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Are older workers more likely to exit employment following unexpected heat waves?

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ABSTRACT

Are older workers more likely to exit employment following unexpected heat waves?

An expanding body of research documents the adverse impact of heat stress on aggregate employment outcomes, particularly in climate-exposed sectors and occupations. Yet, the role of individual-level heterogeneity – especially for what concerns ageing – remains relatively underexplored. By using Italian individual-level labor market survey data over 2004-2017, this study employs a pseudo panel research design to assess the impact of heath waves on the probability of transitioning in and out of employment for different cohort groups. While preliminary individual-level evidence indicates that heat waves significantly increase the probability of employment exit and decrease the probability of employment entry; controlling for unobservable cohort-province characteristics yields that only older cohorts show a higher probability of employment exit – while only younger ones show a lower probability of entry. These findings provide robust evidence of the vulnerability of older workers to climate-related labor market disruptions and underscore the importance of integrating age-sensitive dimensions into labor and climate policy frameworks.

KEYWORDS: climate change, older workers, professional transition
JEL CODES: C51, C55, J00, Q51, Q54

La letteratura economica si è concentrata in maniera vieppiù crescente sugli esiti delle alte temperature sull’occupazione a livello aggregato, in particolare nei settori e nelle professioni più esposte al caldo o al freddo. Tuttavia, il ruolo dell'eterogeneità a livello individuale – e l’effetto su una forza lavoro ad alta età mediana – rimangono relativamente poco analizzati. Utilizzando dati italiani a livello individuale provenienti da indagini sul mercato del lavoro nel periodo 2004-2017, questo studio adotta uno pseudo-panel per valutare l'impatto delle ondate di caldo sulla probabilità di transizione dentro e fuori l'occupazione per diversi gruppi di coorti. Mentre le evidenze preliminari a livello individuale indicano che tali ondate aumentano significativamente la probabilità di uscire dalla condizione di occupato e diminuiscono la probabilità di trovare un lavoro, quando si controllano le caratteristiche non osservabili a livello di coorte di lavoratori e provincia italiana si nota che solo le coorti più anziane mostrano una maggiore probabilità di uscita dall'occupazione: al contrario, solo quelle più giovani mostrano una minore probabilità di trovare lavoro. Questi risultati forniscono prove piuttosto robuste sulla maggiore vulnerabilità dei lavoratori più anziani alle perturbazioni del mercato del lavoro legate alle temperature esterne e sottolineano l'importanza di inserire dimensioni attente alle diverse età dei lavoratori all’interno di misure di politica economica, climatica e del lavoro.

PAROLE CHIAVE: cambiamento climatico, lavoratori anziani, transizione professionale

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1. Introduction

The economic impacts of climate change have emerged as a critical research area across multiple fields, including labor economics, environmental economics, and public health. A particularly important and growing strand of this literature examines the effects of heat stress on labor market outcomes, with evidence consistently pointing to negative consequences for labor productivity, workplace safety, and employment continuity, especially in sectors heavily exposed to outdoor work or heat-generating environments (Zivin and Neidell 2014; Orlov *et al.* 2019, 2021; Borg *et al.* 2021; De Sario *et al.* 2023; Colmer 2021; Somanathan *et al.* 2021; Dasgupta *et al.* 2024). However, while sectoral disparities in heat-related labor outcomes have been well-documented, the role of individual-level heterogeneity and in particular the age dimension, remains underexplored and insufficiently understood.

The vulnerability of older individuals to heat is well-established in the biomedical and epidemiological literature. Older adults are more likely to suffer from chronic cardiovascular and respiratory diseases, reduced sweat gland activity, impaired thermoregulation, and slower physiological adaptation to thermal stress (Basu 2009; Kenny *et al.* 2016; Lundgren *et al.* 2013). These constraints suggest that older workers may be at elevated risk of adverse labor market responses to heat, including job loss or withdrawal from the labor force. However, the economic literature on labor and climate exposure has not yet systematically tested these hypotheses using robust empirical designs at the micro level. Providing evidence on this topic in European countries would gain particular prominence, since mature economies are increasingly characterized by both ongoing population ageing and policy-driven working life extension – as witnessed by the growth of an extensive literature on companies' age management of employees in the field of gerontology in the last decades (Walker 2005; Eurofound 2006; Nurani and Lee 2025).

The literature offers several other examples of older workers' vulnerability to adverse shocks, underscoring the importance of studying age-specific responses to new forms of labor market stress such as heatwaves. For instance, older individuals may be disproportionately affected by exogenous climate shocks such as heatwaves, due to increased physiological vulnerability and reduced adaptability in work conditions (Deryugina and Hsiang 2014). Moreover, evidence suggests that environmental stressors like extreme heat can exacerbate existing social disparities, with older populations being less able to adjust or recover from such shocks, even including school outcomes (Park *et al.* 2020). Age-related frictions – such as skill obsolescence, health-related constraints, and age discrimination – have been shown to compound the effects of such shocks. These findings suggest that older individuals are systematically more exposed to a wide array of labor market risks, and that climate-related risks – including heatwaves – may represent a new and increasingly important vector of age-related inequality in labor outcomes.

The limited existing evidence on age-specific labor market impacts of heat stress is mixed and inconclusive (Borg *et al.* 2021). For example, Ma *et al.* (2019) and Xiang *et al.* (2014) find that younger workers (ages 25-44) tend to bear higher relative costs from heat-attributable occupational injuries. This finding may reflect occupational sorting: younger individuals are more likely to be employed in physically demanding jobs – such as construction or manual labor – that may carry greater risk during periods of extreme heat (Camino López *et al.* 2008). In contrast, Zander *et al.* (2015) and Zander and Mathew (2019) find no significant differences in heat-related labor productivity costs across age groups. These studies, however, generally lack detailed longitudinal identification strategies and often focus on self-reported productivity loss or injury prevalence rather than actual employment transitions.

Borg *et al.* (2021) and Amoadu *et al.* (2023) highlight the fragmented and methodologically inconsistent nature of the literature on labor, heat, and age. While several studies do find suggestive evidence of differential vulnerability across age groups, most rely on either aggregate data, one-off cross-sections, or self-reported survey measures that limit causal inference. Moreover, studies tend to focus on short-term or contemporaneous effects, without fully accounting for underlying heterogeneity in labor market attachment, cohort-specific economic conditions, or persistent regional factors that could confound estimated relationships between heat exposure and employment outcomes.

This study aims to bridge these gaps by developing a two-step empirical approach that combines high-frequency labor force data, detailed climate information, and a pseudo-panel estimation framework capable of addressing key identification challenges. First, quarterly repeated cross-sectional microdata from the Italian Labor Force Survey are used (LFS), which enables us to observe quarter-to-quarter transitions in employment status. Leveraging the panel-like structure of adjacent quarters, two probit models are estimated to obtain preliminary descriptive evidence on the effect of heat stress on overall employment dynamics. The first model is estimated on the sample of individuals employed in quarter t, to capture the probability of exiting employment by quarter t+1; the second is estimated on the sample of non-employed individuals, to assess the likelihood of entering employment in the next quarter. These cross-sectional estimates provide preliminary evidence that, conditional on all observable characteristics, heatwave exposure is positively associated with employment exit and negatively associated with job entry – suggesting that heat waves also act as a barrier to employment participation.

To assess whether these relationships vary systematically with worker age, and to mitigate concerns about unobserved confounders, a pseudo-panel is constructed by aggregating individuals into cohort-province cells. For each cell, mean values of employment transitions and covariates are calculated, and estimate a fixed-effects regression model that controls for all time-invariant characteristics at the province-cohort level – including baseline average health and long-run labor market attachment. This approach allows us to approximate what would otherwise be achieved through individual-level panel data, by using repeated cross-sections to replicate within-group longitudinal variation (Deaton 1985; Verbeek 2008). In doing so, a credible estimate of the differential effect of heatwaves on older versus younger cohorts is obtained, while minimizing the bias from omitted variables that are fixed over time but vary across location and demographic group.

A key strength of our analysis is the integration of daily meteorological data at the province level, matched to each survey quarter. This enables us to construct a precise and policy-relevant definition of heatwave exposure: namely, the number of consecutive days (minimum three) within a given quarter where daily maximum temperatures exceed 30°C. This threshold-based, event-driven measure aligns with international public health standards and should more accurately reflects physiological and behavioral responses to heat stress than traditional average temperature measures or seasonal aggregates (see also Deschenes and Greenstone 2011; Rameezdeen and Elmualim 2017).

In sum, this study advances the literature in several ways. First, it provides micro-level evidence on how heatwaves affect both entry into and exit from employment, which remains a largely unexplored outcome dimension. Second, it systematically investigates age-related heterogeneity in heat responses using a pseudo-panel fixed-effects design that strengthens causal identification. Third, it exploits high-frequency labor and climate data to deliver timely and granular insights on climate vulnerability in the labor market. Together, these contributions offer new empirical foundations for understanding how climate shocks interact with population aging – a critical policy concern in aging societies that are facing intensifying climate risks.

2. Data and descriptive statistics

This study makes use of daily weather data from the JRC AGRI4CAST (MARS) of the European Commission (EC), reporting ground-station gridded daily weather information covering 650 different Italian geographic locations distributed over the Italian territory from 1979 onward, matching 101 Italian provinces[1]. Besides temperature (measured in degrees Celsius, C°), these data include wind speed (mean daily wind speed at a 10-meter altitude measured in m/s) precipitations (mm/day) and solar radiation (KJ/m2/day) – which are included in the analysis due to the fact that environmental factors influencing heat stress may also involve other weather conditions, such as the level of humidity, air movement and radiated heat (ILO 2019; Parsons 2014). To measure the province-level quarterly exposition to heat waves, daily maximum temperature data is first averaged at the NUTS 3-level (101 provinces) and then, for each quarter, the number of consecutive days (minimum three) where daily maximum temperatures exceeded 30°C is totaled, using quarterly provinces' share of national population as weights[2].

Table 1 shows descriptive statistics for those weather variables in the analyzed period per province. The mean of consecutive days with a temperature above 30 degrees is slightly more than 7, the average windspeed is 2.6 meter per second, mean precipitations per province are almost 2 mm per day, mean solar radiations 14618 KJ per square meter per day.

Table 1. Weather variables (quarterly data, 2004-2017)

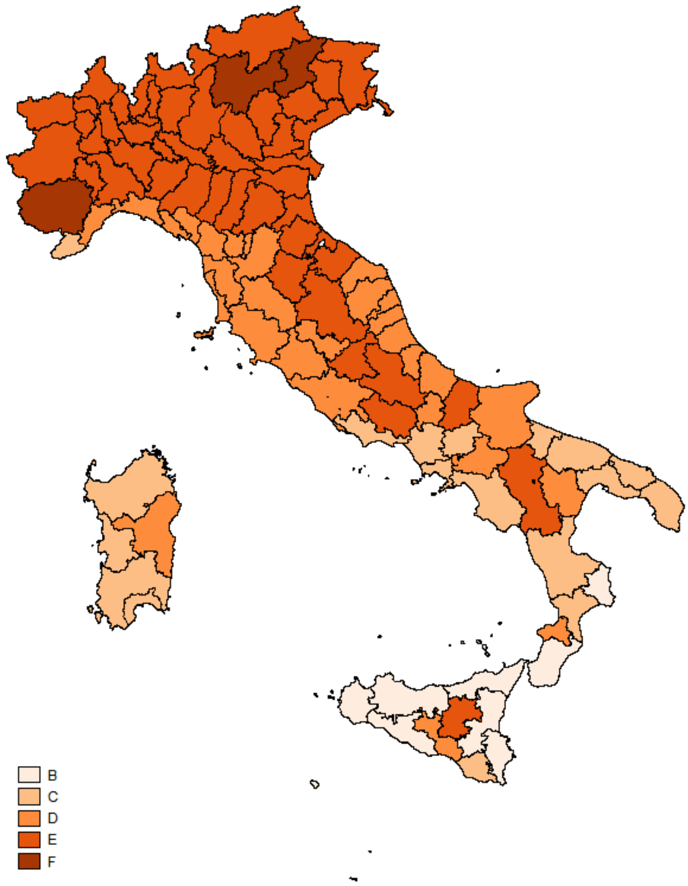
Variable	Mean	Std. dev.	Min	Max
Consecutive days maxT≥30C°	7.085	13.109	0	74
Mean windspeed	2.619	.895	.576	5.935
Mean precipitations	1.985	1.052	.062	7.274
Mean radiation	14618	6561	4685	25877

Notes: N=(101 provinces x 56 quarters)= 5656. Consecutive days maxT≥30C° is the number of consecutive days (minimum three) with maximum temperature ≥30C°.
Source: authors' elaboration on JRC AGRI4CAST data

[1] The provinces of Lecco and Trieste are unfortunately not covered by AGRI4CAST weather data. For spatial unit over-time consistency, only the four historical Sardinian provinces are considered, namely: Cagliari, Sassari, Nuoro, Oristano.
[2] These weights are relevant as they are proportional to the size of local labor markets.

To account for differences in Italian climatic zones, the analysis relies on detailed information from the official Italian classification of municipality-level degree-days (DD). According to such classification, Italy is divided into 6 climate zones defined on a degree-days basis (A, B, C, D, E and F). Figure 1 provides graphical representation of the geographical distribution.

Figure 1. Italian Provinces by climatic zone



Notes: climatic zones are classified by degree days (DD) intervals (B: 601-900, C: - 901-1400, D: 1401-2100, E: 2101-3000. F:>3001). As climatic zone A only covers two Sicilian municipalities (Lampedusa, Porto Empedocle) it has been merged with zone B.
Source: elaborations on data from of the Decree of the President of the Republic (DPR) 412/93, annex A.

For what concerns individual-level data, labor-market information used in this study is drawn from the Italian Labor Force Survey (IT-LFS), providing quarterly data spanning the period 2004-2017. Although the IT-LFS is fundamentally cross-sectional, it exhibits a partial panel structure within each calendar year: most individuals are observed twice over the course of the year[3]. Due to the survey

[3] More specifically, households are interviewed four times: initially, and then again after 3, 12, and 15 months from the first interview. The present analysis focuses on short-term labor market transitions, and therefore uses only adjacent-quarter transitions (i.e., between the first and second interviews at months 0–3, and between the third and fourth interviews at months 12-15). For the purpose of the analysis, observations from months 0-3 and 12-15 are treated as pertaining to different individuals in different years, thereby preserving the cross-sectional structure of the overall sample.

design – where households are never first interviewed in the fourth quarter – individuals are observed across three possible adjacent-quarter transitions: (i) from the first to the second quarter (winter to spring), (ii) from the second to the third quarter (spring to summer), and (iii) from the third to the fourth quarter (summer to fall). As a result, transitions from fall to winter are excluded by default from the analysis. However, as transitions in labor market status are observable only at the second adjacent point of observation for each individual – coinciding with the occurrence of potential heatwave exposure – this exclusion does not compromise the study of climatic effects, as the number of days exceeding the 30°C threshold during winter is systematically zero in all provinces. Consequently, by focusing on the seasonal transitions between spring, summer and fall, the analysis captures the relevant variation in weather conditions without any substantive loss of climatic information.

In the reference period, the sample of working-age individuals observed twice over adjacent quarters totals 4,037,564 observations, representing 72.3% of the working-age population surveyed in the IT-LFS during 2004–2017 [4].This dataset is partitioned into two subsamples:

- Sample A consists of 2,088,096 observations of individuals who declared themselves ‘employed’ in the first within-year observed quarter.
- Sample B includes 1,949,468 observations of individuals who reported being ‘non-employed’ in the first within-year observed quarter.

The dataset is constructed by focusing on the second observation for each individual. For Sample A (the employed), a binary outcome variable Y is constructed which is equal to 1 if the individual has exited employment by the second quarter, and 0 otherwise. Correspondingly, for Sample B (the non-employed) Y equals 1 if the individual has entered employment by the second quarter, and 0 otherwise. For both samples, socio-demographic characteristics as well as weather-related variables – including heatwave exposure – are recorded in the second observed quarter. For Sample A, labor market covariates are measured as recorded in the first observed quarter. Summary statistics of sociodemographic variables and the outcome variable in both samples are reported in Table 2, while labor-market statistics for Sample A are reported in Appendix Table A1.

From Table 2 it can be easily seen that the fraction of the employed who left employment in the second within-year observed quarter (Sample A - 4.6%) is slightly lower than the fraction of non-employed who entered employment (Sample B - 6.8%) – consistently with the overall progressive employment growth over the period observed.

[4] This implies that the remaining 27.7% of working-age individuals, although observed at their first (or third) interview, are not followed up at the second (or fourth) interview. Attrition may occur either due to respondent unavailability or because the individual or household changed municipality of residence between adjacent quarters. Attrition due to relocation can happen even within the same province, as the IT-LFS sampling frame operates strictly at the municipal level. Nevertheless, potential moves in response to heatwave exposure do not pose a major concern for the analysis: first, moving individuals are typically assumed to maintain their employment status; second, the primary objective is to assess the impact of heatwaves on individuals who do not change their workplace location.

Table 2. Summary statistics of selected IT-LFS samples

	Mean	Std. dev.	Min	Max
SAMPLE A (employed) N=1,044,048				
Employment exit	.045	.206	0	1
Female	.411	.492	0	1
Age	42.1	10.67	16	66
Italian Citizen	.723	.447	0	1
Primary education	.052	.222	0	1
Lower secondary education	.306	.461	0	1
Middle secondary education	.079	.269	0	1
Upper secondary education	.386	.487	0	1
Tertiary education	.177	.382	0	1
SAMPLE B (non-employed) N=974,734				
Employment entry	.068	.251	0	1
Female	.628	.483	0	1
Age	40.72	16.60	16	66
Italian Citizen	.804	.397	0	1
Primary education	.173	.378	0	1
Lower secondary education	.412	.492	0	1
Middle secondary education	.051	.219	0	1
Upper secondary education	.292	.455	0	1
Tertiary education	.073	.260	0	1

Notes: quarterly data over 2004-2017 excluding Q1 (winter). Observations weighted by IT-LFS individual frequency weights. Statistics for labor-market dummy variables from Sample A are reported in Appendix Table A1.
Source: authors' elaboration using IT-LFS data

As expected, a quick comparison between sociodemographic variables of the two samples highlights several substantial differences: the fraction of female individuals is considerably lower in Sample A (41%) relative to Sample B (63 %), while on average the employed are older than the non-employed (mean age 42.1 vs. 40.7, respectively). Capturing the fact that the immigrant population is highly concentrated within the labor force, expected differences also emerge with reference to the fraction of natives, which is relatively lower among the employed (72% in Sample A vs. 80% in Sample B). Unsurprising differences between the two samples also emerge with reference to education since in Sample B the fraction of individuals with lower levels of education (primary to lower-secondary) is systematically higher than in Sample A – while the fraction of those with higher education levels (middle-secondary to tertiary) is systematically lower. Note that Sample A statistics on the labor market characteristics at t-1 (i.e. the first within-year observed quarter) such as the type of contract and the broad sector of activity are not displayed for Sample B, as they are of course not available for the non-employed.

3. Methodological Framework

This paper employs a two-step empirical strategy to assess the labor market effects of short-term heatwave exposure, with a particular focus on age-related heterogeneity in employment responses.

The choice to combine an individual-level model and a pseudo-panel design is guided by complementary identification strengths in each approach.

Individual-level probit models are first estimated, using quarterly matched samples from the Italian Labor Force Survey (IT-LFS). These models examine the relationship between unexpected heatwave exposure and the probability of exiting or entering employment between adjacent quarters. The individual-level data structure offers several advantages at this stage. First, it allows us to explore the general association between heatwave exposure and transitions in and out of employment, conditional on a rich set of individual characteristics such as age, gender, education, and, in the case of the employed, labor market characteristics. Second, it allows the use of a large sample and high-frequency time variation, increasing statistical power in detecting baseline effects. Third, it enables the inclusion of province fixed effects, quarter dummies, and year trends interacted with climatic zones, ensuring that identification relies on the unexpected component of heatwaves variation. The probit results serve two purposes: i) they provide preliminary evidence that heatwaves are significantly associated with both increased job exit and reduced job entry at the individual level; ii) they validate the underlying assumption that weather variation, once purged of seasonal and regional trends, exerts meaningful short-term pressure on labor market dynamics. However, while useful in establishing this general relationship, the individual-level model has limitations when it comes to our main research question: are older workers more likely to leave employment in response to heatwaves than younger ones?

To assess whether the relationship between heat waves and employment exit/entry varies systematically by age groups, the second step develops a pseudo-panel design (Deaton 1985; Verbeek and Nijman 1992; Verbeek 2008 – see also Dang and Lanjouw 2023; Colgan 2023, for recent contributions), where cohorts are defined by 5-year birth intervals.

This design allows estimating a fixed-effects model that absorbs all time-invariant differences across cohorts and provinces, including those that are otherwise unobservable – such as baseline health, average occupational exposure, or long-run labor market attachment[5]. This is a key strength of the pseudo-panel strategy, since in contrast to attempting to estimate the effect separately for individuals aged 50+ in each period – which would conflate age with calendar time – the cohort fixed-effects structure allows comparing systematically different age groups, while controlling for unobserved heterogeneity. Moreover, this approach avoids identification issues that would arise from interacting a cohort-age dummy with the heatwave variable in a fixed-effects framework, where such interactions are collinear with the absorbed terms. Another advantage is that the province and quarter fixed effects, as well as the year × climate zone trends, are consistent with those used in the individual-level probit model. This means that across both steps, identification relies on the unexpected, short-term component of heatwave exposure, as measured by the number of days in a quarter with three or more consecutive days above 30°C. In this sense, the pseudo-panel model builds directly on the

[5] The basic assumption of this exercise is that, although within province-cohort cells the individuals observed do differ over-time due to the cross-sectional nature of the data, they nevertheless share the same fixed individual unobservable characteristics that vary systematically by cohort and place. For instance, while millennials have of course fixed systematic characteristics that differ from baby-boomers within provinces, also between provinces millennials and baby-boomers have, respectively, fixed systematic differences (e.g., millennials in Turin have different fixed characteristics compared to millennials in Agrigento etc.).

findings of the individual-level analysis but offers an improved design for capturing heterogeneity across age groups.

To recap, the empirical strategy reflects a logical progression: first the existence of a meaningful average relationship between heatwaves and transitions in and out of employment, conditional on individual characteristics, is documented; then the analysis is shifted to a pseudo-panel framework to consistently estimate differential effects across age groups, taking advantage of fixed-effects at the cohort–province level to address unobserved heterogeneity.

4. Cross-sectional probit estimations

4.1 Identification strategy

As for Sample A, the probit specification adopted to model the probability of exit employment in response to (unexpected) heat waves can be formalized as follows:

$$P\left(Y_{ipq}=1|\mathrm{X}\right)=\Phi(\alpha+\beta T_{pq}+\sigma W'_{pq}+\gamma D'_{ipq}+\delta M'_{ip,q-1}+\varphi_p+\omega_q+\theta_{rt}); \qquad (1)$$

where Y_{ipq} equals 1 if individual *i* in province *p* quarter *q*, is non-employed, 0 otherwise; T_{pq} is the population-weighted total number of consecutive days (minimum three) in which maximum temperatures equaled or soared above the 30 C° threshold in province *p* quarter *q*; W'_{pq} is a vector of province-quarter weather control variables from JRC MARS (precipitations, wind speed, solar radiation – as they may influence heat stress, see ILO, 2019; Parsons, 2014); D'_{ipq} is a vector of individual socio-demographic characteristics (age, age squared, and gender, educational-level and native nationality dummies); $M'_{ip,q-1}$ is a vector of labor-market dummy variables observed in the previous quarter (permanent-job dummy, 12 economic sectors and 9 broad occupational categories); while φ_p, ω_q and θ_{rt} are 101 province, 3 quarter and 5 climatic-zones (subscript *r*) × 14 years (subscript *t*) fixed-effects terms, respectively. For Sample B, the probability of entry is modeled as a function of the same arguments in equation (1) except for labor-market variables. Please note that, as provinces' common trends in weather conditions (climatic change) are modeled both on aggregate (*t*) and as climatic-zone specific (*r*) the inclusion of fixed-effects terms allows interpreting variations in the duration of quarterly heat waves as coming from unexpected and temporary shocks in weather (Schlenker 2010; Dell *et al.* 2014; Kolstad and Moore 2020).

4.2 Results

Results of model in equation (1) are summarized in Table 3. In particular, Column 1 shows that – net of all control explanatory variables – model in equation (1) do indeed detect a statistically significant positive relationship between the unexpected prolongation of quarterly heat waves and the individual probability of employment exit. As shown in Column 2 and 3, the progressive inclusion of individual socio-demographic controls and weather controls, respectively, slightly lowers the baseline estimate. Column 4 tests instead for the inclusion of all individual observable characteristics (sociodemographic and labor market), while Column 5 reports results for the full-fledged version of equation (1), showing no substantial change compared to previous outputs. To allow for a direct interpretation of probabilities predicted by equation (1), marginal effects of heat waves as estimated in the full-fledged model (Table 3, Column 5) are plotted in Figure 2.

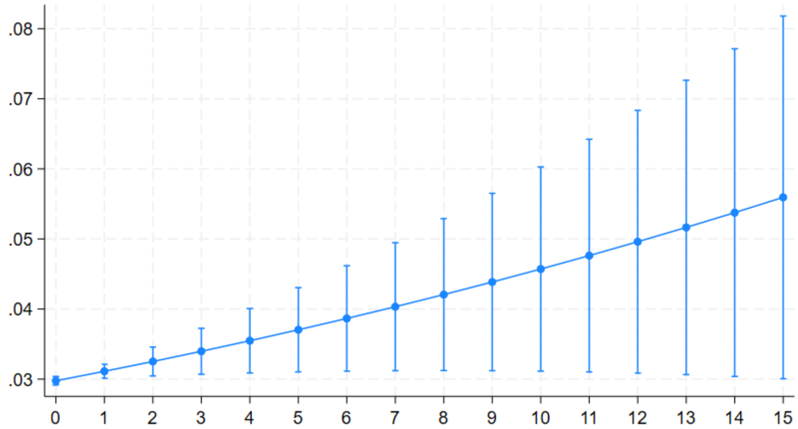
Table 3. Heat waves and probability of employment exit between adjacent quarters (Sample A)

	(1)	(2)	(3)	(4)	(5)
Consecutive days max T≥ 30C°	0.020***	0.017**	0.019**	0.017**	0.019**
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Province FE	x	x	x	x	x
Quarter FE	x	x	x	x	x
year*climatic zone FE	x	x	x	x	x
Sociodemographic controls		x	x	x	x
Labor-market controls				x	x
Weather controls			x		x

Notes: N=1,044,048. Dep. Var.: individual probability of employment exit. Independent Var.: province-level quarterly sum of consecutive days (minimum 3) with $\max T \geq 30C°$. Quarterly data over 2004-2017 excluding Q1 (winter). Standard errors in parenthesis are clustered by province, year and quarter. Observations weighted by official IT-LFS individual frequency weights. Working-age population is [15-65] over 2004-2010 and [15-67] from 2011 onward. Socio-demographic controls include: age, age squared and dummy variables for gender, educational-level and native nationality. Labor market controls include dummy variables for: permanent-job, 12 broad economic sectors and 9 broad occupational categories. Weather controls include average values for: wind speed, precipitations and solar radiation. For weather data availability reasons, observations for the provinces of Lecco and Trieste are not included in the regressions. *** p<0.01, ** p<0.05, * p<0.1.
Source: authors' elaboration using IT-LFS and JRC AGRI4CAST data

As Figure 2 clearly shows, the conditional probability of leaving employment monotonically increase from 3% at day one (*z*=92.2) up to 5.6% at day fifteen (*z*=4.25 – Appendix Table A2) for each additional unexpected day of heat-waves continuation. In other words, margins calculated indicate that when the unanticipated prolongation of heat waves sums up to about two weeks in a quarter, the impact estimated grows by around 80% compared to a single day of extraordinary heat-waves duration (going above the mean sample probability of 0.045 at day 11).

Figure 2. Marginal effects (equation 1, Sample A)



Notes: marginal effects from probit model in Column 4, Table 3. Y axis: probability of employment exit; X axis: quarterly sum of unexpected province-level consecutive days (minimum 3) with maximum temperature equaling or soaring above 30C°. See Appendix Table A2 for more details.
Source: authors' elaboration using IT-LFS and JRC AGRI4CAST data

Turning to the non-employed (Sample B), Table 4 reports the results from an alternative version of equation (1) that models the probability of switching into employment (employment entry) between adjacent quarters (when including controls, as a function of all covariates considered so far with the exception of the labor-market vector $M'_{ip,q-1}$). As shown in Table 4 Column 1, when running the fixed-effect baseline regression, the estimate obtained is negative but not statistically significant, indicating that – compared to employment exit – heat waves and the individual-level probability of employment entry seem to have a negative but somehow weaker relationship. Though increasing in magnitude, the same applies to the estimate obtained when including sociodemographic characteristics in Column 2. As shown in the full-fledged regression in Column 3, the model is able to predict a negative significant impact only after the inclusion of weather controls W'_{pq}. Figure 3 plots marginal predictions from model in Table 4 Column 3.

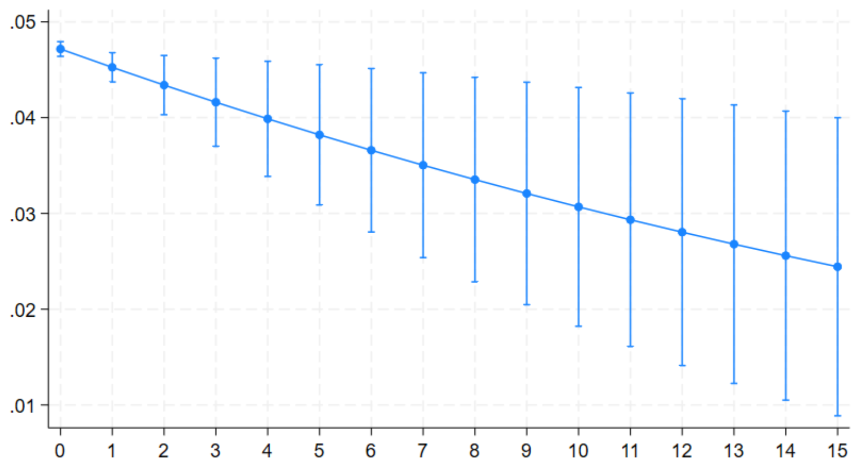
Table 4. Heat waves and probability of employment entry between adjacent quarters (Sample B)

	(1)	(2)	(3)
Consecutive days max T≥ 30C°	-0.009	-0.014	-0.020**
	(0.008)	(0.009)	(0.009)
Province FE	x	x	x
Quarter FE	x	x	x
year*climatic zone FE	x	x	x
Sociodemographic controls		x	x
Weather controls			x
N	974,734	974,734	974,734

Notes: N=974,734. Dep. Var.: individual probability of employment entry. Independent Var.: province-level quarterly sum of consecutive days (minimum 3) with max $T \geq 30C°$. Quarterly data over 2004-2017 excluding Q1 (winter). Standard errors in parenthesis are clustered by province, year and quarter. Observations weighted by official IT-LFS individual frequency weights. Working-age population is [15-65] over 2004-2010 and [15-67] from 2011 onward. Socio-demographic controls include: age, age squared and dummy variables for gender, educational-level and native nationality. Weather controls include average values for: wind speed, precipitations and solar radiation. For weather data availability reasons, observations for the provinces of Lecco and Trieste are not included in the regressions. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration using IT-LFS and JRC AGRI4CAST data

Figure 3. Marginal effects (equation 1, Sample B)



Notes: marginal effects from probit model in Column 3, Table 4. Y axis: probability of employment entry; X axis: quarterly sum of unexpected province-level consecutive days (minimum 3) with maximum temperature equaling or soaring above 30C°. See Appendix Table A3 for more details.

Source: authors' elaboration using IT-LFS and JRC AGRI4CAST data

As illustrated in Figure 3, marginal effects of heat waves calculated for the 'Sample-B version' of equation 1 (Table 3, Column 3) estimate a decreasing probability of entry employment, from 0.047 at day 1 down to 0.026 at day 15, being both these probabilities appreciably below the sample mean of 0.068 (Table 1).

5. Longitudinal pseudo panel estimations

5.1 Identification strategy

In this section, individual-level data used in Section 4 are collapsed by cohort-province cells. This is done in order to assess whether the effects detected in the individual-level setting do systematically vary between older and younger cohorts.

Formally, the pseudo panel design relies on the following specification:

$$\bar{Y}_{cpq} = \alpha + \beta T_{pq} + \mu_{cp} + \omega_q + \theta_{rt} + \varepsilon_{cpq}; \qquad (2)$$

where, for each sample (A and B), $\bar{Y}_{cpq}$ is the fraction – computed by using official IT-LFS frequency weights – of employment transitions by cohort-province cell (subscripts c – i.e. 12 five-years cohorts – and p) in each quarter observed (subscript q), μ_{cp} are the cohort-province fixed-effects, while the remaining covariates are the same of specification (1) excluding time-varying control variables[6]. To test whether the effects estimated in the previous section do systematically differ between older and younger cohorts, separate models are estimated for both samples: one for the overall sample (1212 province-cohort units) and two for cohorts born from 1940 to 1969 and from 1970 to 1999 (606 units each group), respectively[7][8]. Table 5 describes the distribution of the dependent variables, both overall and across the two equal-size cohort groups.

It is important to stress that the choice of not including other time-varying regressors in our main specification is grounded on several influential contributions in environmental economics that have cautioned against the inclusion of time-varying economic covariates – such as sectoral composition, employment structure, or average human capital indicators – when estimating the impact of weather

[6] In particular, the estimation method adopted employs a high-dimensional fixed effects estimator capable of efficiently absorbing multiple levels of fixed effects, as it extends the linear fixed effects framework through an alternating projection algorithm which ensures consistency and computational feasibility even when the number of fixed effect categories is large. This approach has been widely adopted in empirical economics and recommended in applied settings with complex data structures and large panels (see Guimarães and Portugal 2011; Correia 2016 2020).

[7] The average sample size of province-cohorts cells in Sample A is 130 observations, while for Sample B is 111 observations. Averages cohort-province cell size over time are reported in Appendix Figures A1 and A2.

[8] Note that running separate regressions is particularly appropriate given the structure of the pseudo-panel and the identification strategy. By estimating the model separately for each group, the fixed-effects specification is retained while allowing the effect of heatwaves to vary flexibly by age group. The sample-splitting method thus represents a practical and statistically sound alternative to interaction-based testing. Moreover, the balanced number of units in each group ensures comparable estimation precision and allows meaningful inference on differential vulnerability to heat stress across cohorts.

shocks. Indeed, these variables are often endogenously determined and may themselves represent adaptive responses to climatic events, thereby introducing post-treatment bias when included as controls (Dell *et al.* 2014; Kolstad and Moore 2020).

Table 5. Employment-transitions rates by cohort-province cells, summary statistics

Cohorts	N	Mean	Std. dev.	Min	Max
Employment exit					
All	42,298	.0762936	.1481974	0	1
Older	21,634	.0524412	.1004916	0	1
Younger	20,664	.1012658	.1821128	0	1
Employment entry					
All	44,684	.0834462	.1192807	0	1
Older	22,061	.0587322	.0954298	0	1
Younger	22,623	.1075463	.1343349	0	1

Notes: 5-years birth cohorts. Older cohorts: 1940 to 1969; younger cohorts: 1970 to 1999.
Source: authors' elaboration using IT-LFS data

For instance, changes in the local manufacturing share or the prevalence of permanent contracts may be both a consequence of previous climate shocks and a mediator of their effects on labor market outcomes. The risk of bias is especially pronounced in panel (or pseudo-panel) settings, where such structural variables evolve slowly and may absorb part of the weather effect itself (Deschênes and Greenstone 2007; Burke *et al.* 2015)[9]. Consistent with this literature, the main pseudo-panel specification in this paper excludes potentially endogenous covariates, though the inclusion of time-varying controls is considered as a robustness check in Section 6.

5.2 *Main results*

Table 6 presents the baseline estimates of the effect of heatwave exposure on employment transitions using the pseudo-panel of cohort-province cells. The dependent variable is the quarterly employment transition rate (exit or entry), multiplied by 100 for interpretability. In the unweighted regressions (Panel A), heatwave exposure is found to significantly increase the probability of exiting employment. For the full sample, a one-day increase in heatwave exposure is associated with a 0.501 percentage point increase in the quarterly employment exit rate ($p < 0.05$). When disaggregating by cohort, the effect is significant and slightly stronger among older cohorts (0.530, $p < 0.05$), while the estimate for younger cohorts (0.489) results positive but not statistically significant. On the employment entry side,

[9] By contrast, in the individual-level probit models estimated in the first part of the paper, the included covariates – such as age, gender, or education – represent predetermined individual characteristics observed prior to the outcome. As sociodemographic variables are not the result of contemporaneous or prior shocks within the observation window, and as the time frame between baseline labor-market covariates and observed employment transitions is short (one quarter), in the probit model the risk of endogeneity is substantially lower. Therefore, covariates in the individual-level setting help improve model precision without introducing bias, unlike in the aggregated context, where they may reflect adaptive responses or structural transformations triggered by the climate shock itself.

results are consistent with an adverse impact: the coefficient for the full sample is -0.482 ($p < 0.05$), with the effect entirely driven by younger cohorts (-0.718, $p < 0.05$), while estimates for older cohorts are negative but not significant.

To account for potential differences in the reliability of estimates across cells of varying size, in Table 6 Panel B the model is re-estimated weighting each cell by its mean sample size. These weighted regressions yield qualitatively consistent results. The effect of heatwave exposure on employment exit remains significant for the full sample (0.482, $p < 0.01$) and again concentrated among older cohorts, where the magnitude increases to 0.536 ($p < 0.01$). For younger cohorts, the effect on exit remains positive but statistically insignificant. On the entry margin, the full-sample estimate remains -0.482 ($p < 0.05$), and the negative effect among younger cohorts becomes slightly stronger (-0.794, $p < 0.05$), while still not significant among older cohorts.

Taken together, these suggest that heatwave exposure has a significant and robust effect on labor market transitions, particularly by increasing the probability of job exit among older workers and reducing the probability of job entry among younger ones[10]. These patterns are consistent with a differential vulnerability to heat-related stress across age groups and imply that both margins of labor market adjustment are sensitive to short-term climatic shocks, albeit in age-specific ways.

Table 6. Main results

	Panel A					
	Exit			Entry		
VARIABLES	All	Older	Younger	All	Older	Younger
Consecutive days $\max T \geq 30C°$	0.501**	0.530**	0.489	-0.482**	-0.241	-0.718**
	(0.212)	(0.221)	(0.351)	(0.206)	(0.220)	(0.343)
N	42,298	21,634	20,664	44,684	22,061	22,623
R-squared	0.239	0.139	0.270	0.213	0.228	0.164
Number of unit	1,212	606	606	1,212	606	606
	Panel B					
	Exit			Entry		
VARIABLES	All	Older	Younger	All	Older	Younger
Consecutive days $\max T \geq 30C°$	0.482***	0.536***	0.427	-0.482**	-0.237	-0.794**
	(0.178)	(0.197)	(0.311)	(0.211)	(0.237)	(0.363)
N	42,298	21,634	20,664	44,684	22,061	22,623
R-squared	0.236	0.138	0.275	0.208	0.219	0.145
Number of unit	1,212	606	606	1,212	606	606

Notes: Multi-way fixed effects estimator. Dep. Var.: fraction of employment transitions. Independent Var.: province-level quarterly sum of consecutive days (minimum 3) with $\max T \geq 30C°$. Quarterly data over 2004-2017 excluding Q1 (winter). All models include cohort-province fixed effects, quarter fixed effects and climatic-zone dummies interacted with a yearly time trend. Standard errors in parenthesis are clustered by cohort and province. Working-age population is [15-65] over 2004-2010 and [15-67] from 2011 onward. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' elaboration using IT-LFS and JRC AGRI4CAST data

[10] Compared to younger cohorts, in the case of older cohorts these results are even more striking – since descriptive statistics in Table 5 show that the average fraction of transitions out of employment are systematically lower for this group.

6. Robustness checks

This section tests the robustness of results outlined in section 5 to the inclusion of sociodemographic, labor market and weather control variables used in section 4 – averaged by cohort-province cells in each period observed by using IT-LFS frequency weights. To this aim, Table 7 describes the resulting aggregated individual-level variables for both samples, while Table 8 reports the results of a robustness specification that augments the baseline pseudo-panel model with a comprehensive set of time-varying cohort-province covariates[11]. These include demographic characteristics (female share, mean age, and mean age squared), human capital indicators (share of graduates, share of native workers), employment quality proxies (share with open-ended contracts, share of managers and professionals), sectoral composition (broad manufacturing share), and local environmental conditions (average wind speed, solar radiation, and precipitation). The results remain remarkably consistent with those of the main specification. In both the unweighted and weighted models, the effect of heatwave exposure on employment exit is positive and statistically significant for the full sample and for older cohorts. In the weighted regression, the coefficient for older cohorts is 0.485 ($p < 0.05$), while the coefficient for younger cohorts is 0.572 ($p < 0.10$). These estimates are similar in magnitude to those in the baseline model without covariates, reinforcing the conclusion that heatwaves increase the likelihood of job exit particularly among older workers.

Table 7. Pseudo-panel sociodemographic and labor-market control variables

	Mean	Std. dev.	Min	Max
Sample A				
Mean age	42.81	13.27	16	66
Female share	.390	.143	0	1
Italian share	.855	.270	0	1
Degree share	.155	.115	0	1
Manufacturing share $_{q-1}$	.277	.158	0	1
Managers and professionals share $_{q-1}$	.156	.121	0	1
Permanent job share $_{q-1}$	.616	.181	0	1
Sample B				
Mean age	40.65	15.15	16	66
Female share	.658	.189	0	1
Italian share	.845	.270	0	1
Degree share	.082	.128	0	1

Notes: all variables are computed by using official IT-LFS frequency weights. Sample A: N= 42,298; Sample B: N= 44,684.
Source: authors' calculations using IT-LFS data

On the employment entry margin, the negative effect of heatwave exposure persists, again only among younger cohorts, for whom the estimated coefficient is -0.867 ($p < 0.05$) in the weighted

[11] Educational, sectoral and professional categories have been collapsed in aggregated indicators to reduce overfitting, measurement error in small cells and for model parsimony. This is standard practice in pseudo-panel regressions, especially when the goal is not to estimate the effect of individual characteristics per se, but to control for structural or compositional trends (see Antman and McKenzie 2007; Verbeek and Nijman 1992; Browning *et al.* 1985). However, running the regressions with the comprehensive set of (5+12+9) 26 dummy-variables computed at their mean does not qualitatively change our results (available upon request).

model. The effect for older cohorts remains negative but statistically insignificant, suggesting that younger individuals may face heightened entry barriers during extreme heat events, potentially due to the nature of entry-level employment or job search dynamics.
To sum up, albeit time-varying covariates inclusion may potentially introduce post-treatment bias, the comparison between Table 6 and 8 offer reassurance about the robustness of the estimated effects. Indeed, although the latter yields larger estimates for transitions to non-employment among younger cohorts, these are largely not statistically different from zero.

Table 8. Robustness checks

	Panel A					
	Exit			Entry		
VARIABLES	All	Older	Younger	All	Older	Younger
Consecutive days $\max T \geq 30C°$	0.522**	0.469**	0.656*	-0.546***	-0.330	-0.771**
	(0.213)	(0.224)	(0.353)	(0.202)	(0.221)	(0.330)
N	42,298	21,634	20,664	44,684	22,061	22,623
R-squared	0.280	0.152	0.329	0.241	0.246	0.202
Number of unit	1,212	606	606	1,212	606	606
	Panel B					
	Exit			Entry		
VARIABLES	All	Older	Younger	All	Older	Younger
Consecutive days $\max T \geq 30C°$	0.492***	0.485**	0.572*	-0.563***	-0.336	-0.867**
	(0.179)	(0.201)	(0.313)	(0.207)	(0.237)	(0.345)
N	42,298	21,634	20,664	44,684	22,061	22,623
R-squared	0.275	0.152	0.332	0.233	0.238	0.183
Number of unit	1,212	606	606	1,212	606	606

Notes: multi-way fixed effects estimator. Dep. Var.: fraction of employment transitions. Independent Var.: province-level quarterly sum of consecutive days (minimum 3) with $\max T \geq 30C°$. Quarterly data over 2004-2017 excluding Q1 (winter). Standard errors in parenthesis are clustered by cohort and province. Working-age population is [15-65] over 2004-2010 and [15-67] from 2011 onward. Control variables include the female share, mean age, mean age squared, share of graduates, share of native workers, share of open-ended contract workers, share of managers and professionals, broad manufacturing share, and local environmental conditions (average wind speed, solar radiation, and precipitation)*** p<0.01, ** p<0.05, * p<0.1.
Source: authors' elaboration using IT-LFS and JRC AGRI4CAST data

7. Conclusions

This analysis investigated the short-term impact of heatwaves on employment transitions, with particular attention to age-related heterogeneity. Using high-frequency individual-level data from the Italian Labor Force Survey and detailed daily weather records, probit models and pseudo-panel regressions are run to assess whether older workers are more likely to exit employment in response to extreme heat exposure. The results provide consistent evidence that heatwaves significantly increase the probability of employment exit among older cohorts and reduce job entry among younger ones. These effects are robust to various specifications and persist even when controlling for structural labor market characteristics at the cohort-province level.

The obtained findings contribute to a growing literature documenting the economic costs of climate-related stress, while offering novel insights into the differential vulnerabilities across the working-age population. Unlike much of the prior evidence – often focused on productivity loss or developing-country settings (see Dasgupta *et al.* 2024; De Sario *et al.* 2023) – this study demonstrates that even in a relatively advanced labor market such as Italy's, heatwaves can trigger measurable disruptions in employment dynamics, particularly for older individuals. While the literature seems to indicate the existence of short-run positive effects in Northern European countries (Dasgupta *et al.* 2024) – this paper supports the argument that labor market vulnerabilities induced by climate change may be particularly important in Southern Europe (Orlov *et al.* 2021; Szewczyk *et al.* 2021) especially in contexts with aging populations.

The results have important implications for public policy. First, they suggest that population aging may amplify the labor market costs of climate change, particularly in Mediterranean countries, where heatwave frequency and intensity are projected to rise significantly under current emissions scenarios (IPCC, 2022). Policies aimed at extending working lives – such as pension reform or active aging initiatives – will need to account for older workers' heightened physiological and labor market sensitivity to environmental stress (Basu 2009; Kenny *et al.* 2016). Second, occupational health and safety regulations may require revision to better protect vulnerable groups, especially in sectors involving outdoor or physically demanding work (Xiang *et al.* 2014; Dasgupta and Robinson 2023). This could include stricter enforcement of heat protocols, mandatory rest breaks, and dynamic scheduling during extreme temperature events.

Third, the evidence points to the need of a broader role for adaptive labor market institutions, including the promotion of flexible or transitional employment arrangements for older workers during periods of climatic stress. For younger workers, who appear more sensitive to heat on the employment entry margin – possibly due to greater exposure to informal or precarious jobs – job matching programs and targeted hiring incentives in climate-resilient sectors may help offset entry barriers. These policies may be particularly valuable in Mediterranean labor markets, where youth unemployment and seasonal employment volatility are already structural concerns.

Finally, while this paper focuses on short-term labor market transitions, future research should investigate longer-term adjustments – such as permanent labor force withdrawal, changes in sectoral employment composition, or firm-level responses to repeated climatic shocks. These dynamics are likely to become increasingly important as Europe faces the dual pressures of demographic change and climate adaptation, and understanding them is essential for designing labor market policies that are both socially inclusive and climate-resilient.

Appendix

Table A1. Summary statistics for Sample A labor-market dummy variables

	Mean	Std. dev.	Min	Max
Permanent job	0.581	0.493	0	1
Agriculture	0.037	0.189	0	1
Manufacturing	0.107	0.309	0	1
Construction	0.138	0.345	0	1
Trade	0.113	0.316	0	1
Hotels and restaurants	0.103	0.304	0	1
Tansport and storage	0.048	0.214	0	1
ICT services	0.040	0.195	0	1
Finance and insurance	0.031	0.174	0	1
RE, service to businesses	0.104	0.305	0	1
Public administration	0.062	0.242	0	1
Education and health	0.145	0.352	0	1
Personal services	0.071	0.257	0	1
Managers	0.036	0.185	0	1
Professionals	0.119	0.323	0	1
Technicians	0.193	0.395	0	1
Clerks	0.115	0.319	0	1
Sales and service occupations	0.172	0.377	0	1
Craft and agricultural occupations	0.171	0.377	0	1
Machine operators	0.085	0.278	0	1
Elementary occupations	0.100	0.299	0	1
Armed forces	0.011	0.104	0	1

Notes: N=1,044,408.
Source: authors' elaboration using IT-LFS data

Table A2. Marginal effects from probit model in Column 4, Table 3

	Margin	Delta-method std. err.	z	P>z	[95% conf. interval]	
At day:						
1	0.030	0.000314	94.82	0	0.029148	0.030379
2	0.031	0.000506	61.47	0	0.030123	0.032107
3	0.033	0.001051	30.95	0	0.030458	0.034576
4	0.034	0.001671	20.33	0	0.030695	0.037246
5	0.035	0.002344	15.14	0	0.030883	0.040072
6	0.037	0.003066	12.08	0	0.03103	0.043047
7	0.039	0.003837	10.08	0	0.031136	0.046175
8	0.040	0.004657	8.66	0	0.031201	0.049458
9	0.042	0.00553	7.61	0	0.031224	0.052899
10	0.044	0.006455	6.79	0	0.031203	0.056505
11	0.046	0.007434	6.15	0	0.031136	0.060277
12	0.048	0.00847	5.62	0	0.031022	0.064222
13	0.050	0.009562	5.19	0	0.03086	0.068344
14	0.052	0.010714	4.82	0	0.030646	0.072646
15	0.054	0.011927	4.51	0	0.03038	0.077133

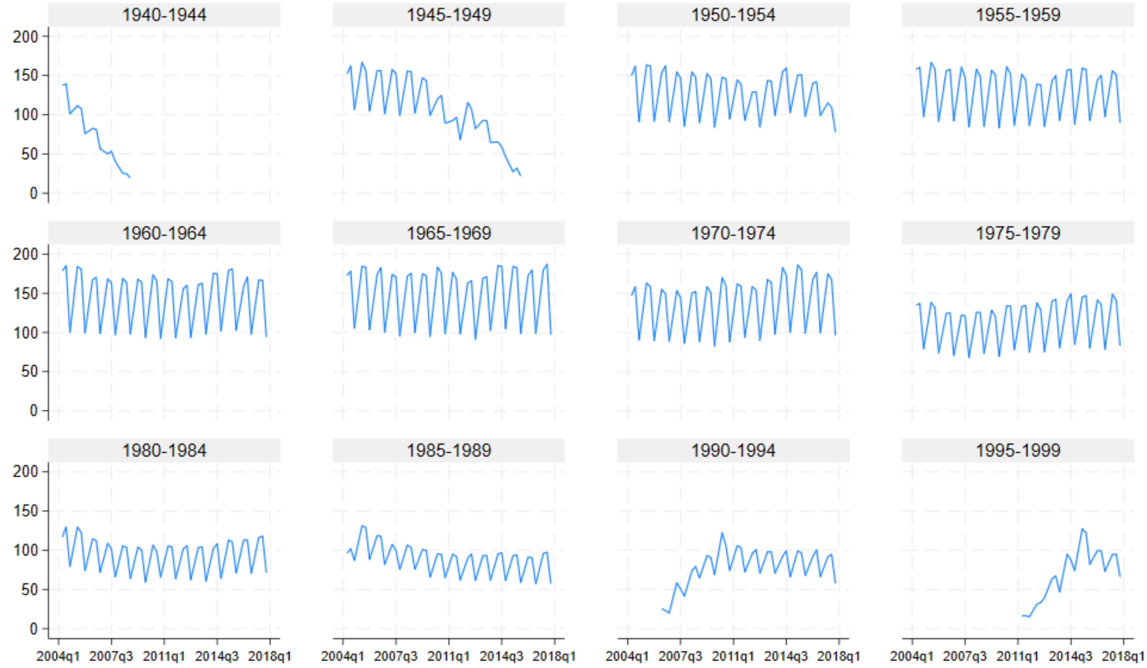
Source: authors' elaboration using IT-LFS data

Table A3. Marginal effects from probit model in Column 3, Table 4

	Margin	Delta-method std. err.	z	P>z	[95% conf. interval]	
At day:						
1	0.047164	0.000391	120.78	0	0.046399	0.047929
2	0.045249	0.00078	58	0	0.04372	0.046778
3	0.043396	0.001578	27.51	0	0.040304	0.046489
4	0.041606	0.002347	17.73	0	0.037007	0.046205
5	0.039875	0.003066	13	0	0.033865	0.045885
6	0.038204	0.003735	10.23	0	0.030883	0.045525
7	0.03659	0.004354	8.4	0	0.028056	0.045124
8	0.035033	0.004924	7.11	0	0.025381	0.044684
9	0.03353	0.005447	6.16	0	0.022854	0.044206
10	0.032081	0.005925	5.41	0	0.020468	0.043693
11	0.030684	0.006359	4.83	0	0.01822	0.043147
12	0.029337	0.006752	4.35	0	0.016105	0.04257
13	0.02804	0.007104	3.95	0	0.014117	0.041964
14	0.026792	0.007419	3.61	0	0.012251	0.041332
15	0.02559	0.007697	3.32	0.001	0.010504	0.040675

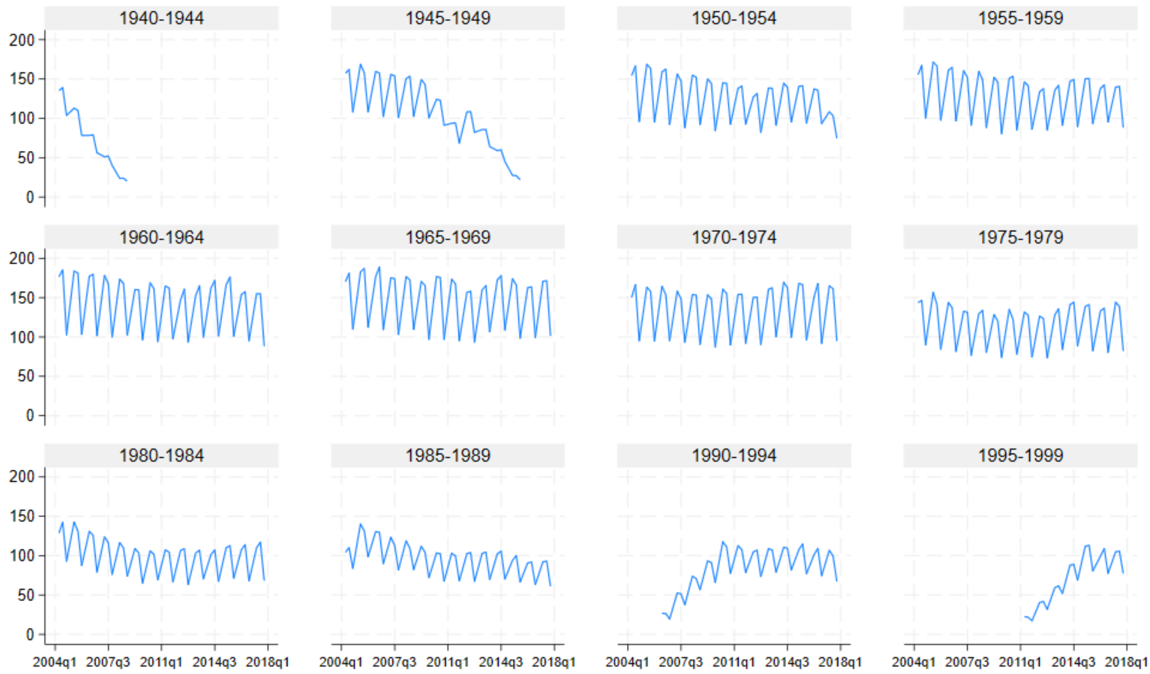
Source: authors' elaboration using IT-LFS data

Figure A1. Sample A average cohort-province cell size by cohort (2004-2017)



Notes: Y axis: average number of observations by province-cohort cells.
Source: authors' calculations using IT-LFS data

Figure A2. Sample B average cohort-province cell size by cohort (2004-2017)



Notes: Y axis: average number of observations by province-cohort cells.
Source: authors' calculations using IT-LFS data

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INAPP
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