Employment Growth, Inflation, and the Distribution of Household Labour Income *

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Research Article

Keywords: Inflation, Employment growth, Labour income, Inequality, Extensive margin, Italy

Posted Date: April 10th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9073032/v1

Additional Declarations: No competing interests reported.

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3 March 2026

Abstract

We quantify how the employment expansion accompanying Italy's post-pandemic recovery mitigated the distributional consequences of the contemporaneous surge in prices, which disproportionately affected households at the bottom of the expenditure distribution. Using linked administrative employment records and household survey and expenditure data, we examine labour income dynamics, employment transitions, differential inflation exposure, and the redistributive role of the tax–benefit system for Italian households without pension or self-employment income over 2018–2023. Despite elevated inflation, households in the lowest expenditure quintile experienced gains in real labour income, whereas those higher in the distribution did not. The decline in inequality is driven primarily by employment entry among previously non-employed household members, while adjustments among continuously employed workers played a limited role. Extensive-margin gains reflect stronger demand for low-skilled labour rather than differential labour-supply responses to inflation. Microsimulations indicate that fiscal measures cushioned disposable incomes at the bottom but did not alter the central role of employment growth in shaping distributional outcomes.

Keywords: Inflation; Employment growth; Labour income; Inequality; Extensive margin; Italy
JEL codes: D31, E24, E31, J21

*We thank participants at the AIEL conference 2025 and MEF-Fondazione Tor Vergata workshop 2026. The views expressed herein are those of the authors and do not necessarily reflect those of the Bank of Italy or INPS.

1 Introduction

Economic recoveries are rarely distributionally neutral. Whether aggregate growth translates into broad-based improvements in living standards depends on how employment adjusts and whether the recovery is accompanied by inflation. Inflationary recoveries pose a fundamental trade-off: rising prices disproportionately erode the purchasing power of poorer households, while sufficiently broad-based employment growth—operating through labour-market entry (the extensive margin) and increases in hours worked (the intensive margin)—may offset or even dominate these losses. Whether these forces reinforce or counteract each other in practice is ultimately an empirical question.

This paper studies the joint distributional effects of employment growth and inflation at the household level during Italy's post–COVID-19 recovery, a period marked by rapid job creation and a sharp inflationary surge. To isolate adjustment along these margins, we restrict our attention to households that, before the shock, are most likely to respond. We then exclude those with retirement-age members and those with self-employed members, whose incomes can more readily adjust to price changes. By jointly observing price exposure and employment transitions at the micro level, we provide direct evidence on the net welfare implications of an inflationary recovery.

We assemble a unique, integrated micro-dataset combining administrative employment records from the Italian Social Security Institute (INPS) with household information from the Survey of Income and Living Conditions (IT-SILC), complemented by detailed consumption data from the Household Budget Survey. This structure allows us to track individual labour-income dynamics and employment transitions while applying price indices specific to different consumption classes that capture heterogeneous inflation exposure. To our knowledge, few studies combine administrative labour-market data with household-level inflation exposure in this way. Related analyses typically rely on tax–benefit microsimulation models (e.g. Curci and Tomasi (2026)). While these approaches comprehensively capture a wide range of mechanisms and focus on all households, they necessarily impose behavioural and employment assumptions. By contrast, we directly observe realised employment transitions and labour-income changes during an inflationary recovery.

The motivation for this analysis builds on two well-established facts. First, recoveries differ markedly in their employment content. Output often rebounds faster than employment, giving rise to "jobless recoveries," and even when job creation occurs it may be skewed toward higher-skilled workers, limiting its equalizing potential (Gordon, 2010; Hurst and Kahn, 2023). Second, a large body of research documents substantial heterogeneity in the welfare effects of inflation across households, depending on consumption baskets and exposure to price increases (Kaplan and Schulhofer-Wohl, 2017). While this literature carefully measures differential price exposure, it typically abstracts from concurrent employment dynamics. Because low-income households devote a larger share of expenditure to non-substitutable goods such as energy and food, inflationary episodes driven by these components tend to be regressive (OECD, 2023). Crucially, however, the distributional consequences of inflation depend on its underlying drivers and the associated labour-market adjustment. Supply-driven inflation—such as that induced by energy price shocks or supply-chain disruptions—typically compresses real incomes while weakening labour demand, exacerbating losses at the bottom of the distribution. By contrast, demand-driven inflation can coincide with expanding employment and increased hours, potentially offsetting part of the regressive impact of rising prices. Rather than attempting to disentangle these shocks structurally, we study an episode in which both supply-driven inflation and expanding employment were present and assess their combined distributional implications. This distinction echoes a long-standing literature emphasizing that unemployment, rather than inflation per se, is the primary driver of income losses among poorer households (Blinder and Esaki, 1978; Blank and Blinder, 1986; Cardoso, 1992; Jäntti and Jenkins, 2010), and is formalized in more recent work highlighting the opposing distributional effects of demand- and supply-driven inflation (Furceri et al., 2018).

The post-pandemic recovery provides a particularly informative setting, as it combined historically high inflation with a rapid rebound in employment, driven by the interaction of supply disruptions, energy price shocks, and strong policy support. Italy represents a particularly informative case. Unlike the United States—where exceptionally tight labour markets during the post-pandemic recovery pushed up low-skill wages and compressed the income distribution (Autor et al., 2023)—Italy experienced rising inflation and employment without comparable labour-market tightness or strong nominal wage growth. By 2023, the price level was approximately 15 percent higher than in 2019, while nominal wages had increased by only about 5 percent. This divergence between prices and wages implies a substantial compression of real labour income in the absence of employment gains.

This setting allows us to isolate the role of employment expansion in the absence of substantial wage-driven compression. Whether job creation in this context disproportionately benefited low-expenditure households, and whether extensive-margin employment gains were sufficient to offset inflation-induced real-income losses, is therefore a priori unclear.

Our findings document an offsetting role for employment growth that qualifies the view of inflation as uniformly regressive. Although poorer households faced higher effective inflation, they benefited disproportionately from employment growth—primarily along the extensive margin. As a result, labour-income inequality declined across expenditure quintiles, and by 2023 real labour income in the bottom quintile exceeded its pre-pandemic level. When excluding individuals who entered employment after 2019, this improvement largely disappears, indicating that extensive-margin employment growth—rather than wage increases—was the primary driver of the distributional shift. Nominal wage growth remained subdued, consistent with declining real labour costs and a muted wage response to labour-market conditions in Italy (and more broadly in Europe, see Arce et al., 2024). More broadly, our results show that the distributional impact of inflation cannot be assessed independently of concurrent labour-market adjustments.[1] Importantly, we present multiple pieces of evidence supporting the hypothesis that higher inflation did not induce stronger labour-supply or job-search responses among poorer households. The employment expansion at the bottom of the expenditure distribution instead reflects favourable cyclical labour-demand conditions rather than behavioural reactions to real-income losses.

[1]While our analysis focuses on labor market adjustments, other transmission channels relevant to wealth inequality may respond heterogeneously across households in different consumption categories. For example, Pallotti et al. (2024) analyze differential effects on pensions, rental income, and asset valuations.

Last, we complement this analysis with a simulation exercise that applies the tax and social-contribution rules in force in each year to observed gross earnings, allowing us to quantify the extent to which fiscal policy mitigated real-income losses during the inflation surge. While discretionary measures substantially buffered disposable income at the bottom of the distribution, they do not overturn the central role of employment growth in explaining the observed decline in labour-income inequality.

Taken together, the evidence shows that inflation's distributional effects cannot be evaluated in isolation from labour-market dynamics. Italy's experience thus provides a benchmark for understanding how inequality evolves when inflationary pressures coincide with employment-rich but wage-moderate recoveries.

The remainder of the paper is structured as follows. Section 2 describes the data and sample construction and reports descriptive patterns by expenditure quintile. Section 3 documents the evolution of household labour income across the expenditure distribution and examines the mechanisms—extensive and intensive margins as well as wage adjustments—that account for these patterns. Section 4 describes the institutional features of wage setting in Italy and evaluates the mechanical distributional implications of contemporaneous fiscal measures during the inflation surge. Section 5 presents robustness checks, including a comparison with the EU-SILC panel. Section 6 concludes.

2 Data, Sample Construction and Descriptive Statistics

2.1 Data sources and matching

Our analysis combines three complementary data sources that together allow us to track precisely the evolution of employment, earnings, and inflation for Italian households between 2018 and 2023.

The first source consists of administrative social security contribution records from the Italian Social Security Institute (INPS), which contain complete information on employment spells, weeks worked, and earnings for all private- and public-sector employees. These records allow us to follow workers longitudinally.

To recover the household as the welfare-relevant unit, we link INPS records to the 2019 Italian wave of the EU Survey on Income and Living Conditions (IT-SILC), which refers to income year 2018. The linkage is performed using individuals' tax identification numbers (*codice fiscale*), subsequently replaced by anonymised unique identifiers. The 2019 IT-SILC sample covers 20,831 households and 43,400 individuals, 95% of whom are found in INPS records. IT-SILC provides information on household composition, demographic characteristics, and educational attainment—variables not available in INPS archives. The merged dataset tracks employment status, weeks worked, and labour income for each household member annually from 2018 to 2023.

Because IT-SILC does not report total household expenditure, we supplement it with detailed consumption information from the Household Budget Survey (HBS) through statistical matching on common covariates. The HBS is the official source used by the Italian National Statistical Office (ISTAT) to construct consumption weights for the Consumer Price Index and to compute inflation rates by expenditure quintile. Following a procedure also adopted by ISTAT (Donatiello et al., 2014), we match each IT-SILC household to the most similar HBS household to impute expenditure profiles. This approach—detailed in Donatiello et al. (2014) and described in Appendix A1—allows us to assign households to expenditure quintiles in accordance with official methodology and to assign quintile-specific price indices that capture heterogeneous inflation exposure (these indices are described in Section 2.3).

Finally, to provide complementary evidence on households' perceptions and labour-market adjustments during the inflationary episode, we use monthly inflation expectations and quarterly employment-status data from the Italian component of the Consumer Expectations Survey of the European Central Bank (CES) for October 2020–April 2024 (European Central Bank, 2026).

2.2 Sample construction and restrictions

Our baseline sample is the merged IT-SILC–INPS dataset. We treat households observed in the 2019 IT-SILC wave as fixed reference units and follow their members over time in the administrative records. This design allows us to isolate labour-market–driven changes in income by holding household composition constant. The corresponding loss of genuine demographic transitions is consistent with our focus on labour-market rather than demographic adjustments.

We then impose the following sample restrictions. First, we exclude all households with at least one member who is ever observed as self-employed between 2018 and 2023, either according to self-reported employment status in IT-SILC or INPS contribution records. Self-employment income is often subject to strategic under-reporting and is exposed to inflation shocks in a different way, as the self-employed can more easily pass cost increases on to consumers. This restriction removes 3,402 of households and 8,642 of individuals from the initial IT-SILC-INPS match.

Second, we exclude all households with any member receiving a public pension (retirement, disability, or invalidity) during 2018–2023. Pension benefits in Italy are largely indexed to inflation, which limits their relevance for analysing labour-market adjustments.[2] This restriction further removes 10,428 households and 19,099 individuals.

Third, to avoid households whose behaviour is dominated by retirement decisions, we further exclude all households with at least one member aged 58 or older in 2019. This ensures that we follow a cohort of prime-age workers well below the minimum eligibility age for retirement. This restriction removes a further 634 households and 1,094 individuals.

Finally, we exclude the 0.3% of remaining observations corresponding to individuals who die between 2018 and 2023. The resulting sample includes 5,850 households and 12,445 individuals observed annually from 2018 to 2023.[3]

[2] We identify pensioners by linking IT-SILC household members to INPS pension archives.

[3] Appendix A2 compares the restricted sample with the full IT-SILC–INPS match and assesses representativeness.

2.3 Inflation exposure and key variables

To quantify heterogeneous inflation exposure, we sort households into expenditure quintiles using consumption profiles imputed from the HBS. The imputed consumption baskets—constructed from COICOP categories[4]—allow us to recover household-specific spending shares and locate each household within the national expenditure distribution. Because ISTAT publishes consumer price indices separately for each expenditure quintile, reflecting systematic differences in consumption patterns (e.g., higher energy and food shares at the bottom of the distribution), we assign to each household the CPI inflation rate corresponding to its quintile.

Figure 1 shows that inflation was low and broadly uniform across the consumption distribution through 2020, but diverged sharply from mid-2021 onwards. By 2023, cumulative inflation since 2018 reached approximately 22.5% for households in the bottom quintile compared with about 16% for those in the top quintile.

Our main outcomes are individual annual labour income, measured from INPS contribution records as total earnings subject to social security contributions. This includes wages and salaries from dependent employment and income received while participating in work-sharing or partial-unemployment schemes or during sickness spells; it excludes transfers unrelated to work (income support, maternity benefits), all self-employment income, and all pension income. Unless otherwise stated, *nominal* income refers to gross annual labour income before employee social security contributions.

To account for heterogeneous exposure to inflation, we deflate nominal income using expenditure-quintile-specific price indices (base year 2018). We also compute weekly wages—defined as annual labour income divided by weeks worked—to capture adjustments along the intensive margin and in wage rates. For part-time, domestic, and public-sector workers, weeks are adjusted using contract information or sector-specific rules to ensure comparability across jobs.[5]

[4]COICOP (Classification of Individual Consumption According to Purpose) is the international classification used by statistical agencies to organise household consumption expenditures into harmonised categories, which form the basis of CPI construction.

[5]The adjustment for part-time employment is based on matched employer-employee data and is imple-

At the household level, labour income is defined as the sum of the individual labour incomes of all household members. In order to properly compare households with different size, we equivalise household income using the Carbonaro (1985) scale.[6] Household characteristics (such as education, age, and region) are taken from the 2019 wave of IT-SILC, and refer to the household head, defined as the member with the highest labour earnings in the survey year.

2.4 Descriptive statistics

Table 1 summarises the characteristics of the final sample by expenditure quintile (observed in 2019). Clear socio-demographic gradients emerge across the distribution, in line with well-documented patterns of inequality in Italy. Lower-expenditure households are younger, less educated, larger, and disproportionately concentrated in the South (ISTAT, 2023).

In the bottom quintile, the average age of the household head is 41.7 and 46% have less than upper-secondary education; in the top quintile, the corresponding values are 42.9 years and 19%, respectively. Regional disparities are pronounced: 49% of households in the poorest quintile reside in the South, compared with only 11% in the richest quintile, with the share living in the North exhibiting the opposite gradient.

Household composition also varies systematically across quintiles. Bottom-quintile households include an average of 2.87 members, of whom 0.8 are children under 16, whereas top-quintile households average 1.62 members and 0.2 children. Despite these differences in size, the number of employed household members is broadly similar across quintiles. However, households in the lower quintiles have a larger pool of working-age individuals who are not employed. As a result, poorer households rely on a comparable number of

mented as follows. For private-sector employees, we use the number of "full-time equivalent" weeks recorded in the administrative data. For public-sector employees, the original source does not report actual hours worked but only whether the contract is part-time; we therefore treat weeks in part-time jobs as half weeks by dividing them by two. For domestic workers, hours are not available in INPS data, so we use information from the 2018 Labour Force Survey on average weekly hours and monthly wages: we multiply weeks by 0.48 when monthly income is below 900 euros and by 0.92 when monthly income is above this threshold. The 900-euro cutoff corresponds to a change in the social security contribution schedule for employers in the domestic work sector and is commonly used to distinguish low- and higher-intensity domestic jobs.

[6] Such a procedure follows the practice by ISTAT. Carbonaro (1985) scale assigns a weight of 1 to the household head, 0.7 to each additional adult, and 0.5 to each child.

earners but must spread labour income over a substantially larger number of dependents.

Consistent with these patterns, equivalised labour income rises monotonically across the expenditure distribution, from approximately €22,000 in the bottom quintile to about €51,000 in the top.[7]

Individual-level characteristics mirror these household-level gradients: individuals in higher-expenditure households are older, more educated, and more likely to be employed.

Taken together, these descriptive patterns indicate that expenditure quintiles capture economically meaningful heterogeneity along dimensions that are central to both inflation exposure and labour-market adjustment.

3 Household Labour Income by Expenditure Quintile

3.1 Average real household labour income

We now turn to labour-income dynamics during the post-pandemic recovery. Inflation and employment growth affect household labour income through distinct channels. Inflation erodes purchasing power—particularly for households with higher expenditure shares on necessities—while employment growth raises earnings through both participation and hours worked. The net effect on the distribution of real household labour income is therefore *a priori* ambiguous.

Figure 2 documents the evolution of average household labour income in nominal and real terms between 2018 and 2023 for the 1st, 3rd, and 5th expenditure quintiles.[8] Panel (a) shows a pronounced increase in nominal household labour income across the distribution. Growth was strongest in the bottom quintile, where equivalised labour income in 2023 was roughly 30% higher than in 2019, compared with gains of around 10% for middle- and upper-quintile households. Panel (b) deflates household income using quintile-specific CPIs. Once differences in inflation exposure are taken into account, the distributional pat-

[7] The last row of Panel (a) of Table 1 indicates that the proportion of households is not perfectly balanced across expenditure quintiles, with the bottom quintile being slightly over-represented (22.8%) relative to the top quintile (18.3%), possibly reflecting larger consumption for the excluded families (self-employed and older).

[8] Results for all quintiles are reported in Appendix Table A5.

tern changes substantially: despite facing the highest inflation, bottom-quintile households still recorded a 9% increase in real income relative to 2019, whereas all other quintiles experienced declines. This pattern qualifies the view of inflation as uniformly regressive and points to the central role of labour-market adjustments in shaping distributional outcomes during this period.

These distributional developments are reflected in modest but persistent changes in inequality between 2019 and 2023. The Gini index for nominal household labour income fell from 0.391 in 2019 to 0.377 in 2023 (after peaking at 0.405 in 2020; Table 2). The equalising effect is more pronounced in nominal terms but remains visible in real incomes despite the higher inflation faced by low-expenditure households. Individual-level inequality also declines, though more modestly, suggesting that the household-level improvement may reflect employment entry and income pooling rather than broad-based compression in individual wages.

3.2 Margins of labour market adjustment

To interpret the income patterns documented above, we next decompose changes in household labour income into the main margins of labour-market adjustment. Holding household composition fixed, labour income can evolve through three channels: (i) members move into or out of employment (extensive margin), (ii) employed members adjust their time spent working (weeks or hours of work; intensive margin), and (iii) wage rates change.

We examine labour-market entries and exits, which account for a substantial share of income growth at the bottom of the distribution, before considering adjustments among continuously employed workers.

Labour market entries and exits. Figure 3 plots individual employment transition rates relative to 2019. Panel (a) shows the share of individuals who were unemployed in 2019 and became employed in year t ($\pi_{U\to E}$), and Panel (b) shows the share who were employed in 2019 and became unemployed in year t ($\pi_{E\to U}$).

Transitions into employment are systematically more frequent among households at the bottom of the expenditure distribution. By 2023, 11% of individuals who were without a job in 2019 and belonged to bottom-quintile households had entered employment, compared with 8% in the third quintile and under 6% in the top quintile. By contrast, transitions out of employment display little systematic variation across quintiles.

To quantify the contribution of the extensive margin, Figure 4 reports a counterfactual series excluding income from individuals who entered employment after 2019 (Panel (a)). Relative to Figure 2b, removing entrants causes average real income to fall in all quintiles. Most notably, in the bottom quintile, the real-income gain disappears. This shows that employment growth along the extensive margin is the primary force behind the relative improvement in real income at the bottom.[9]

When recent labour-market entrants are excluded, poorer households experience real-income declines comparable to those at the top of the distribution. Since bottom expenditure quintile households face higher inflation, this pattern indicates that nominal-income growth at the bottom cannot be attributed to new employment alone. Instead, it may reflect differences in income trajectories among continuously employed individuals, as well as heterogeneity in the characteristics of exits, which are similar in incidence across quintiles. We therefore turn to the income of stayers.

Income of stayers. Panel (b) of Figure 4 focuses on household members who remained continuously employed from 2019 to 2023, allowing for job-to-job transitions but excluding labour-market entries and exits.[10] Real income trajectories are similar across quintiles implying faster nominal income growth among continuously employed individuals at the lower end of the expenditure distribution, consistent with Figure 4a. Such stronger nominal income growth may reflect either larger adjustments along the intensive margin or faster nominal wage growth. We isolate the contribution of each mechanism in Section 3.3.2.

[9]This counterfactual exercise rests on some assumptions; in particular, it assumes that the income of continuously employed members would have remained the same regardless of the labor supply of the other household members.

[10]Mechanically, because household members who experience a loss of labour income are excluded, the decline in average real income is attenuated relative to panel (a), particularly in the third quintile, where exits are more frequent (see Figure 3b).

3.3 Mechanisms behind income dynamics

In this section, we characterize the mechanisms underlying these patterns. In particular, we examine several potential explanations for the rise in entries among the poorest households: the mechanical effects of differential household size, the role of changing cyclical economic conditions, and behavioral responses to heterogeneous price dynamics. Next, we turn to nominal income growth among labor market stayers, decomposing the respective contributions of intensive-margin labor supply adjustments and changes in nominal wages.

3.3.1 Labour-market entrants and labour supply

Lower-expenditure households experienced systematically higher employment entry rates between 2019 and 2023. Interpreting these higher entry rates, however, requires caution. Households differ substantially in the number of members who were non-employed in 2019, and therefore in their scope for transition into employment. In the upper expenditure quintiles—particularly among single-person households and dual-earner couples—a large share of households had no non-employed members in 2019.[11] For these households, the probability of generating an employment entry is mechanically zero.

In addition, expenditure quintiles differ systematically in demographic composition (Table 1). Members of poorer households are, on average, younger and less educated, and therefore more exposed—and potentially more responsive—to changes in labour demand for low-skilled jobs.

As a result, the higher entry rates observed in the bottom quintile may partly reflect compositional differences rather than heterogeneous changes in job-search behaviour. To disentangle composition from behaviour, we implement a formal decomposition and subsequently test for differential labour-supply responses to inflation.

Oaxaca–Blinder framework. We decompose the differences in the proportion of entries and exits across households in different expenditure quintiles using a standard Oaxaca–

[11] Table 1 shows that the share of members with no labour income is 41% in the first quintile and 20% in the highest.

Blinder framework. For each quintile q, we estimate the following equation:

$$e_{i,q} = \beta_q^0 + \mathbf{X}_i' \boldsymbol{\beta}_q + \varepsilon_{i,q},$$

where $e_{i,q}$ is the proportion of members in household i that enter (or exit) employment between 2019 and 2023, and $\mathbf{X}_i$ includes age, education, and region of residence. Let $\pi_{e,q} \equiv E[e_{i,q}]$ denote the entry (or exit) probability for quintile q. The difference between two quintiles—say, the first and the third—can be written as:

$$\pi_{e,1} - \pi_{e,3} = \underbrace{(E[\mathbf{X}_1] - E[\mathbf{X}_3])' \boldsymbol{\beta}_3}_{\text{Explained (composition)}} + \underbrace{(\beta_1^0 - \beta_3^0) + E[\mathbf{X}_1]'(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_3)}_{\text{Unexplained (differences in conditional probabilities)}}.$$

The *explained component* captures how much of the observed gap is accounted for by differences in observable characteristics—e.g., the larger share of low-educated or Southern-resident individuals in the bottom quintile. The *unexplained component* reflects differences in job-finding (or job-loss) probabilities conditional on these characteristics, as well as residual factors not captured by observables.

Results. Table 3 reports the results of the decomposition. For employment entries (columns (1) and (2)), observable characteristics explain a substantial share of the gap between the first quintile and the middle or top quintiles—accounting for around 40% of the $U \to E$ differential between the first and third quintiles. Regional composition plays a central role: bottom-quintile households are disproportionately located in the South, the area that experienced the strongest employment growth between 2019 and 2023 (Istituto Nazionale di Statistica (ISTAT), 2024). Differences in educational attainment also contribute, as lower-educated individuals in our sample exhibited relatively higher job-finding rates over this period, consistent with the sectoral composition of the recovery.

The remaining gap is largely captured by the unexplained component. However, this component is almost entirely driven by the intercept term, which reflects baseline differences in entry probabilities rather than differential returns to observed characteristics. In practice, it captures residual factors such as the much larger pool of non-employed household members in the bottom quintile, which mechanically raises the likelihood of observing at least one employment entry. By contrast, the portion of the unexplained gap attributable to differences in coefficients is small. Conditional on age, education, and region, individuals in bottom-quintile households are not systematically more likely to find a job than observably similar individuals in higher-quintile households, thus suggesting no differential responses to heterogenous inflation exposure across observationally similar individuals.

For employment exits (columns (3) and (4)), differences across quintiles are modest and display no systematic pattern. Both the explained and unexplained components are small, indicating that heterogeneous job-loss risks played a negligible role in shaping cross-quintile differences in employment dynamics.

Taken together, the decomposition indicates that the stronger employment growth observed among bottom-quintile households is partly driven by the larger availability of non-employed workers, but a relevant contribution is due to compositional factors and exposure to more favourable cyclical conditions, rather than by intrinsically higher job-finding probabilities. Low-expenditure households benefited from having more potential entrants concentrated in segments of the labour market where demand expanded most strongly, reinforcing the role of the extensive margin in shaping the distributional consequences of the recovery.

Testing for labour-supply responses to inflation. The decomposition indicates that composition effects account for a substantial share of the higher entry rates observed among bottom-quintile households, with little residual heterogeneity once observed characteristics are controlled for. However, the unexplained component may still reflect differential job-search responses. We therefore examine this channel using two complementary approaches. While not fully causal but primarily suggestive, the evidence consistently point to limited job-search responses among non-employed individuals exposed to heterogeneous (expected or realized) price increases.

First, we draw on external evidence from the Consumer Expectations Survey (CES), which provides nationally representative information on inflation expectations and self-reported job-search activity. Following Pilossoph and Ryngaert (2024), we estimate individual fixed-effects regressions relating job search to inflation expectations and their interaction with non-employment status. Across all specifications—including those interacting inflation expectations with CES-based expenditure quintiles—we find no evidence that higher expected inflation increased job-search activity among the non-employed. If anything, the interaction estimates are slightly negative for low-expenditure households.[12]

Second, we turn to the IT-SILC–INPS dataset and exploit heterogeneity in automatic wage indexation across sectors. Workers in the metalworking and wood industries—covering roughly 15% of all dependent employees—receive contractual wage adjustments mechanically linked to past inflation and therefore experienced smaller real-income losses during the inflation surge. If inflation-induced income declines stimulated job-search effort or labour supply, households headed by non-indexed workers should exhibit larger increases in employment during the high-inflation period. A difference-in-differences specification comparing a pre-inflation year (2018) with a high-inflation year (2023) shows no such pattern: the interaction between indexation status and the post-inflation period is small and statistically insignificant.[13]

Taken together, the CES evidence and the sectoral indexation test indicate that the rise in employment rates at the bottom of the expenditure distribution was driven primarily by cyclical labour-demand conditions rather than by inflation-induced labour-supply responses.

3.3.2 Stayers

Having shown that extensive-margin adjustments largely reflect household composition and cyclical labour-market conditions—rather than heterogeneous behavioural responses—we now turn to the intensive margin. This subsection examines whether income differences across expenditure quintiles also reflect adjustments among individuals who remained con-

[12]See Appendix A3 for details.

[13]Indexation status is measured in 2021, prior to the inflation surge. See Appendix A3 for discussion and robustness checks.

tinuously employed throughout the period, including both workers who stayed with the same employer and those who experienced job-to-job transitions while remaining continuously employed.[14]

Figure 5 shows nominal household labour income among continuously employed members. As mentioned, even among stayers, income growth is stronger in the bottom quintile (15% between 2019 and 2023) than in the in the middle and top quintiles (around 11Gains are larger for job-to-job movers than for workers who remain with the same employer, consistent with higher initial wage and hours levels among non-switchers. [15]. Taken together, these patterns confirm that differences in nominal income dynamics reflect not only entry but also adjustments among the continuously employed.

To quantify the respective contributions of labour supply and wages, we conduct two counterfactual exercises. First, we fix weekly wages at their 2019 level and allow weeks worked to evolve as observed, isolating the role of the intensive labour-supply margin. Second, we fix weeks worked at their 2019 level and allow weekly wages to evolve, isolating the contribution of wage changes. Because these counterfactuals abstract from co-movements between wages and weeks, their sum does not necessarily reproduce the observed change in annual income.[16] Nevertheless, comparing the two counterfactual paths yields a transparent decomposition of labour-supply adjustments and wage contributions.

Panel (a) of Figure 5 shows that, for households in the bottom expenditure quintile, increases in weeks worked account for most of the nominal income gains in 2022 and 2023 relative to 2019. This pattern extends to the continuously employed more broadly and is especially pronounced among job switchers, who worked relatively few weeks in 2019—around 33 per year on average—but by 2023 worked close to 49 weeks, converging

[14] Job-to-job movers account for roughly 30% of the continuously employed population, with a modest gradient across the distribution, ranging from about 33% in the bottom two expenditure quintiles to around 28% in the top two.

[15] Detailed descriptive statistics for job switching and non-switching stayers are available upon request.

[16] Formally, annual income in year t can be written as $w_t y_t$, where w_t is weeks worked and y_t is weekly wage. The change between 2019 and 2023 is

$$w_{23}y_{23} - w_{19}y_{19} = w_{19}(y_{23} - y_{19}) + y_{19}(w_{23} - w_{19}) - (y_{23} - y_{19})(w_{23} - w_{19}),$$

where the first two terms correspond to the two counterfactual components plotted in the figure. The final term captures co-movements between wages and weeks, which are positive on average in our data.

to the levels of those in the top quintiles.[17] Overall, the contribution of the intensive labour-supply margin is several times larger than that of wage growth. This pattern is consistent with a reallocation from more unstable or part-time employment toward stronger labour-market attachment as cyclical conditions improved.

In the third expenditure quintile (Panel (b)), wage growth—holding weeks worked fixed—is similar to that observed at the bottom, particularly in 2023. This indicates that cross-quintile differences in nominal income growth among continuously employed households reflect primarily differential labour supply adjustments rather than heterogeneous wage dynamics.

In the top quintile (Panel (c)), wage growth contributes more relative to changes in weeks worked. As a result, insofar as wage adjustments affected the distribution of income over this period, they tended to widen rather than compress inequality.

3.4 Summary of mechanisms

Bringing the evidence together, the relative improvement in real household labour income at the bottom of the expenditure distribution is driven primarily by extensive-margin adjustments. Excluding post-2019 entrants eliminates the bottom-quintile real-income gain, confirming that employment entry among previously non-employed household members is the dominant mechanism.

Income dynamics among the continuously employed also contributed to overall changes. Nominal labour income increased within this group, driven mainly by adjustments in weeks worked rather than wage growth. Because intensive-margin dynamics are broadly similar across quintiles, they do not account for the relative improvement observed at the bottom of the distribution.

Nominal wages exhibit limited pass-through from inflation, implying a decline in real labour costs over the period. While we do not directly identify labour-demand effects, this pattern is consistent with contained real labour costs facilitated hiring and reinforcing the role of the extensive margin.

[17] Additional analyses distinguishing job stayers from job-to-job switchers are available upon request.

Understanding why wage adjustment remained muted—and how policy intervened to cushion its distributional consequences—requires examining the institutional framework governing wage setting and the policy responses to the inflation surge.

4 Policy responses to inflation

Wage formation in Italy is shaped predominantly by national collective bargaining agreements (*CCNL*), which set contractual pay scales for broad occupational groups. These contracts are negotiated at the sectoral level and are typically renewed every three years, though in practice renewals are often delayed. As a result, nominal contractual wages may remain unchanged for extended periods, even with large macroeconomic shocks.

During the post-pandemic recovery and the inflation surge following the Russian invasion of Ukraine, heightened uncertainty over future price developments contributed to widespread delays in contract renewals. Consequently, nominal contractual wages adjusted only gradually, and their purchasing power declined markedly between 2021 and 2023. According to the ISTAT Annual Report (ISTAT, 2025), real contractual wages declined by more than ten percentage points, while actual gross hourly wages by more than 12 percent. By the end of 2025 they were still 6 pp lower than the value registered in 2019 in real terms. These institutional features provide a natural explanation for the weak wage pass-through documented in the previous sections.

To cushion the resulting decline in real earnings, the Italian Government implemented a sequence of temporary fiscal and social-contribution measures between 2021 and 2023. These included temporary cuts in employee social security contributions, the 2022 reform of the personal income tax (*IRPEF*), and the introduction of new income-dependent work deductions. In particular, the 2022 reform substantially increased work-related tax credits for low- and middle-income earners, with benefits concentrated below approximately €28,000 of annual income and phasing out at higher income levels (see Technical Appendix A4 for details).

To quantify the distributional impact of these measures, we simulate net disposable income by applying the statutory tax and contribution rules in each year to observed gross labour income. We then aggregate net incomes at the household level using the equivalence scale described in Section 2 and deflate them using expenditure-quintile-specific price indices. This exercise quantifies the extent to which the tax–benefit system buffered households against real-income losses in the presence of limited nominal wage adjustment.[18]

Figure 6 presents the results. Panel (a) shows that net nominal household income increased by about 40% for households in the bottom expenditure quintile—roughly ten percentage points more than the corresponding increase in gross income. For upper-quintile households, net income rose by about 15%, around five percentage points above gross income growth. Panel (b) shows that, after deflating by quintile-specific prices, real net income increased by roughly 12% for bottom-quintile households, while households higher in the distribution broadly preserved their 2019 purchasing power. Together with Figure 5, these results indicate that improvements in net income were not driven by wage growth but by labour-supply adjustments and fiscal transfers.

Finally, we find that because of the fiscal measures the Gini index further declined by about one percentage point with respect to gross equivalent household income. A remaining question is whether these fiscal measures also affected labour-supply behaviour at the extensive margin. We provide some suggestive evidence that this is not likely the case in Appendix A5.[19]

Taken together, these results indicate that fiscal policy substantially mitigated real-income losses—particularly at the bottom of the distribution—but does not overturn the central role of employment growth in driving the decline in labour-income inequality. Consistent with the earlier analysis, distributional improvements between 2019 and 2023 primarily reflect strong labour-demand conditions that expanded employment at the bottom of the expenditure distribution, rather than behavioural responses to fiscal incentives.

[18] We abstract from other contemporaneous interventions, such as energy subsidies and family-related policies (e.g. child-related transfers which are indexed to the official inflation rate – i.e. not adjusted for heterogeneous consumption baskets), which also supported household incomes during this period.

[19] Using CES data, we compare job-search activity among non-employed individuals with predicted incomes just above and below the eligibility thresholds for the more generous tax credits introduced in 2022. As reported in Appendix A5, we find no evidence of discontinuous changes in job-search behaviour around the reform, either in the aggregate or across expenditure quintiles.

Finally, we assess whether the documented distributional patterns are robust to alternative data sources by comparing them with newly available official panel data.

5 Robustness checks

The analysis so far relies on an integrated administrative–survey dataset that allows us to assess labour-income dynamics and policy cushioning in near real time. Its main advantage is timeliness. By linking INPS administrative records to the EU-SILC cross-section, we reconstruct the evolution of household labour income with a delay of roughly eighteen months—substantially shorter than the release lag of the official EU-SILC panel. This feature is particularly valuable for assessing thr distributional consequences of macroeconomic shocks while policy responses are still being designed and implemented.

This timeliness comes at the cost of holding household composition fixed at its 2019 level. As discussed in Section 2, this design abstracts from demographic transitions but isolates labour-market–driven income adjustments, the main focus of the paper. With the release of the official EU-SILC panel covering 2018–2023, we can now assess whether our findings hold in data that allow household composition to evolve. We therefore compare the evolution of household labour income in the IT-SILC-INPS dataset with that observed in the Italian EU-SILC panel.

Several differences between the two data sources should be noted. First, due to its rotating design, the EU-SILC panel sample is substantially smaller. Second, some labour-market categories identifiable in administrative data and that we exclude from the sample—such as quasi-self-employed workers (*parasubordinati*)—cannot be separately identified in EU-SILC.

To ensure comparability, we impose the same sample restrictions on the EU-SILC panel as in the main analysis. We retain only individuals younger than 58 in 2019, who are neither self-employed nor receiving pension income, and we exclude the entire household containing excluded members. We then construct equivalised household labour income using the same methodology described in Section 2. For comparability with the main analysis, equivalisation weights are fixed at their 2019 values in both datasets so that differences over time reflect income dynamics rather than shifts in household composition

After these restrictions, the Italian wave of the EU-SILC panel contains approximately 2,200 individuals and 700 households. Given the smaller sample size, to reduce sampling variability, we focus on the median of equivalised household labour income within each expenditure quintile.

Panel (a) of Figure 7 reports median real household labour income by expenditure quintile in the EU-SILC panel. Panel (b) shows the corresponding series from the IT–SILC-INPS dataset.

The comparison confirms the robustness of our findings. In both datasets, bottom-quintile households experience real income growth between 2019 and 2023, while upper-quintile households record flat or declining real incomes. Although the EU-SILC series are noisier—reflecting the smaller sample size—the qualitative pattern is similar.

These results indicate that the decline in household labour-income inequality documented in Section 3 is not an artefact of the IT–SILC-INPS construction or of the assumption of fixed household composition. Rather, it reflects a genuine feature of the Italian post-pandemic recovery that becomes visible—albeit with greater noise—once official panel data are released.[20]

Overall, the robustness exercise supports the validity of our approach and shows that the administrative–survey integration adopted in this paper provides a timely and accurate picture of distributional dynamics later confirmed in official statistics.

6 Conclusion

This paper studies how inflation and employment growth jointly shaped the distribution of labour income during Italy's post-pandemic recovery. The period combined three salient developments: a rapid rebound in employment, a sharp increase in prices that dispro-

[20]Using EU-SILC panel weights (`db095`) leads to a uniform decline in labour income across the distribution, but the drop remains markedly smaller for households in the bottom quintile.

portionately affected low-income households, and diverging distributional signals across inequality measures. While wage inequality rose during the pandemic and receded only gradually thereafter, inequality in household labour income declined modestly but persistently between 2018 and 2023, with gains concentrated at the bottom of the distribution.

We show that this decline in household income inequality is driven primarily by employment growth along the extensive margin. Households in the lower expenditure quintiles benefited disproportionately from labour-market entry among members who were non-employed before the pandemic. Excluding these entrants eliminates the relative improvement at the bottom of the distribution. By contrast, adjustments among the continuously employed—changes in weeks worked and wages—played a secondary and largely distribution-neutral role once heterogeneous inflation exposure is accounted for.

We find no evidence that higher inflation induced stronger labour-supply or job-search responses among poorer households. Rather, employment expansion reflects favourable cyclical labour-demand conditions in a context of contained nominal wage growth and declining real labour costs. While we do not take a structural stance on causality, the evidence indicates that the post-pandemic decline in household labour-income inequality in Italy was driven primarily by macroeconomic conditions that facilitated job creation, rather than by behavioural responses to real-income losses.

These findings underscore the importance of measuring inequality at the household level and of explicitly accounting for employment adjustments when assessing the distributional consequences of inflation. Even in labour markets with only moderate tightness, broad-based employment growth can offset—and in some cases reverse—the regressive effects of rising prices. At the same time, these gains may prove fragile: if labour demand weakens before real wages recover, the recent improvement in household income distribution could dissipate.

More broadly, our results highlight the need to integrate labour-market dynamics into analyses of inflation and inequality. Frameworks that abstract from employment adjustments risk overstating the regressive impact of inflation and overlooking key mechanisms through which macroeconomic recoveries shape distributional outcomes.

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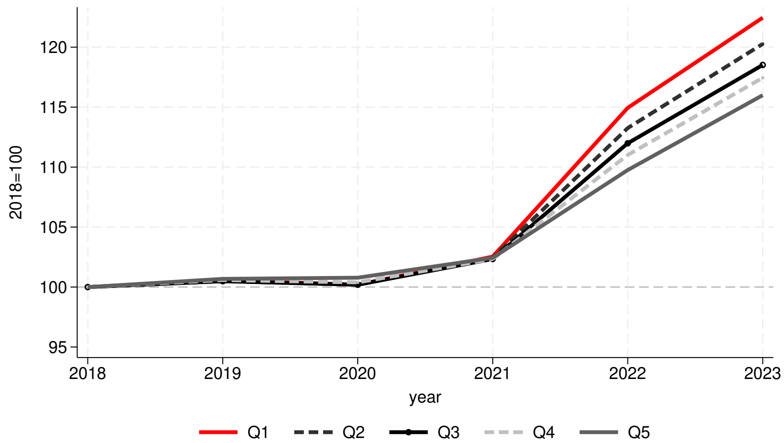
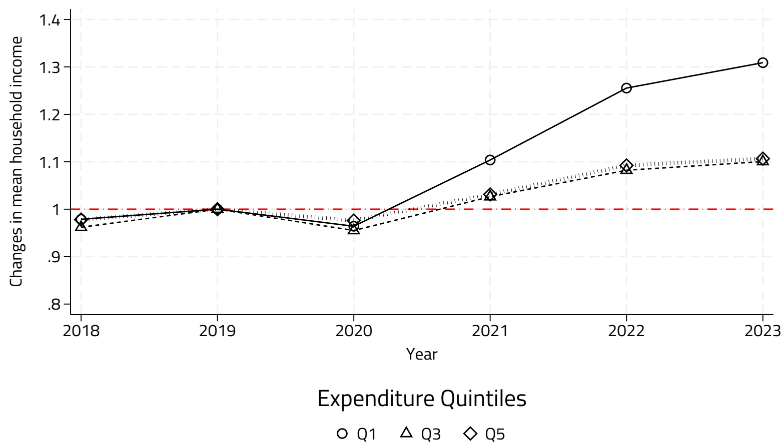
Figure 1: Cumulative inflation rate (%) between 2018 and 2023 by expenditure quintile



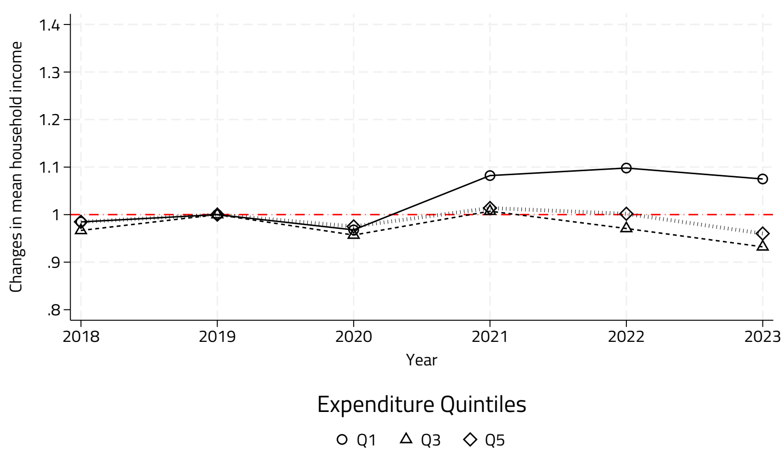
Notes: Authors' calculations based on harmonized consumer price indices (IPCA), computed separately by expenditure quintile (Istituto Nazionale di Statistica (ISTAT), 2025).

Figure 2: Changes in nominal and real household labour income, by expenditure quintile

(a) Nominal



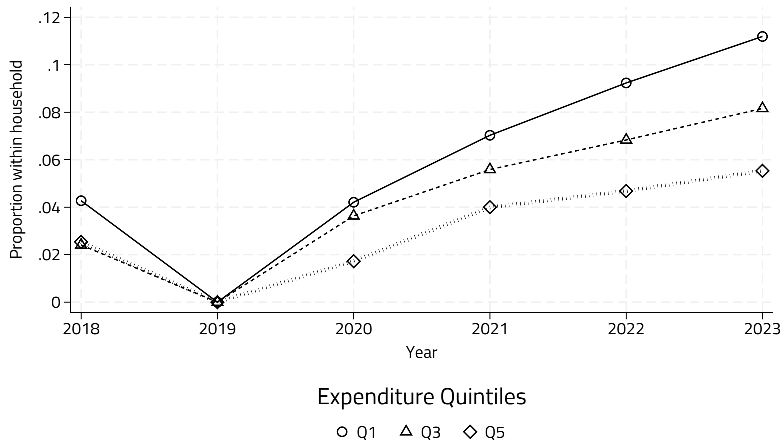
(b) Real



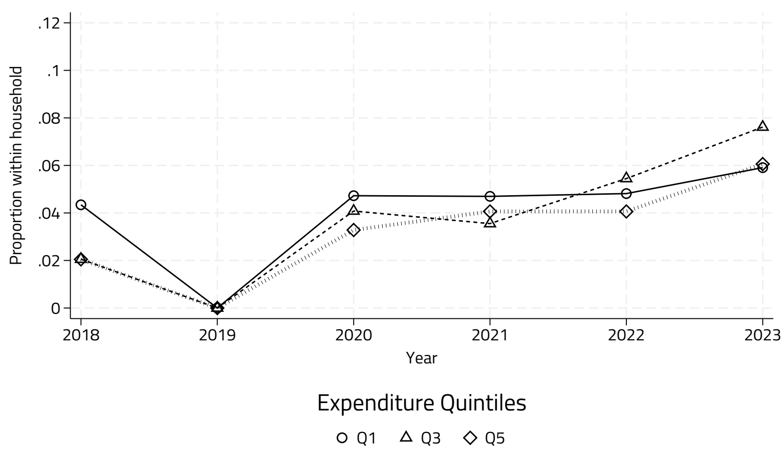
Notes: All series are expressed relative to 2019. Household labour income is equivalized using the Carbonaro scale (Carbonaro, 1985). Weighted by the use of IT-SILC cross-section weight of 2019.

Figure 3: Employment transitions relative to 2019, by year

(a) π_{U-E}: share of 2019 unemployed who become employed



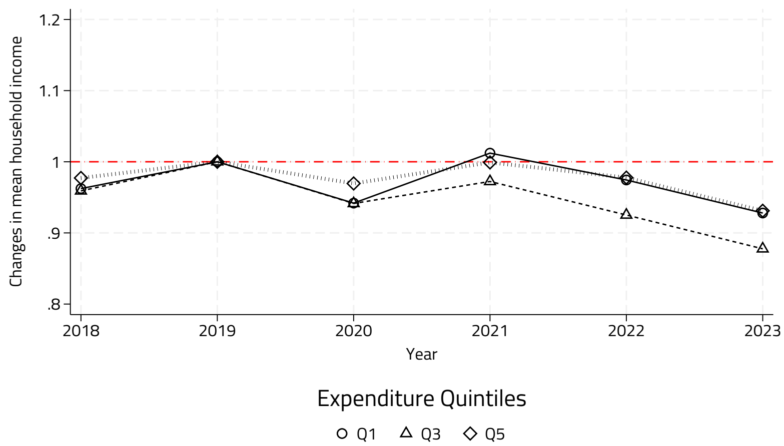
(b) π_{E-U}: share of 2019 employed who become unemployed



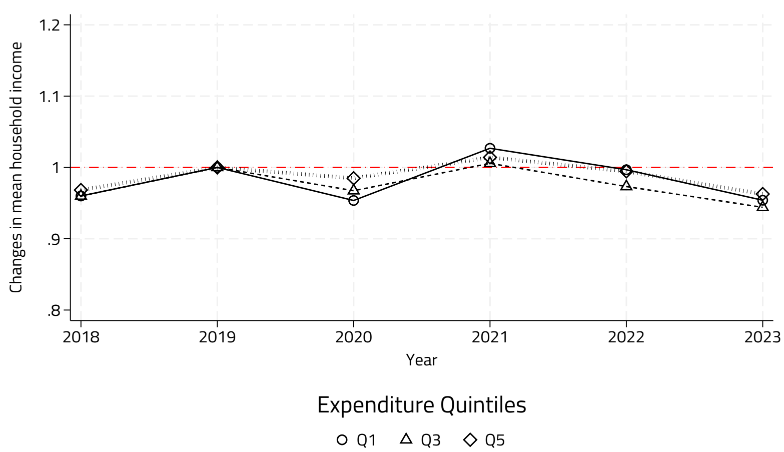
Notes: Panel (a) plots the share of household members who were unemployed in 2019 and become employed. Panel (b) plots the share of household members who were employed in 2019 and become unemployed. Weighted by the use of IT-SILC cross-section weight of 2019.

Figure 4: Decomposition of changes in real household labor income

(a) Excluding U-E



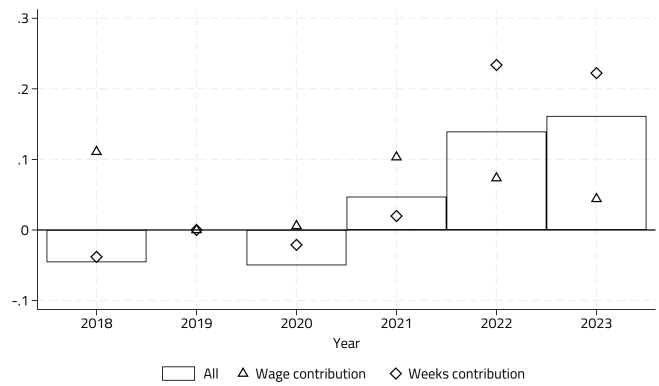
(b) Including only stayers



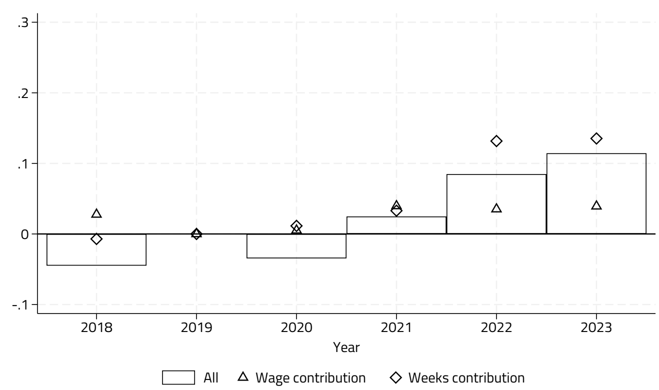
Notes: Panel (a) reproduces the changes in real income shown in panel (b) of Figure 2. Panel (b) excludes individuals unemployed in 2019 who are employed in another year of the observation period. Panel (c) reports changes in real income for individuals employed throughout the observation period. Weighted by the use of IT-SILC cross-section weight of 2019.

Figure 5: Decomposition of nominal household income growth for stayers: weeks worked vs. weekly wages

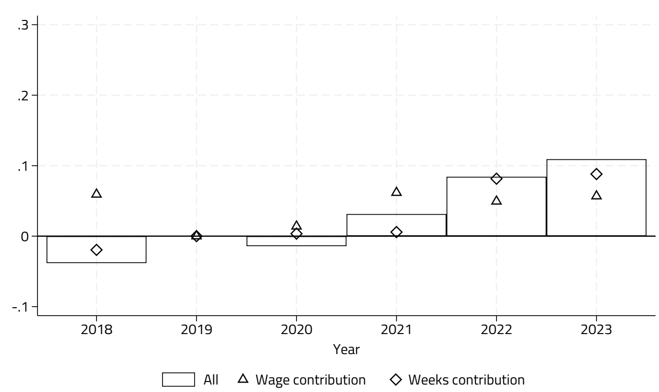
(a) 1^{st} Quintile



(b) 3^{rd} Quintile



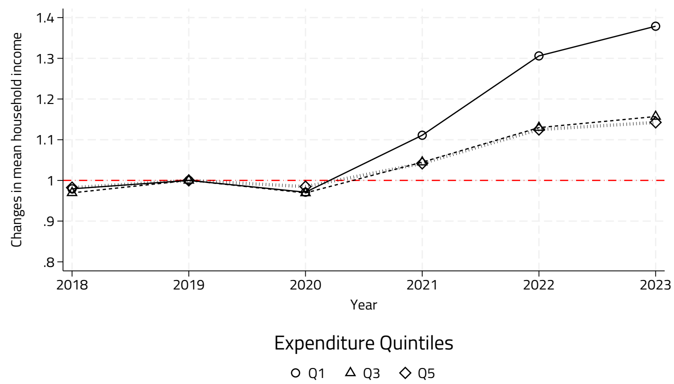
(c) 5^{th} Quintile



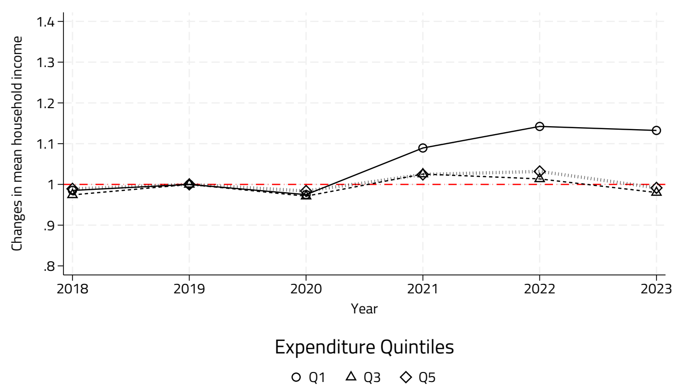
Notes: The figure shows the contribution of changes in weeks worked (holding weekly wages fixed at their 2019 level) and of changes in weekly wages (holding weeks worked fixed at their 2019 level) to the evolution of nominal household labour income for individuals continuously employed ("stayers"). Stayers include job-to-job movers. The reference year for all changes is 2019. The two components do not add up to total income growth because co-movements between weeks and wages are omitted. Weighted by the use of IT-SILC cross-section weight of 2019.

Figure 6: Impact of tax and contribution reforms on net household labour income

(a) Nominal net income



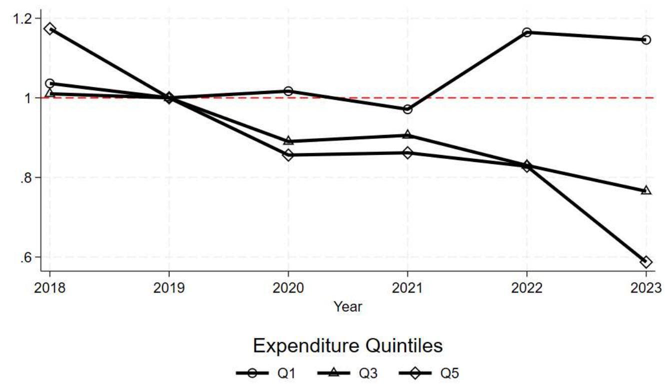
(b) Real net income



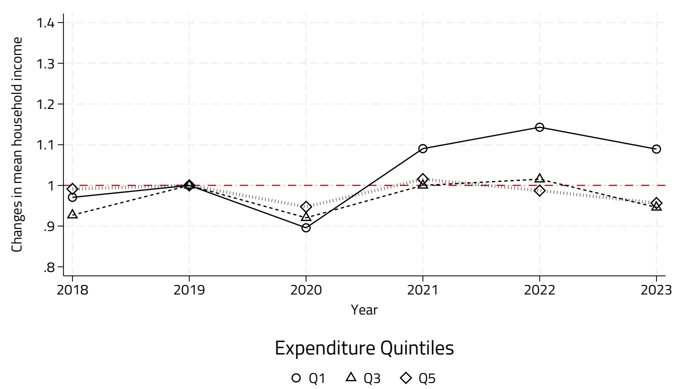
Notes: Net income is computed by applying the tax and social–contribution rules in place in each year to individual gross earnings from the INPS archives, aggregated to the household level using the SILC-INPS sample. The reference year for all changes is 2019. Weighted by the use of IT-SILC cross-section weight of 2019.

Figure 7: Robustness check: median real equivalent household labour income in IT-SILC panel and SILC-INPS, 2018–2023.

(a) IT-SILC: median values by fifth of expenditure



(b) SILC-INPS: median values by fifth of expenditure



Notes: The figures report median real equivalent household labour incomes. In both sources we apply the same sample restrictions as in the main analysis: we exclude self-employed individuals, pension recipients, and households with at least one member aged 58 or older in 2019.

Table 1: Descriptive statistics by expenditure quintile

	Q1	Q2	Q3	Q4	Q5	Total
Panel (a). Household (HH) level						
HH head: Female	0.33	0.34	0.31	0.35	0.34	0.33
HH head: Age	41.71	42.40	42.44	42.57	42.94	42.38
HH head: Education						
Lower secondary	0.46	0.37	0.29	0.24	0.19	0.32
Higher secondary	0.42	0.45	0.50	0.51	0.47	0.47
Tertiary	0.11	0.18	0.21	0.25	0.34	0.21
Region						
North	0.28	0.37	0.45	0.48	0.54	0.42
Center	0.21	0.27	0.29	0.35	0.34	0.29
South	0.49	0.33	0.23	0.15	0.11	0.27
HH structure						
HH members	2.87	2.65	2.38	2.16	1.62	2.36
Children<16	0.80	0.69	0.52	0.37	0.20	0.53
Employment (2018)						
Employed HH members	1.23	1.31	1.33	1.32	1.14	1.27
Equivalent annual income (2018)						
Euros	21,630	27,944	35,977	39,996	50,948	34,726

	Q1	Q2	Q3	Q4	Q5	Total
Panel (b). Individual level						
Female	0.51	0.50	0.48	0.50	0.45	0.49
Age	29.79	30.46	32.30	33.95	37.37	32.12
Education						
Lower sec. educ.	0.49	0.37	0.32	0.27	0.20	0.35
High sec.	0.41	0.47	0.48	0.50	0.48	0.46
Tertiary educ.	0.10	0.16	0.20	0.23	0.32	0.19
Region						
North	0.25	0.37	0.44	0.49	0.55	0.40
Center	0.20	0.25	0.30	0.34	0.33	0.28
South	0.53	0.35	0.23	0.14	0.12	0.30
Individual income (2018)						
Euros	18,280	22,163	25,888	27,024	32,014	24,670
Proportion with zero income	0.41	0.33	0.28	0.26	0.20	0.31

Note: Sample size: 5,850 households and 12,445 individuals. Panel (b) includes only indivduals aged 16 or older. Weighted by the use of IT-SILC cross-section weight of 2019.

Table 2: Gini index for households and individuals (nominal and real labour income, 2018–2023)

	Households (1)		Individuals	
	Nominal	Real (2)	Nominal	Real (2)
2018	0.393	0.393	0.393	0.393
2019	0.391	0.391	0.397	0.397
2020	0.405	0.405	0.417	0.417
2021	0.393	0.393	0.406	0.406
2022	0.380	0.383	0.391	0.393
2023	0.377	0.381	0.389	0.392
diff. 2018–2023	-0.017	-0.013	-0.004	-0.002

Source: SILC-INPS dataset. *Notes:* (1) Values are expressed in equivalent terms. (2) Real values are computed using household-specific inflation rates. Base year: 2018.

Table 3: Oaxaca-Blinder decomposition of differences in the proportion of entry and exit rates across quintiles

	(1)	(2)	(3)	(4)
	Entries (π_{U-E})		Exits (π_{E-U})	
	Q1-Q3	Q1-Q5	Q1-Q3	Q1-Q5
Difference	0.035***	0.059***	-0.017*	0.006
	(0.009)	(0.009)	(0.010)	(0.009)
Explained	0.015***	0.024**	-0.001	0.005
	(0.004)	(0.007)	(0.005)	(0.008)
Unexplained	0.019*	0.035**	-0.016	0.001
	(0.010)	(0.011)	(0.011)	(0.013)
Explained Component				
Southern Regions	0.011**	0.022**	-0.002	-0.005
	(0.004)	(0.007)	(0.004)	(0.008)
No-University	0.004**	0.002	0.001	0.009**
	(0.002)	(0.003)	(0.002)	(0.003)
Under-35	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Unexplained Component				
Southern Regions	0.002	-0.005	0.014	0.016
	(0.010)	(0.011)	(0.011)	(0.012)
No-University	-0.033	-0.006	-0.021	-0.047*
	(0.024)	(0.023)	(0.025)	(0.023)
Under-35	0.002	0.005	0.001	0.007
	(0.005)	(0.005)	(0.006)	(0.005)
Constant	0.048*	0.042*	-0.010	0.026
	(0.026)	(0.024)	(0.026)	(0.024)

Notes: Entries denotes the proportion of household members without a job in 2019 who are employed in 2023. *Exits* denotes the proportion of household members employed in 2019 who are not working in 2023. Columns (1) and (3) report differences between households in the third expenditure quintile and those in the first expenditure quintile. Columns (2) and (4) report differences between households in the fifth expenditure quintile and those in the first expenditure quintile. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix

A1 Statistical Matching Between SILC and HBS

This appendix describes the procedure used to impute household expenditure and consumption baskets from the Household Budget Survey (HBS) to households in the Survey of Income and Living Conditions (IT-SILC). The matching follows the methodology of Donatiello et al. (2014) (developed and used by ISTAT) and is implemented using nearest-neighbour matching based on the Mahalanobis distance.

A1.1 Rationale

IT-SILC provides detailed information on household composition, demographics, labour income and other socio-economic characteristics, but it does not contain a measure of total household expenditure. To assign households to expenditure quintiles and compute household-level inflation exposure, we use the HBS as a donor dataset and statistically match each SILC household to a similar HBS household. This yields an imputed value of total expenditure and an associated consumption basket for each SILC household.

The matching is methodologically sound because: (i) both SILC and HBS are conducted by ISTAT, (ii) they refer to the same target population of private households, and (iii) they share several harmonised variables suitable for donor–recipient matching.

A1.2 Matching Variables

The matching is performed at the household level. Following Donatiello et al. (2014), we use a set of five variables that are common to both surveys and strongly predictive of household consumption:

1. **Household size**: categorised as single person; two persons; and three or more persons.
2. **Geographical macro-area**: North-West, North-East, Centre, South and Islands.

3. **Homeownership status**: indicator for owning the main residence.

4. **Household income decile**: collected with different levels of detail in SILC and HBS; definitions are harmonised by exploiting the richer income information available in the HBS income section to minimise discrepancies.

5. **Food expenditure**: household expenditure on food items, available in both datasets.

These variables jointly capture size, location, income, housing status, and basic consumption patterns, which correspond to the core determinants of household expenditure.

A1.3 Matching Procedure

We use the HBS as the donor dataset and SILC as the recipient dataset. The matching steps are:

1. Standardise the five matching variables across the two surveys.

2. Compute the Mahalanobis distance between each SILC household and each HBS household.

3. For each SILC household, select the nearest HBS neighbour (with replacement) as the donor household.

4. Impute from the donor the total household expenditure, which can then be divided in the expenditure quintiles.

The matching is carried out on approximately 4,000 HBS households and 20,351 SILC households.

A1.4 Output of the Matching

The procedure yields, for each SILC household an imputed level of total expenditure and the corresponding expenditure quintile, used in the main text to assign household-specific inflation rates.

Figure A1 compares the distribution of household expenditure in the HBS with the corresponding imputed distribution in SILC, showing close alignment between the donor and recipient datasets. Table A1 summarises the two distributions. .

A2 Unrestricted vs. restricted IT-SILC-INPS dataset

Table A2 compares the sample obtained from the IT-SILC–INPS match with the sample used in the analysis after applying the restrictions described in Section 2. The restricted sample is younger, exhibits higher employment intensity, and includes fewer households located in the South, reflecting the exclusion of pensioners and self-employed households. Importantly, however, the main gradients in age, education, and regional location remain intact, indicating that the restricted sample preserves the key socio-economic structure of the Italian population relevant for analysing labour-market-driven income dynamics.

We further assess representativeness by comparing individual labour incomes in 2018 from the matched IT-SILC–INPS sample used in the analysis with those of a 13% random sample of the population of all employees drawn directly from INPS administrative archives.

Columns (1)–(2) of Panel (a) in Table A3 show that IT-SILC closely matches the INPS population: mean income amounts to 23,200 versus 23,500 euros, the p90/p10 ratio is approximately 12 in both samples, and the Gini index ranges between 0.42 and 0.43.

After excluding the self-employed (columns (3)–(4)), the matched IT–SILC-INPS sample continues to resemble the population, with a slight increase in mean income and dispersion. Further excluding households with pensioners and members aged 58 and above shifts the income distribution modestly to the right and reduces inequality. Panel (b) shows the p90/p10 ratio declining from 12.7 to 10.3 and the Gini index falling by about 0.10. Weekly wages in the restricted sample are less dispersed than annual income, with a Gini coefficient of 0.28, consistent with the prevalence of part-time and part-year employment (Depalo and Lattanzio, 2025).

Panel (c) reports analogous patterns at the household level. Mean equivalised household labour income increases from 30,600 to 34,700 euros as the restrictions are applied, while the Gini index declines from 0.45 to 0.39 and the share of households with no labour income falls from 51% to 14%. Overall, the restrictions slightly raise average income and compress the lower tail of the distribution, while leaving the main features of the Italian labour-income distribution broadly intact.

A3 Testing for Labour-Supply Responses to Inflation

This appendix provides the empirical details underlying the analysis of whether inflation induces additional job-search effort or labour supply. We use two complementary approaches: (i) fixed-effects regressions using the ECB Consumer Expectations Survey (CES), and (ii) a difference-in-differences analysis exploiting heterogeneity in contractual wage indexation across sectors within the SILC-INPS data.

A. Evidence from the Consumer Expectations Survey The CES provides nationally representative quarterly data on inflation expectations and job-search behaviour. Although it does not cover the same individuals as the IT-SILC-INPS sample, it offers useful external evidence on whether job-search activity responds to changes in inflation expectations, especially for individuals in low-expenditure households.

We follow Pilossoph and Ryngaert (2024) and estimate individual fixed-effects regressions of the form:

$$js_{i,t} = \alpha_0 + \alpha_1 Exp_{i,t} + \alpha_2 NonEmpl_{i,t} + \alpha_3 Exp_{i,t} \times NonEmpl_{i,t} + \alpha_4 age_{i,t} + \gamma_i + \gamma_t + \varepsilon_{i,t}.$$

where $js_{i,t}$ is an indicator for whether individual i reports active job search in quarter t; $Exp_{i,t}$ captures inflation expectations, measured either continuously or as a dummy equal to one if the respondent expects prices to increase over the next 12 months; $NonEmpl_{i,t}$ is a dummy for non-employment; $age_{i,t}$ controls for age; and γ_i and γ_t denote individual and time fixed effects.

We exclude respondents with extreme inflation expectations (top and bottom 1% of the distribution). Individual fixed effects restrict identification to within-person variation over time as individuals transition between employment and non-employment; approximately 12% of respondents experience at least one such transition over the sample period (October 2020–April 2024). In additional specifications, we interact inflation expectations and non-employment status with expenditure-quintile dummies constructed from CES expenditure information.

CES Results Panel (a) of Table A4 reports the coefficient on the interaction term α_3 and its quintile-specific variants. Across all specifications, we find no evidence that higher inflation expectations increase job-search activity among non-employed individuals. If anything, the interaction terms are negative for low-expenditure households. For example, in the specification using a dummy for inflation expectations, expecting a generalised increase in prices reduces the probability of active job search among non-employed individuals in the lowest expenditure quintile by 4.6 percentage points (about 7% of a 68 p.p. baseline).[1]

B. Evidence from automatic wage indexation in INPS–SILC We next examine whether differential exposure to real-wage losses translated into differential employment outcomes within the IT-SILC-INPS data. Under current sectoral agreements, workers in the metalworking and wood industries—covering roughly 15% of dependent employees receive contractual wage adjustments mechanically linked to past inflation. As a result, these workers experienced smaller declines in real wages during the inflation surge.

We classify households according to whether the household head worked in an indexed sector in 2021, prior to the onset of high inflation. If inflation-induced income losses stimulated job-search effort or labour supply, employment growth during the inflationary period should have been stronger among non-indexed households.

To test this hypothesis, we estimate a difference-in-differences model comparing a low-inflation year (2018) with a high-inflation year (2023):

$$empl_{i,t} = \beta_0 + \beta_1 Index_i + \beta_2 y2023_t + \beta_3 Index_i \times y2023_t + \beta_4 \mathbf{X_{i,t}} + u_{i,t}, \qquad (1)$$

where $empl_{i,t}$ is an indicator for employment, $Index_i$ denotes whether the household head is employed in an indexed sector, $y2023_t$ is a dummy for the high-inflation year, and $\mathbf{X_{i,t}}$ includes controls for age, education, and region. In additional specifications, all regressors are interacted with expenditure-quintile dummies.

[1] By contrast, the coefficient α_1 on inflation expectations alone is typically positive and significant, consistent with patterns documented by Pilossoph and Ryngaert (2024).

Indexation results. Panel (b) of Table A4 reports estimates of β_3. The interaction between indexation status and the high-inflation period is small and statistically insignificant across the distribution, including for households in the lowest expenditure quintile. This indicates that greater exposure to real-wage erosion did not translate into higher employment probabilities.

Summary. Taken together, the CES evidence and the sectoral indexation analysis provide no support for the hypothesis that inflation-induced real-income losses triggered stronger labour-supply or job-search responses among low-expenditure households. Instead, the rise in employment rates documented in the main text appears to have been driven primarily by cyclical labour-demand conditions rather than behavioural responses to inflation. This interpretation is consistent with recent work emphasising the dominant role of demand-driven recoveries in shaping post-pandemic labour-market outcomes (Michaillat and Saez, 2021; Balleer et al., 2020).

A4 Main Government Interventions Reducing the Tax Burden on Low-Income Earners

Since 2020, a series of policy interventions has aimed to reduce the effective tax burden on low- and middle-income workers in Italy. We focus on measures affecting income until 2023. These measures combine changes to personal income taxation (IRPEF), reductions in payroll taxes, and enhanced deductions and allowances. Below, we summarize the main reforms implemented between 2020 and 2023 and describe how they are incorporated into our analysis.

Year / Law	Measure	Description and Impact
2020	Introduction of "bonus contributivo" (Law 21/2020)	A permanent reduction in employee social security contributions for earnings up to approximately €40,000. Initially implemented as a monthly benefit of about €80–100, it was later progressively replaced by new tax credits, reducing the effective contribution rate for low-income employees.
2021	Extension of payroll tax cuts	Additional temporary reductions in employee social security contributions (by 2–3 percentage points) for low-income workers, extended multiple times during the COVID-19 recovery period.
2022	Comprehensive IRPEF reform (Budget Law 2022)	A reduction in the number of income tax brackets from five to four, together with lower marginal rates in the second and third brackets (from 27% to 25% and from 38% to 35%), thereby reducing the average tax burden on middle- and lower-income earners.
2022-2023	New tax credits and enhanced work-related deductions	Replacement of the former "bonus Renzi" with an integrated system of employee tax deductions, increasing net disposable income for earnings up to approximately €28,000 per year.

To estimate net income, the measures described above are implemented as changes to the following parameters:

- **Social contribution rate**: reduced by 2–7 percentage points, depending on income level and year.

- **IRPEF schedule**: updated bracket thresholds and marginal tax rates in line with the 2022 reform.
- **Tax credits and deductions**: introduction of income-dependent work-related deductions replacing the former "bonus Renzi", coded as piecewise functions by income bracket.

Finally, when applying the contribution schedules, we also account for the annual *INPS* contribution ceilings (*massimali contributivi*) in force in each year. These ceilings vary by worker category and determine the upper limit of earnings subject to social security contributions. By incorporating year-specific thresholds, the simulation accurately reflects the effective contribution burden faced by employees in each period.

A5 Job Search Behavior and Government Interventions

We investigate whether the policies introduced by the government in 2022 impacted job search behavior of non-employed individuals using CES data. In particular, we select all unemployed individuals from the 13 quarterly surveys conducted between January 2021 and April 2024. For them we recover their search behavior through the answer to the question "Are you currently actively looking for a job?". We exploit a dummy ($js_{i,t}$) which is 1 if they answer positively to this question and we relate this to the predicted probability that their income falls within a bracket of 15,000 and 28,000 euros per year. Workers earning above 15,000 euros, in fact, receive a tax deduction of 3,100 compared to a deduction of 1,800 if they earn less. Such a bonus declines progressively with incomes exceeding 28,000 euros. To predict the probability that the income of a unemployed individuals, once they find a job, falls within this bracket, we train a generalized random forest algorithm on the universe of employed workers in the same waves of the CES. The algorithm predicts such probability starting from observable characteristics such as gender, education level, region of residence, the total expenditure at the household level and the number of children aged 0-17 in the household.

We then run two specifications, where the first relates the searching behavior to the predicted probability of income falling within the specified bracket (controlling for survey wave fixed effects):

$$js_{i,t} = \alpha_0 + \alpha_1 p(y \in (15{,}000, 28{,}000)) + \gamma_t + \varepsilon_{i,t}.$$

The second specification interacts the predicted probability with a dummy indicating whether the survey was conducted in or after January 2022, thus after the policy was introduced:

$$js_{i,t} = \alpha_0 + \alpha_1 p(y \in (15{,}000, 28{,}000)) + \alpha_2 p(y \in (15{,}000, 28{,}000)) \times post2022 + \gamma_t + \varepsilon_{i,t}.$$

We then estimate the same specifications, interacting the variables of interest with dummies for household expenditure quintile.

The estimated parameters are reported in Table A6. Overall, we find little evidence of a systematic relationship between predicted income and job search behavior, either before or after 2022 (columns (1) and (2)). When examining differences across expenditure quintiles, however, the relationship appears negative in the bottom quintile, indicating that a higher probability of falling into this income bracket is associated with lower search effort. By contrast, the relationship is more positive in higher quintiles. This pattern runs counter to the hypothesis that the policy played a meaningful role in encouraging individuals from poorer households to enter the labor market. Moreover, the relationship does not change appreciably in most quintiles after 2022, suggesting that the policy had no discernible impact on job search behavior.

A6 Additional Figures and Tables

Figure A1: Comparison of household-level expenditure in the HBS sample and the corresponding imputed measure in the SILC sample

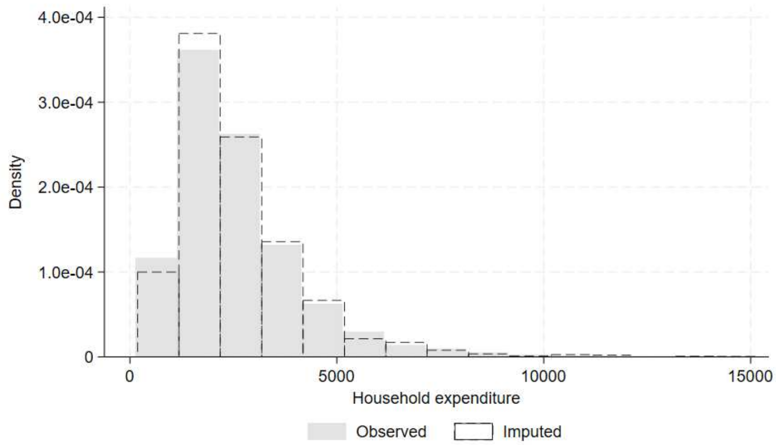


Table A1: Summary statistics of household-level expenditure expenditure (in euros)

Variable	**Mean**	**Std. Dev.**	**p10**	**p25**	**p50**	**p75**	**p90**
Observed Expenditure, HBS	2,561	1,603	1,053	1,504	2,187	3,165	4,472
Imputed Expenditure, SILC	2,845	1,613	1,073	1,469	2,079	3,002	4,240

Table A2: Descriptive statistics by expenditure quintile – Unrestricted sample

	Q1	Q2	Q3	Q4	Q5	Total
Panel (a). Household level						
Female head	0.37	0.40	0.38	0.39	0.41	0.33
Head age	52.69	54.68	55.32	55.02	56.94	42.38
Education (head)						
Lower sec. educ.	0.57	0.52	0.45	0.38	0.33	0.32
High sec.	0.32	0.34	0.38	0.41	0.40	0.47
Tertiary educ.	0.11	0.14	0.17	0.22	0.28	0.21
Region						
North	0.25	0.36	0.45	0.46	0.50	0.42
Center	0.19	0.27	0.27	0.33	0.34	0.29
South	0.53	0.34	0.26	0.18	0.15	0.27
Household structure						
HH members	2.64	2.43	2.25	2.09	1.76	2.36
Children<16	0.47	0.39	0.29	0.22	0.13	0.53
Employment (2018)						
Employed HH members	0.47	0.39	0.29	0.22	0.13	0.30
Equivalent annual income (2018)						
Euros	19,511	24,668	31,081	35,204	44,782	30,643
Share of HH (%)	20.02	20.00	19.95	20.01	20.01	100.00

	Q1	Q2	Q3	Q4	Q5	Total
Panel (b). Individual level						
Female	0.52	0.52	0.52	0.51	0.50	0.51
Age	41.27	43.65	46.16	47.16	51.34	45.46
Education						
Lower sec. educ.	0.57	0.51	0.46	0.40	0.33	0.46
High sec.	0.34	0.37	0.39	0.41	0.40	0.38
Tertiary educ.	0.10	0.13	0.16	0.19	0.26	0.16
Region						
North	0.22	0.36	0.44	0.47	0.50	0.39
Center	0.19	0.27	0.27	0.33	0.33	0.27
South	0.56	0.35	0.26	0.18	0.16	0.32
Individual income (2018)						
Euros	17,322	20,473	24,371	26,019	31,173	23,512
Proportion with zero income	0.62	0.60	0.59	0.59	0.60	0.60

Note: Sample size: 20,314 households and 41,280 individuals. Panel (b) includes only indivd-uals aged 16 or older.

Table A3: Labor income distribution in the population and the SILC-INPS sample under alternative sample restrictions

Panel (a). Individuals

	Overall		Exclude Self-employed		Exclude Self-empl. and Over 58	
	(1) Population (13% random sample)	(2) SILC-INPS sample	(3) Population (13% random sample)	(4) SILC-INPS sample	(5) Population (13% random sample)	(6) SILC-INPS sample
Average	23,534	23,246	23,781	23,592	23,192	23,642
p25	9,848	10,327	9,141	9,628	9,013	9,657
p50	19,625	19,831	20,641	21,098	20,282	21,153
p75	29,894	30,167	30,518	31,063	29,940	31,079
p90/p10	12.319	12.085	14.644	14.161	14.672	14.273
Gini	.433	.418	.442	.424	.438	.424
N	3,167,474	16,236	2,804,019	13,956	2,495,419	13,875

Panel (b). Individuals in selected households (SILC-INPS sample only)

	(1) Overall	(2) Exclude Self-employed	(3) Exclude Self-empl. and Over 58	(4) Weekly wage
Average	23,246	23,688	24,660	638
p25	10,327	10,117	11,032	412
p50	19,831	21,629	22,621	536
p75	30,167	31,389	32,434	739
p90/p10	12.085	12.724	10.269	3.037
Gini	0.418	0.410	0.397	0.284
N	16,236	11,801	7,246	6,891

Panel (c). Households (SILC-INPS sample only)

	(1) Overall	(2) Exclude Self-employed	(3) Exclude Self-empl. and Over 58
Average	30,643	31,818	34,712
p25	12,782	14,032	16,141
p50	24,243	25,992	30,129
p75	40,794	42,695	45,931
p90/p10	11.895	10.507	8.083
Gini	0.435	0.414	0.391
N	9,998	8,289	5,066

Table A4: Behavioral responses to expected real income losses

Panel (a): Job Search as a Function of Inflation Expectation

	Continuous Expectations		High vs. Low Expectations	
	(1)	(2)	(3)	(4)
Expectation	-0.001		-0.019	
× Not employed	(0.001)		(0.018)	
Q1 × Expectation		-0.002*		-0.046*
× Not employed		(0.001)		(0.025)
Q2 × Expectation		-0.003**		-0.034
× Not employed		(0.001)		(0.033)
Q3 × Expectation		0.002		0.018
× Not employed		(0.001)		(0.045)
Q4 × Expectation		-0.001		-0.036
× Not employed		(0.002)		(0.056)
Q5 × Expectation		-0.000		0.186***
× Not employed		(0.002)		(0.066)
N	38,078	38,078	38,078	38,078

Panel (b): Employment as a Function of Household Head Wage Indexation

	(1)	(2)
Indexed Wage	0.0151	0.0243
× Year 2023	(0.0256)	0.0658
Q1 × Indexed Wage		
× Year 2023		
Q2 × Indexed Wage		-0.0254
× Year 2023		(0.0981)
Q3 × Indexed Wage		0.0492
× Year 2023		(0.0806)
Q4 × Indexed Wage		-0.0412
× Year 2023		(0.0803)
Q5 × Indexed Wage		-0.0336
× Year 2023		(0.0810)
N	19,698	19,698

Notes: Panel (a) regressions include individual fixed effects, age in quarter t, and quarter of interview fixed effects. Individuals in the top and bottom 1% of the inflation expectations distribution are excluded. Panel (b) uses only 2018 and 2023 observations from our main dataset and estimates employment status on indicators for automatic inflation indexation of the household head's wage, for year 2023, and their interaction, controlling for age and including region and education fixed effects. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table A5: Changes in average equivalent household labor income, relative to 2019, by expenditure quintile

Nominal equivalent household income w.r.t. to 2019						
Exp. Quintile	2018	2019	2020	2021	2022	2023
1	0.979	1.000	0.964	1.104	1.256	1.310
2	0.971	1.000	0.960	1.052	1.127	1.182
3	0.961	1.000	0.955	1.026	1.081	1.099
4	0.971	1.000	0.959	1.035	1.129	1.169
5	0.979	1.000	0.975	1.030	1.091	1.105
Real equivalent household income w.r.t. to 2019						
Exp. Quintile	2018	2019	2020	2021	2022	2023
1	0.985	1.000	0.968	1.083	1.099	1.076
2	0.976	1.000	0.963	1.031	0.999	0.986
3	0.966	1.000	0.957	1.006	0.969	0.931
4	0.977	1.000	0.961	1.018	1.023	1.001
5	0.986	1.000	0.974	1.012	1.000	0.959

Table A6: Effect of predicted income on job search probability among unemployed individuals, January 2021-April 2024

	(1)	(2)	(3)	(4)
$p(y \in (15{,}000, 28{,}000))$	-0.084	-0.095	-0.340***	-0.506***
	(0.064)	(0.109)	(0.103)	(0.190)
$p(y \in (15{,}000, 28{,}000)) \times post2022$		0.017		0.236
		(0.134)		(0.227)
Q2 $\times p(y \in (15{,}000, 28{,}000))$			0.128	0.112
			(0.168)	(0.280)
Q3 $\times p(y \in (15{,}000, 28{,}000))$			0.541**	0.906**
			(0.214)	(0.357)
Q4 $\times p(y \in (15{,}000, 28{,}000))$			0.725***	1.476***
			(0.275)	(0.469)
Q5 $\times p(y \in (15{,}000, 28{,}000))$			0.829***	0.807*
			(0.294)	(0.489)
Q2 $\times p(y \in (15{,}000, 28{,}000)) \times post2022$				0.055
				(0.352)
Q3 $\times p(y \in (15{,}000, 28{,}000)) \times post2022$				-0.565
				(0.447)
Q4 $\times p(y \in (15{,}000, 28{,}000)) \times post2022$				-1.161**
				(0.580)
Q5 $\times p(y \in (15{,}000, 28{,}000)) \times post2022$				0.067
				(0.614)
N	3,290			

Note: The dependent variable is an indicator for actively searching for a job. The main regressor is a continuous measure of the probability that individual income falls within the €15,000–€28,000 bracket, estimated via a generalized random forest trained on employed individuals using the following set of observable characteristics: gender, education, region of residence, total household expenditure, number of children aged 0-17. All regressions include survey-wave fixed effects and baseline effects when needed (main effect of *post*2022 in column (2), of quarterly dummies in column (3) and of the interaction between the *post*2022 and quarterly dummies in column (4)). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.