Artificial Intelligence Replacement Risk and Labor Market Flows in Portugal

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Abstract

This thesis studies how Artificial Intelligence (AI) affects labor market flows, by focusing on firms and occupations' risk of substitution by AI. We exploit the new Complementarity-adjusted AI Exposure Index (C-AIOE) developed by Pizzinelli et al. (2023), which identifies occupations in which AI is more likely to substitute rather than complement human labor. Using this indicator, we study how firm-occupation groups with different AI replacement risks adjust their hiring, separations, net employment, worker turnover, and job duration. Our analysis relies on matched employer–employee data from the dataset Quadros de Pessoal, covering all Portuguese firms from 2003 to 2021. The results show that firm-occupation groups more vulnerable to AI substitution have experienced differential increases in excess worker turnover over time, with simultaneous increases in hiring and separations, as well as lower job durations. These results suggest that the initial effects of AI on the labor market are not immediate net employment reductions, but rather higher turnover, greater instability, and shorter employment durations for AI-replaceable occupations.

Keywords: Artificial intelligence, Labor Market, Automation, Augmentation.

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Resumo

Esta tese analisa o impacto da Inteligência Artificial (IA) no mercado de trabalho, focando-se no risco de substituição por IA, ao nível das empresas e das ocupações. Utilizamos o Complementarity-adjusted AI Exposure Index, desenvolvido por Pizzinelli et al. (2023), que identifica ocupações nas quais a IA poderá substituir trabalhadores, ao invés de os complementar. Aplicando este indicador, estudamos a forma como ocupações e empresas com diferentes riscos de substituição por IA têm ajustado as suas contratações, separações, emprego, rotatividade de trabalhadores e duração do emprego. Recorremos à base de dados Quadros de Pessoal, que inclui todas as empresas portuguesas, e analisamos o período de 2003 a 2021. Os resultados mostram que os grupos empresa-ocupação mais substituíveis por IA experienciaram um aumento diferencial na rotatividade de trabalhadores ao longo do tempo, com aumentos simultâneos nas contratações e separações, e diminuições na duração do emprego. Segundo estes resultados, os efeitos iniciais da IA no mercado de trabalho não parecem ser reduções imediatas no emprego, mas antes uma maior rotatividade e instabilidade do trabalho, para as ocupações mais substituíveis por IA.

Palavras-chave: Inteligência Artificial, Mercado de Trabalho, Automação, Complementaridade.

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1 Introduction

How is Artificial Intelligence (AI) transforming the labor market? The fast development of AI has created concerns and anxiety about job displacement, as in earlier waves of technological change (Frank et al., 2019; Autor, 2022). Moreover, breakthroughs in Machine Learning and Generative AI in the last two decades have allowed systems to perform complex, non-routine cognitive tasks that were previously considered resilient to automation.

However, labor market disruption depends not only on whether AI can theoretically perform the same tasks as workers, but also on whether firms adopt it to substitute rather than complement human labor. Furthermore, AI's effects may extend beyond employment or wages, the outcomes most commonly feared and addressed. Its earliest consequences may instead be greater labor market turbulence by increasing worker reallocation, turnover, and shortening employment spells.

This thesis studies the impact of AI replacement risk on labor market flows in Portugal from 2003 to 2021. Importantly, we consider AI in a broad sense, including technologies that have progressed over several decades, rather than including only recent developments in Generative AI, such as OpenAI's ChatGPT. Our analysis makes three main contributions. Firstly, it accounts for complementarity and substitution of AI through the C-AIOE index, created by Pizzinelli et al. (2023). Secondly, it provides one of the first analyses of the impact of AI in the Portuguese labor market, a useful case study to investigate the early effects of AI. Thirdly, it introduces excess worker turnover as a new outcome to study the effects of AI on labor market flows.

To achieve the *first contribution*, we exploit the complementarity-adjusted AI exposure index (C-AIOE), recently developed by Pizzinelli et al. (2023), which measures occupations' vulnerability to AI substitution. The C-AIOE builds on the widely used AI Occupational Exposure index (AIOE), created by Felten et al. (2021). The AIOE links occupations' tasks to current AI capabilities, viewing each occupation as a combination of tasks. This AI exposure index measures the extent to which an occupation's main tasks could be performed by AI, without assuming substitution or complementarity.

Several authors have used the AIOE to analyze and forecast the effect of AI on the labor market. Acemoglu et al. (2022) study the impact of AI Occupational Exposure on the labor market, using online vacancy data from the United States. They find that establishments with higher average AI Exposure experienced significant increases in AI-related vacancies and decreases in hirings for non-AI positions, but no aggregate changes in employment or wages. Guarascio et al. (2023) find that European regions with a higher share of occupations exposed to AI experienced more favorable employment patterns during the period 2011-2018. Albanesi et al. (2023), analyzing 16 European countries in the last decade, find that in most countries, occupations more exposed to AI have seen increases in average employment shares.

However, a general exposure index such as the AIOE, which measures how well, in theory, AI can perform the tasks of a given occupation, is insufficient to accurately estimate AI's potential displacement effects on the labor market. Recent theoretical research highlights the importance of distinguishing between substitution and complementarity of AI, as they may have opposing effects on the labor market (Acemoglu, 2025; Acemoglu and Restrepo, 2018a; Autor et al., 2024). Eloundou et al. (2024) take a step toward empirically separating these mechanisms by distinguishing between augmenting exposure and displacing exposure. In their framework, displacing exposure refers to tasks that AI can perform independently, while augmenting exposure covers tasks where productivity gains require complementary software or intensive human input. However, Eloundou et al. (2024)'s measure only applies to large language models (LLMs), a type of artificial intelligence trained on massive amounts of text data to understand and generate human-like language. Johnston and Makridis (2025) apply their classification to the U.S. labor market and find that sectors with higher AI augmentation exposure experienced employment and wage gains, but sectors facing substitution saw employment reductions. Their findings further hint at the importance of disentangling the labor market effects of AI substitution and complementarity, instead of only quantifying exposure.

In this thesis, we use the C-AIOE index by Pizzinelli et al. (2023), which presents two main advantages. Firstly, it extends beyond LLMs by including a broad range of AI capabilities such as image generation and speech recognition, which have been available for over a decade. Secondly, it captures AI replacement risk, rather than merely theoretical AI exposure. The C-AIOE achieves this by negatively weighing the well-known AI Occupational Exposure index (AIOE) by a component that captures complementarity with human labor. Complementarity is assessed by accounting for the context of the occupation, including the criticality of decisions, human interaction, physical conditions and the education required. This is achieved by focusing on two characteristics of occupations described by U.S. Department of Labor's O*NET database: work contexts and job zones. Work contexts capture the physical and social conditions that influence a job, while job zones indicate the level of education, training, and experience required for an occupation. By including these factors, the C-AIOE allows for a more realistic assessment of which occupations are likely to be substituted by AI, rather than complemented.

Pizzinelli et al. (2023) describes the C-AIOE in advanced economies (US and UK) and emerging markets (Brazil, Colombia, India, and South Africa), comparing it across education, gender, and income. Building on this work, we use the C-AIOE to analyze how occupations with different vulnerabilities to AI substitution have experienced differential hiring, separations, net employment and excess turnover in Portugal over time. Consequently, we contribute to the literature by accounting for AI's context-specific complementarity and substitution to estimate displacement effects in the labor market.

Moreover, the *second contribution* of this thesis is to provide one of the first analyses of the impact of AI on the Portuguese labor market. Although the development of AI in Portugal lags behind countries like the US and China, AI technologies such as machine learning and statistical algorithms have been growing for several years (Oliveira and Figueiredo, 2024), approximately since the 2010s. This makes Portugal an interesting case for studying the early effects of AI adoption. Batista et al. (2025) produced the first comprehensive study of AI exposure in the Portuguese labor market, using Felten's AI Occupational Exposure Index and identifying the occupations and, by extension, the regions most exposed to technological change. However, while their report provides a snapshot of AI exposure, it does not distinguish between augmentation and substitution effects or analyze the effects of AI on labor market outcomes over time. This thesis attempts to fill that gap.

Finally, our *third contribution* is to provide the first direct analysis of the impact of AI on labor market churn. To achieve it, we use excess worker turnover as an outcome variable, which captures turnover beyond what is required for net employment changes (Burgess et al., 2000). We argue that AI may increase excess worker turnover through three interconnected channels: (1) task reallocation and skill mismatches, (2) search under technological uncertainty and (3) creative destruction and restructuring. According to task-based frameworks (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018b; Aghion et al., 2018), occupations are defined as bundles of tasks, some of which AI may automate, augment, or transform, leading to frictions that could increase turnover. Similarly, since the capabilities, returns, and timings of AI are uncertain, firms experimenting with it are likely to adjust hiring and separations more frequently, increasing churning. Furthermore, historical evidence from technological breakthroughs suggests that innovation typically increases labor market turbulence rather than causing immediate mass unemployment (Schumpeter, 1942; Aghion and Howitt, 1992; Jovanovic and Rousseau, 2005). Together, these mechanisms suggest that AI's earliest labor market effects may be instability and churning rather than large-scale job losses. Furthermore, AI could also contribute to shortening job duration. As firms adjust their workforce more frequently and workers experience skill obsolescence, employment spells could become shorter in more AI-replaceable occupations. This justifies the need to quantify the impact of AI on excess worker turnover and consequently job duration, in addition to net employment, hiring and separation rates.

Empirically, we combine the C-AIOE at the occupation level with rich administrative employer–employee data for Portugal from Quadros de Pessoal, covering millions of workers and hundreds of thousands of firms. This data allows us to compute firm-level hiring and separation rates, net employment and excess worker turnover, and to study how these outcomes evolve in firms with different concentrations of AI-replaceable occupations. The analysis of labor market flows covers the years 2003 to 2021 and is based on the concepts developed by Davis et al. (1996).

We find that firm-occupation groups more likely to be replaced by AI have experienced larger increases in excess worker turnover over time. Both hiring and separation rates increased relatively more in these firms, pointing to greater churning rather than net employment reductions. Additionally, we find that AI replacement risk is linked to shorter average employment spells. However, this effect is sensitive to the specification and less robust than the findings for excess worker turnover. Overall, our findings uncover a less discussed potential effect of AI: increasing labor instability and insecurity for firms and occupations more vulnerable to substitution. This suggests that the earliest consequences on the labor market may not be immediate and substantial job losses, but rather higher turnover, lower employment duration and more fragile employment relationships. Understanding these dynamics, and identifying the occupations and tasks most resilient and complementary to AI, is essential to design policies that help workers adapt to technological change.

The rest of the paper proceeds as follows. Section 2 describes our measure of AI replacement risk, the Complementarity-adjusted AIOE index. Section 3 describes the theoretical mechanisms through which AI may affect labor flows and turnover. Section 4 presents the data and descriptive statistics. Section 5 describes the empirical strategy. Section 6 presents the main results. Section 7 provides robustness checks, and Section 8 examines heterogeneous effects across firm and worker characteristics. Finally, Section 9 concludes.

2 AI Replacement Risk Indicator (C-AIOE)

2.1 Motivation

Our analysis uses a new indicator developed by Pizzinelli et al. (2023), the complementarity-adjusted AIOE (C-AIOE), quantifying AI replacement risk. This measure builds on the well-known Artificial Intelligence Occupational Exposure index (AIOE), created by Felten et al. (2021), which measures exposure to AI, without distinguishing between substitution and complementarity. The new C-AIOE modifies the original AIOE by negatively weighing it with a potential complementarity index θ, which captures the extent to which occupations are likely to be complemented by AI. Consequently, higher values of the C-AIOE correspond more directly to a higher risk of substitution by AI and thus to more adverse labor-market impacts. This makes the C-AIOE a more precise instrument for analyzing the effects of AI on labor dynamics.

2.2 *Artificial Intelligence Occupational Exposure index (AIOE)*

To construct the C-AIOE indicator, Pizzinelli et al. (2023) used the Artificial Intelligence Occupational Exposure index (AIOE) by Felten et al. (2021). The AIOE links 10 common AI applications[1], such as image recognition and reading comprehension, with 52 O*NET occupational abilities or tasks[2]. The AIOE index was constructed by Felten et al. (2021) in three steps. Firstly, a crowd-sourced dataset provided a matrix of relatedness scores (0–1) for how closely each AI application is connected to each occupational ability. Secondly, the authors computed an exposure score for each ability by summing its relatedness scores across all 10 AI applications, weighing each application equally. Finally, given that each occupation is a weighted combination of the 52 abilities, the occupation-level AIOE score was calculated by combining the ability-level exposure values. Each ability is weighted using two O*NET measures: prevalence, which reflects how frequently the ability is used in the occupation, and importance, which reflects how essential it is for performing the job. Consequently, the AIOE index for each occupation o can be expressed as:

$$\text{AIOE}_o \equiv \frac{\sum_{j=1}^{52} A_{ij} \times P_{jo} \times I_{jo}}{\sum_{j=1}^{52} P_{jo} \times I_{jo}}$$

Where j stands for the occupational ability, i represents the AI application, and A_{ij} corresponds to the exposure to AI of ability j. Exposure to AI is then weighted by the ability's prevalence, P_{jo}, and importance, I_{jo}, in each occupation o[3].

[1]The set of AI applications was based on categories defined by the Electronic Frontier Foundation (EFF). Source: AI Progress Measurement. (2019). Electronic Frontier Foundation. https://www.eff.org/ai/metrics

[2]The O*NET database, created by the U.S. Department of Labor in 1998, provides detailed information on nearly 1,000 occupations, including their skills and abilities. While focused on the U.S., ONET data are frequently used for international studies by leveraging crosswalks from the SOC 2010 occupational code.

[3]The AIOE was originally coded by occupation using the U.S. Standard Occupational Classification (SOC) Code system. Using well-known crosswalks, it can be converted into the ISCO-08 system, used internationally and in Europe, including Portugal since 2010. Additionally, it can be further converted into the CNP 94 and CNP 80 systems, used in Portugal before 2010 and before 1995, as performed in Raposo et al. (2021).

2.3 Potential Complementarity (θ)

To construct the potential complementarity measure θ, Pizzinelli et al. (2023) also used occupation-level data from O*NET, focusing on two less commonly used features: work contexts and job zones. Work contexts describe the physical and social factors that influence a job. The researchers selected the most relevant work contexts to evaluate whether AI is likely to replace humans or instead be adopted in a supervised and complementary manner. They then grouped them into five categories, following O*NET's own structure. Job zones, in turn, denote the level of education, training, and experience required to perform an occupation. The complementarity θ is derived from six components, with the first five corresponding to work contexts and the sixth representing job zones:

1. **Communication:** (i) Face-to-Face, (ii) Public Speaking. Occupations that heavily rely on personal contact and communication are less likely to be entirely substituted by AI. For example, Septiandri et al. (2024) shows that hearing aid specialists perform tasks that require empathy and emotional intelligence, such as counseling patients, which current AI technologies cannot replicate.

2. **Responsibility:** (i) Responsibility for Outcomes, (ii) Responsibility for Others' Health. Jobs requiring responsibility for relevant outcomes and others' health are less likely to be entirely trusted to AI technologies.

3. **Physical Conditions:** (i) Exposure to Outdoor Environments, (ii) Physical Proximity to Others. Occupations performed outdoors and that require close physical proximity to others are typically harder for AI to replace. Josten and Lordan (2022) find that occupations that require physically making objects or broader physicality are less likely to be automated.

4. **Criticality:** (i) Consequence of Errors, (ii) Freedom of Decisions, (iii) Frequency of Decisions. Occupations with high-stakes, frequent, and independent decisions are difficult to substitute entirely, as they rely on human and context-sensitive judgment. Research finds that individuals are less willing to trust algorithms when making higher-stakes decisions

(Horowitz and Kahn, 2024).

5. **Routine:** (i) Degree of Automation, (ii) Unstructured vs. Structured Work. Routine jobs have historically been more susceptible to automation (Autor et al., 2003; Autor, 2022), and are therefore expected to be more vulnerable to AI substitution.

6. **Skills:** Job Zones. Workers in occupations requiring higher levels of education and training are likely to adapt more quickly to AI technologies and use them in a complementary manner, rather than being replaced.

The complementarity θ is calculated as the arithmetic mean of all 6 components and rescaled to lie between 0 and 1. For example, clerical jobs such as data entry clerks have a low complementarity θ due to their routine and easily automated tasks, while airline pilots present a high complementarity θ because their work involves high-stakes and context-dependent decisions.

2.4 Complementarity-Adjusted AIOE (C-AIOE)

Finally, following Pizzinelli et al. (2023), we construct the Complementarity-Adjusted AIOE (C-AIOE), our key measure of AI replacement risk. The C-AIOE for each occupation o is derived from negatively weighing the AIOE by the complementarity θ for that occupation, as follows:

$$\text{C-AIOE}_o = \text{AIOE}_o \times \big[1 - (\theta_o - \theta_{\min})\big],$$

where $\theta_{\min}$ is the minimum value of θ_o across all occupations. Adjusting by $\theta_{\min}$ allows the complementarity measure to be interpreted relative to the original AIOE index. For the occupation with the lowest potential complementarity, the AIOE and C-AIOE measures coincide.

In practice, the second term on the right-hand side reduces the AIOE more significantly for occupations with higher complementarity. Consequently, a higher C-AIOE value indicates a greater risk of substitution by AI at the occupational level.

Clerical workers, such as administrative secretaries and data-entry clerks, illustrate this clearly. They are highly exposed to AI (high AIOE) and tend to have low levels of complementarity (low θ). Therefore, they receive some of the highest C-AIOE scores, meaning they face higher substitution risk from AI. However, some high-skill occupational groups, such as doctors and managers, also face high AI exposure (high AIOE) but possess a much greater potential for complementarity (high θ). As a result, these occupations tend to have lower C-AIOE values and face less substitution by AI.

On the other hand, for occupations with lower AI exposure (low AIOE), complementarity may still vary significantly. For example, firefighters exhibit high complementarity, since the criticality and context-specific nature of their decisions means that AI can support and complement their activity, but cannot replace them entirely. As a result, they obtain some of the lowest C-AIOE values, indicating a minimal risk of replacement by AI. In contrast, housekeepers show both low complementarity and low exposure to AI, as most of their tasks are difficult to substitute or augment with AI cost-effectively. Electricians fall in between these two extremes, showing moderate complementarity, as certain technical tasks may benefit from AI while others remain largely manual.

Figure 1 illustrates these differences by plotting each occupation's exposure to AI (AIOE) against potential complementarity (θ), which divides the graph into quadrants with distinct levels of exposure and complementarity.

Figure 2 presents the average C-AIOE scores by broad occupation, grouped at the 1-digit ISCO-08 code level. This aggregation is used to provide a clearer overview of patterns across major occupational groups, although all main analyses are conducted at the more detailed four-digit ISCO-08 level. The figure also highlights heterogeneity within occupation groups by displaying the proportion of workers in each quartile of the C-AIOE index for each broad occupation. High-skilled workers, such as engineers, present the highest average C-AIOE, and consequently the highest risk of replacement by AI. In contrast, farmers and fishermen, as well as unskilled workers, exhibit the lowest average C-AIOE scores, although the latter show greater heterogeneity within the group.

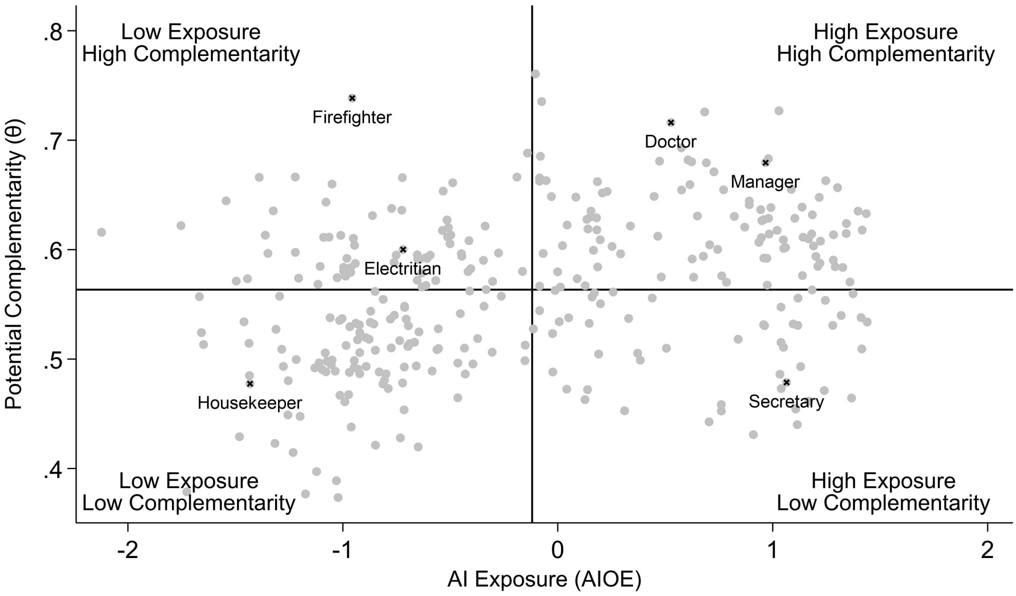


Figure 1: AI Exposure (AIOE) and Potential Complementarity (θ)

Notes: This picture illustrates each occupation as a combination of AI Exposure and Potential Complementarity. AI Exposure (AIOE) refers to the occupation-level exposure measure from Felten et al. (2021). Potential complementarity (θ) is the adjustment term developed by Pizzinelli et al. (2023), measuring the extent to which occupations may be complemented, rather than substituted, by AI. The occupations are specified by ISCO-08 codes at the four-digit level. Both lines dividing the graph are based on the medians of AIOE and θ.

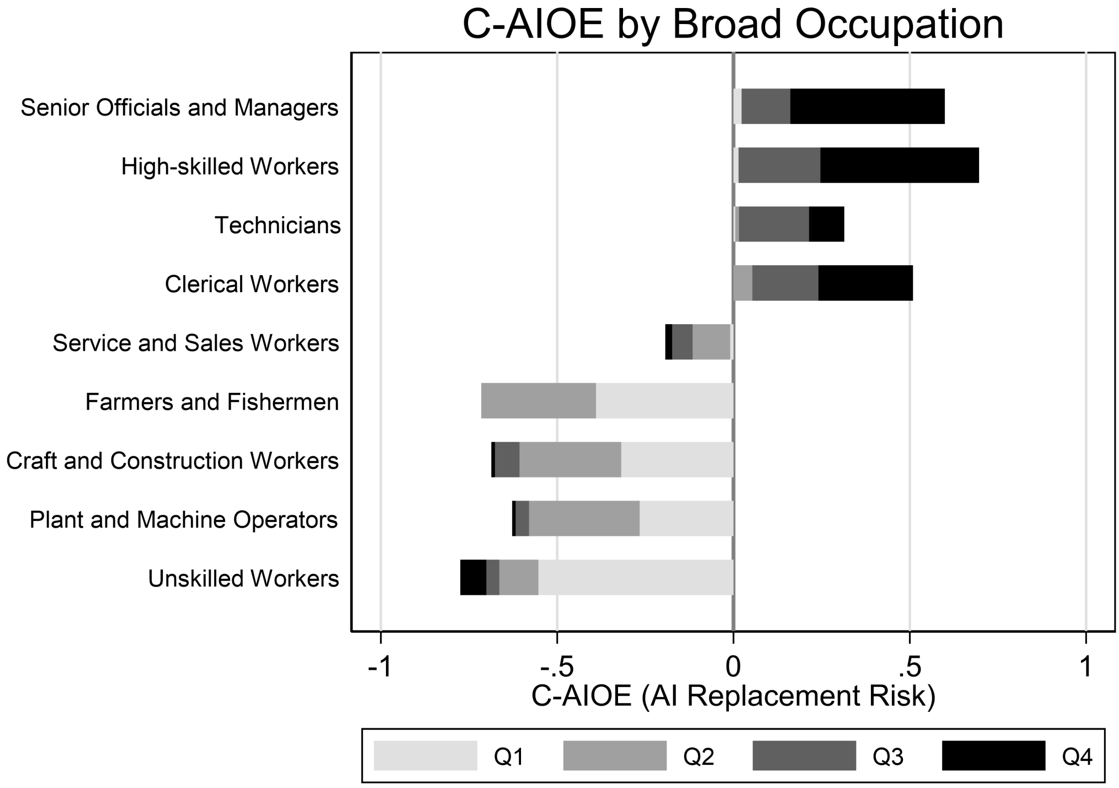


Figure 2: AI Replacement Risk (C-AIOE) by Broad Occupation

Notes: This graph plots average AI Replacement Risk (C-AIOE), the final indicator from Pizzinelli et al. (2023), by broad occupation. The broad occupations are grouped at the one-digit level of the ISCO-08 classification. Additionally, for each occupation group, different colors illustrate the percentage of occupations belonging to each quartile of the C-AIOE. The first quartile corresponds to the least replaceable occupations and the fourth to the most replaceable ones.

3 Theoretical Mechanisms

The literature exploring the effects of AI on the labor market is relatively recent but growing rapidly. Most existing studies focus on how AI technologies influence hirings, separations, employment or wages. We contribute to this literature by introducing an entirely new outcome variable: excess worker turnover. Rather than primarily creating long-term mass unemployment, AI could be more likely to increase labor market turbulence by increasing worker reallocation and turnover. We quantify excess worker turnover following Burgess et al. (2000), defining it as turnover beyond what is required for net employment change. We hypothesize that greater AI exposure is associated with higher excess worker turnover, through three mutually reinforcing channels: (1) task reallocation and skill mismatches, (2) search under technological uncertainty and (3) creative destruction and restructuring.

Firstly, AI could increase excess worker turnover by changing the task content of jobs and creating skill mismatches, thus increasing hiring and separations within firms. This mechanism is based on the task-based framework, which has been used extensively to study how technology affects labor demand (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a; Autor et al., 2003, 2024; Acemoglu, 2025). According to this framework, occupations can be understood as bundles of tasks. Rather than influencing or substituting entire occupations, AI can affect the tasks that compose them, by automating some, augmenting others and generating new ones. This task recomposition creates friction. Workers' skills may no longer match firms' needs, leading to replacement with better-matched employees, more frequent adjustments and increased excess worker turnover. Additionally, the continuous development of AI accelerates skill obsolescence, potentially decreasing the duration of job matches.

Secondly, AI adoption occurs under uncertainty. Firms often do not know which tasks AI will replace, how productive it will be, or how their competitors will respond. Consequently, firms may experiment with hiring and readjust before potentially reaching an equilibrium. This trial-and-error could increase both hirings and separations, raising excess worker turnover, even if total employment remains stable. Caballero and Hammour (1996) argue that, under uncertainty, firms adjust hiring incrementally, influencing job reallocation dynamics.

Third, AI can be seen as part of a broader technological progress. Historically, major technological waves have often increased labor market turbulence, rather than causing long-term mass unemployment. This is related to the process of creative destruction described by Joseph Schumpeter and expanded by Aghion and Howitt (1992), as well as by Jovanovic and Rousseau (2005). Technological progress and innovation often lead to job destruction, but also to the creation of more productive positions elsewhere, increasing excess worker turnover. While this reallocation creates value, it can also increase inequality and exclusion, as well as produce uneven outcomes for workers (Cahuc and Zylberberg, 2006). Firms simultaneously drop, expand, and reorganize roles, leading to job creation and destruction. We argue that AI follows the same pattern, with higher excess worker turnover reflecting this ongoing reallocation.

Taken together, these mechanisms suggest that AI increases labor market turbulence and excess worker turnover through task changes, uncertainty, creative destruction and worker responses, rather than causing generalized job losses.

Analogously, we study the effect of AI on job duration to assess whether these three mechanisms also translate into shorter employment spells for more AI-replaceable occupations. While excess worker turnover measures the intensity of hiring and separation flows, job duration offers a complementary perspective by capturing the stability of employment relationships. If AI technologies change firms' task contents, increase technological uncertainty and contribute to restructurings, existing job matches may become shorter and more unstable. Firms may adjust their workforce more frequently and workers may experience skill obsolescence, leading to shorter employment spells in more AI-replaceable occupations.

However, there could be an alternative possibility. AI could contribute to reduced hiring and increased separations, leading to net employment losses. This view is supported by a branch of the literature that emphasizes the displacement effects of automation, defending that new technologies substitute human labor in several tasks and occupations. In this perspective, firms may adopt AI primarily to reduce labor costs and increase efficiency, resulting in job destruction that is not fully offset by new job creation, at least in the short to medium run. If this mechanism dominates, we would expect lower hiring rates, higher separation rates, and declining employment in more AI-exposed occupations, rather than increased churning. Bessen (2018) discusses how automation can displace workers in the short run, even if other mechanisms offset losses in the long run.

In the following sections, we examine how AI has affected labor market flows in Portugal, focusing on excess worker turnover, hiring and separation rates, net employment, and job duration to assess whether AI has primarily increased labor market churning or contributed to net employment changes.

4 Data

4.1 Quadros de Pessoal

We used data from Quadros de Pessoal (QP), a Portuguese employer-employee matched dataset collected annually by the Ministry of Solidarity, Employment and Social Security. All employers with at least one dependent employee are legally required to report, which reduces panel attrition problems. Additionally, the information is reported by the employers, mitigating measurement errors. The dataset includes over 300,000 firms and 3 million workers. It provides detailed worker-level information on age, gender, education, earnings, and hours worked, among others. Additionally, it contains firm-level information, including geographic location, industry and size. We could have used alternative sources, such as Portuguese Social Security records or the Employment Survey conducted by the Portuguese Statistics Institute (INE). However, Quadros de Pessoal captures the universe of all employers and employees in Portugal and offers detailed information on occupations and worker characteristics, making it the preferred dataset for our analysis. Additionally, it has been widely used to study wages and labor flows. Blanchard and Portugal (2001) find that flows of workers into unemployment in Portugal are three times lower than in the United States. Centeno and Novo (2012) studied how employment protection affects excess turnover and the use of fixed-term versus open-ended contracts in Portuguese firms. More recently, Lehrer and Rawling (2025) used Quadros de Pessoal to show that, over the last two decades, increased exposure of firms and labor markets to immigrants has contributed to the convergence of wages between immigrants and natives.

4.2 Sample

Firstly, in our cleaning procedure, workers not linked to firms or with no regular remuneration are removed. Additionally, individuals working in the agricultural sector are dropped, as the data is often imprecise. Finally, the sample is further restricted to workers aged between 18 and 65. The monthly earnings are calculated as the sum of the base wage, regular payments (e.g., seniority), irregular benefits (e.g., profits and premiums) and overtime payments. When divided by the total number of regular and overtime hours worked, this variable provides the worker's hourly wage. Finally, it is deflated using the Consumer Price Index (with a base year of 1986) and expressed in log terms. The years 1990 and 2001 are missing from the Quadros de Pessoal dataset, which harms the analysis of hiring and separation rates. To accurately measure hiring, we need information on employees in the years before the observation period to identify when a worker enters a firm. Similarly, to capture separations, we need data from the years following the observation period to observe whether employees leave the firm. Consequently, we restrict our sample of analysis to span 2003 to 2021, where complete flow information is available. However, we use data from 2002 to 2023 to calculate hiring, separation and excess worker turnover rates, accounting for workers' presence in the years right before and after each observation.

4.3 Hiring, Separation and Excess Worker Turnover Rates

We continue our analysis by calculating aggregate measures of job and worker flows. Hiring, separation, and excess worker turnover rates are computed following the framework established by Davis et al. (1996).

However, since AI replacement risk (C-AIOE) is defined at the occupational level, our unit of analysis becomes the firm-occupation group. This choice allows us to calculate labor flows typically measured at the firm level, such as hirings, separations, and excess worker turnover rates, while still capturing the heterogeneity in C-AIOE across occupations. A firm-occupation group includes all workers in a specific occupation within a given firm. For example, it could refer to the group of lawyers employed in a particular firm.

For every firm-occupation group fo, hirings $H_{fo,t}$ represent the number of workers who entered in year t, and separations $S_{fo,t}$ correspond to the workers who left in year t. Consequently, the hiring and separation rates are given by:

$$\text{HR}_{fo,t} = \frac{H_{fo,t}}{(X_{fo,t} + X_{fo,t-1})/2} \quad \text{and} \quad \text{SR}fo,t = \frac{S_{fo,t}}{(X_{fo,t} + X_{fo,t-1})/2},$$

where $X_{fo,t}$ represents the number of workers employed at each firm-occupation group in year t, and $X_{fo,t-1}$ represents the number of workers in year $t-1$.

Consequently, the net employment change rate $NEC_{fo,t}$ can be computed as:

$$\text{NEC}_{fo,t} = \text{HR}_{fo,t} - \text{SR}_{fo,t}.$$

Finally, the rate of excess worker turnover is related to the concept of churning described in Burgess et al. (2000). It measures the portion of worker turnover that exceeds what is necessary to achieve the net change in employment. Formally, the excess worker turnover rate, $EWT_{fo,t}$, for each firm-occupation cell, is defined as:

$$\text{EWT}_{fo,t} = \text{HR}_{fo,t} + \text{SR}_{fo,t} - |\text{NEC}_{fo,t}|.$$

4.4 Descriptive Statistics

Table 1 presents descriptive statistics at the worker level for the final sample, covering the period from 2003 to 2021 and containing over 37 million observations. It reports averages and standard deviations separately for workers in occupations classified as: more replaceable by AI (C-AIOE value below the median) and less replaceable by AI (C-AIOE value above the median).

There are fewer workers in occupations categorized as less replaceable by AI, as these jobs tend to be more specialized and represent smaller segments of the labor market, including traditional manual and blue-collar jobs, such as craft and construction workers, farmers, fishermen and machine operators. In contrast, the roles more replaceable by AI comprise higher-skilled occupations, such as managers, professionals, and technicians, that employ more workers and are more widely represented. The share of male workers is substantially higher in occupations not replaceable by AI (71%) than in those classified as replaceable (45%), suggesting that

Table 1: Descriptive Statistics

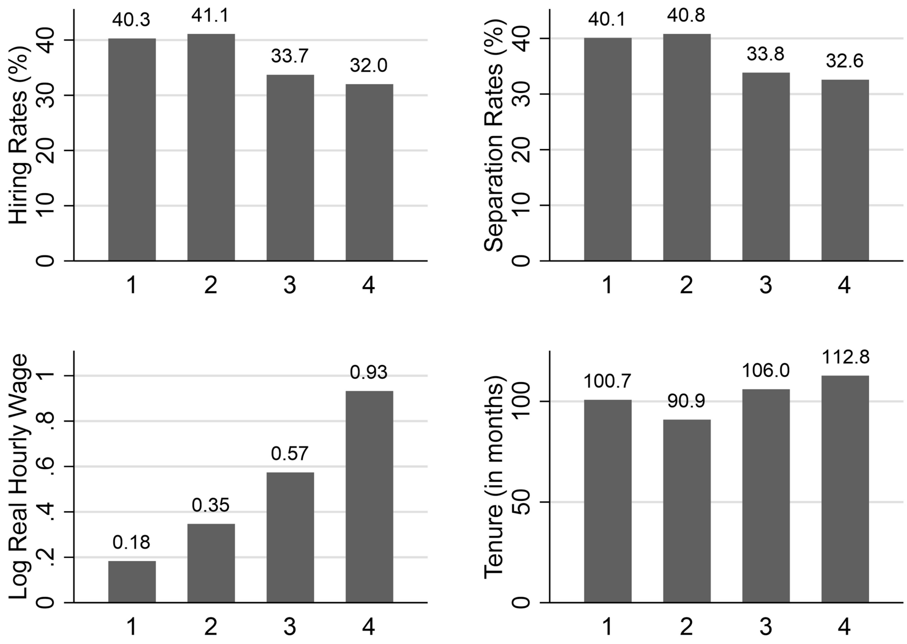
Variable	Not Replaceable by AI Mean	Not Replaceable by AI S.D.	Replaceable by AI Mean	Replaceable by AI S.D.
Male	0.71	0.46	0.45	0.50
Age	40.47	10.94	38.84	10.61
Years of schooling	8.80	3.94	10.31	3.95
Tenure (months)	98.10	103.03	100.59	105.59
Real Hourly wage (logs)	0.49	0.53	0.53	0.59
Hiring Rate (%)	31.08	33.53	29.95	31.62
Separation Rate (%)	29.85	29.79	28.88	28.23
AIOE	-0.52	0.69	0.14	0.92
Observations	14,894,942		22,544,532	

Notes: This table reports means and standard deviations of our main variables, for workers in occupations categorized as replaceable by AI (C-AIOE value below the median) and not replaceable by AI (C-AIOE value above the median) over the 2003-2021 period.

female-dominated occupations tend to be more vulnerable to AI substitution. This is supported by the literature. According to the UN-led report Gmyrek et al. (2025), women are significantly more likely to be replaced by AI than men. In high-income countries, 9.6% of female employment is in jobs at the highest risk of automation, compared to only 3.5% of male employment. Additionally, workers in occupations more replaceable by AI are also slightly younger and have higher educational attainment on average. Finally, occupations with higher AI replacement risk exhibit slightly lower hiring and separation rates, as well as higher real hourly wages. This pattern is unsurprising, as these roles are generally more highly skilled, predominantly white-collar, and tend to exhibit lower churning.

On the other hand, Figure 3 illustrates the levels of hiring rates, separation rates, logged real hourly wages, and job duration, for the four groups of AI exposure and complementarity. Workers in Group 1 (Low Exposure, Low Complementarity) present the lowest logged real hourly wage, while Group 4 (High Exposure, High Complementarity) earns the highest, suggesting that occupations that are more exposed to AI and more complementary to it typically pay higher wages. Additionally, workers in Group 1 and 2 (Low Exposure) have higher hiring and separation rates, as well as shorter tenure, compared to those in Group 3 and 4 (High Exposure). The AI exposure indicator (AIOE) is negatively weighted by the complementarity

θ, producing our measure of AI Replacement risk (C-AIOE), which is used in the subsequent analysis and results.



Legend (AI group categories):

- 1: Low Exposure, Low Complementarity
- 2: Low Exposure, High Complementarity
- 3: High Exposure, Low Complementarity
- 4: High Exposure, High Complementarity

Figure 3: Hiring Rates, Separation Rates, Log Real Hourly Wage and Tenure by AI Exposure and Complementarity Groups

Notes: This table contains average hiring rates, separation rates, log real hourly wages, and job tenure, for the four worker groups defined by their AI exposure and complementarity.

5 Empirical Strategy

Our empirical strategy aims to estimate the relationship over time between AI replacement risk and five outcome variables: hiring rate, separation rate, excess turnover rate, net employment and job duration. AI replacement risk is estimated by the C-AIOE index, which captures the likelihood that an occupation could be replaced by AI technologies.

The following regression model is estimated, at the firm-occupation level:

$$y_{fot} = \sum_{t=2004}^{2021} \beta_t \left(\text{CAIOE}_o \cdot \mathbf{1}_t\right) + \phi X_{fot} + \gamma_t + \mu_f + \varepsilon_{fot} \tag{1}$$

where f denotes the firm, t corresponds to the year and o the occupation. y_{fot} represents the outcome variable, γ_t denote year fixed effects and CAIOE_o represents the risk of AI replacement, at the occupation level, which ranges approximately from 3.2 to 5.9 in our data[4]. X_{fot} is a vector of controls, including gender, years of schooling, age, age squared, tenure, tenure squared, and logged firm size, all averaged at the firm-occupation level. ε_{fot} denotes the error term, capturing all omitted factors. Finally, in some specifications, firm fixed effects, μ_f, are included. Including these fixed effects controls for unobserved factors that are common to the same firm.

The five main outcome variables are hiring rate, separation rate, excess turnover rate, net employment and job duration, all measured at the firm-occupation level each year. Job duration is quantified as the average number of tenure months. Consequently, we omit tenure and tenure squared as controls in the regression for job duration, to avoid multicollinearity.

We interact the CAIOE_o with year dummies from 2004 until 2021, with 2003 acting as the omitted base year. This allows the relationship between AI replacement risk and the outcome variables to change over time, assessing whether more AI-replaceable occupations experienced differential values of the outcomes as AI developed. The coefficients of interest β_{2004}, β_{2005}, ..., β_{2021} capture the differential growth in y_{fot} for occupations with higher CAIOE_o, in each year, relative to the baseline year 2003.

Additionally, to summarize the overall treatment effect, we estimate the average post-treatment effects using a static specification:

$$y_{fot} = \beta \ \cdot \text{CAIOE}_o \times \text{Post}_t + \phi X_{fot} + \gamma_t + \mu_f + \varepsilon_{fot} \tag{2}$$

Where Post_t is an indicator equal to 1 for years from 2015 onward. This threshold is chosen

[4]From Pizzinelli et al. (2023), the C-AIOE index is scaled to range between 3.2 and 5.9, and we adopt their original scale.

following Acemoglu et al. (2022), who document a significant increase in AI adoption around 2014-2015.

6 Results

This section presents our main empirical findings on the effects of AI replacement risk (C-AIOE) on labor market outcomes. We organize the analysis into four parts, analyzing how AI replacement risk relates to excess worker turnover, hiring and separation rates, net employment and job duration over time.

6.1 AI Replacement Risk and Excess Worker Turnover

First, we estimate the effect of the AI replacement risk index (C-AIOE) on excess worker turnover rates over time. Excess worker turnover captures the inflow and outflow of employees beyond what would be necessary to achieve a net change in employment. Figure 3 presents the main results, estimated from Equation (1). We find that, in more AI-replaceable firm-occupation cells, as AI technologies developed, excess worker turnover increased differentially. The coefficients are statistically significant at the 1% level and robust to the introduction of controls for worker characteristics and firm size, as well as to the inclusion of firm fixed effects. When averaged over the entire post-treatment period, as specified in Equation (2), a one-point increase in the C-AIOE index is associated with a 0.96 percentage point increase in excess worker turnover (Table 2).

Figure 5 illustrates the same results. While AI-replaceable firm-occupation groups (C-AIOE above the median) initially had lower excess turnover, their turnover declined more slowly and eventually increased relative to less replaceable ones. By the late 2010s, the gap in excess turnover had significantly decreased. This indicates a differential increase in churning in more AI-substitutable firm-occupation groups over time.

These findings are consistent with the theoretical mechanisms discussed in Section 3. The increase in excess worker turnover in more AI-replaceable firm-occupation groups suggests that AI adoption may be reshaping the task composition of jobs, creating skill mismatches and requiring firms to adjust their workforce more frequently. In addition, technological uncertainty around AI adoption may lead firms to experiment with hiring and restructuring, before reaching a stable workforce composition.

However, we recognize that these differential patterns may not be due to the causal effect of AI adoption and may be the result of other factors. Nevertheless, this analysis is still very informative, providing a first step into uncovering how occupations and firms with different AI replacement risks have behaved over time.

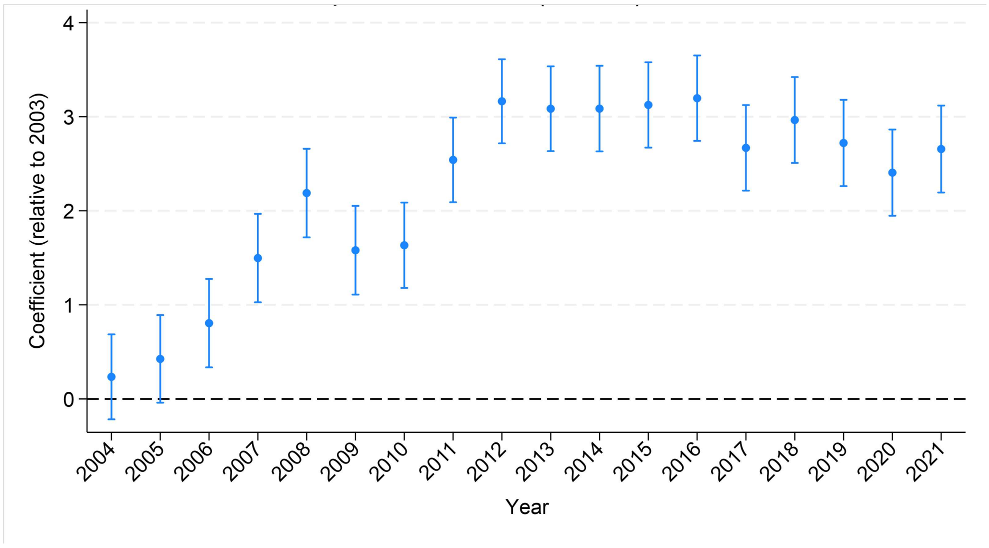


Figure 4: AI replacement risk (C-AIOE) and the Evolution of Excess Worker Turnover

Notes: This figure plots event study estimates of the effect of AI replacement risk (C-AIOE) exposure on excess worker turnover rates (%) at the firm-occupation level. Coefficients are estimated from Equation (1). Firm fixed effects are included. Standard errors are clustered at the firm level. The blue lines denote 95% confidence intervals.

6.2 *AI Replacement Risk and Hiring and Separation Rates*

Additionally, to decompose the mechanisms underlying the observed effect on excess turnover, we study how AI replacement risk (C-AIOE) relates to the evolution of hiring and separation rates over time. While excess turnover captures labor churning, decomposing it into hiring and separation allows us to see whether AI replacement risk affects inflows, outflows, or both. Figure 6 and Figure 7 present the main results, estimated using Equation (1). Overall, we observe that hiring and separation rates tended to increase more in job-occupation groups with higher AI substitutability. The results remain significant after introducing worker and firm

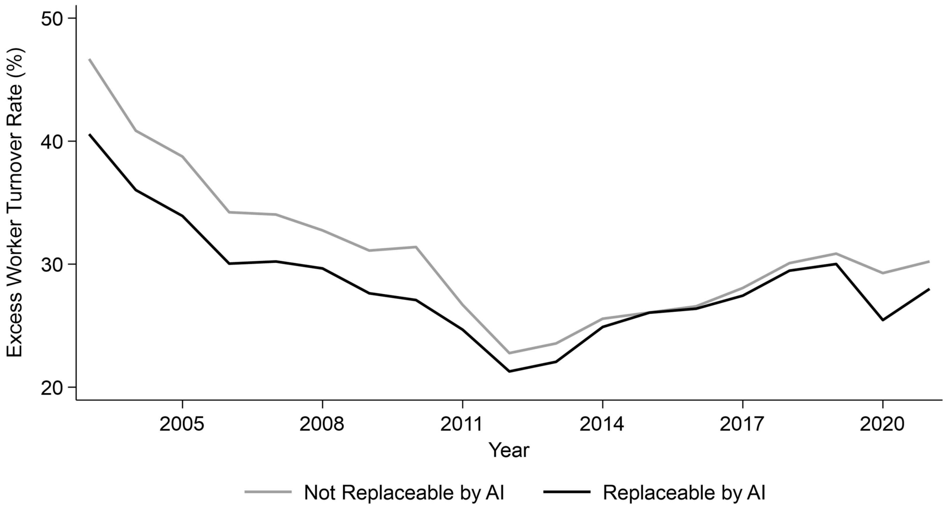


Figure 5: Evolution of Excess Worker Turnover by C-AIOE

Notes: This graph plots average excess worker turnover at the firm-occupation level for occupations facing an AI replacement Risk (C-AIOE) above and below the median, between 2003 and 2021.

Table 2: C-AIOE and Labor Market Outcomes

	Excess Turnover	Hiring Rate	Separation Rate	Duration	Net Employment
C-AIOE	-4.434^{***}	-2.828^{***}	-2.648^{***}	9.344^{***}	-0.179^{***}
	(0.0632)	(0.0378)	(0.0367)	(0.1461)	(0.0351)
Post	-1.996^{***}	-5.967^{***}	1.479^{***}	29.953^{***}	-7.445^{***}
	(0.3847)	(0.2442)	(0.2395)	(0.6470)	(0.2388)
C-AIOE × Post	0.964^{***}	0.907^{***}	0.471^{***}	-1.418^{***}	0.436^{***}
	(0.0802)	(0.0510)	(0.0501)	(0.1363)	(0.0501)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Constant	95.211^{***}	86.140^{***}	75.675^{***}	-71.436^{***}	10.465^{***}
	(0.613)	(0.331)	(0.343)	(1.122)	(0.312)
Observations: 10,507,557					

Standard errors in parentheses (clustered at the firm level).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: This table reports the difference-in-differences estimates of the effect of AI replacement risk (C-AIOE) on firm-occupation level labor outcomes, averaged over the post-treatment period (from 2015 onwards). All regressions include firm fixed effects and controls.

controls, as well as firm fixed effects. When averaged over the post-treatment period, a one-point increase in the C-AIOE index is associated with a 0.9 percentage point increase in hiring rates and a 0.47 percentage point increase in separation rates (Table 2).

Additionally, Figure 8 illustrates this relationship. It shows that firm-occupation groups with a greater AI replacement risk increased their hiring and separation rates differentially over time, closing their initial gap. However, the pattern over time is less pronounced than for excess worker turnover.

This suggests that AI does not manifest in large changes in hirings, separations or net employment for more AI-replaceable firm-occupation groups. Instead, it appears to increase labor market churn, with workers moving in and out of positions more frequently. The fact that both hiring and separation rates increase in more AI-replaceable firm–occupation groups may seem surprising, as it might be expected that groups facing higher substitution risk would reduce hiring. However, this pattern is consistent with the mechanisms described in Section 3. AI adoption may contribute to workforce adjustments in response to changing task requirements, skill mismatches, task reallocation within firms, and experimentation in hiring decisions under technological uncertainty.

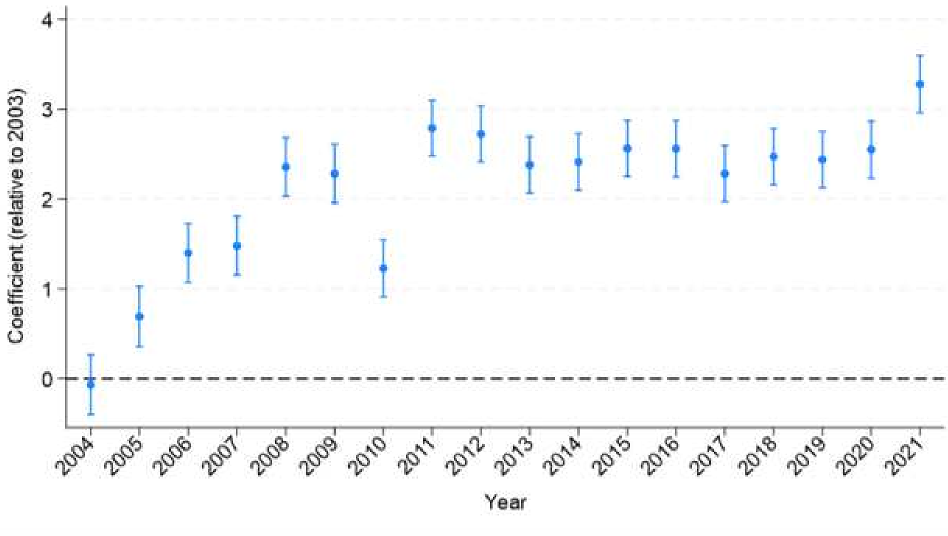


Figure 6: AI replacement risk (C-AIOE) and the Evolution of Hiring Rates

Notes: This figure plots event study estimates of the effect of AI replacement risk (C-AIOE) exposure on hiring rates at the firm-occupation level. Coefficients are estimated from Equation (1). Firm fixed effects are included. Standard errors are clustered at the firm level. The blue lines denote 95% confidence intervals.

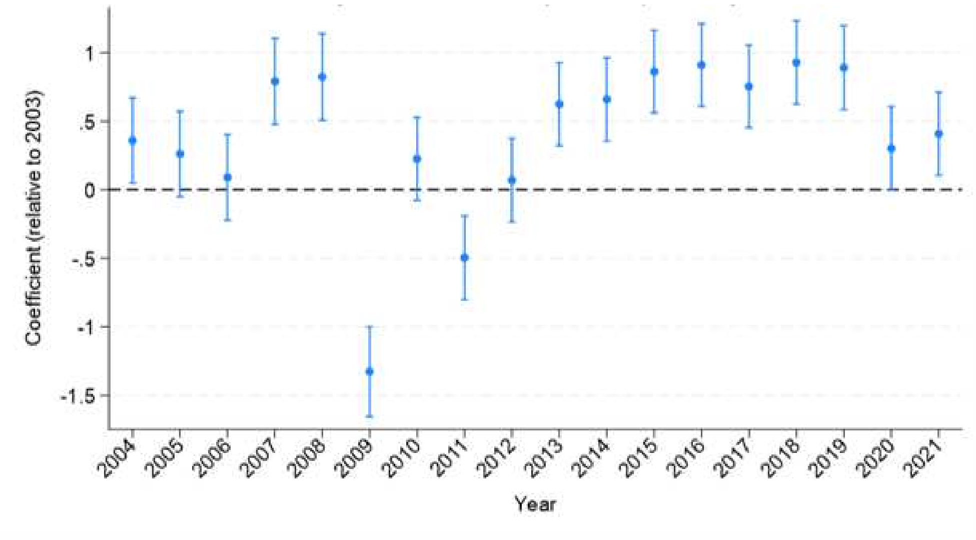


Figure 7: AI replacement risk (C-AIOE) and the Evolution of Separation Rates

Notes: This figure plots event study estimates of the effect of AI replacement risk (C-AIOE) exposure on separation rates at the firm-occupation level. Coefficients are estimated from Equation (1). Firm fixed effects are included. Standard errors are clustered at the firm level. The blue lines denote 95% confidence intervals.

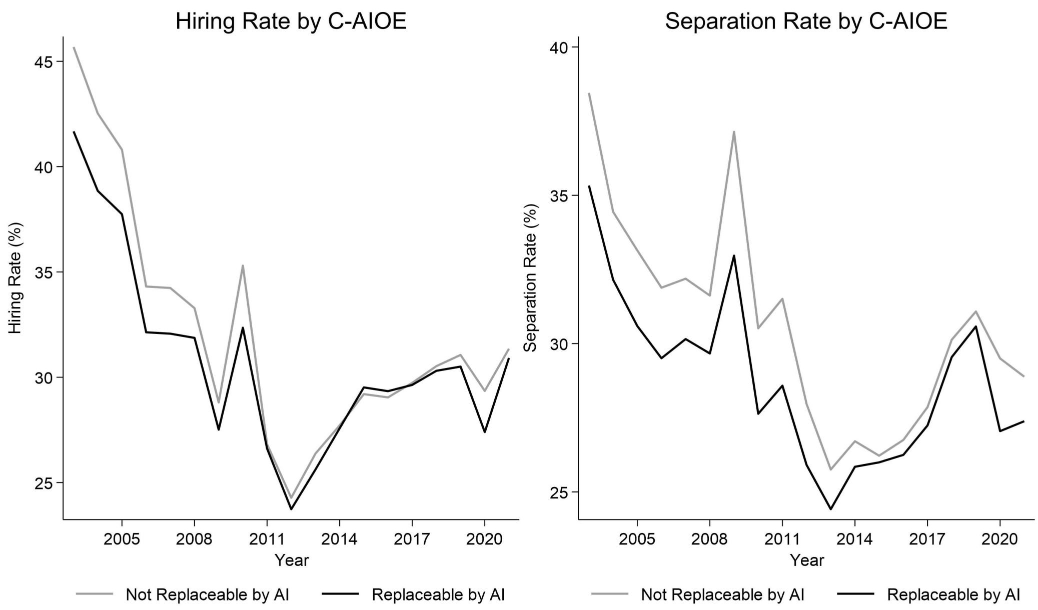


Figure 8: Hiring and Separation Rates by C-AIOE

Notes: This graph plots average hiring and separation rates for occupations facing an AI replacement Risk (C-AIOE) above and below the median, between 2003 and 2021.

6.3 AI Replacement Risk and Net Employment

Moreover, we estimate the effect of the AI replacement risk index (C-AIOE) on net employment rates over time. While measures such as excess turnover, hiring, and separation capture labor market flows, net employment reflects the rate of change in the number of jobs and indicates whether AI affects aggregate employment levels, rather than just labor mobility. Studying this outcome is crucial to understanding whether AI technologies displace workers or instead change the dynamics of job transitions. Figure 9 presents the main results, estimated using Equation (1). Unlike with excess worker turnover or hiring and separation rates, we find no clear differential trajectory in net employment rates between more and less AI-replaceable firm-occupation groups as AI technologies developed. From 2004 to 2009, the coefficients increased slightly, followed by a decline until 2013. Between 2013 and 2019, they remained stable, before rising again in 2020 and 2021. When averaged over the entire post-treatment period, following Equation (2), a one-point increase in the C-AIOE index is associated with a 0.436 percentage point increase in excess worker turnover (Table 2). However, this average effect hides the short-term fluctuations over the years, which rise and fall without showing a sustained differential pattern for more or less AI-replaceable occupations.

Figure 10 illustrates similar results. Initially, more AI-replaceable firm-occupation cells (C-AIOE above the median) exhibit similar net employment levels as less replaceable ones. Over time, temporary increases and decreases in net employment are visible, but no clear or lasting divergence appears. These fluctuations suggest that lasting net employment changes have been less sensitive to AI replacement risk than other labor market outcomes.

Taken together with our findings on hiring, separation, and job duration, these results suggest that AI adoption primarily affects the flow of workers in and out of jobs rather than the overall level of employment. AI-replaceable occupations seem to experience greater labor market turnover rather than substantial net job losses over time. The absence of a clear differential effect on net employment suggests that the displacement effects of AI have not dominated in our period of analysis. Instead of contributing to sustained job losses in more AI-exposed occupations, AI appears primarily to affect the dynamics of worker flows. This pattern is more consistent with labor reallocation, task recomposition and organizational restructuring, than with a simple substitution of labor by technology, at least in the short and medium term.

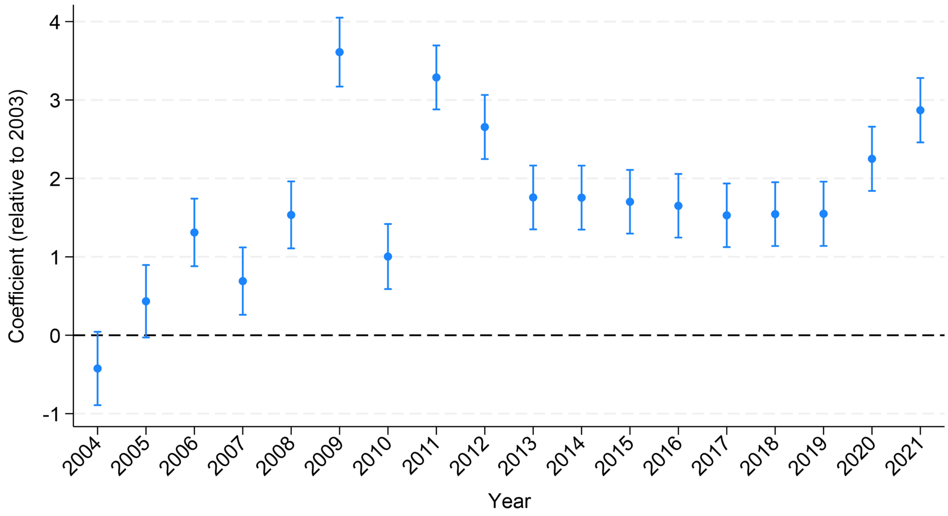


Figure 9: AI replacement risk (C-AIOE) and the Evolution of Net Employment Rates

Notes: This figure plots event study estimates of the effect of AI replacement risk (C-AIOE) exposure on net employment rates at the firm-occupation level. Coefficients are estimated from Equation (1). Firm fixed effects are included. Standard errors are clustered at the firm level. The blue lines denote 95% confidence intervals.

6.4 AI Replacement Risk and Job Duration

Finally, we analyze the effect of the AI replacement risk index (C-AIOE) on the evolution of job duration, to evaluate whether the observed increase in worker turnover reflects shorter employment spells. Job duration is a key indicator of employment stability: shorter spells may indicate weaker labor relationships or higher labor market turnover in response to AI adoption. Figure 11 plots average job duration, measured as the number of tenure months, by the indicator for AI replacement, C-AIOE. At the beginning of the sample, workers in more AI-replaceable job-occupation groups (C-AIOE above the median) exhibited slightly higher tenure than those in less replaceable occupations. However, starting in the late 2000s, tenure in less AI-replaceable occupations increased more rapidly, creating an increasing gap that remained through the 2010s. These findings suggest that higher AI replacement risk is associated with a relative decrease in job duration over time, consistent with a weakening of employment relationships in more AI-substitutable occupations.

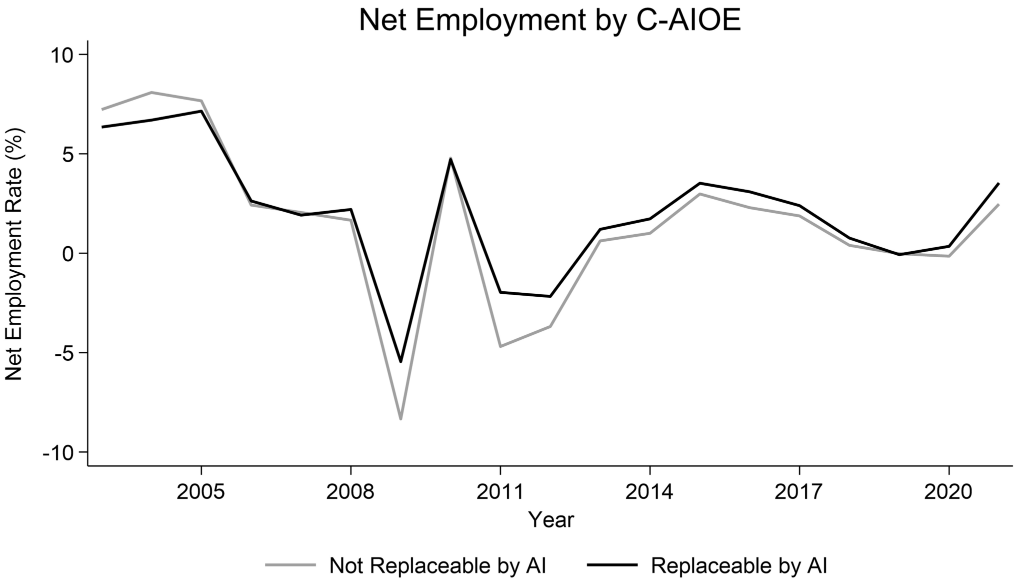


Figure 10: Net Employment by C-AIOE

Notes: This graph plots average net employment rates for firm-occupation groups facing an AI replacement Risk (C-AIOE) above and below the median, between 2003 and 2021.

However, when estimating Equation (1) and introducing firm fixed effects, as well as worker and firm controls, the pattern becomes less clear (Figure 12). While the results initially indicate a decline in tenure in more AI-substitutable occupations, the pattern slightly reverses from 2013 onward. Nevertheless, over the post-treatment period, a one-point increase in the C-AIOE index is associated, on average, with a 1.4 month decrease in job duration (Table 2). Taken together, these results indicate that while AI substitutability is linked to shorter employment spells on average, the effect is sensitive to specification and less robust than the findings for excess worker turnover.

The decrease in job duration in more AI-replaceable occupations provides some additional evidence that AI may weaken the stability of employment relationships. This pattern is consistent with the theoretical mechanisms discussed in Section 3. With the adoption of AI, some skills may become obsolete and existing matches between workers and firms may become less suitable, leading to more frequent job changes and shorter employment spells.

Overall, the results provide evidence that AI replacement risk is associated with higher labor market turbulence, rather than clear net employment decreases. The combination of higher

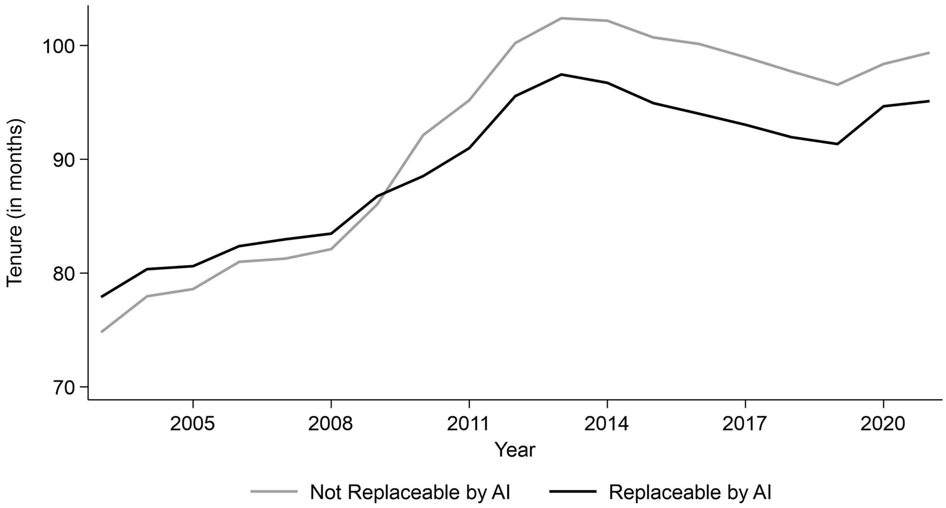


Figure 11: Evolution of Job Duration by C-AIOE

Notes: This graph plots average job duration for occupations facing an AI replacement Risk (C-AIOE) above and below the median, between 2003 and 2021.

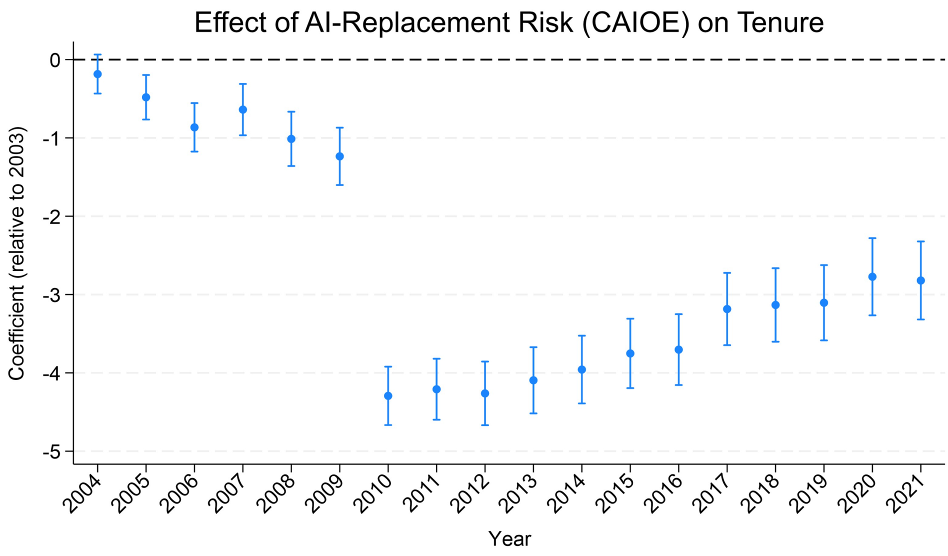


Figure 12: AI replacement risk (C-AIOE) and the Evolution of Job Duration

Notes: This figure plots event study estimates of the effect of AI replacement risk (C-AIOE) exposure on job duration at the firm-occupation level. Coefficients are estimated from Equation (1). Firm fixed effects are included. Standard errors are clustered at the firm level. The blue lines denote 95% confidence intervals.

excess worker turnover, increases in both hiring and separation rates, and somewhat shorter job durations suggests that AI initially operates through mechanisms of task reallocation, technological uncertainty, and organizational restructuring. These findings support the view that the earliest effects of AI are to accelerate worker reallocation and churning rather than destroying jobs on a large scale.

However, while the patterns found are consistent with the theoretical mechanisms through which AI may affect labor market dynamics, they should not necessarily be interpreted as fully causal effects of AI adoption. The evolution of labor flows may also reflect economic changes, technological trends, or other factors that are correlated with AI replacement risk. In this sense, part of the observed variation may capture broader structural changes in the Portuguese labor market rather than the isolated impact of AI. Nevertheless, the results remain informative. By introducing excess worker turnover as an outcome variable and using a new AI replacement risk index, this paper provides one of the first empirical studies of how AI substitutability relates to labor market flows in Portugal. Consequently, the findings offer a first descriptive benchmark on the relationship between AI replacement risk and labor market dynamics, and help identify patterns that future research can investigate using stronger identification strategies.

7 Robustness Checks

In this section, we conduct several tests to assess the robustness and sensitivity of our results to alternative specifications and restrictions.

7.1 Relevance and Validity of the C-AIOE Index

We begin by assessing the relevance and validity of our measure of AI replacement risk (C-AIOE), in two separate ways. Firstly, we test whether the C-AIOE is significantly correlated with AI adoption, to ensure that it captures meaningful variation in firms' actual AI implementation. This test provides an external validation of our indicator: if occupations and firms with higher AI replacement risk were not associated with higher observed AI adoption, the interpretation of the C-AIOE index would be weakened. To perform this robustness check, we use the official Portuguese Survey on the Use of Information and Communication Technologies

(IUTIC), conducted by the National Statistics Institute. The survey contains an indicator that measures firm-level adoption of seven different AI technologies. This indicator is available for 2023 and for 1,078 firms. Table 4 contains the results of regressing the AI adoption indicator on our measure of AI replacement risk, C-AIOE, at the firm-occupation level. Across specifications, the coefficient for C-AIOE is positive and highly statistically significant, meaning that firms employing workers in more AI-replaceable occupations are more likely to adopt AI technologies. These results provide external validation for our measure, confirming that the C-AIOE index captures meaningful variation in AI adoption.

Secondly, we explore whether our results depend on the particular index used to measure AI exposure by considering two alternative indicators from the literature. The first is from Eloundou et al. (2024), who construct an occupation-level measure of exposure to large language models (LLMs) based on the extent to which these technologies can accelerate task completion within each occupation. The second measure is from Webb (2020), who identifies AI exposure by matching AI patent claims to task descriptions in O*NET. To adapt these measures to our framework, we construct the original indexes C-Eloundou and C-Webb, which capture AI replacement risk by negatively weighting baseline exposure by the complementarity θ developed by Pizzinelli et al. (2023). The Eloundou index is strongly correlated with AIOE, and C-Eloundou shows a significant correlation with C-AIOE, supporting the validity of our measure. In contrast, the Webb index and C-Webb are uncorrelated with AIOE and C-AIOE. However, this divergence is not very unexpected, as Webb captures a different dimension of AI exposure. As noted by Acemoglu et al. (2022), AIOE is particularly high for managers, professionals, and administrative occupations and low for manual jobs, whereas the Webb index is less concentrated in sales occupations and is strongly positively correlated with occupational wage percentiles.

7.2 Sensitivity to Post-Treatment Period

Moreover, we test whether our findings for the static specifications depend on the choice of the post-treatment period. In our main analysis, 2015 is used as the threshold separating the pre-treatment and post-treatment periods, since this year saw a substantial increase in AI-related

Table 3: Correlation Between Baseline AI Exposure Measures

	AIOE	Eloundou GPT Index	Webb AI Patent Index
AIOE	1.0000		
Eloundou GPT Index	0.9084***	1.0000	
Webb AI Patent Index	-0.0242	0.0098	1.0000

Notes: This table presents the correlation between the AI Occupational Exposure Index (Felten et al., 2021), the Eloundou GPT Index (Eloundou et al., 2024) and the Webb AI Patent Index (Webb, 2020). Significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Correlation Between Complementarity-Adjusted AI Measures

	C-AIOE	C-Eloundou	C-Webb
C-AIOE	1.0000		
C-Eloundou	0.4404***	1.0000	
C-Webb	-0.0383	-0.0549	1.0000

Notes: This table presents the correlation between the Complementarity-Adjusted AI Occupational Exposure Index (C-AIOE), the Complementarity-Adjusted Eloundou GPT Index (C-Eloundou) and the Complementarity-Adjusted Webb AI Patent Index. The C-AIOE corresponds to the measure developed by Pizzinelli et al. (2023). The C-Eloundou and the C-Webb were created originally in this paper, to follow the same framework of the C-AIOE. They are constructed by negatively weighting the Eloundou GPT Index (Eloundou et al., 2024) and the Webb AI Patent Index (Webb, 2020) by the complementarity θ developed by Pizzinelli et al. (2023). Significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

vacancies (Acemoglu et al., 2022). However, AI adoption progressed gradually over time, and 2015 was not the only year of change. Consequently, to ensure that our results are not dependent on the exact cutoff chosen, we replicate the analysis using 2013, 2014, 2016, and 2017 as alternative thresholds. By examining multiple plausible cutoffs, we account for the possibility that short-term fluctuations, the timing of AI adoption, or other labor market shocks could affect the findings. Across all alternative specifications, the results remain significant and present similar magnitudes. This consistency suggests that the observed relationships are not dependent on the specific year chosen, but instead reflect a relevant pattern in the data.

7.3 Entry-Cohort Specification for Job Duration

Lastly, estimating Equation (1) for job duration may raise econometric concerns due to the structure of the Quadros de Pessoal dataset. This dataset can be analyzed as a stock with follow-up (Lancaster, 1990), since it is collected annually in October and records only employer-employee relationships active at that time. This design creates two statistical issues: length bias and right censoring. Length bias exists because longer employment spells are more likely to appear in the stock, leading to an over-representation of long-tenure jobs. In addition, many spells are right-censored, as they do not end within the observation period. To address these issues, we construct a robustness specification that approximates a flow by focusing on an entry cohort of workers. Specifically, we identify individuals who first appear in QP in 2003, are younger than 30 at entry, and have no prior record in the dataset. We then follow their employment trajectories until 2021. This mitigates length bias by observing workers from the beginning of their careers and excluding long-term jobs that began before the observation window. Additionally, it reduces right censoring relative to cohorts starting later, although spells that continue beyond 2021 remain censored. The results for this entry-cohort specification are different from the initial ones. Within this cohort, the negative association between AI replacement risk and tenure growth disappears. Instead, higher AI exposure is associated with relatively longer job durations over time. This contrast suggests that our findings are likely driven by compositional changes in the stock of employment relationships rather than by decreasing tenures within more AI-replaceable occupations.

8 Mechanisms and Heterogeneity

In this section, we examine the potential heterogeneous effects of AI on excess worker turnover along two key dimensions: firm size and education.

Prior evidence suggests that AI adoption is significantly more common among larger firms. For instance, OECD cross-country surveys show that larger firms are more likely to adopt multiple AI technologies. In the UK in 2020, 15% of small firms, 34% of medium-sized firms, and 68% of large firms had adopted AI (OECD/BCG/INSEAD, 2025). Furthermore, using the 2023 IUTIC data, we confirm that AI adoption is strongly correlated with firm size. Consequently, we split the sample by firm size and replicate our main results, standardizing excess worker turnover within each group to ensure comparability across them, as firm size directly influences the magnitude of excess worker turnover. The results indicate that, in large firms, the differential increase in excess worker turnover for more AI-replaceable occupations is substantially higher (Figure 13 and Table 5). This supports the interpretation that the effect of C-AIOE on excess turnover reflects AI adoption, as the impact is strongest where the implementation of AI is most prevalent. It reinforces our main findings and highlights firm size as an important mechanism through which AI influences labor dynamics.

We also examine how the effect of AI-replaceable occupations on labor turnover dynamics varies by worker education. Figure 14 plots coefficients for high and low education groups, following Equation (1) for excess worker turnover. Firm-occupation groups with higher average education experience a faster initial increase in the excess worker turnover, with coefficients rising steadily from 2004 to 2014. However, after 2014, the coefficients, while still elevated, stagnate and slightly decrease through 2021. In contrast, for low-education firm-occupation groups, the increase in excess worker turnover appears to grow more gradually over the entire period. Additionally, over the post-treatment period, the increase in excess worker turnover associated with each one-point increase in the C-AIOE index is higher for low-education firm-occupation groups (Table 6). This pattern suggests both educational groups exhibit a differential increase in excess worker turnover for more AI-replaceable firm-occupation groups, but with some heterogeneity. Lower-educated workers seem to experience slightly higher and steadier labor market

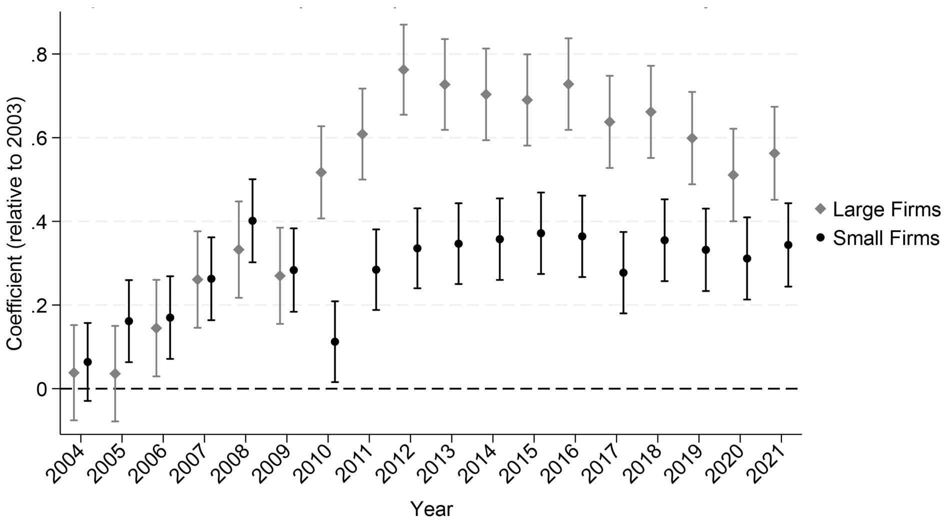


Figure 13: AI replacement risk (C-AIOE) and the Evolution of Excess Worker Turnover by Firm Size

Notes: This figure plots event study estimates of the effect of AI replacement risk (C-AIOE) exposure on excess worker turnover at the firm-occupation level, by firm size. Coefficients are estimated from Equation (1). Firm fixed effects are included. Standard errors are clustered at the firm level. The gray and black lines denote 95% confidence intervals.

Table 5: C-AIOE and Excess Worker Turnover by Firm Size

	SMALL FIRMS	LARGE FIRMS
C-AIOE	-0.570***	-0.848***
	(0.015)	(0.014)
Post	-0.021	-0.454***
	(0.084)	(0.089)
C-AIOE × Post	0.083***	0.226***
	(0.018)	(0.018)
Observations	5,428,773	5,071,644
Firm Fixed Effects	Yes	Yes
Controls	Yes	Yes
Clustered SE (Firm)	Yes	Yes

Notes: This table reports the difference-in-differences estimates of the effect of AI replacement risk (C-AIOE) on firm-occupation level excess worker turnover, averaged over the post-treatment period (from 2015 onwards), by firm size. All specifications include worker-level and firm-level controls, as well as firm fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

adjustments in response to AI replacement risk. This could be due to lower-education workers tending to have less firm-specific human capital and weaker bargaining power, making separations and replacements more likely when firms reorganize their task structure.

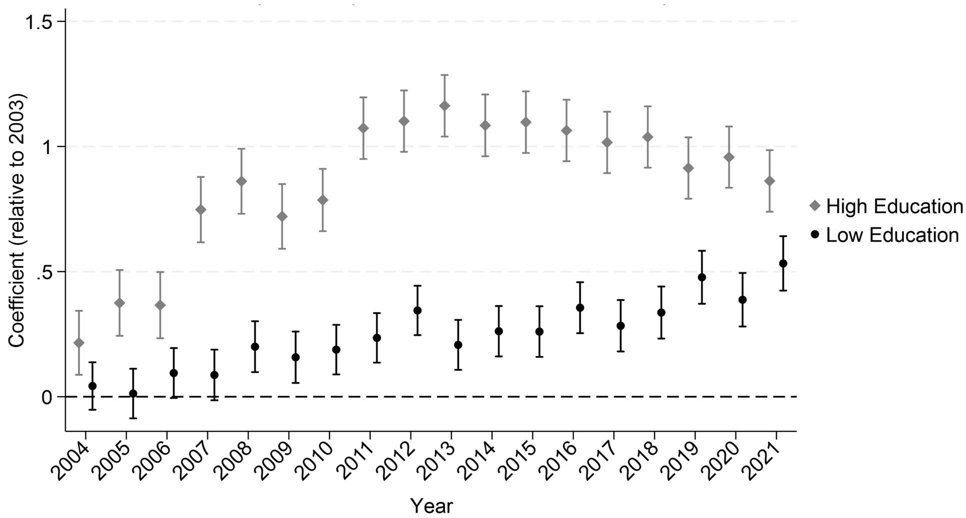


Figure 14: AI replacement risk (C-AIOE) and the Evolution of Excess Worker Turnover by Average Education Levels

Notes: This figure plots event study estimates of the effect of AI replacement risk (C-AIOE) exposure on excess worker turnover at the firm-occupation level, by average firm-occupation education level. Coefficients are estimated from Equation (1). Firm fixed effects are included. Standard errors are clustered at the firm level. The gray and black lines denote 95% confidence intervals.

Table 6: C-AIOE and Excess Worker Turnover by Educational Level

	LOW EDUCATION	HIGH EDUCATION
C-AIOE	-0.678***	-0.769***
	(0.015)	(0.015)
Post	-0.421***	-0.358***
	(0.093)	(0.091)
C-AIOE × Post	0.192***	0.172***
	(0.020)	(0.018)
Observations	5,620,682	4,812,069
Firm Fixed Effects	Yes	Yes
Controls	Yes	Yes
Clustered SE (Firm)	Yes	Yes

Notes: This table reports the difference-in-differences estimates of the effect of AI replacement risk (C-AIOE) on firm-occupation level excess worker turnover, averaged over the post-treatment period (from 2015 onwards), by average education levels. All specifications include worker-level and firm-level controls, as well as firm fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

9 Conclusion

This thesis analyzes the impact of AI replacement risk on labor market dynamics in Portugal, focusing on hiring, separations, excess worker turnover, net employment and job duration. Using the complementarity-adjusted AI Exposure Index (C-AIOE) by Pizzinelli et al. (2023) and matched employer–employee data from Quadros de Pessoal, we examined how firms and occupations with different vulnerabilities to AI substitution adjust over time.

Our findings indicate that more AI-replaceable firm-occupation groups experienced faster growth in both hiring and separation rates, manifesting in significantly higher excess worker turnover. These patterns suggest that the initial effects of AI are not large-scale employment reductions, but greater instability and more frequent job transitions. We also found some evidence that more AI-replaceable firms and occupations experienced differential decreases in employment durations, although the pattern was less pronounced.

The results also highlight the importance of distinguishing between AI substitution and complementarity. Occupations with high complementarity can benefit from AI adoption without displacement, while more substitutable roles may face greater instability. This has clear policy implications: supporting reskilling, upskilling, and complementary AI adoption can help reduce excessive turnover and instability in vulnerable occupations.

Overall, this thesis contributes to the literature by providing empirical evidence on the early effects of AI replacement risk in the labor market. While AI adoption is still emerging in Portugal, since the 2010s, its first labor-market impacts appear to be increased turnover and turbulence, rather than immediate mass net employment reductions. However, these patterns should not be interpreted as fully causal, as other socioeconomic and technological factors may be influencing the results. Nevertheless, this analysis offers an important first step, establishing a descriptive benchmark for future research to analyze the relationship between AI replacement risk and worker turnover, which remains largely unexplored. It could be very relevant to further test the theoretical mechanisms behind this relationship, including task reallocation, search under technological uncertainty, as well as creative destruction and restructuring.

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Appendix

Table 7: C-AIOE and Labor Market Outcomes - Without Controls or Fixed Effects

	Excess Turnover	Hiring Rate	Separation Rate	Duration	Net Employment
C-AIOE	-7.178^{***}	-4.026^{***}	-4.468^{***}	4.874^{***}	0.442^{***}
	(0.0448)	(0.0309)	(0.0296)	(0.0638)	(0.0372)
Post	-10.456^{***}	-7.192^{***}	-8.215^{***}	12.626^{***}	1.023^{***}
	(0.3341)	(0.2300)	(0.2204)	(0.4756)	(0.2770)
C-AIOE × Post	1.784^{***}	1.041^{***}	1.302^{***}	-0.924^{***}	-0.260^{***}
	(0.0716)	(0.0493)	(0.0472)	(0.1019)	(0.0593)
Firm Fixed Effects	No	No	No	No	No
Controls	No	No	No	No	No
Constant	63.585^{***}	50.897^{***}	51.047^{***}	64.588^{***}	-0.150
	(0.2080)	(0.1432)	(0.1372)	(0.2961)	(0.1724)
Observations: 10,614,659					

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the difference-in-differences estimates of the effect of AI replacement risk (C-AIOE) on firm-occupation level labor outcomes. All columns report OLS estimates without fixed effects or controls.

Table 8: Robustness Check: Effect of C-AIOE on Excess Turnover with Alternative Post-Treatment Years

	Post 2015	Post 2013	Post 2014	Post 2016	Post 2017
C-AIOE	**-4.434*****	-4.750***	-4.578***	-4.311***	-4.203***
	(0.063)	(0.069)	(0.066)	(0.061)	(0.059)
Post	**-1.996*****	-4.191***	-2.801***	-1.222**	-0.268
	(0.385)	(0.386)	(0.384)	(0.390)	(0.400)
C-AIOE × Post	**0.964*****	1.351***	1.150***	0.780***	0.572***
	(0.080)	(0.080)	(0.080)	(0.081)	(0.084)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	10,507,557	10,507,557	10,507,557	10,507,557	10,507,557

Standard errors in parentheses, clustered at the firm level.
Significance: *** p<0.01, ** p<0.05, * p<0.1.
Notes: This table reports robustness checks of the main difference-in-differences estimates of C-AIOE on excess turnover using alternative definitions of the post-treatment period (2013–2017). All regressions include age, age squared, gender, tenure, tenure squared, education, log firm size, and firm fixed effects.

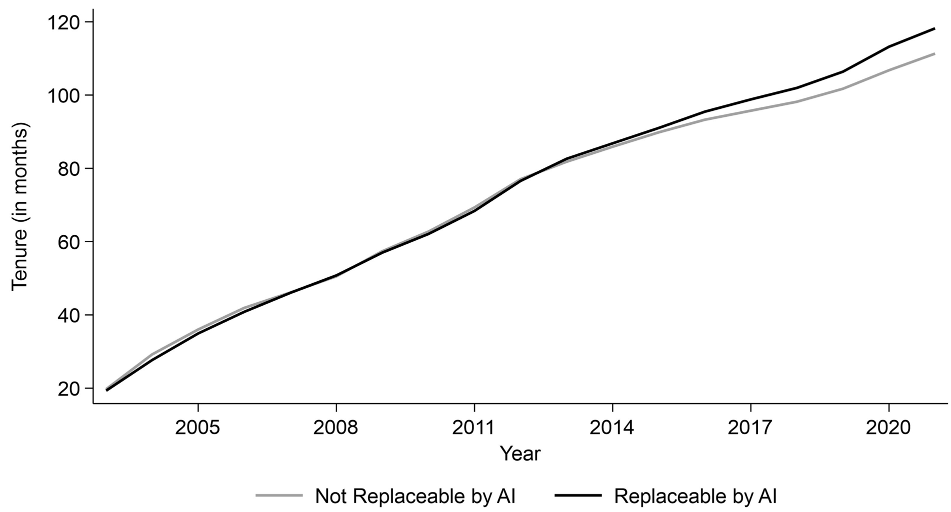

Figure 15: Robustness Check: Evolution of Job Duration by C-AIOE, for the Entry-cohort specification

Notes: This graph plots average job duration for occupations facing an AI replacement Risk (C-AIOE) above and below the median, between 2003 and 2021, for the robustness check described in section 7.3, the entry-cohort specification.

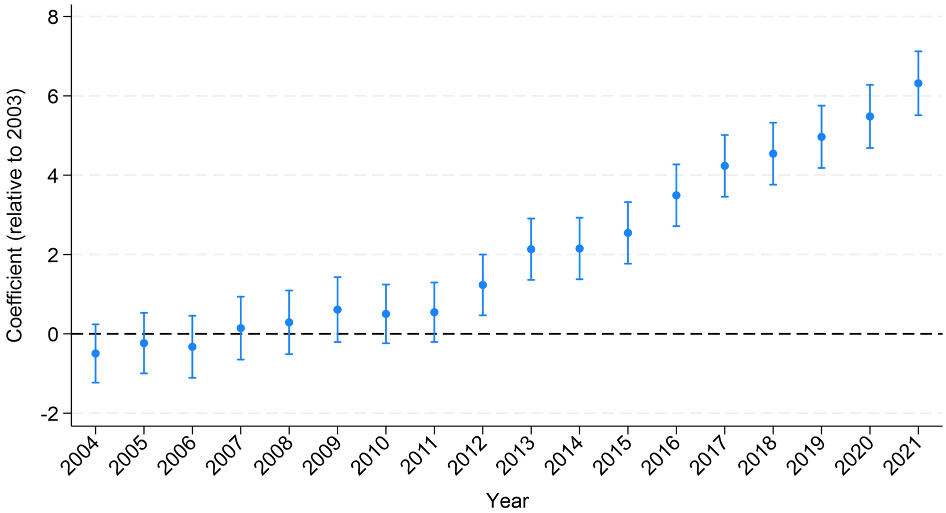

Figure 16: Robustness Check: AI replacement risk (C-AIOE) and the Evolution of Job Duration, for the Entry-cohort specification

Notes: This figure plots event study estimates of the effect of AI replacement risk (C-AIOE) exposure on job duration at the firm-occupation level, for the robustness check described in section 7.3, the entry-cohort specification. Coefficients are estimated from Equation (1). Firm fixed effects are included. Standard errors are clustered at the firm level. The blue lines denote 95% confidence intervals.

Table 9: C-AIOE and Accession Rates by Firm Size

	SMALL FIRMS	LARGE FIRMS
C-AIOE	-0.657***	-0.673***
	(0.013)	(0.012)
Post	-1.126***	-1.421***
	(0.079)	(0.081)
C-AIOE × Post	0.156***	0.255***
	(0.017)	(0.017)
Observations	5,428,773	5,071,644
Firm Fixed Effects	Yes	Yes
Controls	Yes	Yes
Clustered SE (Firm)	Yes	Yes

Notes: This table reports the difference-in-differences estimates of the effect of AI replacement risk (C-AIOE) on firm-occupation level accession rates, averaged over the post-treatment period (from 2015 onwards), by firm size. All specifications include worker-level and firm-level controls, as well as firm fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10: C-AIOE and Separation Rates by Firm Size

	SMALL FIRMS	LARGE FIRMS
C-AIOE	-0.422***	-0.812***
	(0.013)	(0.012)
Post	0.679***	0.077
	(0.081)	(0.084)
C-AIOE × Post	0.028	0.205***
	(0.017)	(0.017)
Observations	5,428,773	5,071,644
Firm Fixed Effects	Yes	Yes
Controls	Yes	Yes
Clustered SE (Firm)	Yes	Yes

Notes: This table reports the difference-in-differences estimates of the effect of AI replacement risk (C-AIOE) on firm-occupation level separation rates, averaged over the post-treatment period (from 2015 onwards), by firm size. All specifications include worker-level and firm-level controls, as well as firm fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11: C-AIOE and Accession Rates by Educational Level

	LOW EDUCATION	HIGH EDUCATION
C-AIOE	-2.653***	-2.955***
	(0.058)	(0.057)
Post	-3.854***	-8.101***
	(0.388)	(0.364)
C-AIOE × Post	0.461***	1.337***
	(0.085)	(0.073)
Observations	5,620,682	4,812,069
Firm Fixed Effects	Yes	Yes
Controls	Yes	Yes
Clustered SE (Firm)	Yes	Yes

Notes: This table reports the difference-in-differences estimates of the effect of AI replacement risk (C-AIOE) on firm-occupation level accession rates, averaged over the post-treatment period (from 2015 onwards), by education levels. All specifications include worker-level and firm-level controls, as well as firm fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12: C-AIOE and Separation Rates by Educational Level

	LOW EDUCATION	HIGH EDUCATION
C-AIOE	-2.572***	-2.605***
	(0.056)	(0.055)
Post	-2.530***	3.211***
	(0.383)	(0.348)
C-AIOE × Post	1.383***	0.229***
	(0.084)	(0.070)
Observations	5,620,682	4,812,069
Firm Fixed Effects	Yes	Yes
Controls	Yes	Yes
Clustered SE (Firm)	Yes	Yes

Notes: This table reports the difference-in-differences estimates of the effect of AI replacement risk (C-AIOE) on firm-occupation level separation rates, averaged over the post-treatment period (from 2015 onwards), by education levels. All specifications include worker-level and firm-level controls, as well as firm fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.