the UK and it is also the age at which individuals can begin paid traineeship and apprenticeships. In Brazil, the legal working age also starts at 16. Similarly, 64 is two to three years below the minimum eligibility age for state-provided social security pensions in the UK but roughly aligns with the effective retirement age (OECD, 2021). In Brazil, up until 2019, the minimum eligible age for state-provided social security pensions was 65 for men and 60 for women.[2]

Our interest lying in the characteristics of workers' employment with respect to AI, we merge the surveys' occupation classifications with the AI occupational exposure (AIOE) measure constructed by Felten et al. (2021) and the AI potential complementarity measure constructed by Pizzinelli et al. (2023). These measures have been used in recent analyses of the expected impact of AI on the labor markets, such as OECD (2023a) and Cazzaniga et al.

[2]However, early retirement ages were also possible for male (female) workers that had contributed for 35 (30) years to social security. The average age for this type of retirement was 56.5 for men and 53.4 for women (Constanzi and dos Santos, 2022). "Time contributed" pensions accounted for 38 percent of pensions granted in 2019, compared to "minimum age" pensions as 41 percent of the total (Brazil, 2019). In November 2019, Brazil approved a pension reform which ended pensions for "time contributed" and raised the minimum retirement age to 62 for women. The new rules would gradually come into effect until 2033.

(2024). The AIOE index is based on the degree of overlap between 10 AI applications (such as image recognition, image generation, reading comprehension, and translation) and 52 human abilities needed to perform a given occupation as listed in O*NET, a large repository of information regarding standard occupations in the US. As such, the AIOE appraises the degree to which AI can replicate the skills essential to each occupation. While this measure can be interpreted as the potential for AI to be integrated into the productive activities performed in a given job, it remains agnostic over the likelihood that AI adoption would either serve as a complement or a substitute to human labor. To provide a tentative answer to this question, Pizzinelli et al. (2023) propose a measure of potential AI complementarity based on a set of broader social considerations–such as the level of responsibility for others' health, the importance of in-person interactions–, the physical environment of a job, and the educational and technical training required to be qualified for it. This measure is constructed using the "job contexts" and "job zones" indicators also contained in O*NET. Taken together, the two measures can provide a broad indication of which occupations are relatively more likely to i) face high risk of labor substitution from AI adoption (high exposure and low complementarity), possibly resulting in lower returns to labor or even employment displacement, ii) which are more likely to experience boosts in productivity and wages (high exposure and high complementarity), and iii) which occupations are less likely to see substantial effects from AI (low exposure).[3]

Occupations are classified following the four-digit ISCO-08 classification. For the UK LFS, occupation codes are converted from the Standard Occupational Classification (SOC) codes to ISCO-08 using crosswalks. While the granularity of the ISCO-08 classification can be helpful to understand the nuances and diversity in exposure across the labor market, for analytical simplicity we group the classification into broad categories. Following Pizzinelli et al. (2023), an occupation is considered as being a "high exposure" occupation if its AIOE score is above the median AIOE for the ISCO-08 occupation codes. Similarly, an occupation is labeled as "high complementarity" if its complementarity score is above the median score for all occupation codes.

For example, in the legal field, AI's role illustrates how technology can enhance but not supplant professional roles. Judges are considered "high exposure and high complementarity" due to the advanced textual analysis capabilities of natural language processing technologies. These systems can rapidly parse through vast volumes of legal documents to

[3]While in theory jobs with low exposure can also be differentiated into those with high and low complementarity, the definition of exposure itself suggests that within these occupations the effect of AI adoption on employment outcomes would likely be less economically significant.

identify relevant precedents and inconsistencies, significantly speeding up case processing. However, due to the significant repercussions of judicial decisions on individual lives, it is unlikely that societies would allow unsupervised AI algorithms to make final judgments. Thus, AI is expected to complement judges by enhancing their productivity rather than replacing them. In contrast, paralegals, engaged in tasks like research, textual analysis, and drafting, are categorized as "high exposure and low complementarity." The clerical nature of their work and lower decision-making stakes make their roles more susceptible to displacement by AI. Last, an occupation such as ballet dancing is found to have "low exposure" to AI, reflecting its inherently creative and physical nature that technology cannot replicate.

Formal workers in Brazil are categorized as those with a formal labor contract that is registered with the government and complies with labor legislation. This type of contract grants employees access to benefits such as social security and unemployment insurance. In contrast, workers without this type of employment registration (including unregistered self-employed individuals) are classified as informal.

To examine labor earnings dynamics, we use usual gross (pre-tax) hourly pay for the main job in local currency as our measure of earnings. For Brazil, hourly pay is calculated by dividing the usual gross monthly earnings by four times the hours worked weekly. The UK LFS already reports gross hourly wages in the survey data, but only for the first and last quarters that a household participates in the survey (waves 1 and 5), while PNADc reports it for all five waves. Thus, in Sections 3 and 4 we consider transitions over a quarter, while in Section 5.2 we consider transitions and wage variations taking place over a year (between waves 1 and 5 of the surveys). To compare across periods, we use the real wages for 2019Q4 using the price indices and deflators provided with both surveys; and to compare across countries, we convert these values to 2019 PPP dollars using the rates available in OECD (2023b).

Throughout the analysis, we examine workers' transitions across employers and occupations. We define a job-to-job transition (J2J) as the event where a worker changes employers over a given time period. A J2J occurs when a worker is employed in both the current and previous time period of analysis but reports being with the current employer for less than 3 months (quarterly transitions) or 12 months (yearly transitions). For yearly J2J transitions, we can also identify workers that transition through unemployment (EUE transitions), an event that occurs when an individual is with different employers in waves 1 and 5 of the survey, but reports being unemployed in waves 2, 3, or 4.

Another outcome we define is the occupation switch (OS). Specifically, this occurs when a worker is employed in the current and previous period, but the reported occupational code is different. Occupational switches can happen via a J2J transition or "on-the-job"; that is, remaining with the same employer. Similarly, a J2J transition may or may not also entail a change in occupation code.

3 Labor Market Characteristics

In this section, we first present an overview of labor market characteristics for Brazil and the UK, along with the average employment flows and job switching rates for Brazil and the UK. We then break down the employment flows over workers' education levels.

3.1 Worker Characteristics

We begin by establishing summary descriptive statistics in Table 1 to compare the main characteristics of labor markets in the countries over the period of analysis.

Table 1: Labor Market Summary Statistics for the UK and Brazil

	UK	Brazil
Median Worker Age	42	36
Share of Women in Employment (%)	47	42.5
Share of Workers with a College Degree (%)	36.7	17.3
Share of Workers in High AI Exposure Occupations (%)	66.4	39.7
Median Hourly Wage (2019 PPP Dollars)	18.4	3.8
Informality Rate (%)	-	42

Note: The table displays summary statistics for the UK and Brazil for the time period considered in the analysis. "Share of Women in Employment" refers to the share of total employment corresponding to women. The informality rate is defined only for Brazil.

A visible difference emerges in terms of the average age of workers. Reflecting the general structure of the population in the two countries, the median worker age is markedly lower in Brazil (36 years) than in the UK (42 years). With regard to women's participation in the labor market, female workers represent a higher share of the employed population in the UK (47 percent) compared to Brazil (42 percent). In terms of educational attainment, the difference is also pronounced. The percentage of workers with a college education in the UK is over twice as high (36 percent) as in Brazil (17 percent). This educational disparity correlates with significant wage differences; the median wage in the UK, adjusted for purchasing power parity, is nearly five times higher than in Brazil. Additionally, the proportion of employment in occupations with high exposure to artificial intelligence (AI) in the UK exceeds that of

Brazil by over 50 percent. A noteworthy aspect of the Brazilian labor market is the high level of employment informality, with almost 42 percent of workers.[4]

3.2 Labor Market Transitions

Next, we document average quarterly flows between employment, unemployment, and inactivity. These statistics are reported in Table 2 for the UK and Table 3 for Brazil. Each cell on the table represents the transition rate of workers from employment, unemployment, and not in labor force (NLF) status over two adjacent quarters.

Table 2: UK Employment Flows

	Status in the subsequent quarter		
Status in the quarter	Employed	Unemployed	Not in labor force
Employed	97.8	0.9	1.3
Unemployed	24.5	60.1	15.4
NLF	4	3.7	92.3

Note: The table shows the transition flows for the UK for the three states considered. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter.

Table 2 presents a detailed analysis of the labor market status persistence for workers in the UK. Remarkably, 97.8 percent of individuals employed at the beginning of the quarter survey entry remain employed. A smaller proportion, 1.3 percent, transition from employment to not being in the labor force, while only 0.9 percent shift from employment to unemployment. Among those classified as unemployed in the quarter, 24.5 percent transition to employment by the next quarter, whereas the majority continue to be unemployed, and 15.4 percent leave the labor force. In contrast, for individuals not in the labor force in the first quarter, 92.3 percent retain this status until the following quarter, 3.7 percent eventually move into unemployment, and the remaining participants become employed.

Table 3: Brazil Employment Flows

	Status in the subsequent quarter		
Status in the quarter	Employed	Unemployed	NLF
Employed	90.7	3.2	6.1
Unemployed	31.9	42.9	25.2
Not in labor force	13.3	7	79.7

Note: The table shows the transition flows for Brazil for the three states considered. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter.

[4]In the context of Latin America, Brazil's informality rate is similar to that of other major economies in the region, like Mexico and Colombia, but lower than Peru's and higher than Chile's.

Table 3 provides the same analysis for Brazil. In Brazil, a significant majority of workers who were employed in the first quarter are found to be still employed in the next one, accounting for 90.7 percent. A smaller proportion of these workers, 6.1 percent, transition to not being in the labor force, while 3.2 percent end up unemployed. For those who were initially unemployed, 42.9 percent remain in this status by the second quarter, 31.9 percent successfully find employment, and 25.2 percent shift to not being in the labor force. Finally, among those initially not in the labor force, the majority, 79.7 percent, maintain this status in the subsequent quarter, while 13.3 percent gain employment, and 7 percent transition to unemployment.

The comparative analysis between the UK and Brazil reveals distinct dynamics within their respective labor markets. Notably, labor market status in the UK is more persistent across all three categories: employed, unemployed, and not in the labor force, as compared to Brazil. In the UK, workers are more likely to remain employed across two quarters. While not all transitions out of employment are involuntary, this difference does suggest overall lower employment risk in the UK than in Brazil. On the other hand, in the UK workers who are either unemployed or inactive are less likely to move to employment across two quarters. This suggests that unemployment is on average longer-lasting in the UK. In this sense, the higher employment risk that workers face in Brazil might also be of a more temporary nature.

While here we focus on aggregate results, a detailed examination of gender-specific employment flows, reported in Annex A.1, reveals similar patterns for male and female workers in both countries. Brazil has a more dynamic labor market for both men and women. Similarly, in both countries, job flows between men and women are alike; men have a more significant probability of staying employed than women, and women have a higher chance of leaving the labor force than men across different employment statuses.

3.2.1 Education

We also examine the substantial variation in labor market transitions by educational attainment. Table 4 presents the employment flow data for workers with a college education, while Table 5 reports flows for individuals without a college degree, hereafter referred to as "non-college" workers.

Our initial analysis focused on comparing college-educated workers in the UK and Brazil. Surprisingly, the flow of workers between these two countries exhibits marked similarity when considering only those with a college education. In the UK, 98 percent of

Table 4: College Educated Employment Flows

Status in the subsequent quarter

Status in the quarter	UK Employed	UK Unemployed	UK NLF	Brazil Employed	Brazil Unemployed	Brazil NLF
Employed	98	0.8	1.2	96.3	1.5	2.2
Unemployed	34.6	50.8	14.8	31.2	49.5	19.3
NLF	8	4.6	87.4	15	8.8	76.2

Note: The table shows the transition flows for Brazil and the UK for the three states considered. The analysis considers only individuals with college-level education. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter.

college-educated workers employed in the initial quarter maintain their employment status in the subsequent quarter, compared to 96.3 percent in Brazil. This results in a slightly lower separation rate among UK workers at 2 percent, versus 3.7 percent among their Brazilian counterparts. Notably, in both countries, a significant proportion of separated workers exit the labor force, with 1.2 percent in the UK and 2.2 percent in Brazil doing so.

Focusing on those college-educated workers who start the quarter unemployed, in both the UK and Brazil nearly half of them remain unemployed in the subsequent quarter. However, 34.8 percent in the UK and 31.2 percent in Brazil secure employment. The higher employment finding rate in the UK correlates with a lower rate of workers leaving the labor force (14.8 percent) compared to 19.3 percent in Brazil. Examining those not in the labor force at the beginning of the quarter, a majority remain so in both countries, with 87.4 percent in the UK and 76.2 percent in Brazil continuing in this status. However, in Brazil, a higher percentage of these workers (15 percent) transition into employment, compared to only 8 percent in the UK, with the remainder moving into unemployment.

Table 5: Non-College Educated Employment Flows

Status in the subsequent quarter

Status in the quarter	UK Employed	UK Unemployed	UK NLF	Brazil Employed	Brazil Unemployed	Brazil NLF
Employed	97.7	0.9	1.4	89.6	3.5	6.9
Unemployed	21.7	62.6	15.7	31.9	42.3	25.8
NLF	3.1	3.5	93.4	13.2	6.8	80

Note: The table shows the transition flows for Brazil and the UK for the three states considered. The analysis considers only individuals with an education level lower than a college degree. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter.

Our analysis extends to non-college educated workers, revealing distinct patterns in the UK and Brazil. In the UK, a high percentage of non-college educated workers who are employed at the start of the quarter, 97.7 percent, remain employed in the subsequent quarter. In contrast, in Brazil, this figure is lower, with 89.6 percent retaining their employment. The separation rates differ significantly; in the UK, only 0.9 percent of employed workers transition to unemployment and 1.4 percent to out of the labor force, while in Brazil, these figures are 3.5 percent and 6.9 percent, respectively.

Turning to those initially unemployed, in the UK, 62.6 percent of non-college educated workers remain unemployed in the next quarter, whereas 21.7 percent find employment, and 15.7 percent move to inactivity. Comparatively, in Brazil, a smaller proportion, 42.3 percent, stay unemployed, while 31.9 percent find employment, and a notably higher percentage, 25.8 percent, transition to out of the labor force. For non-college educated workers starting the quarter not in the labor force, the majority in the UK, 93.4 percent, continue in this status, with only 3.1 percent gaining employment and 3.5 percent becoming unemployed. The scenario is different in Brazil, where 80 percent remain out of the labor force, a larger share, 13.2 percent, become employed, and 6.8 percent shift to unemployment.

The comparison of labor market transitions by education level in the UK and Brazil highlights the striking similarity of college-educated workers' experiences in the two countries. Among this demographic, employment retention is remarkably high, with 98 percent in the UK and 96.3 percent in Brazil consistently maintaining employment from one quarter to the next. This high level of job stability contrasts with the more varied experiences of non-college educated workers, where the UK shows a higher retention rate (97.7 percent) compared to Brazil (89.6 percent). This discrepancy underscores the potentially higher return of educational attainment on job security in emerging market economies. On the other hand, when focusing on transition rates from non-employment (both unemployment and not in the labor force) to employment, the gap by education group is substantial for the UK but small or non-existent for Brazil. This suggests that, while lower-education workers in emerging market economies may experience a more dynamic labor market than in advanced economies where, despite higher risk, they may also face greater flexibility in finding job opportunities.

3.3 Occupation and Job Transitions

In this section, we examine job and occupational mobility. This analysis complements that of the previous subsection by considering dynamics not across labor market statuses but *within* the pool of employed workers. Historical patterns of job and occupation transitions reflect the overall dynamics of the labor market, which provides insights into the likely ability of workers to respond to shifts in labor demand that could arise due to structural transformation and disruptions.

We categorize employed workers based on their job and occupation status between two consecutive quarters, distinguishing those who changed employers (labeled as "switch employer") from those who have remained with the same employer ("same employer").[5] Additionally, we identify workers who changed their occupation ("switch occ.") versus those who have retained their original occupation ("same occ."). Quarterly occupation switching rates are estimated at the 4-digit ISCO-08 in Brazil and UK.

Table 6: UK Job and Occupation Switching Probabilities

	Same Employer	Switch Employer	
Same Occ.	87.3	0.8	88.1
Switch Occ.	10.7	1.2	11.9
	98	2	

Note: The table shows the probabilities of switching employers and occupations over a quarter. Switching employer is defined as when the individual reports having been with their current employer for less than three months and having been employed in the previous quarter. The last row shows the marginal probabilities of switching jobs and the last column, the marginal probabilities of switching occupations.

Table 6 reports the employer and occupation switching dynamics in the UK. A significant majority of the workforce, 87.3 percent, remains with the same employer and occupation from one quarter to the next, indicating a high level of job stability within their current occupation and employer. However, a small fraction, 0.8 percent, exhibit job mobility within the same occupational category. On the other hand, 10.7 percent of workers maintain their employer but switch occupations, highlighting a notable level of occupational mobility that does not necessarily involve changing employers. An additional 1.2 percent of the workforce not only change their occupation but also switch to a different employer, indicating a more substantial shift in their professional trajectory. The total occupation switching rate stands at 11.9 percent, reflecting a modest but significant level of occupational dynamism. Overall, 98 percent of workers either stay with the same employer or within the same occupation, with only 2 percent engaging in both employer and occupation switches. These figures underscore a labor market characterized by a high degree of job persistence.

Table 7 presents the job and occupation switching probabilities in Brazil, revealing that 65.2 percent of workers retain both their employer and occupation from one quarter to the next. This figure, while representing a majority, indicates a lower rate of job and

[5] The distinction between job and occupation switches is relevant since a large share of occupation changes occur while a worker remains within the same employer (see for instance Huitfeldt et al., 2023)

Table 7: Brazil Job and Occupation Switching Probabilities

	Same Employer	Switch Employer	
Same Occ.	65.2	0.8	66
Switch Occ.	32.4	1.6	34
	97.6	2.4	

Note: The table shows the probabilities of switching employers and occupations over a quarter. Switching employer is defined as when the individual reports having been with their current employer for less than three months and having been employed in the previous quarter. The last row shows the marginal probabilities of switching jobs and the last column, the marginal probabilities of switching occupations.

occupational stability in Brazil compared to the UK. In addition to this, a relatively small segment of the workforce, 0.8 percent, transitions to a different employer within the same occupational field. This suggests some level of job mobility, albeit limited, within the same professional area. Furthermore, a considerable proportion of Brazilian workers, 32.4 percent, maintain their employment but switch occupations, underscoring a significant degree of occupational mobility. This is contrasted by a smaller group, 1.6 percent, who change both their employer and occupation. Collectively, these figures show that 34 percent of workers in Brazil experience some form of occupation switching. The data overall suggest that while a majority of Brazilian workers exhibit job stability, there is a notable propensity for occupational mobility.

Comparing the job and occupation switching probabilities between Brazil and the UK unveils distinct labor market features. In Brazil, workers are more likely to switch employers or to switch occupations or both, indicating greater overall dynamism. The combined job and occupation stability (65.2 percent) is notably lower than in the UK (87.3 percent).[6] While these higher rates might suggest greater flexibility in the labor market, it should be noted that not all transitions are necessarily voluntary. In some cases, they may be linked to lower wages or be forced due to separations from a previous job. Nevertheless, especially when set against the higher job separation rate in Brazil (as discussed in the previous subsection), higher job and occupational mobility may be reflective of greater labor market flexibility and potentially of capacity to adjust to structural shocks.

[6]One possibility is that the Brazilian data contains greater measurement error in the classification of workers' occupations. To check this, we also computed occupation switching rates for 3-digit and 2-digit occupation codes rather than 4-digit ones. Arguably classification errors are more likely to occur across occupations that are similar to each other. Hence, using more aggregate occupational levels would reduce significantly the share of spurious occupation switches relative to real ones. If such share were to be substantially higher for Brazil than for the UK when using 4-digit codes, then the occupation switching rates for 3- and 2-digit codes would be closer to each other in the two countries. Our analysis, not reported in the paper, finds that even at higher levels of aggregation Brazil shows greater occupational mobility.

Annex A.2 presents the analysis from this subsection broken down by education level. Overall, college-educated workers are slightly more likely to switch occupations than non-college workers in both countries. Meanwhile, no clear pattern emerges regarding job-switching probabilities.

4 Transitions and AI Exposure

In this section, we look at the historical patterns of workers' transitions across occupations with different levels of exposure to AI. Although AI exposure is a forward-looking concept, capturing the expected impact of labor demand from AI adoption, historical transition patterns can be informative of the potential ability of workers to respond to these labor demand shifts. For instance, historically low transitions from occupations that are more likely to be disrupted from AI to those more likely to face higher labor demand would suggest *a priori* a low degree of adaptability to AI-induced structural transformation. However, given the large degree of uncertainty regarding the impact of AI on the labor market at this early stage, the extent to which historical patterns in transitions predict those resulting from a structural change remains unclear. Hence, the analysis in this section should be interpreted with significant caution. Consequently, our main focus is on the relative magnitudes of transition probabilities across the two countries and for different groups of workers within each country rather than on their absolute levels of these flows.

We follow the approach of Pizzinelli et al. (2023) in classifying occupations into three broad categories: Low Exposure (LE) occupations, which are those less likely to be affected by widespread AI adoption; High Exposure, High Complementarity (HEHC) ones, which would likely experience large AI adoption but where human input is more likely to experience increases in productivity and little displacement; and High Exposure, Low Complementarity (HELC), which includes occupations most likely to be disrupted by AI, where workers may be adversely affected by lower labor demand and potentially job displacement.

These categorizations provide an *ex ante* view on the likely effects of widespread AI adoption on the labor market based on occupations' exposure to AI, as measured by Felten et al. (2021), and on a broader set of social and technological considerations which play into occupations' potential for complementarity to AI. Moreover, while the approaches used to construct these categorizations are not intrinsically linked to any measure of workers' earnings, Pizzinelli et al. (2023) note that a large fraction of LE jobs is in elementary occupations and the agricultural sector, which tend to be in the lower end of the earnings distribution. Meanwhile, the share of HELC occupations is fairly homogeneous across the income distributions while HEHC occupations are highly concentrated in the top quantiles. Hence, with large generalization, and as discussed further below, HEHC occupations tend to have the highest wages of the three groups, followed by HELC and LE.

We begin by showing how employment is distributed according to AI exposure and education in both countries in Table 8. We see that AI exposure is highly correlated with education: over 85% of college-educated workers are in highly exposed occupations in both the UK and Brazil. For both levels of education, however, the UK has more HE jobs than Brazil (though the distribution is similar for workers with a college degree).

Table 8: Distribution of Employment by AI Exposure and Education (percent)

	UK				Brazil			
	LE	HELC	HEHC	Total	LE	HELC	HEHC	Total
No College	29	19.1	14.9	63	57.7	15.8	9.2	82.7
College	4.3	12.6	20.1	37	2.6	5.0	9.7	17.3
Total	33.3	31.7	35		60.3	20.8	18.9	

Figure 1 shows the probability of switching occupations between categories[7], conditional on an occupational switch and the category of the occupation the worker had in the previous quarter (such that the bars in each “from” category add up to one). Figure 1 first shows that each occupation group is persistent, and workers in the UK and Brazil are more likely to change occupations within a broad category of HEHC, HELC, and LE occupations.[8]

At first glance, the figure suggests that workers in Brazil are overall more exposed to “downward” movement along the occupational ladder: conditional on switching, workers in all three categories have a greater chance to move to LE occupations. Meanwhile, in the UK, the probability that high-exposure workers move to LE occupations is about half of those of Brazil, and workers, even those in LE jobs, have a greater probability of moving to HEHC occupations, provided they switch.[9]

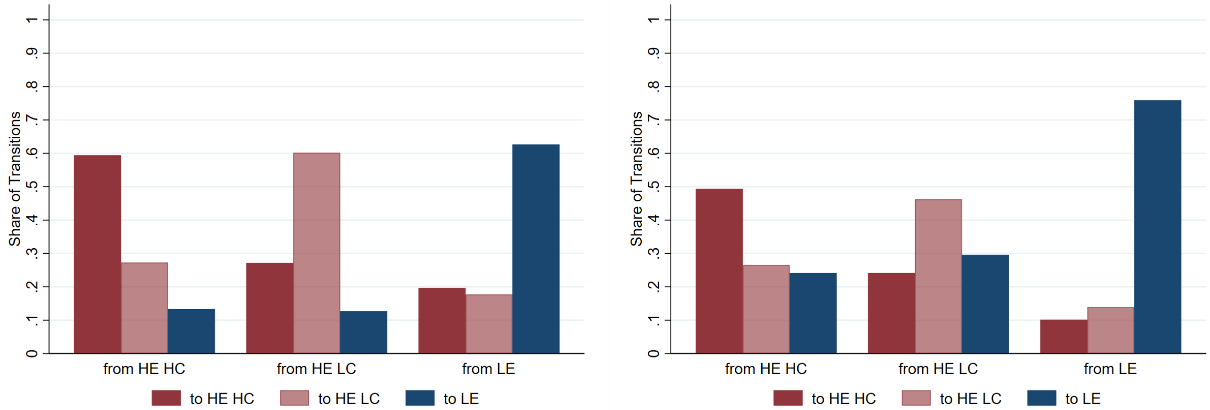
[7]Annex A.3 breaks down employment flows to and from unemployment and NLF for workers in high and low exposure occupations.

[8]The transition probabilities are robust to several sample restrictions, such as excluding public sector workers. One factor that does, however, condition the result is differentiation by urban or rural location. As discussed for instance in Moszoro et al. (2023) digital infrastructure in rural areas, particularly in emerging market economies, is substantially more limited than in urban ones. This in turn affects the composition of jobs in these regions and the likelihood of transitions to or from jobs that are exposed to AI.

[9]In the Annex, Figure B.1 shows the transition probabilities conditional only on the “from” category. While the bars in this chart are simply the bars in Figure 1 scaled by each ”from” category’s probability of switching occupations, it illustrates how labor markets in Brazil are more dynamic and workers are more likely to change occupations between quarters.

Figure 1: Transition Probabilities Conditional on Occupation Switching

(a) UK (b) Brazil



Note: The bars in the chart represent the share of occupational switches from each of the three exposure categories to each of them for the UK and Brazil. The transition probabilities are conditional on switching occupations and on the "from" category, such that the three "to" bars add up to one.

These differences, however, do not account for heterogeneity in education levels and differences in labor force composition. Figure 2 shows the share of transitions conditioning on workers with and without a college degree. The profile of these transitions is actually similar across both countries for college-educated workers: they have higher chances of moving "upwards" in terms of exposure (that is, to HEHC occupations) - this is even slightly higher for workers in Brazil, which could be interpreted as a higher premium for education.

In contrast, workers without a college degree have higher chances of moving "downwards" in Brazil compared to the UK. It should be noted that this difference is not merely a composition effect coming from the fact that non-college workers in Brazil include a higher share of individuals with only elementary education or even no formal education. When breaking down the non-college group further, the transition probabilities conditional on workers with a full high school degree, for example, show a similar difference between countries.[10]

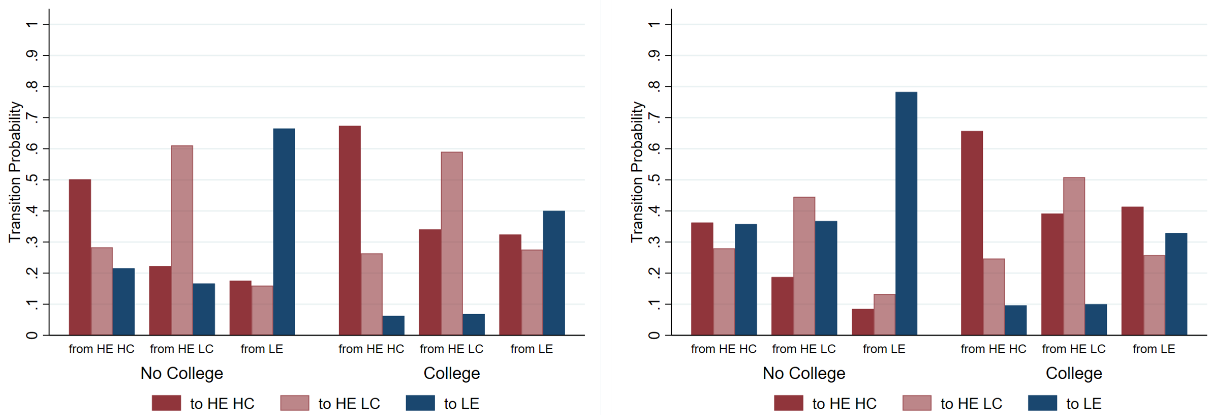
To move beyond the descriptive statistics, we also check the relation between individual characteristics and occupational switches with the following regression:

$$y^k_{irt} = \alpha + \sum_{j \neq HEHC} \delta_j C^j_{ir(t-1)} + \beta X_{irt} + \gamma_t + \eta_r + \varepsilon_{irt} \qquad (1)$$

[10]See Figure B.2.

Figure 2: Transition Probabilities by Education

(a) UK (b) Brazil



Note: The bars in the chart represent the share of occupational switches from each of the three exposure categories to each of them for the UK and Brazil, split by education level. The transition probabilities are conditional on switching occupations, on the "from" category, and on worker education level, such that the three "to" bars add up to one.

The outcome y^k_{irt} is a dummy variable that equals one if the worker switched occupations to one in category k (which can be LE, HELC, or HEHC). The subscript r represents the geographical region within the country and t the time period, so γ_t and η_r are time (year-quarter) and region fixed effects, respectively. X_{irt} is a matrix of demographic covariates, including age, gender, education, and informality (for Brazil).

Tables 9 and 10 show the results for the UK and Brazil, respectively. The base category is represented by workers employed in HEHC, aged below 25, male, and with a middle school education or below.[11]

The regression results from Table 9 underscore the significant role of educational qualifications in determining occupational mobility in the UK. Notably, higher levels of education, such as General Certificate of Education (GCE), Higher Education, and Degree qualifications, are positively associated with transitions to HEHC occupations. Specifically, holding a degree increases the probability of moving into HEHC occupations by 2.26 percentage points relative to workers with middle school education, highlighting the importance of advanced education in accessing HEHC occupations. Conversely, higher educational attainment is linked with a decreased likelihood of remaining in or transitioning to Low Exposed

[11] In the labor economics literature, it is a well-documented phenomenon that R^2 or $pseudo - R^2$ values derived from regression analyses of occupational transitions tend to be modest. This is attributed to the models' inherent limitations in capturing the complex, underlying forces that drive these transitions. Notwithstanding, our findings align closely with those reported in the studies by Bluedorn et al. (2022) and Carrillo-Tudela et al. (2016). These studies similarly assess the significance of individual worker characteristics in influencing the likelihood of occupational change.

Table 9: Transition Probabilities for the UK

	(1) HE HC	(2) HE LC	(3) LE
HE LC	-0.0753***	0.0886***	-0.00261***
	(0.00103)	(0.00107)	(0.000794)
LE	-0.124***	-0.0489***	0.0516***
	(0.000939)	(0.000772)	(0.000923)
Age 25-44	0.0247***	-0.0228***	-0.0299***
	(0.000539)	(0.000742)	(0.000996)
Age 45-59	0.0413***	-0.0305***	-0.0513***
	(0.000681)	(0.000797)	(0.00114)
Age 60+	0.0454***	-0.0283***	-0.0605***
	(0.00124)	(0.00114)	(0.00184)
female	-0.0102***	0.0110***	-0.0737***
	(0.000477)	(0.000482)	(0.000708)
High School	0.0286***	0.0360***	-0.0465***
	(0.000393)	(0.000445)	(0.000919)
Some College	0.0757***	0.0895***	-0.128***
	(0.00118)	(0.00144)	(0.00139)
College	0.114***	0.0392***	-0.160***
	(0.00110)	(0.000900)	(0.00111)
L.informal	-0.0000286	-0.000377	0.00571***
	(0.000432)	(0.000443)	(0.000744)
Constant	0.143***	0.112***	0.374***
	(0.00223)	(0.00209)	(0.00471)
Observations	4552677	4552677	4552677
R^2	0.080	0.058	0.061
State FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Note: The table shows the estimated coefficients for the specification in equation 1. The dependent variable for each column is a dummy that indicates if the individual switched occupations between quarters to an occupation in the corresponding exposure category. Base demographic categories for the coefficients are male workers in HEHC, aged below 25, with middle school education or below. Standard errors in parentheses, clustered at the household/PSU level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(LE) occupations.

Gender and age also play crucial roles in occupational switching patterns in the UK. Being a woman reduces the probability of switching to HEHC occupations by approximately 0.63 p.p. and to LE occupations by about 1.12 p.p. Age impacts are also evident, with older workers (ages 45-59 and 60+) showing a reduced likelihood of switching occupations relative to young workers.

Table 10: Transition Probabilities for Brazil

	(1) HE HC	(2) HE LC	(3) LE
HE LC	-0.0753***	0.0886***	-0.00261***
	(0.00103)	(0.00107)	(0.000794)
LE	-0.124***	-0.0489***	0.0516***
	(0.000939)	(0.000772)	(0.000923)
Age 25-44	0.0247***	-0.0228***	-0.0299***
	(0.000539)	(0.000742)	(0.000996)
Age 45-59	0.0413***	-0.0305***	-0.0513***
	(0.000681)	(0.000797)	(0.00114)
Age 60+	0.0454***	-0.0283***	-0.0605***
	(0.00124)	(0.00114)	(0.00184)
female	-0.0102***	0.0110***	-0.0737***
	(0.000477)	(0.000482)	(0.000708)
High School	0.0286***	0.0360***	-0.0465***
	(0.000393)	(0.000445)	(0.000919)
Some College	0.0757***	0.0895***	-0.128***
	(0.00118)	(0.00144)	(0.00139)
College	0.114***	0.0392***	-0.160***
	(0.00110)	(0.000900)	(0.00111)
L.informal	-0.0000286	-0.000377	0.00571***
	(0.000432)	(0.000443)	(0.000744)
Constant	0.143***	0.112***	0.374***
	(0.00223)	(0.00209)	(0.00471)
Observations	4552677	4552677	4552677
R^2	0.080	0.058	0.061
State FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Note: The table shows the estimated coefficients for the specification in equation 1. The dependent variable for each column is a dummy that indicates if the individual switched occupations between quarters to an occupation in the corresponding exposure category. Base demographic categories for the coefficients are male workers in HEHC, aged below 25, with middle school education or below. Standard errors in parentheses, calculated according to the survey design.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Brazil, the regression analysis in Table 10 highlights similar results. Higher levels of education, specifically high school, some college, and college degrees, demonstrate a strong positive association with transitions to HEHC occupations. For instance, holding a college degree increases the likelihood of moving into HEHC occupations by 11.4 p.p. relative to workers with middle school education. Conversely, higher educational levels are linked with decreased probabilities of staying in or moving to LE occupations.

Gender and age also play crucial roles. Being a woman in Brazil reduces the probability of switching to HEHC occupations by about 1.02 p.p. relative to men, while it significantly increases the likelihood of transitioning to HELC occupations by 1.10 p.p. and decreases the probability of moving to LE occupations by a substantial 7.37 p.p. Older workers (ages 45-59 and 60+) are more inclined to switch to HEHC occupations relative to young workers but less likely to switch to HELC and LE occupations.

Comparing occupational mobility in Brazil and the UK, the role of education emerges as a key factor in both countries, albeit with different magnitudes. In Brazil, the impact of holding a college degree on moving to HEHC occupations (11.4 p.p. increase) is notably higher than in the UK. This suggests a stronger link between higher education and access to HEHC in Brazil. The importance of gender on occupational mobility also differs between the countries. In Brazil, being a woman significantly decreases the likelihood of remaining in LE occupations, while in the UK, the reduction in probability is more pronounced for transitioning into HEHC occupations. Age-wise, both countries show a greater tendency for older workers to move to HEHC occupations, but this trend is more accentuated in Brazil.

5 Life-cycle Dynamics

In this section, we explore the life-cycle profiles of workers to better understand how transitions between different AI exposure categories influence career progression. By examining these life-cycle profiles, we gain valuable insights into typical career paths and how various stages of a worker's career might intersect with the opportunities and challenges presented by AI. This analysis is particularly pertinent in assessing how AI-induced labor market dynamics could impact workers of in different career stages.

5.1 Employment Shares

To construct these life-cycle profiles, we estimate the probability of employment in specific occupations as a function of the worker's age. Following the approach of Dabla-Norris et al. (2023), this is modeled through a cubic polynomial regression specification:

$$C_{it}^{k} = \beta_0 + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 age_{it}^3 + \delta female_{it} + \gamma_t + \varepsilon_{it} \tag{2}$$

where C_{it}^k is a dummy variable that equals one if individual i is employed in an occupation in exposure category k, where $k \in \{HEHC, HELC, LE\}$. The model coefficients $\beta_0, \beta_1, \beta_2$ and β_3 capture the baseline probability and the effect of age (linear, quadratic, and cubic) on the likelihood of being employed in these categories. We also add a dummy for gender, δ, and year-quarter fixed effects γ_t.

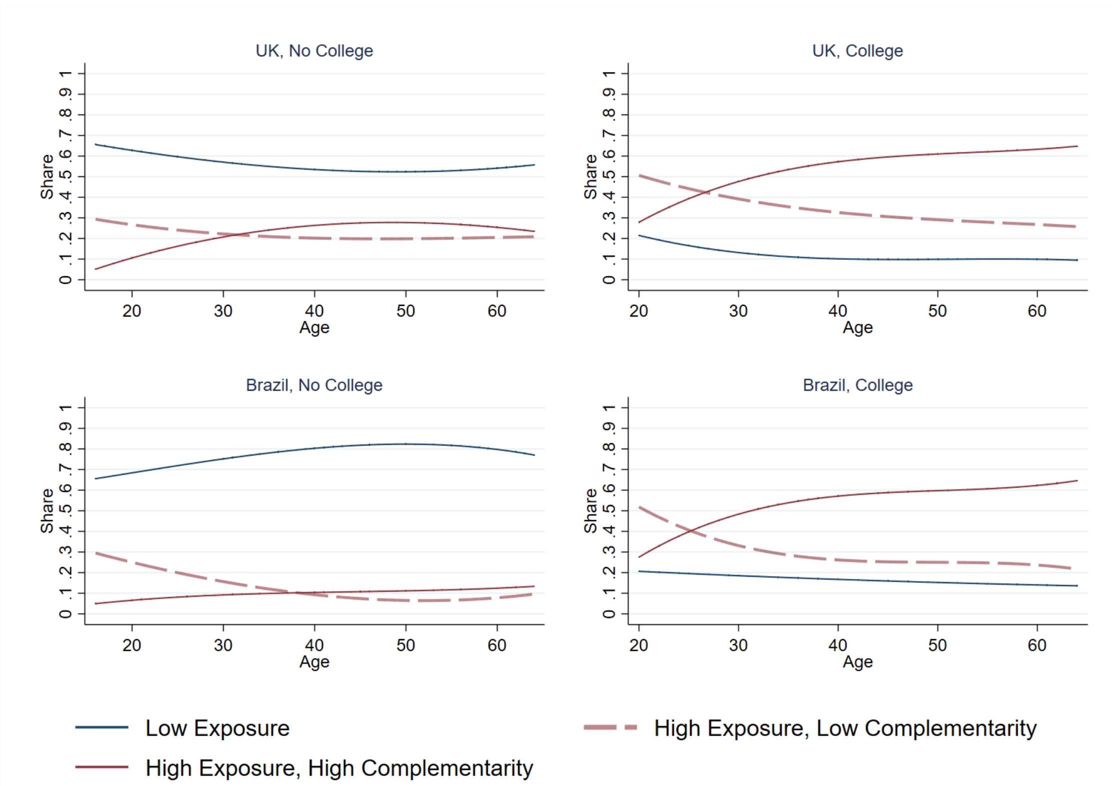
Figure 3 plots the fitted values of the polynomial (without δ and γ) against age. The y-axis represents the estimated share of workers in a given age who are employed in that AI exposure category. For example, looking at the bottom-left chart, we estimate that 80 percent of Brazilian workers without a college degree at age 40 are in jobs that have low exposure to AI.

Although the chart shows a picture of the distribution of exposure categories of the current population by age, it can be used as a proxy to infer the life-cycle profile of transitions a worker. These inferences are corroborated by the estimated regressions from Equation (1). As shown in Tables 9 and 10, workers usually change occupations when they are younger. These young-age transitions are typically from HELC to HEHC jobs. In Figure 3, this period is captured by the steep upward slope of the share of HEHC occupations, and the steeply declining share of HELC ones before age 40. This feature is particularly evident for college-educated workers, but it also applies to some extent to non-college workers (more so in the UK than in Brazil). In contrast, the share of LE jobs is relatively constant over age. A recurring result is also that the life-cycle profiles for college educated workers are very similar in both countries while those of non-college workers differ markedly.

One likely interpretation is that part of HELC occupations corresponds to entry-level jobs, which are important "stepping stones" for younger workers to move up the ladder into high-complementarity jobs in their late twenties and thirties. The pre-forties age period possibly represents a key stage in workers' careers, associated with progression into jobs with greater compensations and requiring greater skills and responsibilities. This means that AI-led disruption to HELC jobs could have the adverse effect of making entry into the job market and the transition to better-earning HEHC more difficult for college graduates.

One caveat to this analysis is that it relies on the estimates of average shares for workers of a given age in the time period considered in the data. Although we can use this as a proxy to infer the career path of a worker, there could be cohort or composition effects in the shares. For example, the share of non-college workers in LE in Brazil may increase with age due to older workers having less access to education in the past.[12]

Figure 3: Lifecycle Profile of Employment Shares



Note: the y-axis represents the estimated share of workers in each category for a given age, represented in the x-axis. Shares are estimated according to the polynomial specified in equation (2). The equation is estimated by country and level of education.

5.2 Wages

In this section, we consider how moving between occupations in different AI exposure categories is related to changes in earnings to infer how job disruptions from AI might affect income dynamics.

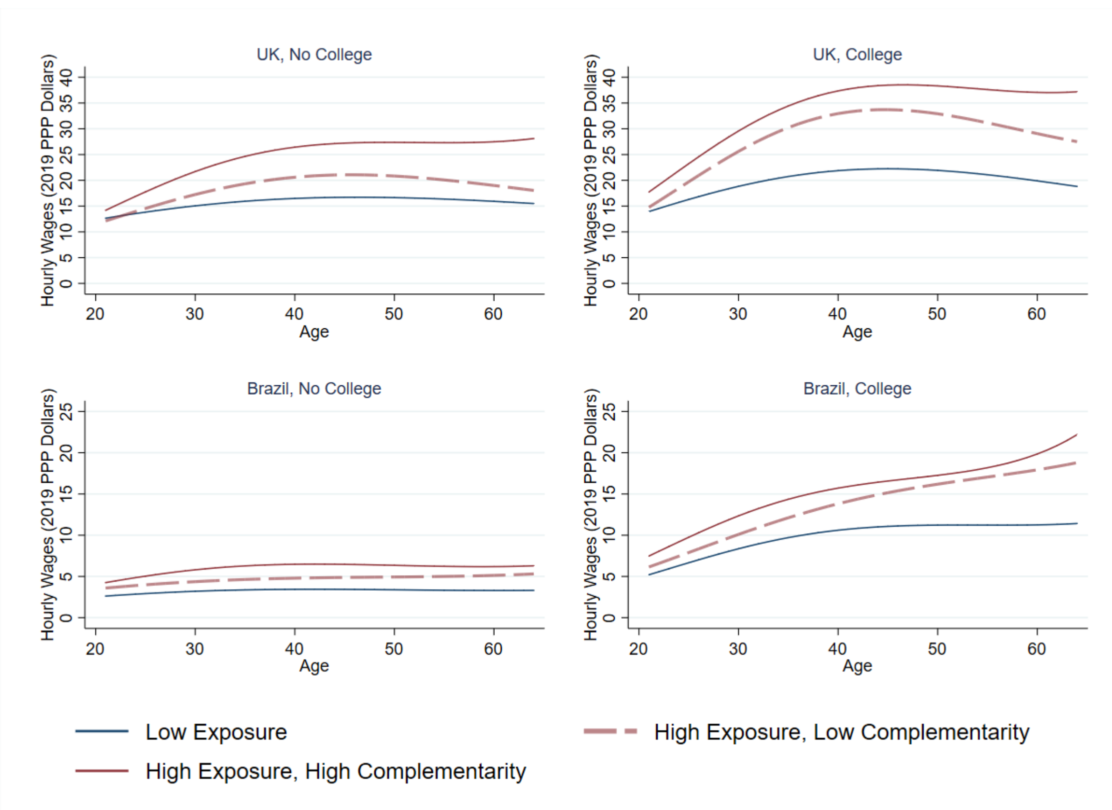
In a similar manner to Figure 3, we consider the life-cycle profile of wages. Examining the age profile of hourly wages for each occupation sheds light on differences in earnings across occupations at different stages of workers' careers. For instance, two types of occupations generally feature similar wages early on but one may entail a steeper rise in earnings than

[12]Unfortunately, the time period of the analysis, covering less than a full decade, is not long enough to also include cohort effects. In their simplest form, these would represent additive terms to the β_0 coefficient, entailing vertical shifts of the polynomial function. More importantly, however, adding them to the estimation could change the estimated values of the other coefficients and thus the overall shape of the polynomial.

the other. Transitions across occupations (or lack thereof) therefore have implications for a worker's wage not only at the time when the occupation switch occurs but also in the following years. To this end, we estimate cubic polynomials of wages with respect to age as follows.

$$y_{it}^{k} = \beta_0 + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 age_{it}^3 + \delta female_{it} + \gamma_t + \varepsilon_{it} \tag{3}$$

Figure 4: Lifecycle Profile of Wages



Note: the y-axis represents the estimated hourly wage (in 2019 PPP dollars) of workers in each category for a given age, represented in the x-axis. Wages are estimated according to the polynomial specified in equation (3). The equation is estimated by country, level of education, and exposure category.

where y_{it}^{k} refers to the log hourly earnings of individual i at time t in occupations of AI exposure category k, where $k \in \{HEHC, HELC, LE\}$. We add a dummy for gender, δ, and year-quarter fixed effects γ_t.

Figure 4 plots the fitted values from the estimated parameters (without δ and γ). Individuals typically experience most of their wage growth up until 35 to 40 years old, which matches up with the period when workers typically experience career changes. Not only that, but the average growth is higher for those in occupations more exposed to AI, particularly for those with college degrees.[13]

However, this is not sufficient to conclude that switching "upwards" in terms of AI exposure carries a wage boost (or vice-versa). We thus use a linear regression model that can inform about the association between occupational transitions, in terms of exposure categories, and wage variations. As noted in Section 2, the panel for wage data is annual instead of quarterly. For reference, the average yearly J2J switching rate in the UK is 9.2 percent and 11.7 percent in Brazil; the average occupation switching rate is 28 percent for the UK and 39 percent for Brazil.

We propose the following specification:

$$\begin{aligned}\Delta \log(y_{irt}) = \delta_1 J2J_{irt} + \delta_2 OS_{irt} \times J2J_{irt} + \delta_3 EUE_{irt} \\ + \sum_k \theta_k C^k_{ir(t-1)} C^k_{irt} + \sum_k \sum_j OS_{irt} \phi_{kj} C^k_{ir(t-1)} C^j_{irt} \\ + \beta X_{irt} + \gamma_t + \eta_r + \varepsilon_{irt}\end{aligned} \tag{4}$$

Where y_{irt} are hourly wages, OS a dummy for occupation switches, $J2J$ a dummy for job switches, EUE a dummy for transitions through unemployment, and X_{irt} a matrix of demographic covariates, which includes age-education interactions. γ_t and η_r are year-quarter and region fixed effects, respectively.

Recall that C^k_{irt} is a dummy that takes the value of one if worker i is in a job in exposure category k for time period t. Then, θ_k represents the average log wage change for a worker that did not change occupation in category k, while ϕ_{kj} measures the average log wage change for workers that switched occupations from category k to category j. We are interested in the wage premium of switching exposure categories compared to those workers who did not change occupations ("stayers"). Thus, the relative log wage premium of a worker switching from a HELC job to a HEHC one is computed as $\phi_{HELC,HEHC} - \theta_{HELC}$.

Figure 5 shows the above point estimates along with the 95 percent confidence intervals represented in bars. The regression results are also displayed in Table B.2. It is worth noting that coefficients might not be statistically significant for the UK due to the smaller sample size.

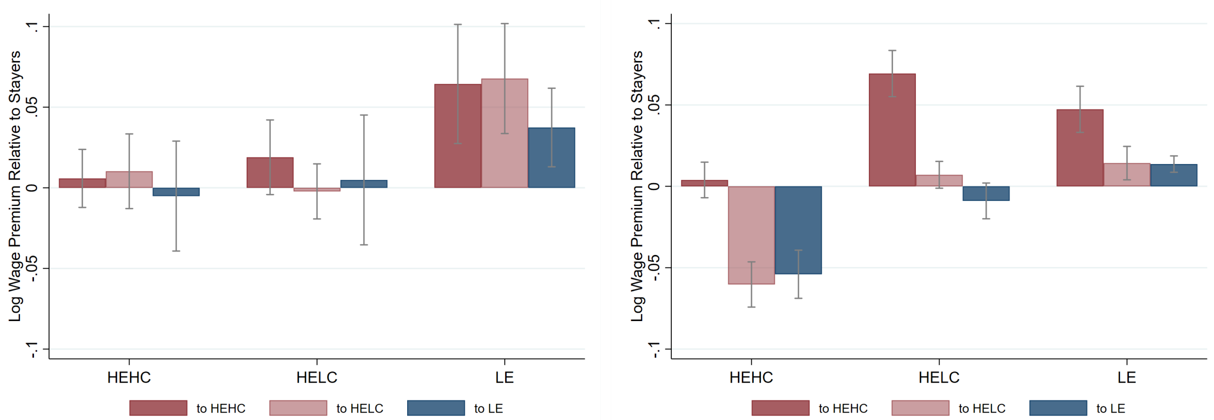
[13] Figure B.3 reports the life-cycle profiles of wages only for workers who have stayed in each occupation for longer than one year. The profiles are very similar to those in Figure 4, suggesting that the steep parts of the curve are to a large part due to wage growth *within* each occupation and not just to workers moving across occupations.

The first conclusion that can be drawn for both countries is that there is a premium associated with switching "Upwards", both from LE to HE and from HELC to HEHC. This latter transition was described in Section 4 as typical of college-educated workers leaving entry-level jobs for more experienced positions. An implication of this result is that higher demand for HEHC jobs would increase opportunities for higher earnings, particularly so for young college-educated workers, who account for a large share of these transitions.

On the other hand, we also see a penalty in "downward" transitions in Brazil. While college-educated workers in Brazil do not face higher "risks" of transitioning to LE than their counterparts in the UK, for non-college workers, who might be more at risk due to higher skill barriers and more chance of transitioning to LE occupations, AI might imply some degree of wage compression. In Brazil, however, this is counterbalanced by the small share of non-college workers in HE occupations.[14]

Figure 5: Wage Premia for Transitions

(a) UK (b) Brazil



Note: The log wage premium relative to stayers represented in the y-axis is calculated as the value of the estimate $\phi_{kj} - \theta_k$ as specified in equation 4; that is, it is the log of the wage change in a year for those who changed occupations minus the wage change for those who did not change occupations. Estimates for the coefficients are shown in Table B.2. The grey bars indicate the 95% confidence intervals of the estimates.

5.3 Expected Impact of AI Lifetime Earnings

In this section, we conduct a set of simulations to appraise the possible effect of shifts in labor demand induced by AI on workers' lifetime earnings in Brazil and the UK. Through counterfactual exercises focusing on different channels discussed above, we quantitatively gauge the potential effects of AI on the expected earnings of new entrants to the labor market

[14]See Figure B.4 for a breakdown of how wage premia change depending on education. We find that college-educated workers see higher gains from transitioning to high-exposure occupations.

throughout their entire careers. A change in expected lifetime earnings signifies a shift in the market equilibrium for a labor market entrant, suggesting long-term alterations in the structure of the market. While only considering partial-equilibrium adjustments and with many simplifying assumptions, the purpose of the exercise is to provide a proof-of-concept illustration of the channels discussed above through which structural changes induced by AI shape future workforce dynamics and have heterogeneous effects on workers' lifetime income.

We follow the methodology outlined in Dabla-Norris et al. (2023). Let a denote the age of an individual and k their employment category in terms of AI exposure. Then, for a worker entering the labor market at age a_0, the expected earnings at a later age a are given by

$$\mathbb{E}_{a_0}[w_a] = \sum_k p_a^k w_a^k$$

Where p_a^k is the share of employment and w_a^k the average wage in occupation k at age a. Besides three occupation groups for LE, HELC, and HEHC, we add a fourth category for unemployment, which we assume has a wage of 0. Given a discount factor β, the lifetime expected earnings at the age of entry will be

$$W_{a_0} = \sum_{a \geq a_0} \beta^{a-a_0}\, \mathbb{E}[w_a]$$

The lifetime expected earnings can be considered as a measure of welfare for an average entrant into the labor market at age a_0. We can estimate $\hat{p}_a^k$ by using the fitted values from Equation 2 and $\hat{w}_a^k$ with the fitted values from 3. Using this framework, we are then able to obtain an estimate for the expected lifetime earnings for labor market entrants as follows:

$$\hat{W}_{a_0} = \sum_{a \geq a_0} \beta^{a-a_0} \sum_k \hat{p}_a^k \hat{w}_a^k$$

The underlying assumption is that in this baseline scenario, new entrants face labor market prospects that are based on historical patterns in terms of what occupations they are likely to be employed in and what wages to expect. For this calculation, we split the sample into college- and non-college-educated workers, as in the previous life-cycle charts. We consider a discount rate of 2.5% for the UK and 5% for Brazil. We then conduct three counterfactual exercises related to the advent of AI. In the first one (Exercise 1), all HELC jobs are destroyed and no new jobs are created, so unemployment rises to the same extent. For Exercise 2, all HELC jobs are destroyed but all the displaced workers find jobs in LE occupations so that total employment remains constant. In the third exercise (Exercise 3) we consider the case where all HELC jobs are displaced but workers move to better-paying HEHC jobs (Exercise 3). Finally, Exercise 4 considers a positive consequence of AI by raising wages in HEHC jobs by 10%. These are extreme cases devised for the illustrative purpose of highlighting the roles of individual channels: job destruction, reallocation, and wage growth. However, other scenarios can easily be constructed as linear combinations of these four counterfactuals. The findings from our simulation are presented in Table 11. The table is organized as follows: the first row displays the expected total lifetime wage, while the subsequent rows detail the percentage changes in expected lifetime earnings resulting from the exercises.

Table 11: Changes in Expected Lifetime Earnings

Scenario	College		No College	
	Brazil	UK	Brazil	UK
Baseline (2019 Thousand PPP Dollars)	423.3	1567.5	251.5	1128.8
HELC to Unemployment (% Change)	-29.3	-24.1	-33.6	-28.5
HELC to LE (% Change)	-6.5	-6.6	-2.2	-2.7
HELC to HEHC (% Change)	5	4	11.4	10.8
HEHC Wage Increase (% Change)	5.8	6.9	3.9	4.9

Note: The first row of the table presents the lifetime expected earnings for both education groups across both countries (in 2019 thousand PPP dollars), which is the baseline scenario. This considers a 40-hour work week with 52 weeks in a year. The other rows show the percent change of lifetime expected earnings in the counterfactual scenario in relation to the baseline. In scenario 1, all HELC jobs are permanently destroyed and unemployment increases. In scenario 2, all HELC jobs are destroyed, but LE jobs increase in the same proportion so unemployment does not increase. In scenario 3, average wages in HEHC jobs increase 10%. In scenario 4, all HELC jobs are destroyed, but HEHC employment increases in the same proportion.

Beginning with Exercise 1, which assumes that all workers in HELC occupations become unemployed, our analysis reveals a decline in lifetime earnings. Within countries, non-college-educated workers experience a greater financial impact than their college-educated counterparts, primarily due to a higher initial concentration of non-college-educated individuals in HELC jobs. Across countries, the negative impact is more pronounced for Brazilian workers compared to those in the UK, with college-educated individuals facing a -29.3% vs. -24.1% impact, and non-college-educated workers seeing a -33.6% vs. -28.5% impact, respectively. This disparity suggests that the effects of increased unemployment are more severe in Brazil than in the UK and are particularly acute for those without a college education, who are already more vulnerable due to generally lower wages.

Moving to Exercise 2, when HELC jobs are displaced to LE jobs, all workers are again negatively affected because, over the life cycle, HELC jobs pay, on average, more than LE jobs. However, workers with a college degree are more negatively impacted since the pay difference between HELC and LE jobs is larger for college-educated workers in the two countries. More precisely, the lifetime loss for college-educated workers is equal to -6.5% in Brazil, and -6.6% in the UK. Meanwhile, the lifetime losses for non-college-educated workers amount to -2.2% in Brazil, and -2.7% in the UK.

In Exercise 3, we consider another positive scenario, assuming all HELC jobs are displaced but that all affected workers are able to improve their condition by moving to HEHC employment. Outcomes are similar between countries but differ across education levels; the effect is larger for those without a college degree, given that they tend to have lower expected wages and lower probabilities of being in HEHC jobs.

In Exercise 4, we explore the implications of a hypothetical 10 percent wage increase for workers in HEHC jobs. This wage boost positively affects both college and non-college educated workers. However, the advantage is more pronounced for college-educated individuals due to their higher representation in HEHC jobs. Specifically, college-educated workers in Brazil experience a 5.8% increase in earnings, while their counterparts in the UK see a 6.9% rise. For non-college educated workers, the gains amount to 3.9% in Brazil and 4.9% in the UK. The larger overall increases in the UK can be attributed to the greater proportion of both college and non-college educated workers in HEHC positions compared to Brazil.

As already mentioned, more realistic scenarios would entail a combination of the three exercises. For example, we can consider the effect of 20% of HELC jobs being displaced, where half of these (10%) turn into permanent unemployment, while the other half relocate between HEHC and LE jobs according to the probabilities specified in Figure 2. For example, given that 40% of college-educated HELC workers in Brazil transition to HEHC and 10% to LE, we assume 80% (computed as $\frac{0.4}{0.4+0.1}$) relocate to HEHC after displacement.

For the UK, we find that in this combined scenario the expected lifetime earnings drop by 2.4% for non-college-educated individuals and by 2.2% for those with a degree. In Brazil, the decrease in earnings is 3.1% and 2.6% for each group, respectively. Brazil has worse outcomes on average since lost income due to unemployment represents a higher share of lifetime earnings. Compared to the UK, Brazil also shows greater disparity between workers with and without a college degree, since it is harder for those without higher education to relocate to HEHC jobs.

The second scenario considered is the same as before, but now HEHC jobs receive a 10% wage boost as in Exercise 4. This is enough to counter the negative effects of displacement on expected lifetime earnings: in the UK, they go up by 5% for workers with a college education and 2.75% up for those without. In Brazil, however, gains are more modest given the lower wages, and the lower share of and lower probability of transitioning to HEHC employment: 3.4% for individuals with higher education and 1% for those without. Thus, this is a scenario where the average net effect of AI could be positive. However, inequality rises: there are more people earning lower wages and those at the top earn more.

There are three main limitations to this analysis. The first, as discussed previously, is that we are unable to estimate cohort effects, so the estimated propensity to be in each occupational category at a given age might be due to composition effects. In this case, the starting occupational prospects faced by new labor market entrants in the pre-AI baseline would not necessarily resemble the life-cycle pattern traced by past cohorts. Second, although we include unemployment, we do not include "not in the labor force" (NLF) as a category. This is because NLF typically means "not looking for work" when considering younger individuals, but "retired" for those who are older, and so considering the wage for this category would be more complicated and involve accounting for endogenous selection effects. Lastly, our analysis does not account for general equilibrium effects, whereas changes in productivity and consequent wage adjustments in AI-impacted occupations could influence workers' job search behaviors. This channel may affect the supply of labor in occupations not directly impacted by AI, as well as the returns associated with these jobs.

6 Informality in Brazil

Given that Brazil has a large informal labor market, in this section we analyze how informal work relates to labor market dynamics and AI exposure. This allows us to investigate whether informal workers are more exposed to AI, if they have an easier or harder time adjusting to shocks, or if displacement could increase informality.

We begin by segmenting employment flows by formal and informal jobs in Brazil, as shown in Table 12, where F denotes formal employment and I informal. While the flow of informal to formal (12 percent) is higher than formal to informal (7.9 percent), informal workers have lower job permanence rates (86 percent) than formal ones (94 percent). Unemployed and inactive workers are also more likely to return to employment via informality, given that this group tends to transition in and out of unemployment more frequently.

Table 13 also shows the occupation and job switching rates for both formal and informal workers. While informal workers have a much higher job switching rate, as expected from the more dynamic labor arrangements, they switch occupations less frequently than

Table 12: Employment Flows for Informality in Brazil

	2F	2I	2U	2N
F2	86.1	7.9	2.2	3.8
I2	12	74	4.7	9.3
U2	11.4	20.5	43	25.1
N2	4.2	9.1	7	79.7

Note: The table shows the transition flows for Brazil for the four states considered: F (formal employment), I (informal employment), U (unemployment), and N (not in the labor force). Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter.

formal workers. One possible explanation is the higher rate of on-the-job transitions for formal employees (30.8 percent), which could correspond to promotions, for example, compared to informal employees (23.7 percent).

Table 13: Job and Occupation Switching Probabilities for Brazil

(a) Formal

	Same Job	Switch Job (Formal)	Switch Job (Informal)	
Same Occ.	60.6	0.3	3.6	64.5
Switch Occ.	30.8	0.4	4.3	35.5
	91.4	0.7	7.9	

(b) Informal

	Same Job	Switch Job (Formal)	Switch Job (Informal)	
Same Occ.	61.2	5.7	1.1	68
Switch Occ.	23.7	6.3	1.9	31.9
	84.9	12	3.1	

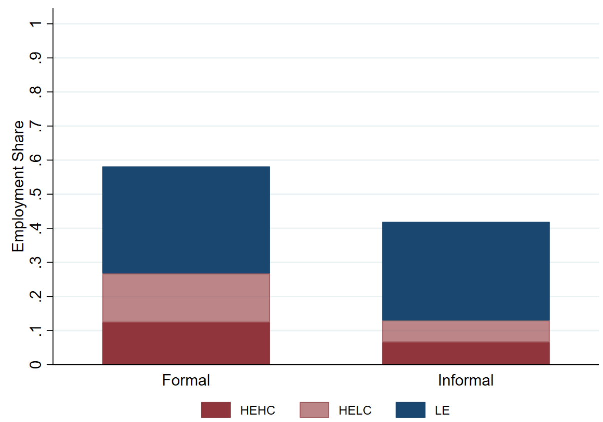
Note: The table shows the probabilities of switching jobs and occupations over a quarter. Switching jobs to the same status is defined as when the individual reports having been with their current employer for less than three months and having been employed with the same formality status in the previous quarter. The last row shows the marginal probabilities of switching jobs and the last column, the marginal probabilities of switching occupations.

6.1 Informality and AI Exposure

We now turn to how informal labor markets relate to AI exposure categories and workers' transitions between them.

Figure 6 plots the employment shares in Brazil by formality and AI exposure category. While LE jobs seem to be evenly distributed between the formal and informal sectors, the formal market accounts for almost twice the amount of HE jobs compared to the informal one. Nevertheless, a substantial fraction of employment (approximately 12 percent) is comprised of HE jobs in the informal sector.

Figure 6: Employment Share by Formality and Category



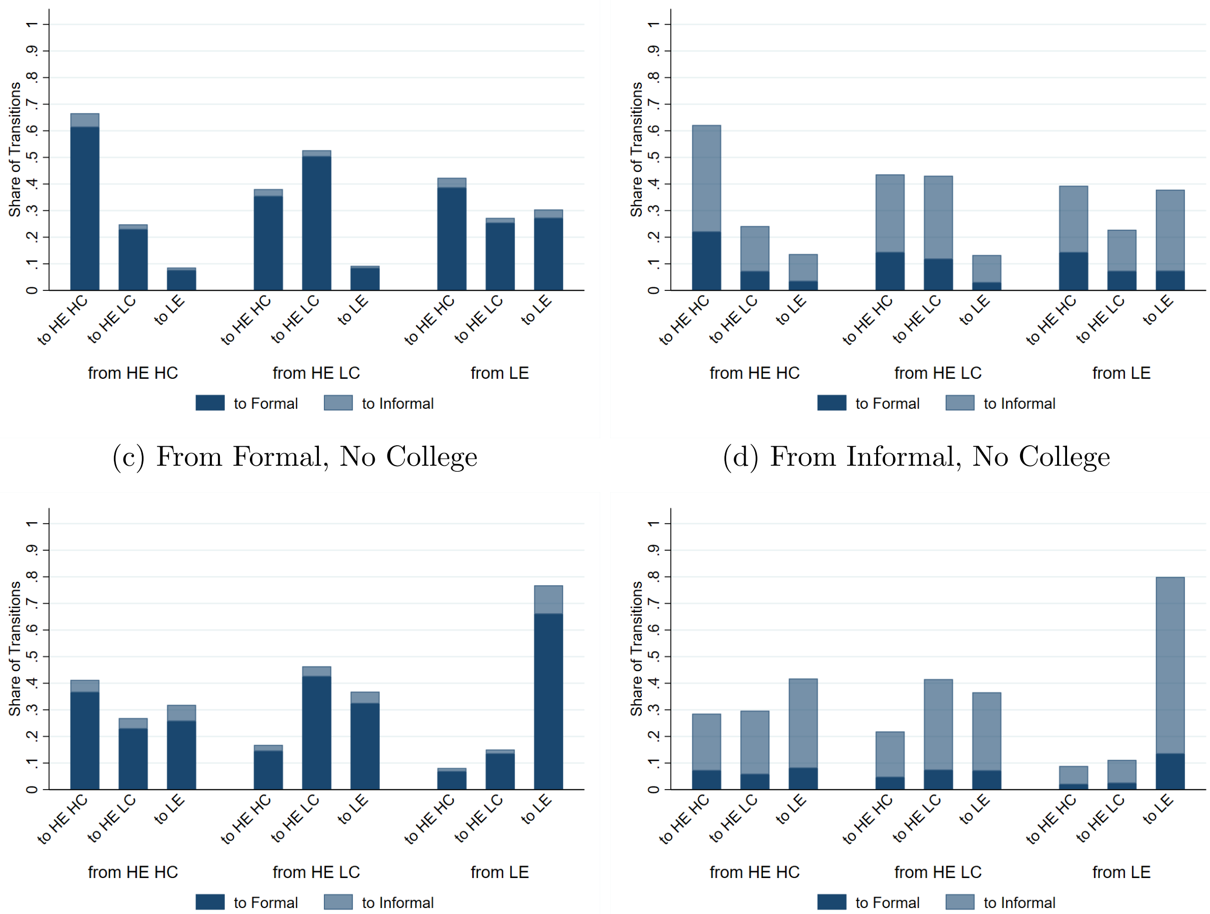
Note: The chart plots the share of employment in the formal and informal sectors in Brazil. For each sector, the share is broken down into the three AI exposure categories (low exposure, high exposure low complementarity, and high exposure high complementarity).

We then show the transition probabilities conditional on formality status and exposure category. Given that education is also correlated with formality (22.5 percent of formal workers have a college degree, versus only 10 percent of informal), we also condition on education. The transition probabilities (conditional on switching occupations) are plotted in Figure 7.

Even for those with a college education, being informal means they have a higher chance of moving to less exposed occupations. However, the probability of a formal worker moving to the informal sector is also relatively low (below 20 percent for all transitions in both education groups). This suggests displaced workers are unlikely to suffer a "double blow" of losing their formal status if they are able to adjust to other occupations.[15] Note, however, that this does not take into account the possibility of going to informality after becoming unemployed. Figure B.5 in the Annex discusses this case. We find that transitioning through unemployment carries a higher risk of becoming informal.

[15] As acknowledged by a large literature, for example, Leyva and Urrutia (2020) and Ulyssea (2018), in emerging economies informality cannot be seen as a solely negative phenomenon because it provides opportunities to workers who may otherwise remain out of the labor market. Nevertheless, in general terms, a transition from a formal job to an informal one can be considered an adverse development or a negative shock for a worker. Table B.1 shows that informal workers tend to have lower wage growth and that going to informality is also associated with a wage penalty.

Figure 7: Transition Probabilities cond. on Occupation Switch, Formality, and Education



(a) From Formal, College

(b) From Informal, College

(c) From Formal, No College

(d) From Informal, No College

Note: The bars in the chart represent the share of occupational switches from each of the three exposure categories to each of them for Brazil, conditional on formality and level of education. The transition probabilities are conditional on switching occupations and, the "from" category, level of education, and previous formality status, such that the three "to" bars add up to one. The chart also breaks down the probability of transitioning to a formal job (in dark blue) and to an informal job (in light blue).

7 Conclusion

In this paper, we documented patterns of workers' transitions across occupations, grouped by their exposure and complementarity to AI, in Brazil and the UK. Our analysis informs the debate over the likely impact of AI adoption on labor markets by moving beyond the concept of "static" exposure to these technologies. Moreover, the study highlights the diverse consequences that AI may entail across the world by considering two countries with very distinct characteristics that more reflect the main features of emerging markets and advanced economies.

In the comparison of these two countries, and different demographic groups within them, some key takeaways emerge from the analysis. First, more dynamic labor markets, such as those of emerging market economies, reflect greater idiosyncratic risk for individual workers but potentially also higher flexibility to adjust to changing production methods via labor reallocation across sectors. However, this aggregate-level fluidity may mask substantial differences across demographic groups. For instance, in Brazil, college-educated workers experience transitions to occupations poised to benefit from AI with a frequency that is similar to that of highly educated workers in the UK. Meanwhile, workers without a college education in Brazil experience much more frequent transitions to non-employment and to low-exposure occupations. In this sense, these findings suggest that the effect of AI adoption on the labor market experience of high-education workers may be more similar across countries with different income levels than that of workers without a university education. Second, with regards to age, the analysis shows that young workers, especially those with a college degree, are those who may see both the greatest opportunities from growth in AI-complementary jobs and the greatest risks from the disruption in low-complementarity jobs, particularly in the beginning of their career.

Given the great uncertainty over the ongoing development of AI-based technologies and their applications, the evidence presented should be interpreted with some caution. A key limitation of interpreting historical patterns in a forward-looking way is that past transitions across these occupation groups were not induced by a wave of structural transformation bringing deep changes in the economy as a whole. Such a shift might also entail workers updating their expectations of different career paths, possibly also acquiring new skills in order to adjust to a changing economy. Moreover, the analysis cannot account for the emergence of new occupations related to AI. The effect of new occupations on labor reallocation would crucially depend on whether such jobs require skills more similar to those of negatively affected low-complementarity jobs or of the high-complementarity ones. In the former case, the adverse impact of job destruction would be partly offset by emerging occupations. Finally, the analysis cannot factor in the effect that policies enacted by government and the design of labor market institutions may have in easing these transitions or in protecting workers from job displacement. We leave these considerations to future research, likely requiring a theoretical framework to model individual workers' decisions over their careers, general equilibrium forces, and the impact of policy measures.

Despite the caveats and the need for further research, the results hold some takeaways for policymakers applicable to both advanced economies and emerging markets. The analysis points to the importance of devising labor market interventions targeted to the intersection of demographic groups; for instance, while high-education workers overall may be less vulnerable to adverse shocks, young college graduates may be more at risk if the period of their careers where key professional transitions take place is disrupted. Moreover, policies to support the labor market through structural change should not only limit income losses once workers are displaced but also prevent job displacement by increasing workers' ability to transition from shrinking occupations to growing ones.

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A Additional Employment Flow Analysis

This Annex contains an additional analysis of workers' flow, looking at the gender implications, Annex A.1. It also includes further analysis of the occupation and job transition by education in Annex A.2. Last, it analyzes additional employment flows by AI exposure only in Annex A.3.

A.1 Employment Flow Analysis by Gender and Education

This Annex contains the workers' flows between employment, unemployment, and not in the labor force by gender. Table A.1 presents the employment flows data for female workers, while Table A.2 delineates the employment flows for male workers.

Table A.1: Employment Flows by Gender: Females

	Status in the subsequent quarter					
Status in the quarter	UK			Brazil		
	Employed	Unemployed	NLF	Employed	Unemployed	NLF
Employed	97.4	0.8	1.8	88.4	3	8.6
Unemployed	24.5	55.8	19.7	26	43.4	30.6
NLF	4	3.3	92.7	11.4	6.1	82.5

Note: The table shows the transition flows for the UK for the three states considered for male individuals. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter.

Table A.2: Employment Flows by Gender: Males

	Status in the subsequent quarter					
Status in the quarter	UK			Brazil		
	Employed	Unemployed	NLF	Employed	Unemployed	NLF
Employed	98.1	1	0.9	92.5	3.3	4.2
Unemployed	24.4	63.6	12	38.3	42.4	19.3
NLF	4	4.3	91.6	17.9	8.9	73.2

Note: The table shows the transition flows for Brazil for the three states considered for male individuals. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter.

In the UK, female workers exhibit high job retention, with 97.4 percent staying employed from one quarter to the next. A similar, albeit slightly higher, trend is observed among male workers, with 98.1 percent remaining employed. In both genders, a small proportion transitions to unemployment (0.8 percent for females and 1 percent for males) and to not in the labor force (NLF) (1.8 percent for females and 0.9 percent for males). For those starting as unemployed, males have a higher likelihood of staying unemployed (63.6

percent) compared to females (55.8 percent). Conversely, females are more likely to leave the labor force (19.7 percent) compared to males (12 percent).

In Brazil, the employment retention rate for female workers is lower at 88.4 percent, and even lower for male workers at 92.5 percent. The transition to unemployment is higher for both genders compared to the UK, with 3 percent for females and 3.3 percent for males. The move to NLF is also more pronounced, at 8.6 percent for females and 4.2 percent for males. Among those initially unemployed, a significant portion of males (42.4 percent) and females (43.4 percent) remain unemployed, but females are more likely to transition to NLF (30.6 percent) compared to males (19.3 percent).

These findings indicate that gender dynamics in employment flows differ between the UK and Brazil, with the UK showing greater job retention and less movement into unemployment or NLF for both genders compared to Brazil.

A.2 Occupation and Job Transitions by Education

In this section, we break down job and occupation switching probabilities by education level for both countries. Tables A.3 and A.4 show the results for the UK and Brazil, respectively.

The main result found is that college-educated workers switch occupations more frequently than those without a college degree: the probability is 1 percentage point higher in the UK and 4.6 percentage points higher in Brazil. Possible explanations could be career changes or advancement being easier for those with higher education. When considering job switching, there is no clear pattern across countries. While rates are similar for both groups in the UK, in Brazil, it is very infrequent for college-level individuals (1%) but more likely for those without a degree (3.2%). This may be due to lower job stability and higher rates of informality for those with a lower level of education.

A.3 Employment Flow Analysis by AI Exposure

We also analyze employment flows by dividing employment in jobs with low exposure to AI (LE) and those with high exposure (HE). Table A.5 shows the rates for the UK and A.6 for Brazil.

While most other results discussed in the paper still hold, an interesting difference is that LE workers show higher transition rates to unemployment and outside of the labor force

Table A.3: UK Job and Occupation Switching Probabilities by Education

Status	No College			College		
	Sm J	Sw J	Total	Sm J	Sw J	Total
Sm Occ.	87.7	0.7	88.4	86.4	1.0	87.4
Sw Occ.	10.4	1.2	11.6	11.4	1.2	12.6
	98.1	1.9			97.8	2.2

Note: The table shows the probabilities of switching jobs and occupations over a quarter. “Sm J” stands for Same Job, while “Sw J” corresponds to Switch Job; “Sm Occ.” stands for Same Occupation while “Sw Occ.” is for Switch Occupation. Switching jobs is defined as when the individual reports having been with their current employer for less than three months and having been employed in the previous quarter. The last row shows the marginal probabilities of switching jobs and the last column, the marginal probabilities of switching occupations.

Table A.4: Brazil Job and Occupation Switching Probabilities by Education

Status	No College			College		
	Sm J	Sw J	Total	Sm J	Sw J	Total
Sm Occ.	65.9	0.9	66.8	61.9	0.3	62.2
Sw Occ.	31.4	1.8	33.2	37.1	0.7	37.8
	97.3	2.7			99.0	1.0

Note: The table shows the probabilities of switching jobs and occupations over a quarter. ”Sm J” stands for Same Job, while ”Sw J” corresponds to Switch Job; ”Sm Occ.” stands for Same Occupation while ”Sw Occ.” is for Switch Occupation. Switching jobs is defined as when the individual reports having been with their current employer for less than three months and having been employed in the previous quarter. The last row shows the marginal probabilities of switching jobs and the last column, the marginal probabilities of switching occupations.

compared to their HE counterparts. In Brazil, those not currently working are also more likely to return to employment via low exposure jobs, while the opposite holds for the UK. Some factors that could contribute to this could be the higher share of individuals with a college degree and the higher supply of HE jobs in the UK, along with informality in Brazil.

The employment flows also lend credibility that switching ”upwards” in terms of exposure is more common in the UK than in Brazil: 1.7% of HE workers move to LE jobs in the UK (vs. 3.3% of LE workers to HE jobs), while in Brazil, the flows are of 11% from HE to LE and 7.1% from LE to HE.

B Additional Job Transition Analysis

This annex brings further discussion of some of the results shown in the main text. Figure B.1 plots the unconditional transition probabilities between exposure categories (in contrast to Figure 1 which shows the probability conditional on an occupational switch). Figure B.1 is a scaled version of 1 by the probability of changing occupations, such that it

Table A.5: AI Exposure Employment Flows for the UK

Status in the quarter	Status in the subsequent quarter: Employed (HE)	Employed (LE)	Unemployed	NLF
Employed (HE)	96.2	1.7	0.8	1.3
Employed (LE)	3.3	94.2	1.1	1.4
Unemployed	13.7	10.8	60.1	15.4
NLF	2.6	1.4	3.7	92.3

Note: The table shows the transition flows for the UK for the four states considered. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter. HE represents high exposure to AI and LE represents low exposure.

Table A.6: AI Exposure Employment Flows for Brazil

Status in the quarter	Status in the subsequent quarter: Employed (HE)	Employed (LE)	Unemployed	NLF
Employed (HE)	81.4	11	2.7	4.9
Employed (LE)	7.1	82.3	3.7	6.9
Unemployed	10.2	21.7	42.9	25.2
NLF	4.3	7	7	79.7

Note: The table shows the transition flows for Brazil for the four states considered. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter. HE represents high exposure to AI and LE represents low exposure.

highlights how workers are more likely to change functions in Brazil than in the UK.

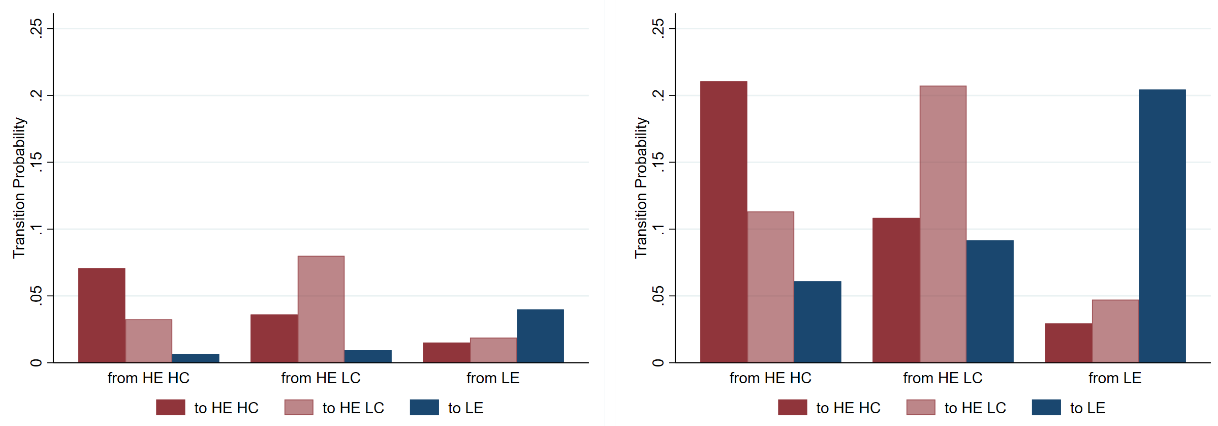
Figure B.2 shows the occupation transition probabilities for Brazil and the UK for workers with a high school degree or equivalent as their highest attained education level. We see that, unlike Figure 2, where college-educated workers show similar probabilities for both countries, workers with a high school degree in Brazil are more likely to transition to low exposure occupations (and less likely to high exposure ones) than their counterparts in the UK. This implies that the differences in the "non-college" category in Figure 2 may not be attributed only to compositional differences in this group across countries (for example, non-college in Brazil includes more workers without a high-school level education).

Figure B.3 conducts a wage lifecycle analysis similar to the one shown in 5.2 and Figure 4. However, here we restrict the analysis only to "stayers" - workers who did not change occupation in the one-year period we follow them in the panel data.

Given the similarity to Figure 4, this suggests that wage boosts owing to transitions might not be responsible for the bulk of wage growth, especially for younger workers. How-

Figure B.1: Transition Probabilities

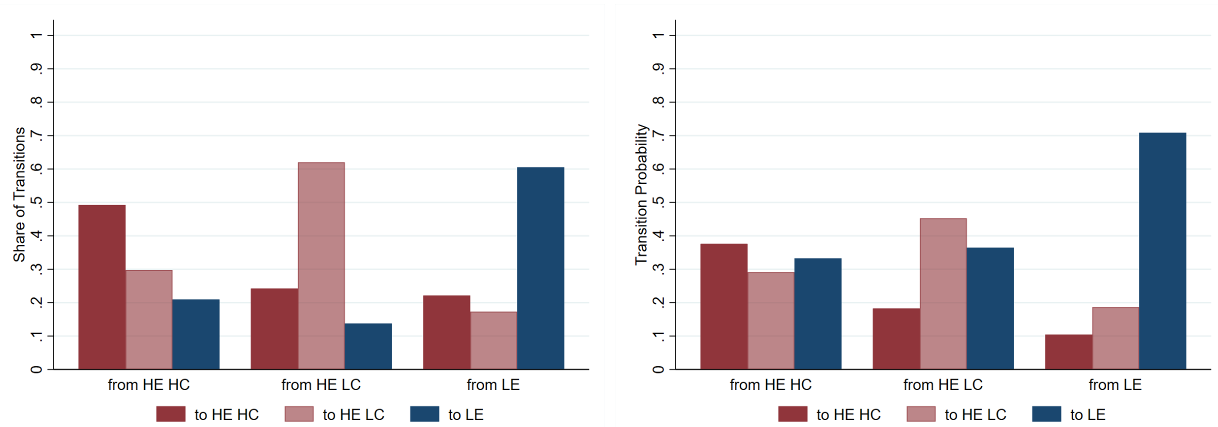
(a) UK (b) Brazil



Note: The bars in the chart represent the probability of a worker in the “from” exposure category switching occupations to one in the “to” category. The transition probabilities are conditional on the ”from” category.

Figure B.2: Transition Probabilities, Only Workers with HS Degree

(a) UK (b) Brazil

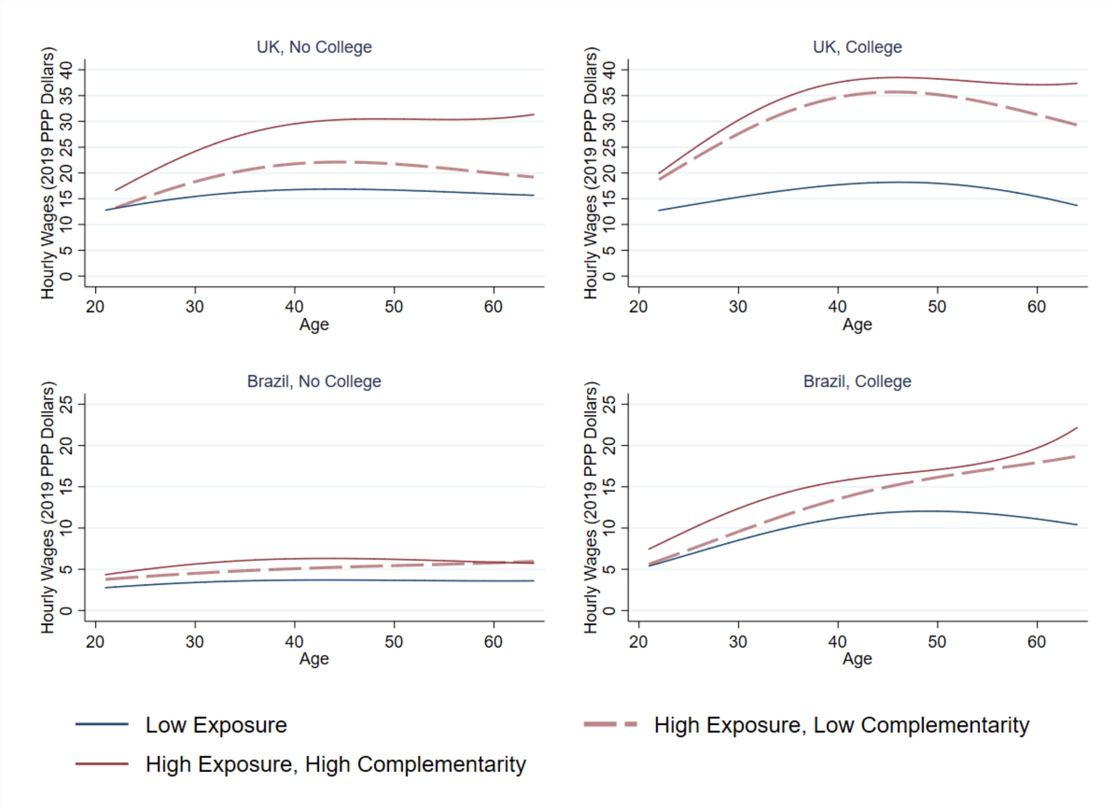


Note: The bars in the chart represent the share of occupational switches from each of the three exposure categories to each of them for the UK and Brazil. The transition probabilities are conditional on workers who have a high school level of education, switching occupations, and on the “from” category, such that the three “to” bars add up to one.

ever, since we only follow a given worker for the period of one year, restricting the analysis to stayers does not necessarily rule out the possibility of transitions being responsible for some of the wage growth.

Table B.1 shows the estimated coefficients of a regression of the log wage changes on demographic coefficients. We can write this specification as a simplified version of equation 4 without the transition terms. This allows us to check how demographic characteristics affect wage growth. Base categories are males aged below 25, with an education level of middle

Figure B.3: Lifecycle Profile of Wages, Only Stayers



Note: the y-axis represents the estimated hourly wage (in 2019 PPP dollars) of workers in each category for a given age, represented in the x-axis. Wages are estimated according to the polynomial specified in equation (3). The equation is estimated by country, level of education, and exposure category. The regression is restricted only to those individuals who did not change occupations across the one year we observe them in the panel data.

school or below, and in a formal job.

$$\Delta \log(y_{irt}) = \delta_1 J2J_{irt} + \delta_2 OS_{irt} \times J2J_{irt} + \delta_3 EUE_{irt} + \beta X_{irt} + \gamma_t + \eta_r + \varepsilon_{irt} \tag{5}$$

Overall, the estimates confirm what can be inferred from Figure 3: wage growth is greater for younger workers with college degrees. There is also a penalty associated with becoming informal (-0.074 log points) and we can also see that informal workers experience lower wage growth (summing the "was" and "is" informal coefficients, we get a penalty of -0.012 log points).

Table B.2 now presents the estimates of the transition terms of equation 4. Figure B.4 shows the impact on wages of transitioning between exposure categories, broken down by education (with or without a college degree). We find that, for both countries, workers

Table B.1: Wage Variation

	(1) UK	(2) Brazil
Switch Occ	0.0166***	0.00560***
Switch Emp	0.0454***	0.00876*
Occup. and Employer Change	-0.0224	-0.0150***
EUE Employer Change	-0.115***	-0.0280***
Age 25-44	-0.0234	-0.0423***
Age 45-59	-0.0347	-0.0507***
Age 60+	-0.0537*	-0.0404***
High School	-0.0109	0.00165
Some College	-0.00686	0.00894
College	0.0692**	0.0553***
Age 25-44 × High School	0.0187	0.000424
Age 25-44 × Some College	0.0239	-0.000104
Age 25-44 × College	-0.0634*	-0.0296**
Age 45-59 × High School	-0.00394	0.00371
Age 45-59 × Some College	-0.00678	-0.00395
Age 45-59 × College	-0.0844**	-0.0421***
Age 60+ × High School	0.0252	-0.0168
Age 60+ × Some College	0.0366	-0.0983*
Age 60+ × College	-0.0781**	-0.0352*
Female	-0.00125	0.000395
Is Informal		-0.0739***
Was Informal		0.0621***
Constant	0.0757**	0.146***
Observations	50700	687501
R^2	0.007	0.005
State FE	Yes	Yes
Year-Quarter FE	Yes	Yes

Note: The table shows the estimated coefficients for equation 5 using data from the UK and Brazil. Base categories are males aged below 25, with an education level of middle school or below, and in a formal job. The dependent variable is the log change in wages from one year to another. Standard errors calculated using the survey design.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

with a college degree experience higher gains for transitioning to high-exposure occupations (though they also suffer larger losses for going to low-exposure occupations). Individuals without higher education also see gains when transitioning to occupations more exposed to AI, although more modest.

Figure B.5 shows the probability of switching between formality and informality given that the worker remained unemployed for one quarter before beginning the new job (that is, going from employed to unemployed and then employment again in the span of three quarters). We present the results conditional on exposure category and education.

Table B.2: Wage Premia

	(1) UK	(2) Brazil
Switch Emp	0.0461***	0.00858*
Switch Occ	0.00582	0.00391
Switch Emp × Switch Occ	-0.0255	-0.0172***
EUE	-0.114***	-0.0277***
Same Occ × HE LC × HE LC	0.0130**	-0.00131
Same Occ × LE × LE	-0.00815	0.00932**
Switch Occ × HE HC × HE LC	0.00445	-0.0642***
Switch Occ × HE HC × LE	-0.0109	-0.0579***
Switch Occ × HE LC × HE HC	0.0261*	0.0641***
Switch Occ × HE LC × HE LC	0.00494	0.00185
Switch Occ × HE LC × LE	0.0120	-0.0142**
Switch Occ × LE × HE HC	0.0504**	0.0527***
Switch Occ × LE × HE LC	0.0538***	0.0197***
Switch Occ × LE × LE	0.0234	0.0191***
Constant	0.0756**	0.136***
Observations	50700	687501
R^2	0.007	0.007
State FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Individual Characteristics	Yes	Yes

Note: The table shows the estimates of the δ, θ and ϕ coefficients specified in equation 4 for the UK and Brazil. The dependent variable is the log change in wages from one year to another. Standard errors calculated using the survey design. Individual characteristics include age-education interactions.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

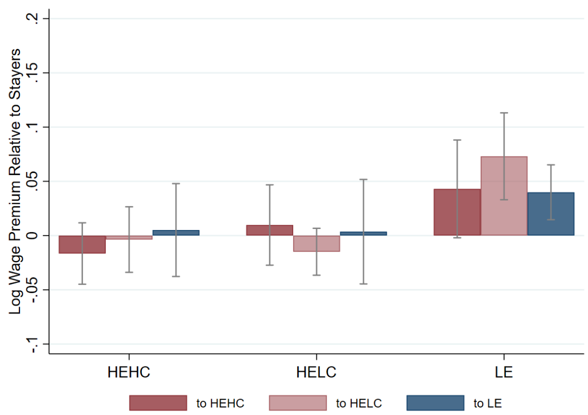
In contrast to the results in Figure 7, where the probability of going informal after switching occupations was below 20%, here it averages around 30% to 40% (going as high as 50% for workers transitioning from HE to LE jobs). This suggests that while becoming informal does not carry a significant risk of a "double blow" to earnings, transitioning jobs through unemployment can carry a higher risk of this (alongside the associated wage penalty found in Table B.1).

C Industry Distribution of AI Exposure

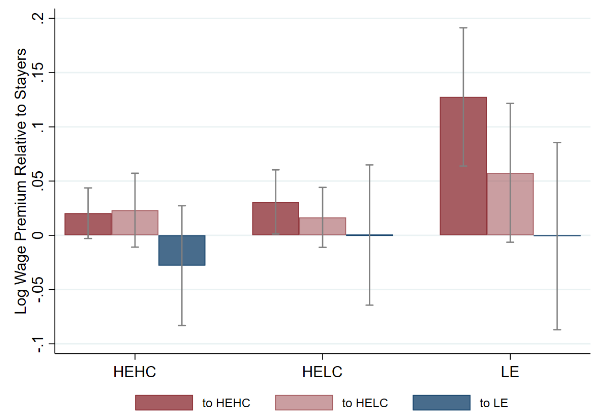
We briefly discuss how AI-exposed occupations are distributed across industry sections in both economies. Figure C.1 plots the share of total employment of high-exposure jobs in both countries by industry section, distinguishing high and low complementarity occupations.

Figure B.4: Wage Premia for Transitions by Education

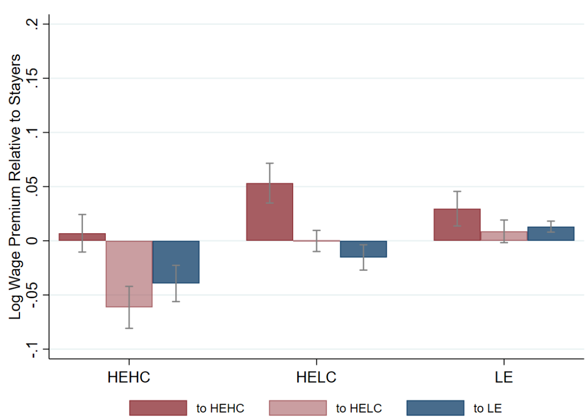
(a) UK (No College)



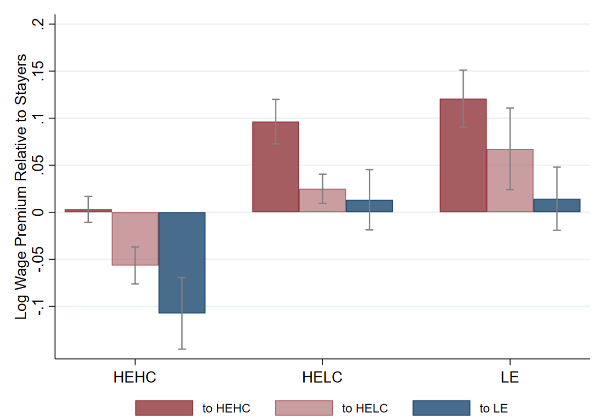
(b) UK (College)



(c) Brazil (No College)



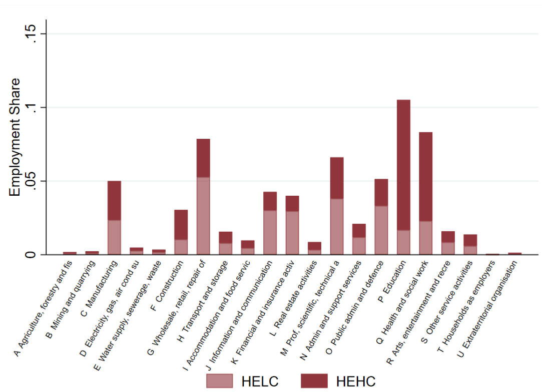
(d) Brazil (College)



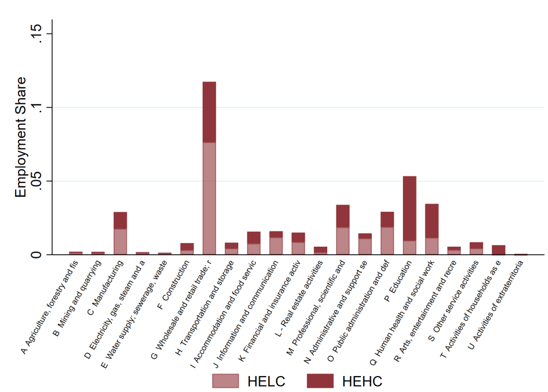
Note: The log wage premium relative to stayers represented in the y-axis is calculated as the value of the estimate $\phi_{kj} - \theta_k$ as specified in equation 4; that is, it is the log of the wage change in a year for those who changed occupations minus the wage change for those who did not change occupations. We restrict the sample to only individuals with a college degree (right figures) or without (left figures). The grey bars indicate the 95% confidence intervals of the estimates.

Figure C.1: High-Exposure Employment Shares by Industry Section

(a) UK



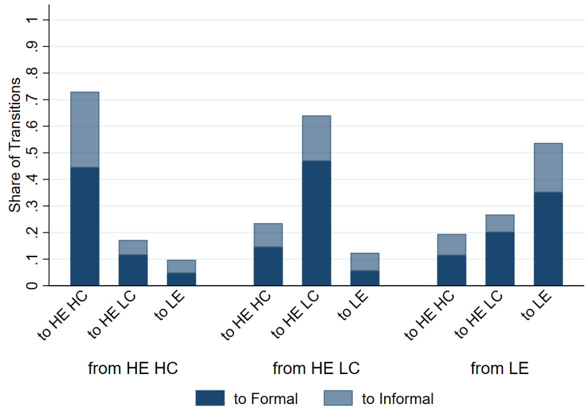
(b) Brazil



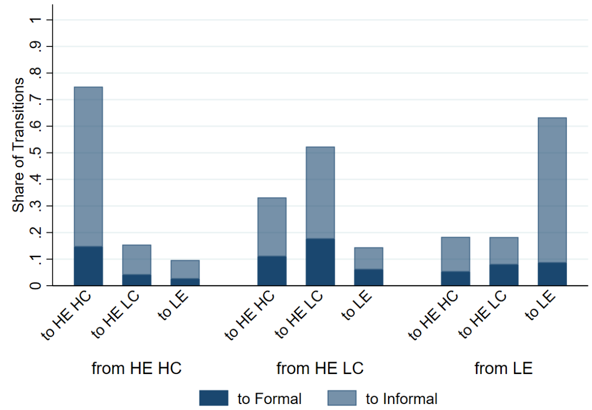
Note: The chart shows the employment share over total employment in high exposure occupations for each industry section, shown in the x-axis. Jobs in high exposure occupations are broken down into low complementarity (light red) and high complementarity (dark red).

Figure B.5: Transition Probabilities Through Unemployment cond. on Occupation Switch, Formality and Education

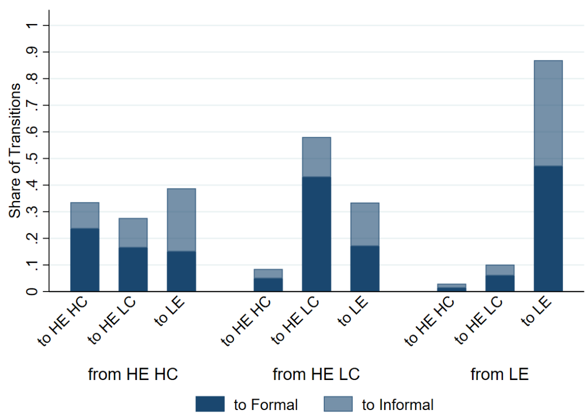
(a) From Formal, College



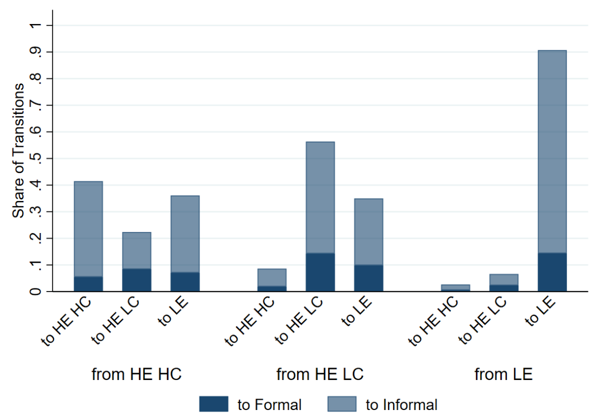
(b) From Informal, College



(c) From Formal, No College



(d) From Informal, No College



Note: The bars in the chart represent the share of occupational switches from each of the three exposure categories to each of them for Brazil, conditional on formality and level of education, for workers who have gone through unemployment for one quarter. The transition probabilities are conditional on switching occupations and, the "from" category, level of education, and previous formality status, such that the three "to" bars add up to one. The chart also breaks down the probability of transitioning to a formal job (in dark blue) and to an informal job (in light blue).

The services sectors concentrate most of AI-exposed employment; although they also account for most of total employment, the share of HE jobs in some services sections goes up to around 90 percent. In Brazil, jobs are more concentrated in trade, which has a higher share of low complementarity occupations; this contrasts with the UK, where there are more jobs in other services activities such as communications and finance. A highlight is the education sector, where almost 85 percent of workers are in high-exposure, high-complementarity jobs.