



Istituto Nazionale Previdenza Sociale

gennaio 2026 – numero 111



WorkINPS *Papers*

Rigid wages? Inflation and wage growth in Italy, 1974–2024

Fabrizio Mattesini

Franco Peracchi

Jacopo Pitari

ISSN 2532 -8565

Lo scopo della serie WorkINPS papers è quello di promuovere la circolazione di documenti di lavoro prodotti da INPS o presentati da esperti indipendenti nel corso di seminari INPS, con l'obiettivo di stimolare commenti e suggerimenti.

Le opinioni espresse negli articoli sono quelle degli autori e non coinvolgono la responsabilità di INPS.

The purpose of the WorkINPS papers series is to promote the circulation of working papers prepared within INPS or presented in INPS seminars by outside experts with the aim of stimulating comments and suggestions.

The views expressed in the articles are those of the authors and do not involve the responsibility of INPS.

Responsabile Scientifico

Tommaso Nannicini

Comitato Scientifico

Vito La Monica, Tommaso Nannicini, Gianfranco Santoro.

In copertina: uno storico "Punto cliente" a Tuscania

INPS, Direzione generale, Archivio storico

I WORKINPS PAPER

Le basi dati amministrative dell'*INPS* appresentano una fonte statistica unica per studiare scientificamente temi cruciali per l'economia italiana, la società e la politica economica: non solo il mercato del lavoro e i sistemi di protezione sociale, ma anche i nodi strutturali che impediscono all'Italia di crescere in modo adeguato. All'interno dell'Istituto, questi temi vengono studiati sia dai funzionari impiegati in attività di ricerca, sia dai *VisitInps Scholars*, ricercatori italiani e stranieri selezionati in base al loro curriculum vitae e al progetto di ricerca presentato.

I **WORKINPS** hanno lo scopo di diffondere i risultati delle ricerche svolte all'interno dell'Istituto a un più ampio numero possibile di ricercatori, studenti e policy markers.

Questi saggi di ricerca rappresentano un prodotto di avanzamento intermedio rispetto alla pubblicazione scientifica finale, un processo che nelle scienze sociali può chiedere anche diversi anni. Il processo di pubblicazione scientifica finale sarà gestito dai singoli autori.

Tommaso Nannicini

Rigid wages? Inflation and wage growth in Italy, 1974–2024*

Fabrizio Mattesini

(Tor Vergata University of Rome and EIEF, Italy)

Franco Peracchi

(EIEF and Tor Vergata University of Rome, Italy)

Jacopo Pitari

(Tor Vergata University of Rome, Italy)

Rigid wages? Inflation and wage growth in Italy, 1974–2024*

Fabrizio Mattesini

Tor Vergata University of Rome and EIEF, Italy

Franco Peracchi

EIEF and Tor Vergata University of Rome, Italy

Jacopo Pitari

Tor Vergata University of Rome, Italy

Abstract

In this paper we use the rich information contained in the administrative archives of the Italian National Social Security Institute (INPS) to study the relationship between inflation and wage growth in Italy over the last 50 years. Our analysis uncovers a number of important facts about the Italian labor market. We find that during our sample period, the distribution of nominal wage growth changed substantially, and as inflation went down, so did the center and spread of this distribution. With the decrease of inflation, the frequency of nominal wage cuts also increased, revealing a high degree of wage flexibility achieved mainly through changes in non-standard forms of compensation such as bonuses and overtime. Our analysis is able to uncover what type of worker manages to better defend themselves from inflation. In particular, we find that stayers have a smaller probability of nominal and real wage cuts than movers, even if workers voluntarily quit their job. The empirical evidence we provide is consistent with the view that inflation is a way to “grease the wheels of the labor market”.

Keywords: Inflation; wage growth; wage rigidity; Italy; distribution regression

JEL classification codes: E24, E31, J31

* Corresponding author: Fabrizio Mattesini (fabrizio.mattesini@uniroma2.it). We thank the Istituto Nazionale della Previdenza Sociale (INPS) for allowing access to the VisitINPS datasets, and Bruno Anastasia, Gian Luca Clementi, Giuseppe Dachille, Maria De Paola, Guido Menzio and Monica Paiella for help and comments. The realization of this paper has been possible thanks to the sponsorships and liberal donations in favor of the “VisitINPS Scholars” programme. The findings and conclusions expressed are solely those of the authors and do not represent the views of INPS.

Rigidità dei salari? Inflazione e crescita dei salari in Italia, 1974–2024*

Fabrizio Mattesini

Università degli studi di Roma Tor Vergata ed EIEF, Italia

Franco Peracchi

EIEF e Università degli studi di Roma Tor Vergata, Italia

Jacopo Pitari

Università degli studi di Roma Tor Vergata, Italia

Abstract

In questo lavoro utilizziamo la ricchezza di informazioni contenuta negli archivi amministrativi dell'Istituto Nazionale della Previdenza Sociale (INPS) per studiare la relazione tra inflazione e crescita dei salari in Italia negli ultimi 50 anni. Troviamo che durante il periodo preso in considerazione la distribuzione dei tassi di crescita dei salari nominali ha subito cambiamenti sostanziali e che, con il diminuire dell'inflazione sono diminuiti anche il centro e la dispersione della distribuzione. Al diminuire dell'inflazione, è anche aumentata l'importanza dei tagli nei salari nominali, rivelando un alto grado di flessibilità salariale, ottenuta soprattutto tramite cambiamenti nelle componenti non standard delle retribuzioni quali premi e straordinari. La nostra analisi è in grado di individuare quali categorie di lavoratori sono stati in grado di difendersi meglio dall'inflazione. In particolare troviamo che coloro che rimangono nel posto di lavoro hanno una probabilità più bassa di subire un taglio salariale di coloro che cambiano lavoro, anche di coloro che si licenziano volontariamente. L'evidenza empirica fornita in questo lavoro è consistente con l'idea che l'inflazione è uno strumento per “ungere le ruote del mercato del lavoro”.

Parole chiave: Inflazione; crescita dei salari; rigidità salariale; Italia; regressione distributiva

Codici JEL: E24, E31, J31

* Autore corrispondente: Fabrizio.Mattesini (fabrizio.mattesini@uniroma2.it). Ringraziamo l'Istituto Nazionale della Previdenza Sociale (INPS) per l'accesso ai dati del programma VisitINPS, e Bruno Anastasia, Gian Luca Clementi, Giuseppe Dachele, Maria De Paola, Guido Menzio e Monica Paiella per l'aiuto e i commenti ricevuti. La realizzazione di questo articolo è stata possibile grazie alle sponsorizzazioni e alle donazioni liberali a favore del programma “VisitINPS Scholars”. I risultati presentati e le conclusioni sono unicamente quelle degli autori e non riflettono i punti di vista dell'INPS.

1 Introduction

Since the times of [Keynes \(1936\)](#), a long-standing issue in macroeconomics has been to what extent nominal wages respond to underlying economic conditions, particularly to changes in the aggregate price level. This issue has regained importance in recent years, due to the resurgence of inflation in the post-Covid period. The commonly held view is that nominal wages are rigid and that inflation is a way to “grease the wheels of the labor market” ([Tobin, 1972](#)), meaning that through inflation firms are able to obtain real wage cuts that they could not implement otherwise. This view is popular not only among economists but also among the public at large. In fact, recent empirical evidence from surveys ([Stantcheva, 2024](#)) shows that people dislike inflation because they associate it with a decrease in their living standards, as wages fall systematically behind the pace of price increases.

Although it is hard to dispute the existence of some nominal wage stickiness, as all of us have wages set in nominal terms and see them adjusted infrequently, the way this stickiness impacts the working of the labor market at the microeconomic level is not obvious. Although older studies based on self-reported data found that decreases in nominal wages are quite rare, the most recent work has provided evidence that challenges this view. Studies based on administrative data or payroll data covering various countries, recently surveyed by [Elsby and Solon \(2019\)](#), find that nominal wage cuts from one year to the next are in fact quite common. These findings call for further investigation. Since these studies use data before the period 2022–2023, when inflation was particularly low, it would be interesting to learn how the distribution of wage changes behaves during periods of high inflation. Moreover, little is known about what types of worker are more likely to get a nominal wage cut, what happens to wages when workers change jobs, depending on the level of inflation, and the role of labor contracts in wage adjustments.

In this paper, we delve deeper into the nature of wage adjustments and their response to inflation by exploiting a unique data set that covers the universe of private-sector employees in Italy from 1974 to 2024. In addition to providing a description of the relationship between inflation and movements in the distribution of weekly wage changes in Italy over the last 50 years, our goal is to present a set of stylized facts that can guide and discipline models of wage adjustment. Our data set comes from the administrative archives of the Italian National Social Security Institute (INPS). This data set is unique not only for its broad coverage of the Italian labor force but also because it covers periods characterized by different macroeconomic and institutional conditions. In fact, in the last 50 years, the Italian economy has experienced periods of high inflation (the 1970s), periods of decelerating inflation (the 1980s and 1990s), and periods of extremely low inflation (the 2000s and 2010s) until the recent inflationary bout in 2022 and 2023. At the same time, the Italian labor market has undergone significant institutional changes, such as the end of the indexation regime prevailing in the 1970s and

1980s, and various reforms which have progressively introduced more flexible labor contracts.

The first question we address in our paper is whether the distribution of nominal wage growth changed over the last half century. In particular, we ask whether its distribution in periods of high inflation differs from that in periods of low inflation. Evidence from the estimated densities of wage growth show that, as long as we move from the high inflation environment of the 1975–1995 period to the low inflation environment of the 2000–2020 period, the distribution of nominal wage growth becomes more peaked at zero and less dispersed. A close inspection of the recent period 2022–2024 reveals that most wage changes do not exceed the rate of inflation, and that only in 2024 does their modal value rise above an inflation rate that had returned to a relatively low level (0.9%).

Our second question is whether the fraction of workers experiencing nominal or real wage cuts increased over time. We also ask whether this fraction is higher or lower in periods of high inflation and what types of workers are more likely to experience a wage cut. We find that the fraction of workers with nominal wage cuts increased over time, from 5% in 1975–1979 to 31.6% in 2013–2021. As inflation spikes in recent years, the fraction of nominal wage cuts falls to 28.5% in 2022 and about 20% in 2023 and 2024. Hence, it is clear that, in periods of high inflation, nominal wage cuts are less frequent. We also find that the fraction of workers with a real wage cut fluctuates around a slightly upward trend. Unlike for nominal wages, the fraction of workers with a real wage cut is the highest during the recent inflationary spell of 2022–2023. Then it falls back in 2024, when inflation is extremely low. These numbers suggest a high degree of wage flexibility for the Italian labor market, even greater than that surveyed by [Elsby and Solon \(2019\)](#), who find wage cuts ranging between 15% and 25% in the countries considered. The comparison of these two important facts suggests that real wage reductions during periods of high inflation are mainly accomplished through inflation, consistently with the view that inflation helps “grease the wheels of the labor market”. On the other hand, in periods of low inflation, firms rely less on inflation in their effort to lower labor costs, though inflation still plays an important role.

Our third question is whether our descriptive evidence still holds after controlling for compositional effects that reflect the changes over time in the characteristics of workers. To this purposes, we estimate distribution regression models for the probability of nominal wage cuts, freezes and raises, and for the probability that nominal wages do not keep up with inflation. This also allows us to carry out a *ceteris paribus* exercise, in which we predict this probability by varying one observable characteristic at a time, keeping all the others fixed. Our results reveal that the probability of a nominal or real wage cut is generally higher for females than for males, for blue collars than for white collars, and for workers in the Southern Italian provinces than for those in the North. In addition, older or more experienced workers are slightly more likely to experience nominal or real wage cuts. We also distinguish between two types of workers, “stayers” and “movers”, depending on

their employment patterns in consecutive years. Both types have only one employment relationship in the first year, but while stayers maintain their employment relationship with the same firm in the second year, the movers are those who change employer. We find that stayers are less likely to experience a nominal wage cut, while the probability of a real wage cut is similar for movers and stayers in the first half of our period, but higher for movers thereafter. This suggests that, different from what has been found for other countries, in Italy changing jobs is not a way to climb the wage ladder.

The fourth question we address is whether the probability of experiencing nominal or real wage cuts varies with local labor market conditions. We show that this is indeed the case by estimating these probabilities for a reference worker in the different Italian regions and then performing a panel data analysis by regressing them on business cycle indicators such as the unemployment rate or the real GDP growth rate. We find that the probability of experiencing nominal or real wage cuts is highly cyclical and sensitive to local labor market conditions. In particular, its increase is typically associated with an increase in the unemployment rate or a decrease in the real GDP growth rate.

We then extend the specification of our distribution regression model by including other characteristics that are only available in more recent years. In particular, we study whether variations in the probability of experiencing nominal or real wage cuts are associated with variations in other firm-level characteristics by exploiting balance sheet information coming from the Cerved dataset. We also study whether these variations are associated with variations in contract duration (temporary vs. open-ended), or with contract renewal, or with particular events such as sick leave or parental leave.

The information available for the period 2005-24 also allows us to investigate the causes behind job changes. Although stayers tend to experience a lower probability of a nominal or real wage cut, we find that this probability is higher for workers who move because of the termination of a fixed-term contract and for workers who are laid off. The probability of a nominal or real wage cut is lower for workers who voluntarily quit their job, but still higher than that experienced by stayers.

Since these results point to a substantial degree of wage flexibility, our last question is how such flexibility is achieved in a labor market, such as the Italian one, characterized by centralized wage bargaining. For the period 2013–2024, we can distinguish between actual and “base” or contractual wages. We find that actual earnings are almost always above “base” earnings and that, while negative changes in “base” wages are quite rare, negative changes in actual wages are instead quite frequent. This suggests that, to achieve some degree of wage flexibility, firms mainly intervene on bonuses, overtime work, and other forms of non-standard compensation.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature. Section 3 describes the institutional framework relevant for understanding the patterns of wage changes

in Italy during 1974–2024. Sections 4 and 5 describe the data and present some descriptive statistics. Sections 6 and 7 present the results of our modeling exercise. Finally, Section 8 concludes.

2 Literature review

Early empirical studies on nominal wage rigidity, such as [Card and Hyslop \(1997\)](#), [McLaughlin \(1994\)](#) and [Kahn \(1997\)](#), were based on the US Panel Study of Income Dynamics (PSID) and the Current Population Survey (CPS). Contrary to the commonly held view, these articles found substantial evidence of nominal wage cuts and wage freezes among those who did not change job (the “stayers”). However, these findings were criticized on the ground that data from household surveys are notoriously prone to response error ([Akerlof et al., 1996](#); [Altonji and Devereux, 1999](#)).

More recent empirical studies rely on the availability for several countries of accurate wage information from individual pay slips or administrative payroll records. We can divide them into two groups: those based on surveys in which respondents are allowed to check their pay slips when reporting wages, and those based on administrative data. The studies in the first group include [Smith \(2000\)](#) who uses the British Household Panel Study (BHPS), [Nickell and Quintini \(2003\)](#), [Elsby, Shin, and Solon \(2016\)](#) who analyze wage data in the New Earnings Survey (NES) for Great Britain, [Doris, O’Neill, and Sweetman \(2015\)](#) who uses Irish data, [Park and Shin \(2017\)](#) who used South Korean data, and [Ekberg \(2004\)](#) who uses Swedish data. The studies in the second group include [Kurmann and McEntarfer \(2019\)](#) and [Jardim, Solon, and Vigdor \(2019\)](#) who use data for the State of Washington in the US, [Bauer et al. \(2007\)](#) who use data for Germany, and [Castellanos, García-Verdú, and Kaplan \(2004\)](#) who use data for Mexico. All of these studies find that nominal wage cuts occur more frequently than is commonly assumed ([Elsby and Solon, 2019](#)).

Using payroll data from the largest US payroll processing company, [Grigsby, Hurst, and Yildirmaz \(2021\)](#) are able to distinguish the base contractual wage of a worker from other forms of compensation, such as overtime work, bonuses, reimbursements, etc. They find substantial downward nominal rigidity in the base wage, but not in the other forms of compensation. Similar results are found by [Schaefer and Singleton \(2022\)](#) who analyze a decade of representative payroll data from Great Britain. [Guvenen et al. \(2021\)](#) study the earnings dynamics of males over the life cycle using panel data on millions of US workers focusing on non-normality and non-linearity. [Barattieri, Basu, and Gottschalk \(2014\)](#) use quarterly data from the US Survey of Income and Program Participation (SIPP) and find that the average quarterly probability of a nominal wage change is between 21.1 and 26.6% and that wage changes are much more likely when workers change jobs. [Avouyi-Dovi, Fougère, and Gautier \(2013\)](#) use data sets on wage agreements at both industry and firm levels in France to document stylized facts on wage stickiness.

Nominal and real wage rigidities in Italy have been analyzed by [Devicienti, Maida, and Sestito](#)

(2007) using longitudinal data for the period 1985–1999 extracted from the INPS database. Studies that focus mainly on the Italian indexation scheme, called “scala mobile”, include [Erickson and Ichino \(1995\)](#), [Manacorda \(2004\)](#) and [Leonardi, Pellizzari, and Tabasso \(2019\)](#). There are also several papers that have used the INPS database. Among these, [Guiso, Pistaferri, and Schivardi \(2005\)](#) study the allocation of risk between firms and their employees using matched employer-employee panel data, [Hoffmann, Malacrino, and Pistaferri \(2022\)](#) study the effects of Italian labor market reforms during the period 1985–2016, while [Lucifora and Vigani \(2021\)](#) study the evolution of sector-level collective agreements in Italy and estimate the wage effects of the diffusion of non-representative agreements, i.e., agreements signed by unknown organizations (the so-called “pirate” agreements).

Despite this large literature, little is known about how key aspects of the distribution of wage growth change with the inflation regime. Our main contribution in this paper is to provide such a description, together with a detailed analysis of how the risk of experiencing nominal or real wage cuts has changed across the various inflation regimes that have characterized the Italian economy over the last 50 years. In addition, we provide an in-depth investigation of what types of workers are more likely to experience nominal or real wage cuts, how these differences evolved over time, and how changes over time relate to local labor market conditions.

3 Inflation and labor relations in Italy, 1974–2024

The fifty-year period between 1974 and 2024 can be broken down into seven subperiods: 1974–1979 (high inflation), 1980–1986 (disinflation), 1987–1992 (the gradual dismantling of Scala Mobile), 1993–1998 (a new industrial relations system and the end of inflation), 1999–2012 (Italy joins the EMU); 2013–2021 (deflation), and 2022–2024 (the inflation flare-up). The first four periods that we identify largely correspond to those proposed by [Visco \(2024\)](#).

3.1 1974–1979: High inflation

The 1970s in Italy were a turbulent period after two decades of exceptional growth accompanied by substantial price stability. Although the annual growth of gross domestic product (GDP) remained high in historical terms (3.2% on average over 1970–1979), inflation got completely out of control. As shown in [Figure 1](#), the annual rate of inflation jumped from 9.4% in 1973 to 25% in the fourth quarter of 1974, following the first oil shock, more than halved in 1975, rose again after the currency crisis of 1976, and then remained quite high throughout the decade, reaching 21.2% in 1980 following the second oil shock. Italy was not the only country to experience high inflation, as many saw a dramatic growth in consumer prices largely due to the dynamics of energy prices. However, Italian inflation

was one of the highest in the industrialized world.¹

Although analyzing the causes of the phenomenon is beyond the scope of this paper, it is worth mentioning the two most obvious ones. The first and probably the most important was a monetary policy aimed at stabilizing interest rates and facilitating the financing of the large deficits run by the government. During those years, the Bank of Italy was required to acquire all the unsold bonds issued by the government in the primary market and the government could satisfy up to 14% of its cash needs by withdrawing money from its special account at the central bank. Another important factor was the repeated devaluation of the Italian currency, with consequent increases in import prices.

Trade unions responded to inflation by negotiating with the association of Italian industrialists (Confindustria) a revision of the wage indexation scheme (*Scala Mobile* or SM) that had been set up in the aftermath of World War II. The agreement of 1975 established that for each point increase in the quarterly consumer price index, nominal wages would increase by a flat amount (the so-called “SM point”). This agreement had a strong egalitarian inspiration, since the new SM awarded the same absolute wage increase (as opposed to the same percentage wage increase) to both high- and low-wage workers. As a consequence, the SM now offered a degree of protection for purchasing power that decreased as the worker’s wage increased, causing a compression of wage differentials.

In addition to its redistributive effects, the new SM had important macroeconomic effects. In the presence of external supply shocks, such as oil shocks, indexation amplified these shocks, causing additional increases in labor costs which could then be translated into further price increases. Moreover, in a situation characterized by tense labor relations, such as the Italian one during the 1970s, the SM favored the possibility of wage-price spirals. Given the protection given to wages by the indexation mechanism, firms would try to reduce real wages by increasing prices, which would then automatically determine an increase in wages and cause again an increase in prices.²

3.2 1980–1986: Disinflation

The beginning of the 1980s marked two important changes in monetary policy and income policy. First, after Italy joined in 1979 the European Monetary System (EMS) of quasi-fixed exchange rates, the Bank of Italy was released of the obligation to acquire government bonds left unsold in the primary market. This policy change, called the “divorce between the Bank of Italy and the Treasury” by the popular press, ended the monetization of government deficits, resulting in a significant drop in the rate of inflation. After reaching a peak of 22.15 in August 1980, inflation fell dramatically during the decade, reaching 4.4% in March 1987 but rising again to 6.2% in December 1989.³

¹ For example, the inflation differential with the US rose from 1.1% in the decade 1960–1969 to 6.2% in the next decade 1970–1979 (Fратиanni and Spinelli, 1997).

² See Lorenzoni and Werning (2023) for a recent analysis of wage-price spirals.

³ An unintended consequence of this agreement was a significant increase in government deficits due to the inability of governments to contain public spending. During the 1980s, the debt-to-GDP ratio rose to unsustainable levels.

Second, in January 1983, Confindustria and the three major trade unions (CGIL, CISL and UIL) reached an agreement for a revision of the SM. This agreement was a consequence of the growing dissatisfaction of white collars and high-skilled workers with the equalizing force of the indexation mechanism. In 1980, a spontaneous demonstration against the policy of the trade unions by about 40,000 white collars in front of the FIAT headquarters in Turin (known as the *marcia dei quarantamila*) sent a shockwave to the Italian system of industrial relations. Emboldened by the changing climate in the country, Confindustria decided in 1982 to withdraw from the 1975 agreement. The 1983 revision of the SM scheme implied a 15% decrease in the SM point. Moreover, to slow down the dynamics of the SM, it was agreed that an increment in the SM point would be paid only if it amounted to an integer increase over the last SM point. A controversy arose on whether the fractional increases would be lost or should be rather recovered by workers.

During those years, the prevailing view was that inflation could be tamed only through policies aimed at curbing wage increases. At the beginning of 1984, the government and the trade unions started negotiating an agreement that implied setting in advance the number of SM increases (only 4 in 1985). In exchange, the government would provide tax cuts and lower increases in the price of public utilities. As the trade union close to the Communist party (CGIL) withdrew from the agreement, the government led by the socialist leader Bettino Craxi, with the consensus of the other two trade unions, issued a decree (*Decreto di San Valentino*) which was then converted into law, containing the provisions of the agreement. As a reaction, the Communist party promoted in 1985 a referendum aimed at recovering the lost increments of the SM, but was defeated.

3.3 1987–1992: Dismantling the Scala Mobile

Despite the initial success achieved in the fight against inflation, Italy was unable to close the gap with the other European countries and, in fact, inflation rose again to 6% in 1986. This fact and the result of the 1995 referendum, which represented a significant loss of consensus for the trade unions, led to a gradual dismantling of the indexation mechanisms.

In 1986, there was a major reform of the SM. According to this reform, wages would be adjusted to inflation only every six months and the adjustments would be differentiated among wage levels. Moreover, the adjustment of wages to inflation would be 100% only for a third of the wage; for the other two thirds, the increase in wages would amount only to 25% of inflation. In 1991, Confindustria announced that it would not renew its membership in the SM, and in 1992 the three major trade unions agreed on the abolition of the SM.

The beginning of the 1990s was a period of great turmoil for Italy, as the consensus for the main parties fell dramatically, as the investigations of the Milan magistrates (*Mani Pulite*) unveiled a widespread corruption system. At the same time, due to the enormous debt accumulated during the

1980s, the Italian currency fell under intense speculative attacks, which led to its withdrawal from the EMS and a consequent devaluation of about 35%.

3.4 1993–1998: A new industrial relations system and the end of inflation

In 1993, the technocratic government headed by Carlo Azeglio Ciampi, a former Governor of the Bank of Italy, promoted an agreement with the trade unions establishing a new system of industrial relations in which the government, the trade unions and the representatives of the entrepreneurs cooperated in view of a common objective (the so-called *concertazione*). This agreement established two types of contract, one at the national level and a complementary one at the firm level. Moreover, wage increases would no longer be based on past inflation, as in the SM scheme, but on some inflation target set by the government.

This new system of industrial relations produced significant results but lasted only five years. Italy's growth was satisfactory, especially in the aftermath of the currency devaluation, with no resurgence of inflation. If we consider the whole decade, inflation fell from 6.5% in January 1990 to 2.2% in December 1999. The cooperation between government, trade unions and associations of entrepreneurs ended when the government undertook the first of several reforms of the Italian pension system (the so-called "Dini Reform"), which transformed it from defined benefits (with pensions computed on the basis of the last 3/5 years of a worker's career) to defined contributions (with pensions depending on the capitalized value of contributions over the whole career of a worker).

To address the high unemployment rate of the 1980s and 1990s (11.4% at the end of 1999), important labor market reforms were introduced aimed at making the Italian labor market more flexible. The first was the "Treu Reform" of 1997, which liberalized the wages of new entrants into the labor market and made it easier for firms to use fixed-term or part-time labor contracts.

It is important to notice that, during the same period, the European Monetary Union was established. The process started in July 1990 with the removal of capital controls in the whole area (Stage 1), followed by the Maastricht treaty signed in 1992 and the creation of the European Monetary Institute in 1994 (Stage 2).

3.5 1999–2012: Italy joins the EMU

With the launch of Stage 3 of the European Monetary Union (EMU) on January 1, 1999, Italy was one of the eleven countries that adopted the euro as their single currency. On the same date, the conduct of monetary policy was entrusted to the Eurosystem and the European Central Bank (ECB).

During this period, Italian inflation fluctuated around 2%, with a peak of 4.1% in August 2008, a trough of .22% in August 2009 and another peak of 3.3% in 2012. Growth was sluggish and productivity stagnated. In the years between 2007 and 2012, Italy was hit by the Great Financial

crisis (with GDP growth of -5.28% in 2009) and the sovereign debt crisis, which threatened the survival of the EMU.

The labor market was characterized by a substantial loss of bargaining power by the three main trade unions that also suffered from the birth of other smaller “autonomous” trade unions. In the meantime, the trend initiated by the Treu reform of 1997 continued, and there were several policy interventions aimed at increasing the flexibility of the labor market. In 2000, Italy followed the EU directive on part-time work and made it easier to access this form of employment. Then, in 2003, the “Biagi Reform” introduced several new types of flexible employment contracts (*contratti atipici*) and, in 2012, the “Fornero Reform” made it simpler for firms to rely on temporary employment contracts, although it introduced limits to their use and duration.

3.6 2013–2021: Deflation

After the sovereign debt crisis of 2007–2009, the Italian economy entered a deflationary period with inflation below the 2% target and actually negative in some years. GDP growth and productivity stagnated but unemployment, after peaking at 13.2% in November 2014, fell gradually. Like all other countries in the world, Italy was hit in March 2020 by the COVID crisis which caused a 8.97% drop in GDP relative to 2019.

Two important reforms of labor market were enacted in 2014: the “Poletti reform” (Law 78/2014) further liberalized the use of fixed-term contracts, while the “Jobs Act” (Law 183/2014) modified an existing law (Law 300/1970, known as *Statuto dei Lavoratori*), which protected workers against dismissals, by introducing a new employment contract (*contratto a tutele crescenti*), in which protection against dismissal increases with the worker’s tenure on the job.

3.7 2022–2024: The inflation flare-up

The post COVID period has been characterized by a flare-up of inflation. A peak was reached in October 2022 (11.8% on an annual basis), but since then inflation has gradually decreased, returning at the end of 2023 to the pre-COVID levels, well below 2%. Meanwhile, unemployment continued to decline.

It is interesting to note the differences between the rapid disinflation of 2023 and its slow descent during the 1980s, which likely reflects the lack of an indexation scheme and the firm monetary stance of the European Central Bank.

4 Data

Our main source of data consists of the INPS administrative archives, which provide annual earnings, annual weeks worked and basic demographic characteristics of all individual private-sector workers

from 1974 to 2024. These data also contain the sector of activity and the total number of employees of the firm in which a worker is employed. Data for the main macroeconomic aggregates, such as annual inflation, GDP and labor market conditions at the national and regional level, are drawn from the official statistics produced by the Italian Statistical Institute (Istat). For balance-sheet information about individual firms, we rely on the archive of Italian firms maintained by Cerved on behalf of the Italian Union of the Chambers of Commerce (*Unioncamere*).

4.1 The INPS data

We use data from the three INPS archives described in more detail in Appendix B.2, namely the employment relations registry (containing detailed information on all employment relations held by a worker during a year), the workers registry (containing background information on all workers present in the employment relations registry), and the establishment registry (containing information on all establishments in which a worker from the workers registry has been employed).

4.1.1 Sample selection

We focus on non-agricultural, non-domestic private-sector employees who are present in the INPS archives for two consecutive years, $t - 1$ and $t = 1975, \dots, 2024$, with positive total earnings in both years, only one full-time full-year employment relation in year $t - 1$ and at most two full-time employment relations in year t , each with a positive number of weeks worked. Given the dualistic nature of the Italian labor market, with a “primary sector” offering stable jobs and a “secondary sector” mostly offering low-paying insecure jobs and worse working conditions, we refer to workers who meet our sample selection criterion as “primary workers”. Since these workers are arguably better able to defend themselves against inflation, our analysis is likely to offer a best-case scenario for the universe of all Italian workers. Notice that our primary workers include not only the job stayers (those who did not change job between years $t - 1$ and t) but also those who changed job in year t . We include this second type of worker in our sample because we are interested in understanding the relation between wage changes and job changes. Our primary workers also include fixed-term workers provided they worked full-time in both years.

Table 1 shows the sample size at each stage of our sample selection process. For each year considered, there are no big sample losses in going from column (1) to column (2), since the majority of the workers in the INPS data has at most two employment relations. After 1990, we start losing an increasing number of workers when going from column (2) to column (3). This likely reflects the fact that, following their introduction in 1984, part-time contracts became increasingly popular. We observe a huge drop in sample size going from column (3) to column (4), as we lose workers who either were not full-time full-year or present in the original INPS data in year $t - 1$, or were present

in year $t - 1$ but did not satisfy our criteria in year t . We only experience minor losses going from column (4) to column (5), and then from column (5) to column (6), as the majority of the workers in column (4) is aged 17–59 in the first year and worked a total of 26–54 weeks in the second year.

4.1.2 Earnings and wages

For each job held by a worker during a year, the INPS archives provide information on annual earnings, defined as the sum of earnings subject to Social Security contribution (*imponibile previdenziale*), which are capped after the year 2000, and earnings in excess of the amount subject to Social Security contribution (*imponibile eccedente il massimale*). Annual earnings from a job are computed before taxes or other deductions. Thus, they measure the gross compensation received by the worker on that job during a year, including the thirteenth month’s salary (*tredecimesima mensilità*) paid to workers each year in December on top of the regular wage, paid overtime work, bonuses, reimbursements, and other non-standard payments. The total annual earnings of a worker are then defined as the sum of the annual earnings from all jobs held by the worker during a calendar year. All monetary quantities are in nominal terms and denominated in euros.

Unfortunately, the INPS data suffer of two major limitations. First, we have no information on the individual components of earnings. Hence, unlike Grigsby, Hurst, and Yildirmaz (2021), we cannot tell to what extent changes in earnings reflect changes in overtime pay or bonuses. Although cuts in bonuses can be considered wage cuts, it is less obvious that a reduction in overtime compensation should be considered a reduction in the wage since it also implies a decrease in work hours. An attempt at separating “regular” earnings from other components is made in Section 7.6 using the fact that, starting in 2012, the INPS archives also contain information on base earnings (*retribuzione teorica*), namely the annual earnings corresponding to the contractual obligations that the firm has with the worker. Base earnings include the thirteenth month’s salary but, unlike actual earnings, they do not include paid overtime work, bonuses, reimbursements, and other payments that are unlikely to accrue every month to the worker.

Second, although we have information on the number of weeks worked during a calendar year, we have no information on the number of hours worked per week, so we cannot construct a measure of hourly wages, which is often regarded as the standard measure of the price per unit of effort. Since our primary workers may work less than 52 weeks per year, we construct a nominal wage measure for each job held by a worker by dividing total earnings on that job by the corresponding number of weeks worked. This quantity, denoted by W_{it} for those holding only one job and by $W_{it}^{(j)}$, $j = 1, 2$, for those holding two jobs, is our measure of nominal wages.

The presence of outliers in W_{it} is an important issue. They arise because of outliers in either annual earnings (the numerator) or annual weeks worked (the denominator). This issue is especially

serious for workers who only work a few weeks during a year. Our focus on full-year workers in year $t - 1$ and workers with at least 26 weeks worked in year t alleviates but does not eliminate the issue.

4.1.3 From cross-section to panel data

By linking workers and firms across the three INPS archives, we convert the available sequence of consecutive annual cross-sections into a sequence of rolling matched employer-employee panels, each with two years of employment and earnings information on every individual worker in our sample. The linking of records is made possible by the fact that each worker, establishment, or firm is characterized by a fixed and unique identifier.

After constructing our sequence of two-year panels, for each worker in our sample, we compute the relative change in wages between two consecutive years as $\dot{W}_{it} = W_{it}/W_{i,t-1} - 1$. We henceforth refer to \dot{W}_{it} as the (nominal) wage growth of worker i in year t although, as shown in Section 5, this measure is zero or even negative for a non-negligible fraction of workers, especially in recent years. More details are provided in Appendix A.

Nominal wages may change for several reasons. First, they may change because of renewal of national-level contracts. These contracts, which have dominated industrial relations in Italy throughout our sample period, are signed at the sector level by firms’ representatives and trade unions. A peculiar feature of the Italian system of industrial relations is that they are taken by the courts as the reference contracts in labor disputes. In our analysis, we refer to the wages determined by these contracts as “base wages”. After 1992, national-level contracts can be supplemented by firm-level contracts. Wages may also vary, beyond what is agreed upon in national- or firm-level contracts, because of bargaining at the individual level between a firm and a worker on earnings components such as bonuses, overtime compensation, and reimbursements.

The presence of outliers in wages is exacerbated when considering wage growth. To limit their impact, we trim the top and bottom 0.5% of wage growth and rely on percentile-based statistics in the descriptive analysis of Section 5, and use the distribution regression approach in Section 6 to model wage growth.

For each pair of consecutive years, we distinguish between two types of primary workers: the “stayers” and the “movers”. The stayers are those employed at the same firm in both years – full time and full year in year $t - 1$ and full time but not necessarily full-year in year t .⁴ The movers are instead those employed full-time and full-year at the same firm in year $t - 1$ but employed full-time at two different firms in year t .⁵

⁴ A stayer may have more than one employment relation with the same firms during a year, for example, because of a change of contract, a change of occupational classification, or a change of establishment within the same firm.

⁵ We exclude workers with less than 26 weeks, to ensure that each worker is not unemployed for more than half of

In our descriptive analysis, regardless of whether a worker is a mover or a stayer, the wage growth is computed as the percentage change between the wage in year t (which, for movers, is a weighted average of the wages in the two jobs held in year t) and the wage in year $t - 1$. In the modeling exercises in Sections 6 and 7, we instead keep only movers who in year t switch from the firm they worked for in year $t - 1$ to a new one. Then, the wage growth of stayers is computed as we do in the descriptive analysis, while that of movers is computed as the relative change between the wage in the second job held in year t and the wage in the unique job held in year $t - 1$.

Finally, to limit the impact of changes in labor supply at the extensive margin, we exclude workers younger than 17 or older than 59 in year $t - 1$ (younger than 18 or older than 60 in year t). The last three columns of Table 1 show the size of our working sample for selected years and its breakdown between stayers and movers.

4.1.4 Covariates

We consider two sets of covariates: basic covariates available for the whole period 1975–2024, and additional covariates only available for more recent years. We describe these additional covariates in Section 7.

Our basic covariates are derived from the information contained in the workers and job relations registries. This information is only collected for administrative purposes and is therefore somewhat limited. For example, it does not include the educational attainment of a worker.

The workers registry contains information on sex, year of birth, year of the first non-agricultural private-sector job, and country of citizenship of a worker. From this information, we derive the age and number of years of labor market experience of each worker.

The employment relations registry instead contains information on annual earnings, weeks worked, occupational category, and province of employment of each worker. We collapse all occupational categories into just three: blue collars, white collars, and managers.⁶ Also, using data on annual earnings and weeks worked, we rank workers according to their wages.⁷ Finally, our measure of firm size is the total number of full-year equivalent employees. We refer to Appendix B for more details.

the year. We also exclude workers with more than 54 weeks of work, to allow changes of establishment, occupational category or firm within the same week or with at most one week of overlap between the two employment relations.

⁶ More precisely, we consider the following seven occupational categories: apprentices, blue collars, *equiparati o intermedi*, white collars, managers, and the “other” category. Then, in the descriptive analysis, we collapse these seven categories into just two (blue collars and white collars), while we include an indicator for each of the seven categories in the distribution regression model, but we present only the estimated probabilities for white collars, blue collars and managers).

⁷ This raises the issue of which occupation to assign to a worker with more than one job in a given year. By convention, all time- and job-specific variables refer to the unique job a worker has in the initial year (year $t - 1$).

4.2 The Istat data

Istat provides three different consumer price indices at the national level: FOI (*Indice nazionale dei prezzi al consumo per le famiglie di operai e impiegati*) available for the whole period 1974–2024, NIC (*Indice nazionale dei prezzi al consumo per l'intera collettività*) only available from 1995, and IPCA (*Indice armonizzato dei prezzi al consumo*) only available from 2001. Given a national price index P_t , we define the annual national inflation rate in year t as $\dot{P}_t = P_t/P_{t-1} - 1$.

Figure C.1 in the appendix shows that the differences in inflation rates resulting from the three indices (FOI, NIC and IPCA) are very small. We also plot a measure of expected annual inflation, published by the Italian Ministry of Economy and Finance (MEF) and called TIP (*Tasso di inflazione programmata*), which is used for the indexation of public contracts, garbage and water bills, etc. Unsurprisingly, the TIP is typically lower than the actual inflation rates resulting from the three Istat indices.

We focus on FOI because is available for the whole period, not only for the whole country but also for several regional capitals.⁸ When regional data are available, the annual inflation rate in region r is defined as $\dot{P}_{rt} = P_{rt}/P_{r,t-1} - 1$. Figure 1 shows the time profile of annual inflation in Italy and some of its regional capitals.⁹ Somewhat surprising, there is little evidence of inflation inequality between regions, as regional differences in inflation appear to be small and unsystematic (Figure C.2).

Istat also provides data on annual labor force participation rates, employment rates, and unemployment rates over time and across regions, obtained from the Italian Labor Force Survey.

Finally, regional GDP data are available from Istat only from 1995 onward. For earlier years, we use the dataset constructed by the *Centro Ricerche Economiche Nord-Sud* (CRENOS), a joint initiative of the Universities of Cagliari and Sassari, also based on previous official releases of regional GDP.

4.3 The Cerved data

The last step in constructing our working data set consists of matching our sequence of two-year employer-employee longitudinal data with the annual balance-sheet information for 1996–2018 available at the firm level from Cerved. More details are provided in Appendix B.2.

Using the INPS establishment registry, we first create a rolling sequence of 3-year panels of firms containing information on the total number of workers employed and the sector of activity (ATECO 2007 code) of each firm. The total number of workers is computed as the sum of the workers in each establishment of a given firm, while the sector of activity corresponds to the ATECO 2007 code of the establishment with the highest number of employees.

⁸ It is missing in some years for some regional capitals (like L'Aquila, Campobasso, etc.).

⁹ The vertical bands correspond to recession years according to the OECD.

We then merge this sequence of panels with another sequence of 3-year panels¹⁰ containing the information on the firm’s performance derived from the annual balance sheets, namely operational value added, return on assets, financial debt, total assets and profits. Finally, we merge our sequence of 3-year panels of firms for years with our sequence of 2-year panels of workers. The sample size at each stage of this sample selection process is described in Table C.1.

5 Descriptive statistics

This section presents descriptive statistics on nominal wage growth during the period considered. Section 5.1 presents moments and percentiles of its empirical distribution over the period considered, Section 5.2 describes the changes over time in its histograms, while Section 5.3 focuses on the probability of nominal wage growth in some specific interval.¹¹

5.1 Moments and percentiles of wage growth

Table 2 presents summary statistics of nominal wage growth and annual inflation for six of the seven subperiods identified in Section 3, namely 1975–1979, 1980–1986, 1987–1992, 1993–1998, 1999–2012, and 2013–2021. To provide more detail on the recent inflationary period 2022–2024, we consider each year separately. Table 3 also presents the mean, median and standard deviation of nominal wage growth conditional on receiving a wage cut or a wage raise.

We focus on four features of the distribution of nominal wage growth: its center, spread, asymmetry, and “tailedness”. We present both moment-based measures – namely mean, standard deviation, skewness and kurtosis – and the corresponding percentile-based measures.¹² Because of the presence of a few large outliers in nominal wage growth, we trim .5% of the observations at the top and .5% of the observations at the bottom of the distribution. Note that trimming is not needed for percentile-based statistics.

Nominal wage growth tends to fall as inflation decreases, the big exceptions being 2023 and 2024 when it remains essentially unchanged despite the sharp decline in inflation. Mean wage growth exceeds the rate of inflation in all subperiods except the inflation flare-out of 2022–2023, which implies that average real wages increased over time in most of the last 50 years despite the stagnant

¹⁰ We use three years for each firm in order to smooth out the volatility in the annual measures of firm’s performance.

¹¹ In Section 5.1 and 5.2, we restrict our sample to workers employed in Italian provinces in both years. In Section 5.3, we also drop workers with missing province of employment or type of occupation. The resulting loss of observations is really negligible (much less than 1%), and therefore is not reported.

¹² Our percentile-based measures of center and spread are the median (the 50th percentile) and the interdecile range (the difference between the 90th and 10th percentiles). Our percentile-based measure of skewness is the ratio of the difference between the 90th percentile and the median to the difference between the median and the 10th percentile. Finally, our percentile-based measure of tailedness is the ratio of the difference between the interdecile range and the interquartile range (the difference between the 75th and 25th percentiles).

productivity of the Italian economy. The same observation can be made if, instead of the mean, we consider the median.

The picture becomes more nuanced once we consider other features of the distribution of nominal wage growth. All moment-based measures fell as inflation declined, again except for the period 2022–2023. On the other hand, while the interdecile range shows the same behavior of the standard deviation, the percentile-based measures of asymmetry and “tailedness” remained stable throughout the period considered. In particular, the fall in the standard deviation of wage changes was quite rapid as Italy transitioned from the high inflation of 1974–1979 to the low inflation of the post-1992 period, and then slowed down in the subsequent low-inflation environment. We find this result quite surprising, considering that until 1992 the indexation mechanism provided a high degree of protection to lower wages. Rationalizing this result is beyond the scope of this paper. A possible explanation is that inflation makes contracting more difficult, as it becomes harder to extract from prices information regarding the growth of productivity. As a consequence, in a high inflation environment, the more productive workers are less able to obtain the wage increase they would get in a low inflation environment, and the less productive workers are more able to obtain the wage increase they would not get otherwise. As a consequence, the higher the inflation, the greater the dispersion in nominal wages. The distribution of nominal wage growth is also skewed to the right for the entire period considered, which reflects the fact that wage changes above their mean value are more frequent than wage changes below their mean value.

Finally, Table 2 shows that the distribution of wage growth is consistently leptokurtic, with kurtosis always above 7, quite far from the value of 3 that characterizes the normal (Gaussian) distribution. This reveals that the right tail of the distribution of wage growth is quite fat, that is, a significant fraction of wage changes is well above the mean. Again, both moment-based and percentile-based measures of asymmetry and “tailedness” lead to the conclusions that the distribution of nominal wage changes is skewed to the right and that the right tail of the distribution is quite fat. On the other hand, while moment-based measures suggest that both skewness and kurtosis fell over time, percentile-based measures suggest that they remained quite stable. For this reason, we do not address the issue of how these features changed with inflation regimes and institutional settings.

5.2 Histograms of wage growth

Figure 2 illustrates the changes over time in the entire distribution of nominal wage growth by presenting the histograms computed for each of the first six subperiods identified in Section 3 and separate histograms for 2022, 2023 and 2024.

The shape of the histograms has changed substantially over the period considered. First, it has become more peaked at zero. Second, the dispersion in the distribution of nominal wage growth

rates has decreased substantially. Third, our histograms reveal the presence of a spike at zero in the first part of our period, although its size is smaller than that found by [Card and Hyslop \(1997\)](#) and [Devicienti, Maida, and Sestito \(2007\)](#).

Our difference with respect to [Card and Hyslop \(1997\)](#) may reflect the different wage setting mechanisms in Italy and the US, the different time periods considered, and the fact that we use administrative data rather than self-reported survey data (which are prone to systematic rounding or “heaping”).¹³ Our difference with respect to [Devicienti, Maida, and Sestito \(2007\)](#), who also use a matched employer-employee panel data set drawn from the INPS archives, may instead reflect the fact that we focus on primary workers, as defined in Section 4.1.1, while they focus on full-time workers who have been in the labor market for at least three months and worked at least 50 paid days in the year.

5.3 Changes in nominal and real wages

Figure 3 shows the relationship between annual inflation and the fraction of workers with a nominal wage cut. These two quantities are negatively related: the fraction of worker with a nominal wage cut is lower in years of high inflation and higher in years of low inflation.¹⁴ It is highest (almost 60%) in 2020, when inflation was actually negative (about -0.2%).

Table 4 shows the fraction of workers who respectively experienced a wage cut, a wage freeze or a wage raise in each of the subperiods identified in Section 3.¹⁵ We start with the second column of the table, which refers to all workers in our sample. The percentage with a wage cut increases as inflation decreases, from 5% in 1975–1979 to 31.6% in 2013–2021. As inflation spikes in recent years, the percentage with a wage cut falls back from 28.5% in 2022 to 19.7% in 2023, and remains virtually unchanged in 2024. Similarly, the fraction with a wage freeze grows from .8% in 1975–1979 to 8.7% in 2013–2021, falling back to 7.7% in 2022, 5.7% in 2023, and 4.7% in 2024. The pattern for the percentage with a wage raise is just the specular reflection of these trends.

Although the small fraction of workers with a wage cut in periods of high inflation is unsurprising, the high fraction of workers with a wage cut or a wage freeze during the low inflation period of 2013–2021 is surprisingly. In their survey of country-specific studies of nominal wage rigidity, [Elsby and Solon \(2019\)](#) find that “nominal wage cuts from one year to the next appear quite common,

¹³ [Card and Hyslop \(1997\)](#) also find that “the size of the spike tends to be larger during periods of lower inflation.” In our sample of primary workers, the mass around zero tends to increase over time, while the mode of the distribution tends to decline with the decline in inflation. The only exceptions are the year 2022, when the mode is just zero despite inflation reaching its highest value since 1986, and the year 2023, when the mode is between 0 and the inflation rate. These histograms make the presence of asymmetry and point masses at zero much more visible.

¹⁴ The fitted red curve is a locally linear regression smoother. A simple linear regression of the fraction with nominal wage cuts on the inflation rate yields a coefficient of $-.304$.

¹⁵ A wage cut is defined as wage growth below $-.5\%$, a wage freeze as wage growth between $-.5\%$ and $.5\%$, and a wage raise as wage growth above 0.5% .

typically affecting 15–25 percent of job stayers in periods of low inflation.” Consistent with this picture of downward wage flexibility, they find that nominal wage freezes are much less frequent, typically affecting less than 8% of job stayers. By comparison, we find a much higher fraction of workers experiencing a wage cut. Thus, our evidence does not support the commonly held view that nominal wages are downward rigid in Italy. This is quite interesting, especially considering that the Italian system of industrial relations is characterized by centralized wage bargaining and that the wages set by union contracts are usually taken by the courts as the reference wages in labor disputes.

The remaining columns of Table 4 distinguish by sex, age, type of occupation and geographical area of employment. They show that the fraction of workers with a wage cut is higher for males (from 1993 onward), older workers, and workers employed in the South.

Table 5 shows the fraction of workers with nominal wage growth below the inflation rate, i.e. the fraction with real wage cuts, for the whole sample (the last column) and separately by observable characteristics of the workers. The table consists of three panels: one for workers with wage growth not exceeding price inflation in the previous year (top panel), one for those with wage growth not exceeding price inflation in the current year (middle panel), and one for those with wage growth not exceeding price inflation in the next year (bottom panel). When we consider the percentages for the entire sample (the second column of the table, labeled “All”), the three panels point to a long-run average of about 40%, with much higher percentages (between 59% and 75%) during the last inflationary spell in 2022 and 2023. Again, the data provide little indication of wage rigidity.

6 Statistical modeling

The descriptive evidence in Section 5 partly reflects compositional effects due to long-term changes in the characteristics of the workers. To control for these effects, we now consider distribution regression models for the probability of nominal wage cuts, freezes or raises, and for the probability that nominal wage growth does not exceed past, current or future inflation. The use of distribution regression also avoids the need to remove outliers. Section 6.1 describes our distribution regression model, Section 6.2 examines the role of personal characteristics of a worker, while Section 6.3 explores the role of regional labor market conditions.

6.1 The distribution regression model

Our distribution regression model (Foresi and Peracchi, 1995; Chernozhukov, Fernández-Val, and Melly, 2013) is of the form

$$\pi_t(\mathbf{x}) = \mathbb{P}[\dot{W}_{it} \in C_t | \mathbf{X}_{it} = \mathbf{x}] = \frac{\exp(\alpha_t + \boldsymbol{\beta}_t^\top \mathbf{x})}{1 + \exp(\alpha_t + \boldsymbol{\beta}_t^\top \mathbf{x})}, \quad t = 1975, \dots, 2024, \quad (1)$$

or equivalently

$$\lambda_t(\mathbf{x}) = \ln \frac{\pi_t(\mathbf{x})}{1 - \pi_t(\mathbf{x})} = \alpha_t + \beta_t^\top \mathbf{x}, \quad t = 1975, \dots, 2024, \quad (2)$$

where \mathcal{C}_t is an interval of values for nominal wage growth and \mathbf{X}_{it} is a vector of observable covariates specific to worker i in year t . Model (1) is estimated separately for each year in our sample.

In our baseline specification, \mathbf{X}_{it} includes binary indicators for sex (the reference is male), citizenship (the reference is Italian), age, labor market experience, type of worker, occupational category, relative position in the distribution of wages, firm size (the reference category is employment at a firm with 16–200 full-year equivalent employees), province of employment, and type of worker (with job stayer as the reference category). All job-specific and time-varying variables refer to the (unique) job in the initial year (year $t - 1$).

Specifically, age is represented by binary indicators for being aged 17–29, 30–49 or 50–59 years (the reference is 30–49 years), labor market experience by binary indicators for the number of years of experience, namely 9 or less, 10–19, 20–29 or 30+ (the reference category is 10–19 years), and occupational category is represented by binary indicators for being an apprentice (*apprendista*), a blue collar worker (*operaio*), an intermediate category between blue and white collars (*equiparato* or *intermedio*), a white collar (*impiegato* or *quadro*), a manager (*dirigente*), or a small residual category that we call “other” (with white collar as the reference category). The relative position in the distribution of wages is represented by a set of binary indicators for the individual wage rank in year $t - 1$, namely below the first quintile, between the first and the second, between the second and the third, between the third and the fourth, and above the fourth (with ranking between the second and the third quintile as the reference category). Our reference worker is an Italian male, aged 30–49 years, with 10–19 years of labor market experience, with wages in the previous year between the second and the third quintile, with only one full-time job in year t (job stayer), employed as a white collar in a firm operating in the province of Milan with 16–200 full-year equivalent employees.

The choices for the interval \mathcal{C}_t are as in Section 5.3. Hence, we employ (1) to model the probability of a nominal wage cut, i.e. $\mathcal{C}_t = (-\infty, -0.5\%]$, a nominal wage freeze, i.e. $\mathcal{C}_t = (-0.5\%, 0.5\%)$, or a nominal wage raise, i.e. $\mathcal{C}_t = [0.5\%, +\infty)$. We also use (1) to model the probability that nominal wage growth does not exceed past inflation, i.e. $\mathcal{C}_t = (-\infty, \dot{P}_{t-1}]$, current inflation, i.e. $\mathcal{C}_t = (-\infty, \dot{P}_t]$, or future inflation, i.e. $\mathcal{C}_t = (-\infty, \dot{P}_{t+1}]$.

Due to our huge sample sizes, the standard errors on the estimated coefficients and the width of the confidence intervals are essentially indistinguishable from zero and therefore not reported.

6.2 Comparisons across types of worker

Since interpretation of the logit coefficients is not straightforward, Figures 4–10 compare the time profiles of the estimated probabilities for our reference worker to those of other workers who have

exactly the same characteristics except one. To reduce the impact of sampling noise and highlight trends over time, we consider 3-year uncentered running averages of the estimated probabilities. Tables C.2–C.5 also show the average values of the estimated probabilities over the subperiods described in Section 3 and the entire 1975–2024 period.

For each of the characteristics considered, the time profiles of the estimated probabilities are much the same. The estimated probabilities of a nominal wage cut and of a nominal wage freeze fluctuate around a clear positive trend, whereas the estimated probability of a nominal wage raise fluctuates around a clear downward trend. On the other hand, the estimated probabilities that nominal wage growth does not exceed past, current or future inflation show some evidence of a slightly positive trend. In this case, the pattern of variation is dominated by several spikes, typically corresponding to recession years. In particular, there is a spike in the first half of the 1990s (which may reflect the consequences of the abolition of the SM and the European recession of 1992–1993), at the end of the 2000s (which may reflect the consequences of the Great Recession of 2007–2009), and in 2021 (which may reflect the consequences of the Covid-19 pandemic).

Figure 4 shows that a reference female worker is slightly more likely to suffer a nominal wage cut than an otherwise similar male worker, but there are no gender differences in the estimated probability of a nominal wage freeze. Our results also suggest that the probability of keeping up with inflation (past, current or future) is higher for a reference male worker, although the initially larger gender differences become quite small by the end of the 2000s. In particular, on average over the entire period, a reference male worker has a 2.6% lower probability of a wage cut compared to a female worker and a 4.9% lower probability of wage growth not exceeding current inflation.

Figures 5 and 6 show that older or more experienced workers are slightly more likely to suffer a nominal wage cut compared to younger or less experienced workers, although the differences are small. For example, a reference worker aged 50–59 has on average a slightly higher probability of nominal wage cuts (about 0.8 percentage points higher than workers aged 17–29). An older or more experienced worker is also less likely to keep up with current and future inflation. For example, a worker with more than 30 years of experience has a 3.8% higher probability that her wage growth does not exceed current inflation compared to one with at most 9 years of experience.

Figure 7 shows that blue collars are more likely to suffer a nominal wage cut compared to white collars and managers, and slightly more likely to suffer a nominal wage freeze. Analogously, they have a higher probability that their nominal wage growth is lower or equal to past, current and future inflation. In particular, a reference blue collar has on average a 6.8% higher probability of nominal wage cuts and a 8.7% higher probability of not keeping up with inflation compared to a reference white collar. The corresponding figures for managers are 7.2% and 12.5% respectively. This suggests that low skilled workers found it increasingly difficult to protect their real wages compared to high

skilled workers.

Figure 8 shows that the differences in the estimated probabilities between workers employed in firms of different sizes are quite small, while Figure 9 shows that the geographical differences are greater. In particular, a reference worker in the South (Naples or Palermo) has a higher probability of a nominal wage cut compared to a similar worker in the North (Milan or Venice) or the Center (Rome). This is also true for the probability that nominal wage growth falls below price inflation, corresponding to a real wage cut. For example, a reference worker in Palermo has a 3.8% higher probability of a nominal wage cut and a 6.4% higher probability of not keeping up with inflation compared to a reference worker in Milan. On the other hand, we find little evidence of geographical differences in the probability of a nominal wage freeze.

The conventional wisdom is that job movers tend to enjoy higher wage growth compared to job stayers, since workers often change jobs in order to join more productive firms, and therefore increase their earnings. Somewhat surprisingly, Figure 10 shows the opposite: the probability of a wage cut is clearly higher for job movers compared to job stayers. This phenomenon is relatively recent and becomes quite evident starting from the late 1990s. In contrast, the probability of a wage freeze is almost always the same for the two categories of workers, except in the last ten years, when the probability of a wage freeze tends to be lower for the movers. Finally, the probability of not keeping up with inflation (past, current or future) is similar for movers and stayers until the early 2000s, but becomes higher for movers afterwards. A possible explanation for these findings involves the labor market reforms that started in 1997 and continued through the second decade of the 2000s. These reforms have introduced a variety of fixed-term labor contracts that have certainly contributed to “fluidify” the labor market but, at the same time, have also increased involuntary labor mobility. Many workers, especially young ones, do not change jobs to obtain higher wage but because they have to, and often they must accept a wage cut if they want to remain employed.

6.3 Cyclicity of wage growth and regional labor market conditions

The long time span of our data is ideal for evaluating how the probabilities estimated by fitting the distribution regression model 1 vary with the business cycle. In particular, it allows us to investigate whether the probability of nominal or real wage cuts or freeze depends on local economic conditions and, if so, by how much.

To do so, we exploit the cross-regional and time-series variation in business cycle conditions during the period considered. Our object of interest is the probability $\pi_{rt}(\mathcal{C}_t)$ that nominal wage growth \dot{W}_{it} for a reference worker in region r , namely one with $\mathbf{X}_{it} = \mathbf{0}$, falls in a particular interval \mathcal{C}_t . If $\hat{\pi}_{rt}(\mathcal{C}_t)$ denotes the estimate of $\pi_{rt}(\mathcal{C}_t)$ based on model (1), we fit the following regression equation

$$\hat{\pi}_{rt}(\mathcal{C}_t|\mathbf{0}) = \delta_1(p_{rt} - \bar{p}) + \delta_2(u_{rt} - \bar{u}) + \delta_3 G\dot{D}P_{rt} + \gamma_r + \gamma_{\mathcal{P}} + \eta_{rt}, \quad (3)$$

where p_{rt} and u_{rt} are, respectively, the labor force participation rate (LFPR) and the unemployment rate in region r in year t , \bar{p} and \bar{u} are their Italian average over the entire period, $G\dot{D}P_{rt}$ is regional GDP growth, γ_r is a region-specific fixed effect, $\gamma_{\mathcal{P}}$ is a period-specific fixed effect,¹⁶ and η_{rt} is the error term. The intervals considered for \mathcal{C}_t are the same as in Sections 5.2 and 6.

The results of estimating model (3) are shown in Table 6. The probability of a wage cut is negatively associated with regional GDP growth and regional LFPR, and positively associated with regional unemployment, while the probability of a wage freeze is positively associated with regional unemployment and negatively associated with regional GDP growth and regional LFPR, although the latter relationship is not statistically significant. In quantitative terms, a 1-percentage point increase in $u_{rt} - \bar{u}$ is associated with an increase by .22 percentage points in the probability of a wage cut. On the other hand, a 1-percentage point decrease in $G\dot{D}P_{rt}$ or in $p_{rt} - \bar{p}$ is associated with a decrease by 1.0 and 0.15 percentage points respectively. The association between these three variables and the probability of a wage raise is just specular.

Analogously, the probabilities that nominal wage growth is below past, current or future inflation are positively associated with the regional unemployment and negatively associated with regional GDP growth. In this case, both coefficients are highly statistically significant.¹⁷ A 1-percentage point increase in $u_{rt} - \bar{u}$ is associated with an increase in the probability of a real wage cut (in term of current inflation) of about .54 percentage points and a 1-percentage point decrease in $G\dot{D}P_{rt}$ is associated with an increase of about 1.03 percentage points. According to our results, there is no association between this probability and LFPR given that the estimated coefficient is neither statistically nor economically significant.

These results show that the estimated probabilities of nominal or real wage growth are highly cyclical and quite sensitive to local labor market conditions. When regional unemployment goes up, or regional GDP goes down, wages respond and the likelihood of receiving a nominal or real wage cut increases.

Specification (3) allows us to interpret the estimated coefficients on the subperiod dummies as the averages (across regions) of our estimated probabilities if the regional unemployment rate and the LFPR were exactly equal to the Italian long-run averages and the real GDP growth was exactly equal to zero. In all the regressions, the coefficients on the subperiod dummies are highly significant. Hence, the results in Table 6 show that the probability of a nominal wage cut or freeze follows an increasing trend until 2021, while the probability of a nominal wage raise follows a specular downward trend. On the other hand, consistently with our results in Sections 5.3 and 6.2, the probability of a

¹⁶ Instead of year-specific fixed effects, we include period-specific fixed effects, with \mathcal{P} any of the seven periods described in Section 3.

¹⁷ The only exception is the association between the probability of nominal wage growth below future inflation and real GDP growth which is neither economically nor statistically significant.

real wage cut fluctuates around a slightly upward trend.

7 Extensions

This section presents the results from several extensions of the baseline specification of the distribution regression model (1). Section 7.1 introduces a rich set of firm-level characteristics, Section 7.2 adds controls for the duration of labor contracts, Section 7.3 adds controls for the reasons of job-to-job mobility, Section 7.4 adds controls for contract renewal, Section 7.5 adds controls for information on “notional events”, while Section 7.6 compares the growth rates of actual and base wages. These extensions are only possible for the most recent years because of the richer information available in the INPS archives.

7.1 Controlling for firm-level characteristics

To control for firm-level characteristics, we use the Cerved firm-level information available for 1996–2018 and described in Section 4.3 and Appendix B.3.

Figure 11 shows that the probability of real wage cuts, nominal or real, is lowest for workers employed in firms that rank highest in terms of labor productivity,¹⁸ while there are basically no differences when we consider the probability of a nominal wage freeze. We also find hardly any difference when considering workers employed in firms that differ in their ROA (Figure 12).

As a measure of the financial risks taken by the firm, we consider the leverage ratio, i.e. the firm’s debt divided by the total amount of assets. As shown in Figure 13, the probability of a wage cut, nominal or real, is slightly higher for workers employed in firms with a higher leverage ratio, but the difference is small. Similarly, there are only small differences between workers employed in firms with a different number of years of negative profits (Figure 14).

Finally, when considering the estimated probabilities for workers employed in different sectors, we find no significant differences among those working in manufacturing, commerce and transportation, while the probabilities of a wage cut, nominal or real, are higher for workers employed in construction (Figure 15).

7.2 Controlling for contract duration

Until 1997, all Italian labor contracts were open ended (*a tempo indeterminato*) and could be terminated only for a “justified motive” (*giusta causa*). In June 1997, a reform of Italian labor law (*Riforma Treu*) introduced fixed-term contracts (*contratti a tempo determinato*). Hence, starting

¹⁸ In Figures 11–13, for each measure of performance, we create binary indicators corresponding to the percentile to which the firm belongs (the reference belongs to the third quintile, that is, corresponds to a firm between the 40th and the 60th percentile of a given measure of performance).

from 1998, the information available in the INPS employment relations registry also includes the type of contract – open-ended or fixed-term. We exploit this information to study whether the probabilities of a nominal wage cut, a nominal wage freeze, or a nominal wage growth below the rate of inflation differ between the two types of contract.

To ease the interpretation, we focus on workers who have only one employment relation in two adjacent years and distinguish among situations in which the contract is fixed-term or open ended in both years or in only one year.¹⁹ Hence, we augment the specification of the distribution regression model (1) with 3 dummies indicating whether a worker had a fixed-term contract only in the first year, only in the second year, or in both years (the reference category is an open-ended contract in both years). We then compare the estimated probabilities between reference workers in each of the above categories and our reference worker with an open-ended contract in both years. The results are shown in Figure 16.

We do not find much differences between workers with open-end or fixed-term contracts in both years. However, the probability of a nominal or real wage cut increases substantially for workers who switch from an open-ended to a fixed-term contract between years $t - 1$ and t . Such a transition is not common (only about .1% of the sample) and is usually due to traumatic events, such as restructuring or closing of a firm. A worker who loses her open-ended job finds herself in a difficult situation, so it is plausible that, when accepting a fixed-term contract, she may also be forced to take a wage cut.

7.3 Controlling for the reasons of job-to-job mobility

In Section 6.2, we examined how the probabilities of nominal wage cuts, freezes or raises, or of a real wage cut, differ between movers and stayers. We found that the probability of a nominal wage cut is systematically higher for movers compared to stayers, and that the difference between the two groups became more pronounced during the past 20 years. We also found that the probability of a real wage cut is similar between stayers and movers during the first half of our period, but is higher for movers thereafter.

One limitation of this analysis is that it ignores the reasons why workers change jobs. Fortunately, starting from 2005, the INPS archives provide information on the reason why an employment relation ended (*motivo cessazione*). This may happen for several reasons. We collapse them into four categories: layoffs, voluntary quits, end of contract, and a residual category that we call “other”.²⁰ We then augment our distribution regression model (1) with four indicators for the end of an employment relation: one for a layoff, one for a voluntary quits, one for the end of the contract, and one for other reasons. The reference is a job stayer, defined in Section 4.1.1. On average, workers in the first

¹⁹ Recall that our workers can have more than one employment relation in the second of each two consecutive years.

²⁰ The “other” category includes the suspension of a job contract, union leave (*aspettativa sindacale*), and leave of absence for electoral duties (*aspettativa elettorale*).

category represent about 12% of the movers, those in the second about 57%, those in the third about 4%, and those in the “other” category the remaining 27%.

The results are presented in Figure 17. Notice first that stayers are less likely to suffer a nominal wage cut than movers. In particular, being a stayer is associated with a lower probability of a nominal wage cut even with respect to voluntary quitters. Interestingly, the probability of a nominal wage cut is lower for voluntary quitters than for laid-off workers or workers whose contract ended. In particular, the average probability of a nominal wage cut is about 20% for stayers and about 42% for quitters. In turn, it is about 11 percentage points lower than that experienced by laid-off workers and about 6 percentage points lower than that experienced by movers whose contract ended.

Our results suggest that when workers start a new employment relation, especially after a layoff or after the end of a fixed-term contract, there is a high chances that the new contract implies a lower wage. This is consistent with the results of Hoffmann, Malacrino, and Pistaferri (2022) who find that the introduction of fixed-term contracts in Italy has significantly increased the variability of earnings.

As for the probability of a real wage cut, we find that it is lower for stayers than for quitters,²¹ who in turn have a lower probability compared to laid-off workers or movers whose contract ended. Averaged over the entire period 2006–2024, these estimated probabilities are about 36% for stayers, 49% for quitters, 61% for laid-off workers and 60% for movers whose contract ended. These results suggest that changing job tends to be quite costly for Italian workers, especially when the job change is not voluntary. Note that, while a fixed-term contract need not imply substantial income risks for our primary workers (see Figure 16), failure to renew an existing fixed-term contract can lead to a wage cut in the new one.

7.4 Controlling for contract renewal

One of the most influential theories of nominal wage rigidity is the staggered wage contract hypothesis, first proposed by Fischer (1977) and Taylor (1979) and more recently revived by Gertler and Trigari (2009). According to this theory, rigidity of nominal wages is the natural consequence of the fact that labor contracts set wages for a fixed period of time and not all contracts are renegotiated at the same time. Although testing the validity of this theory is beyond the scope of this paper, our data can shed light on whether the time profile of wage adjustments is compatible with the staggered wage hypothesis. If nominal wage stickiness is caused by the lack of continuous wage negotiation, we should observe wage adjustments mainly in the years when contracts are renegotiated.

In Italy, wages are typically negotiated at the national level by large trade unions (e.g., CGIL, CISL or UIL) and correspondingly large enterprise federations (e.g., *Confindustria*). Since 1992, national contracts may be complemented by firm-level agreements. Labor contracts usually last three

²¹ Except during the Covid-19 pandemic.

or four years, but there are substantial deviations from this norm.

Starting from the year 2005, the INPS archives provide reliable information on the specific national labor contract associated with each employment relation. We combine this information with that obtained from the database maintained by CNEL (*Consiglio Nazionale dell'Economia e del Lavoro*), which is tasked by law with collecting data on all national labor contracts.²² Further, we only consider contracts that are renewed regularly, i.e. at least every four years.

Table C.6 shows the evolution of the sample size at each stage of the sample selection process. The starting point is column (1), which corresponds to the working sample in column (6) of Table 1. Overall, we lose almost half of our working sample by excluding workers covered by contracts that are not in the CNEL database (column (2)). On the other hand, going from column (2) to column (3) we only lose the relatively small number of workers covered by contracts not signed by CGIL, CISL and UIL.

In what follows, we augment the distribution regression model (1) by including three indicators of contract renewal: only in year $t - 1$, only in year t , or in both years (the reference category is a worker without contract renewal).²³ This specification allows us to study differences in the probabilities of interest for workers with and without contract renewal by CGIL, CISL and UIL.

The results in Figure 18 show that workers with a contract renewal have a slightly lower probability of a nominal or real wage cut compared to workers who do not. If we consider the entire period 2006–2024, the probability of a nominal wage cut for a reference worker without contract renewal is about 20% on average against about 17.5% for workers with renewal only in year $t - 1$ and 18% for workers with renewal only in year t . Further, the estimated probability of a real wage cut for a reference worker with no renewal in both years is about 3.5 percentage points higher than that of a worker with renewal only in year $t - 1$ and 3 percentage points higher than that of a worker with renewal only in year t . Moreover, the estimated probability of a nominal wage freeze for a reference worker without renewal is 7.1% on average, is 6.7% for those with renewal only in year $t - 1$, and is 7% for those with renewal only in year t . We conclude that contract renewal is associated with a slightly lower probability of a nominal or real wage cut. This marginal association suggests that staggered wage setting is not a major source of wage stickiness.

²² The CNEL database provides information on whether a labor contract is signed by the three large Italian trade unions, namely CGIL, CISL and UIL (*Sindacati confederali*) or by some “autonomous” union (*Sindacato autonomo*). Since the number of workers covered by contracts signed by an autonomous union is negligible, we restrict our sample to workers covered by contracts in the CNEL database that have been signed by CGIL, CISL and UIL.

²³ It can happen that a worker who changes job also changes contract, in which case her contract can be renewed in both years. We control for these workers but, since they are very few, we show the estimated probabilities only for workers with a contract renewal either in year $t - 1$ only or in t only.

7.5 Controlling for notional events

According to Italian law, workers must be partially compensated for the loss of earnings caused by events such as sick leave, parental leave, or temporary layoffs during which workers receive financial support from a special redundancy fund (*Cassa Integrazione Guadagni* or CIG). The INPS archives flag these events as “notional events” (*eventi figurativi*). When one of them occurs, the worker receives a compensation by INPS which is typically less than full, so the occurrence of a notional event usually lowers annual earnings and therefore also our wage measure. Starting in 2005, INPS provides information that allows us to determine whether a worker experienced at least one notional event during the year.

Table C.7 shows mean, median and standard deviation of nominal wage growth for workers who experience a notional event only in year $t - 1$, only in year t , or in both years.²⁴ To facilitate the interpretation of our results, we focus on workers who did not experience any notional event in year $t - 1$. Table C.8 shows that this sample selection implies a loss of approximately 1.5 million workers on average, with large year-to-year changes that reflect the occurrence of big negative shocks to the economy, such as the Great Recession of 2007–2009 or the Covid-19 pandemic of 2020–2022. The final three columns of Table C.8 provide a breakdown of the number of workers experiencing at least one notional event in year t into three categories: workers experiencing only CIG, workers experiencing notional events other than CIG, and workers experiencing both CIG and other notional events.

We augment the distribution regression model (1) with two indicators, one for whether the worker experienced only CIG in year t and one for whether she experiences only some other notional event.²⁵ The results shown in Figure 19 indicate that the probability of a nominal or real wage cut is much higher for workers with a notional event in year t , compared to those who did not experience notional events. In addition, the probability of a nominal or real wage cut is higher for CIG than for other types of notional event. In particular, on average over the period 2006–2024, the estimated probability of a nominal wage cut is about 16% in the absence of notional events, 45% for CIG and 40% for other types of notional event. On the other hand, the average probability of a real wage cut is about 34% versus 61% for CIG workers and 57.5% for workers with other types of notional event.

These results suggest that notional events may have an important impact on wage dynamics and may help explain why we observe such a high fraction of nominal and real wage cuts. But is this the whole story? In order to better understand the observed patterns, in the next section, we only

²⁴ Average and median wage growth are highest for workers who experienced a notional event only in year $t - 1$, and lowest for workers who experienced a notional event only in year t . This is not surprising: if the notional event occurs only in year $t - 1$, the earnings reduction in that year should lead to a higher wage growth compared to the case when the notional event did not occur.

²⁵ We also include an interaction term between these two indicators, but we report estimated probabilities only for these two types of workers.

consider workers who did not experience notional events.

7.6 Actual v. base wage growth

The evidence presented so far points to a surprisingly high degree of wage flexibility in the Italian labor market. To understand how this is originated, we focus on the years 2013–2024, a period for which we have information on both actual wages and “base” wages, defined as annual base earnings divided by the number of weeks worked. Starting in 2008, firms must report to INPS the contractual monthly earnings of each worker.²⁶ Multiplying this quantity by the contractual number of months worked (usually 12 for full-year contracts) gives annual base earnings, which represent the basis for computing unemployment benefits, CIG payments, and other benefits. Base earnings do not include annual or monthly premiums, production premiums, payments for unused vacation time, arrears, and overtime compensation (except the part normally included in monthly compensation).

In this section, we study the growth of actual wages W_{it} and base wages W_{it}^b , along with that of “residual wages” $R_{it} = W_{it}/W_{it}^b$. Unlike Grigsby, Hurst, and Yildirmaz (2021), who analyze payroll data from the largest payroll processing company in the US, we cannot distinguish between the individual components of total compensation, such as paid overtime work, bonuses, and reimbursements. We can only gauge their overall importance by looking whether $R_{it} > 1$, under the maintained assumption that bonuses and overtime pay do not substitute for the base wage but represent an addition to it. In order to have a better sense of the importance of these extra components, we only keep workers who do not experience a notional event. The size of our sample can be inferred from Table C.8 by taking the difference between columns (2) and (3). Actual wages are generally higher than base wages. In particular, on average over the period 2013–2024, both R_{it} and $R_{i,t-1}$ are greater than one for about 96% of the workers who did not experience a notional event. This suggests that employers set wages using base wages as a lower bound, but then make extra payments to compensate workers for their effort. The fact that we cannot distinguish between bonuses and payments for overtime work complicates the interpretation of the residual wage, as the former are genuine wage increases, while the latter remunerate extra work hours, usually at a higher rate. However, the importance of these components indicates that, even in settings characterized by centralized labor contracts, like the Italian one, firms and workers tend to form a surplus-sharing relationship.

Since $W_{it} = R_{it}W_{it}^b$, taking log-differences gives the following decomposition of actual wage growth:

$$\dot{w}_{it} = \ln W_{it} - \ln W_{it-1} = \dot{w}_{it}^b + \dot{r}_{it}, \quad (4)$$

where \dot{w}_{it}^b and \dot{r}_{it} denote the log-differences in W_{it}^b and R_{it} respectively. Thus, after approximating \dot{W}_{it} with \dot{w}_{it} , we can express the growth rate of actual wages as the sum of two components: the

²⁶ Accurate and complete data on base earnings are available only from 2011, hence base wage growth can reliably be assessed only from 2012. For consistency with the periodization in Section 3, we start from 2013.

growth rate of base wages, \dot{w}_{it}^b , and that of residual wages, \dot{r}_{it} . We now examine separately these three quantities.

Table 7 shows moment-based and percentile-based statistics for the three elements of the decomposition (4). Actual wage growth is on average higher than base wage growth, but also more dispersed. Figure 20 compares the histograms of actual and base wage growth. The differences between the two are quite striking. Negative values are very rare for base-wage growth. In addition, its histograms show sizable spikes at zero. Finally, as noted in Section 5.2, the histograms of actual wage growth show that nominal wage cuts were quite frequent during the low inflation period 2013–2021, while real wage cuts were quite frequent during the inflationary years 2022 and 2023. The histograms of \dot{r}_{it} in the bottom panel of Figure 20 show that positive and negative deviations of actual wage growth from base wage growth have about the same importance.

Table 8 shows the joint empirical distribution of actual and base wage growth, along with their marginals in terms of nominal wage cuts, freezes and raises. During 2013–2021, raises in both actual and base wages represent more than half of the cases, while cuts in actual wages along with raises in base wage represent nearly 15% of the cases, and cuts in both actual and base wages represent only 4% of the cases. Interestingly, the fraction of workers with a reduction in the actual wage but an increase in the base wage is above 10% in each subperiod. Consistently, we also find that base wage freezes are much more frequent than actual wage freezes, that actual wage cuts are more frequent than base wage cuts, and that actual wage raises are less frequent than base wage raises.

Table 9 shows the joint distribution of actual and base wage changes relative to current inflation. When inflation is low, i.e. in 2013–2021 and 2024, increases in real wages, both actual and base, represent the norm, while the opposite is true during the inflationary years 2022 and 2023. Interestingly, in years of low inflation, increases in real terms are more frequent for base wages than for actual wages, whereas the opposite is true in years of high inflation.

Thus, while base wages display the typical downward rigidity found in many studies, actual wages are instead much more flexible. This flexibility is possible because firms tend to pay wages in excess of contractual wages. Since “residual wages” are the result of bilateral agreements, they tend to vary in response to market conditions, productivity shocks, or incentive considerations.

We have so far ignored compositional effects arising from changes over time in the characteristics of the workers. To take these into account, we estimate distribution regression model of the same form as (1) for the probability of a cut in nominal wages, actual or base, and for the probability that wage growth, actual or base, does not exceed current inflation. Table 10 presents the results. In each panel of the table, the first column shows the estimated probability for our reference worker, while the other columns show the estimated probabilities for workers that differ from the reference worker only by one characteristic at the time. The top panel of Table 10 shows the estimated probabilities of a nominal

cut in actual wages. As we drop workers who experienced a notional event, these probabilities are well below those presented in Section 6.2. On average, they are slightly higher for females, for older or more experienced workers, and for workers in larger firms. Differences among workers are larger when we account for occupation, mobility pattern, or region of employment. The second panel of the table shows the estimated probabilities of a nominal cut in base wages. These probabilities are much lower than for nominal cuts in actual wages for almost all types of workers except the movers. The third and fourth panels of the table show the estimated probabilities that actual or base wage growth does not exceed current inflation. Interestingly, while there are substantial differences between the probability of experiencing an actual and a base nominal wage cut, these differences vanish in real terms. We estimate that these probabilities are typically higher for female workers, older or more experienced workers, blue collars, and workers in southern regions. Moreover, in low inflationary environments such as the period 2013–2021, the stayers face a lower risk that their actual and base wage growth does not exceed current inflation compared to the movers, while the opposite is true when inflation is high, e.g. 2022 and 2023.

8 Conclusions

We have studied the relationship between the distribution of nominal wage changes and inflation in Italy over the past half-century using a rich dataset covering the universe of non-agricultural private-sector employees. Our analysis uncovers several interesting facts about the Italian labor market that can be useful to discipline macroeconomic models.

During the last fifty years the distribution of nominal wage growth changed significantly and, as inflation went down, so did the center and the spread of the distribution. Moreover, with the decrease in inflation, the fraction of nominal wage cuts has increased substantially: more than 30% of nominal wage changes were negative during the more recent 2013–2021 period. Similar numbers were obtained after controlling for compositional effects. On the other side, the fraction of workers with real wage cuts fluctuated around a slightly positive trend, with spikes between 59 and 75% during the post-Covid inflation. These findings suggest that the Italian labor market has been characterized by a high degree of flexibility. Our evidence also indicates that inflation has been used to “grease the wheels of the labor market”, especially after the abolition of wage indexation in the early 1990s.

To better understand how such flexibility was achieved in a highly centralized labor market such as the Italian one, we use data available for the last 11 years to compare the distribution of actual and “base” or contractual wage changes. We find that base wages do not show significant decreases and that cuts in actual wages are usually implemented through cuts in bonuses, overtime and other types of compensation.

Our distributional regression estimates show that the probability of nominal wage cuts are higher

for females than for males, for blue collars than for white collars, and for workers in the Southern provinces than for those in the Northern provinces. They also show that these probabilities are cyclical and sensitive to local labor market conditions.

Interestingly, we find evidence that stayers have a higher probability of experiencing a nominal wage cut compared to movers, which suggests that, contrary to what has been found for other countries, changing jobs in Italy is not a reliable way to climb the wage ladder. Starting from 2005, we are also able to investigate the reasons behind job changes and we find that the probability of experiencing a nominal or real wage cut is systematically lower for workers who voluntarily quit their job than for laid-off workers or workers who move because of the end of a fixed-term contract. However, unlike stayers, voluntary quitters have a higher probability of experiencing a decrease in nominal or real wages, with the exception of the Covid and post-Covid years.

Our analysis focuses on “primary” workers, namely those with only one full-time full-year employment relation in year $t - 1$ and at most two full-time employment relations in year t , each with a positive number of weeks worked. Since these workers are arguably better able to defend themselves against inflation, our analysis may not apply to other types of workers, such as part-time workers, and therefore is likely to offer a “best-case scenario” for the universe of all Italian workers. Moreover, although we analyze how the probability of receiving a wage cut correlates with various measures of firm performance, we are silent about how the within-firm distribution of wages and wage changes correlates with firms’ productivity and productivity growth. We leave these questions for future research.

References

- Akerlof, George A, William T Dickens, George L Perry, Robert J Gordon, and N Gregory Mankiw. 1996. "The macroeconomics of low inflation." *Brookings papers on economic activity* 1996 (1):1–76.
- Altonji, Joseph and Paul Devereux. 1999. "The extent and consequences of downward nominal wage rigidity." NBER Working Paper 7236. Available at <http://www.nber.org/papers/w7236>.
- Amuedo-Dorantes, Catalina and Ricardo Serrano-Padial. 2007. "Wage growth implications of fixed-term employment: An analysis by contract duration and job mobility." *Labour Economics* 14 (5):829–847.
- Avouyi-Dovi, Sanvi, Denis Fougère, and Erwan Gautier. 2013. "Wage rigidity, collective bargaining, and the minimum wage: evidence from French agreement data." *Review of Economics and Statistics* 95 (4):1337–1351.
- Barattieri, Alessandro, Susanto Basu, and Peter Gottschalk. 2014. "Some evidence on the importance of sticky wages." *American Economic Journal: Macroeconomics* 6 (1):70–101.
- Bauer, Thomas, Holger Bonin, Lorenz Goette, and Uwe Sunde. 2007. "Real and nominal wage rigidities and the rate of inflation: Evidence from West German micro data." *Economic Journal* 117 (524):F508–F529.
- Card, David and Dean Hyslop. 1997. "Does inflation 'grease the wheels of the labor market'?" In *Reducing Inflation: Motivation and Strategy*, edited by C. Romer and D. Romer. University of Chicago Press, Chicago, 71–121.
- Castellanos, Sara G, Rodrigo García-Verdú, and David S Kaplan. 2004. "Nominal wage rigidities in Mexico: evidence from social security records." *Journal of Development Economics* 75 (2):507–533.
- Chernozhukov, Victor, Iván Fernández-Val, and Blaise Melly. 2013. "Inference on counterfactual distributions." *Econometrica* 81 (6):2205–2268.
- Devicienti, Francesco, Agata Maida, and Paolo Sestito. 2007. "Downward wage rigidity in Italy: micro-based measures and implications." *Economic Journal* 117 (524):F530–F552.
- Doris, Aedín, Donal O'Neill, and Olive Sweetman. 2015. "Wage flexibility and the great recession: the response of the Irish labour market." *IZA Journal of European Labor Studies* 4:1–24.
- Ekberg, John. 2004. *Essays in Empirical Labor Economics*. Ph.D. thesis, Nationalekonomiska institutionen.

- Elsby, Michael, Donggyun Shin, and Gary Solon. 2016. “Wage adjustment in the Great Recession and other downturns: Evidence from the United States and Great Britain.” *Journal of Labor Economics* 34 (S1):S249–S291.
- Elsby, Michael and Gary Solon. 2019. “How prevalent is downward rigidity in nominal wages? International evidence from payroll records and pay slips.” *Journal of Economic Perspectives* 33 (3):185–201.
- Erickson, Christopher and Andrea Ichino. 1995. “Wage differentials in Italy: Market forces, institutions, and inflation.” In *Differences and Changes in the Wage Structure*, edited by R. Freeman and L.F. Katz. University of Chicago Press, Chicago, 265–305.
- Fischer, Stanley. 1977. “Long-term contracts, rational expectations, and the optimal money supply rule.” *Journal of Political Economy* 85 (1):191–205.
- Foresi, Silverio and Franco Peracchi. 1995. “The conditional distribution of excess returns: An empirical analysis.” *Journal of the American Statistical Association* 90 (430):451–466.
- Fratianni, Michele and Franco Spinelli. 1997. *A Monetary History of Italy*. Cambridge University Press.
- Gertler, Mark and Antonella Trigari. 2009. “Unemployment fluctuations with staggered Nash wage bargaining.” *Journal of Political Economy* 117 (1):38–86.
- Grigsby, John, Erik Hurst, and Ahu Yildirmaz. 2021. “Aggregate nominal wage adjustments: New evidence from administrative payroll data.” *American Economic Review* 111 (2):428–471.
- Guiso, Luigi, Luigi Pistaferri, and Fabiano Schivardi. 2005. “Insurance within the firm.” *Journal of Political Economy* 113 (5):1054–1087.
- Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song. 2021. “What do data on millions of US workers reveal about lifecycle earnings dynamics?” *Econometrica* 89 (5):2303–2339.
- Hoffmann, Eran B, Davide Malacrino, and Luigi Pistaferri. 2022. “Earnings dynamics and labor market reforms: The Italian case.” *Quantitative Economics* 13 (4):1637–1667.
- Jardim, Ekaterina S, Gary Solon, and Jacob L Vigdor. 2019. “How prevalent is downward rigidity in nominal wages? Evidence from payroll records in Washington State.” NBER Working Paper 25470. Available at <http://www.nber.org/papers/w25470>.
- Kahn, Shulamit. 1997. “Evidence of nominal wage stickiness from microdata.” *The American Economic Review* 87 (5):993–1008.

- Keynes, John Maynard. 1936. *The General Theory of Unemployment, Interest and Money*. Harcourt Brace, London.
- Kurmann, André and Erika McEntarfer. 2019. “Downward nominal wage rigidity in the United States: New evidence from worker-firm linked data.” Drexel University School of Economics Working Paper Series WP 2019-01.
- Leonardi, Marco, Michele Pellizzari, and Domencio Tabasso. 2019. “Wage compression within the firm: Evidence from an indexation scheme.” *Economic Journal* 129:3256–3291.
- Lorenzoni, Guido and Iván Werning. 2023. “Wage price spirals.” Available at <https://economics.mit.edu/sites/default/files/inline-files/WagePriceSpirals.pdf>.
- Lucifora, Claudio and Daria Vigani. 2021. “Losing control? Unions’ representativeness, pirate collective agreements, and wages.” *Industrial Relations: A Journal of Economy and Society* 60 (2):188–218.
- Manacorda, Marco. 2004. “Can the Scala Mobile explain the fall and rise of earnings inequality in Italy? A semiparametric analysis, 1977–1993.” *Journal of Labor Economics* 22 (3):585–613.
- McLaughlin, Kenneth J. 1994. “Rigid wages?” *Journal of Monetary Economics* 34 (3):383–414.
- Nickell, Stephen and Glenda Quintini. 2003. “Nominal wage rigidity and the rate of inflation.” *The Economic Journal* 113 (490):762–781.
- Park, Seonyoung and Donggyun Shin. 2017. “The extent and nature of downward nominal wage flexibility: An analysis of longitudinal worker/establishment data from Korea.” *Labour Economics* 48:67–86.
- Schaefer, Daniel and Carl Singleton. 2022. “The extent of downward nominal wage rigidity: new evidence from payroll data.” *Review of Economic Dynamics* 51:60–76.
- Smith, Jennifer C. 2000. “Nominal wage rigidity in the United Kingdom.” *The Economic Journal* 110 (462):176–195.
- Stantcheva, Stefanie. 2024. “Why do we dislike inflation?” NBER Working Paper 32300. Available at <http://www.nber.org/papers/w32300>.
- Taylor, John. 1979. “Staggered wage setting in a macro model.” *The American Economic Review* 69 (2):108–113.
- Tobin, James. 1972. “Inflation and unemployment.” *American Economic Review* 62 (1/2):1–18.

Table 1: Sample size (thousands of workers) at each stage of our sample selection process.

Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1975	9,181.0	9,063.7	9,063.7	2,993.4	2,880.0	2,826.5	2,743.2	83.3
1980	10,639.1	10,471.6	10,470.9	5,640.9	5,435.5	5,354.2	5,080.1	274.1
1985	9,636.0	9,520.2	9,372.9	5,068.6	4,861.3	4,775.4	4,539.7	235.7
1990	10,507.9	10,346.0	9,788.3	5,479.0	5,270.9	5,182.9	4,825.0	357.9
1995	10,154.3	10,023.0	9,085.0	5,378.2	5,191.8	5,123.2	4,837.7	285.5
2000	11,986.1	11,679.5	10,097.4	5,489.9	5,326.0	5,250.4	4,877.8	372.6
2005	13,130.5	12,649.7	10,272.8	6,084.2	5,883.4	5,817.5	5,512.9	304.6
2010	14,029.0	13,467.5	10,182.8	5,767.6	5,581.9	5,491.6	5,215.5	276.1
2015	13,950.1	13,306.1	9,174.6	5,528.2	5,379.5	5,192.9	4,988.6	204.3
2020	15,118.8	14,475.7	9,700.6	5,944.8	5,718.0	5,385.5	5,168.2	217.3
2021	15,463.8	14,667.4	9,867.6	4,105.6	4,014.9	3,749.8	3,541.7	208.1
2022	16,345.4	15,348.6	10,387.2	5,606.0	5,472.1	5,116.7	4,799.6	317.1
2023	16,755.1	15,781.9	10,728.8	6,134.8	5,990.7	5,555.5	5,224.0	331.6
2024	16,543.1	15,617.6	10,522.6	6,051.8	5,894.8	5,423.8	5,090.0	333.8

(1): Total number of workers with positive annual earnings and positive weeks worked in the original INPS data.

(2): Excluding workers with more than 2 employment relations in year t .

(3): Excluding (2), workers with at least one part-time employment relationship in year t .

(4): Total number of workers in (3) that were working full-time and full-year in year $t - 1$.

(5): Excluding workers with total number of weeks worked not in 26–54 in year t .

(6): Excluding workers not aged 17–59 in year $t - 1$.

(7): Total number of stayers among workers in (6).

(8): Total number of movers among workers in (6).

Table 2: Moment-based and percentile-based summaries of wage growth.

Period	Moment-based				Percentile-based				\dot{P}
	Mean	Spread	Skew	Kurt	Median	Spread	Skew	Kurt	
1975–1979	.220	.162	1.205	9.059	.203	.323	1.384	2.206	.155
1980–1986	.171	.146	1.066	8.532	.156	.294	1.392	2.027	.138
1987–1992	.101	.113	1.039	8.579	.086	.225	1.559	2.269	.057
1993–1998	.057	.095	.737	7.755	.047	.193	1.442	2.459	.035
1999–2012	.042	.097	.592	7.694	.033	.197	1.378	2.497	.022
2013–2021	.020	.088	.442	7.293	.015	.181	1.209	2.627	.006
2022	.041	.101	1.300	7.729	.024	.210	1.751	2.378	.079
2023	.052	.095	1.016	7.354	.039	.195	1.596	2.353	.053
2024	.052	.094	.780	7.040	.043	.196	1.327	2.377	.009

Percentile-based spread is measured by the interdecile range, percentile-based skewness by the ratio of the difference between the 90th percentile and the median to the difference between the median and the 10th percentile, percentile-based kurtosis by the ratio of the interdecile and the interquartile ranges. Also, \dot{P} is the inflation rate.

Table 3: Mean, median and standard deviation (SD) of nominal wage growth conditional on a wage cut or a wage raise.

Period	Wage cut			Wage raise		
	Mean	Median	SD	Mean	Median	SD
1975–1979	-.116	-.085	.099	.238	.210	.146
1980–1986	-.106	-.070	.100	.190	.165	.130
1987–1992	-.079	-.050	.081	.122	.097	.098
1993–1998	-.067	-.042	.069	.086	.061	.079
1999–2012	-.067	-.043	.071	.080	.054	.079
2013–2021	-.063	-.041	.064	.067	.042	.071
2022	-.054	-.036	.053	.088	.058	.092
2023	-.058	-.038	.058	.085	.059	.082
2024	-.062	-.042	.060	.085	.062	.077

Table 4: Fraction of workers with nominal wage growth not exceeding past, current or future inflation. Breakdown by sex, age, type of occupation and geographical area.

Period	Sex		Age group			Occupation		Area			
	All	M	F	17–29	30–49	50–59	BC	WC	N	C	SI
Cuts											
1975–1979	.050	.045	.066	.052	.047	.061	.053	.043	.050	.047	.054
1980–1986	.061	.055	.075	.063	.057	.074	.069	.049	.058	.064	.072
1987–1992	.098	.096	.103	.091	.097	.118	.112	.078	.090	.103	.124
1993–1998	.171	.176	.158	.144	.176	.205	.188	.149	.158	.175	.215
1999–2012	.227	.231	.218	.181	.230	.263	.243	.209	.222	.229	.242
2013–2021	.316	.320	.308	.253	.311	.348	.342	.293	.312	.321	.328
2022	.285	.284	.285	.208	.274	.321	.305	.265	.276	.288	.312
2023	.197	.200	.190	.141	.189	.225	.223	.171	.196	.202	.195
2024	.200	.202	.195	.146	.194	.225	.217	.182	.197	.203	.206
Freezes											
1975–1979	.008	.007	.009	.006	.008	.011	.008	.007	.006	.009	.014
1980–1986	.009	.009	.008	.007	.009	.011	.009	.008	.008	.009	.011
1987–1992	.019	.019	.017	.016	.019	.022	.021	.016	.018	.020	.022
1993–1998	.040	.041	.038	.032	.042	.047	.041	.039	.038	.043	.045
1999–2012	.055	.056	.054	.041	.056	.065	.055	.055	.055	.056	.055
2013–2021	.087	.085	.091	.061	.085	.100	.080	.094	.086	.087	.091
2022	.077	.075	.082	.049	.073	.090	.072	.082	.076	.077	.083
2023	.057	.056	.060	.035	.054	.068	.056	.059	.057	.056	.058
2024	.047	.046	.050	.031	.045	.055	.044	.050	.046	.048	.049
Raises											
1975–1979	.942	.948	.924	.942	.945	.929	.939	.949	.943	.944	.931
1980–1986	.930	.936	.917	.930	.934	.915	.922	.943	.934	.927	.917
1987–1992	.883	.884	.879	.893	.883	.860	.867	.906	.892	.878	.854
1993–1998	.789	.783	.804	.824	.782	.748	.771	.812	.804	.782	.740
1999–2012	.717	.713	.728	.778	.713	.672	.702	.735	.723	.715	.702
2013–2021	.597	.595	.601	.686	.604	.552	.578	.613	.602	.592	.581
2022	.638	.641	.633	.743	.652	.590	.624	.653	.648	.636	.605
2023	.746	.744	.749	.824	.757	.707	.721	.770	.747	.742	.747
2024	.753	.752	.756	.824	.761	.720	.739	.768	.756	.749	.746

The column labeled “All” refers to all workers. The columns labeled “Sex” give the fraction by sex: males (M) and females (F). The columns labeled “Age group” give the fraction by age group: 17–29, 30–49, and 50–59. The columns labeled “Occupation” give the fraction by occupation: blue collars (BC, i.e. “operai” + “apprendisti”) and white collars (WC, i.e. “altro” + “equiparati o intermedi” + “impiegati” + “quadri” + “dirigenti”). The columns labeled “Area” give the fraction by geographical area of employment: North (N), Center (C), and South and Islands (SI).

Table 5: Fraction of workers with nominal wage growth not exceeding past, current or future inflation. Breakdown by sex, age, type of occupation and geographical area.

Period	Sex		Age			Occupation		Area			
	All	M	F	17-29	30-49	50-59	BC	WC	N	C	SI
Not exceeding past inflation											
1975-1979	.328	.339	.300	.275	.348	.370	.323	.340	.333	.311	.321
1980-1986	.485	.487	.482	.436	.503	.518	.486	.483	.491	.480	.470
1987-1992	.326	.322	.336	.292	.335	.363	.353	.287	.317	.334	.351
1993-1998	.452	.452	.452	.387	.471	.505	.467	.433	.437	.464	.494
1999-2012	.407	.408	.402	.320	.415	.463	.418	.392	.402	.408	.421
2013-2021	.435	.435	.435	.345	.429	.475	.451	.420	.429	.439	.451
2022	.465	.462	.474	.330	.448	.528	.476	.456	.454	.468	.505
2023	.714	.709	.726	.543	.698	.783	.724	.703	.708	.719	.728
2024	.566	.559	.584	.405	.552	.634	.565	.568	.560	.573	.579
Not exceeding current inflation											
1975-1979	.289	.300	.260	.235	.307	.336	.279	.311	.289	.280	.301
1980-1986	.395	.401	.380	.338	.413	.439	.398	.391	.397	.390	.391
1987-1992	.319	.316	.327	.282	.328	.357	.345	.281	.310	.327	.343
1993-1998	.406	.407	.403	.348	.422	.458	.423	.385	.391	.417	.451
1999-2012	.412	.414	.408	.324	.421	.470	.424	.398	.407	.414	.427
2013-2021	.413	.415	.411	.321	.405	.459	.430	.399	.408	.418	.428
2022	.749	.748	.753	.605	.736	.807	.762	.737	.743	.749	.774
2023	.593	.589	.603	.422	.574	.667	.606	.579	.587	.598	.606
2024	.270	.270	.269	.191	.261	.306	.282	.257	.266	.275	.278
Not exceeding future inflation											
1975-1979	.372	.381	.347	.315	.392	.419	.359	.401	.368	.379	.390
1980-1986	.280	.286	.264	.237	.291	.322	.284	.273	.277	.281	.288
1987-1992	.317	.313	.325	.280	.327	.355	.344	.278	.308	.324	.342
1993-1998	.374	.377	.366	.323	.386	.425	.390	.352	.358	.385	.419
1999-2012	.413	.415	.407	.327	.421	.467	.425	.398	.408	.414	.426
2013-2021	.441	.443	.437	.343	.430	.495	.451	.432	.436	.446	.455
2022	.658	.656	.664	.502	.642	.724	.671	.646	.649	.658	.693
2023	.282	.283	.280	.194	.270	.325	.306	.258	.281	.286	.282

The column labeled “All” refers to all workers. The columns labeled “Sex” give the fraction by sex: males (M) and females (F). The columns labeled “Age group” give the fraction by age group: 17-29, 30-49, and 50-59. The columns labeled “Occupation” give the fraction by occupation: blue collars (BC, i.e. “operai” + “apprendisti”) and white collars (WC, i.e. “altro” + “equiparati o intermedi” + “impiegati” + “quadri” + “dirigenti”). The columns labeled “Area” give the fraction by geographical area of employment: North (N), Center (C), and South and Islands (SI).

Table 6: Results of panel data analysis based on model (3).

	\mathcal{C}_t					
	$(-\infty, -.5\%]$	$(-.5\%, .5\%)$	$ [.5\%, +\infty)$	$(-\infty, \dot{P}_{t-1}]$	$(-\infty, \dot{P}_t]$	$(-\infty, \dot{P}_{t+1}]$
$u_{rt} - \bar{u}$.217*** (.038)	.103*** (.013)	-.331*** (.047)	.872*** (.164)	.535*** (.078)	.263** (.105)
$p_{rt} - \bar{p}$	-.146** (.058)	.008 (.011)	.148** (.062)	-.168 (.131)	-.106 (.084)	-.308*** (.048)
$G\dot{D}P_{rt}$	-1.013*** (.070)	-.062*** (.008)	1.082*** (.073)	-1.761*** (.126)	-1.030*** (.114)	.015 (.100)
1975–1979	.069*** (.007)	.014*** (.001)	.916*** (.007)	.393*** (.013)	.278*** (.007)	.308*** (.009)
1980–1986	.067*** (.004)	.009*** (.001)	.923*** (.004)	.529*** (.010)	.368*** (.006)	.213*** (.006)
1987–1992	.094*** (.003)	.016*** (.001)	.891*** (.004)	.334*** (.010)	.290*** (.005)	.262*** (.004)
1993–1998	.136*** (.003)	.038*** (.001)	.827*** (.003)	.462*** (.008)	.384*** (.004)	.324*** (.004)
1999–2012	.172*** (.003)	.055*** (.001)	.773*** (.003)	.393*** (.011)	.373*** (.005)	.362*** (.007)
2013–2021	.263*** (.004)	.090*** (.001)	.647*** (.004)	.403*** (.011)	.365*** (.006)	.402*** (.006)
2022–2023	.224*** (.003)	.071*** (.001)	.704*** (.003)	.634*** (.009)	.672*** (.005)	.442*** (.008)

Linear panel data regression of $\hat{\pi}_{rt}(\mathcal{C}_t|\mathbf{0})$, the estimated probabilities from model (1), on the deviations of region- and year-specific labor force participation rates and unemployment rates from their long-run Italian averages \bar{p} and \bar{u} , real GDP growth, and region and period-specific fixed effects. Standard errors (in parentheses) are clustered by region. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Moment-based and percentile-based summaries of actual wage growth and its components. Top and bottom .5% of the sample is dropped separately for each variable, as well as for those with a notional event in years $t - 1$ or t .

Period	Moment-based				Percentile-based				\dot{P}
	Mean	Spread	Skew	Kurt	Median	Spread	Skew	Kurt	
Actual									
2013–2021	.025	.069	.686	7.075	.017	.142	1.478	2.641	.006
2022	.042	.083	1.214	6.716	.025	.177	1.945	2.355	.076
2023	.051	.080	1.044	6.753	.038	.167	1.827	2.271	.052
2024	.055	.076	.892	6.488	.046	.164	1.495	2.312	.009
Base									
2013–2021	.024	.049	2.317	16.509	.014	.070	3.834	2.710	.006
2022	.033	.051	2.240	11.129	.016	.092	4.630	2.623	.076
2023	.044	.053	2.217	11.345	.029	.101	2.808	2.443	.052
2024	.052	.049	1.615	8.725	.043	.104	1.732	2.227	.009
Residual									
2013–2021	.000	.073	-.492	1.157	.000	.134	1.034	3.046	.006
2022	.009	.074	.786	8.205	.001	.150	1.387	2.803	.076
2023	.007	.071	.270	8.605	.002	.139	1.259	2.751	.052
2024	.003	.068	.496	8.160	.001	.136	1.056	2.892	.009

Percentile-based spread is measured by the interdecile range, percentile-based skewness by the ratio of the difference between the 90th percentile and the median to the difference between the median and the 10th percentile, percentile-based kurtosis by the ratio of the interdecile and the interquartile ranges. Also, $\dot{p}_t = \ln P_t - \ln P_{t-1}$ is the inflation rate.

Table 8: Joint distribution of wage cuts, freezes and raises for base and actual nominal wages. The rows refer to base wages, the columns to actual wages.

2013–2021					2022				
	Cuts	Freezes	Raises	Total		Cuts	Freezes	Raises	Total
Cuts	.040	.007	.033	.080	Cuts	.027	.004	.029	.060
Freezes	.067	.040	.092	.199	Freezes	.050	.037	.076	.163
Raises	.146	.058	.518	.721	Raises	.145	.054	.578	.777
Total	.252	.105	.643	1.000	Total	.222	.095	.683	1.000

2023					2024				
	Cuts	Freezes	Raises	Total		Cuts	Freezes	Raises	Total
Cuts	.016	.003	.020	.039	Cuts	.018	.003	.018	.039
Freezes	.026	.018	.040	.084	Freezes	.019	.012	.032	.064
Raises	.119	.046	.713	.877	Raises	.110	.032	.755	.897
Total	.161	.067	.772	1.000	Total	.148	.048	.805	1.000

Table 9: Joint distribution of base or actual nominal wage growth and current inflation, $\dot{p}_t = \ln P_t - \ln P_{t-1}$. The rows refer to base wages, the columns to actual wages.

2013–2021				2022			
	$\leq \dot{p}_t$	$> \dot{p}_t$	Total		$\leq \dot{p}_t$	$> \dot{p}_t$	Total
$\leq \dot{p}_t$.164	.125	.289	$\leq \dot{p}_t$.716	.146	.862
$> \dot{p}_t$.206	.505	.711	$> \dot{p}_t$.038	.100	.138
Total	.370	.630	1.000	Total	.754	.246	1.000

2023				2024			
	$\leq \dot{p}_t$	$> \dot{p}_t$	Total		$\leq \dot{p}_t$	$> \dot{p}_t$	Total
$\leq \dot{p}_t$.531	.191	.722	$\leq \dot{p}_t$.072	.061	.133
$> \dot{p}_t$.071	.207	.278	$> \dot{p}_t$.147	.720	.867
Total	.602	.398	1.000	Total	.219	.781	1.000

Table 10: Estimated probabilities of nominal actual or base wage cuts and of actual or base wage growth not exceeding current inflation for workers without notional events in both years.

Period	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Actual cut																
2013–2021	.196	.200	.197	.201	.181	.204	.210	.262	.196	.207	.211	.421	.237	.237	.214	.198
2022	.188	.195	.189	.199	.161	.206	.216	.243	.200	.188	.179	.353	.230	.251	.197	.198
2023	.101	.111	.099	.106	.091	.107	.108	.174	.143	.117	.103	.304	.132	.129	.119	.108
2024	.099	.109	.101	.104	.093	.100	.100	.145	.134	.108	.108	.361	.130	.134	.114	.091
Base cut																
2013–2021	.035	.036	.036	.039	.038	.035	.037	.048	.042	.038	.037	.387	.054	.055	.043	.034
2022	.021	.025	.024	.025	.021	.021	.024	.033	.023	.024	.022	.211	.037	.038	.027	.022
2023	.012	.015	.014	.014	.011	.013	.013	.019	.019	.015	.012	.202	.025	.023	.019	.013
2024	.013	.015	.014	.016	.013	.014	.015	.018	.022	.015	.012	.239	.025	.024	.019	.013
Actual wage growth not exceeding current inflation																
2013–2021	.310	.324	.301	.331	.277	.335	.345	.366	.308	.341	.315	.464	.363	.356	.331	.316
2022	.710	.734	.683	.760	.626	.777	.799	.758	.592	.729	.703	.510	.735	.745	.722	.726
2023	.511	.542	.473	.566	.436	.581	.608	.575	.479	.599	.497	.449	.559	.532	.524	.528
2024	.164	.183	.158	.179	.152	.169	.171	.210	.218	.177	.175	.413	.209	.210	.187	.156
Base wage growth not exceeding current inflation																
2013–2021	.237	.241	.217	.270	.211	.274	.288	.249	.340	.255	.233	.480	.278	.275	.260	.240
2022	.786	.805	.755	.850	.683	.864	.884	.846	.704	.804	.827	.431	.835	.830	.806	.786
2023	.625	.632	.588	.715	.517	.727	.765	.649	.599	.707	.640	.425	.686	.679	.635	.636
2024	.091	.111	.079	.111	.088	.099	.101	.074	.271	.096	.087	.371	.127	.122	.128	.087

(1) Male, aged 30–49, with 10–19 years of experience, white collar in $t - 1$, working in a firm with 16–200 full-year equivalent employees, stayer, employed in Lombardy; (2) same as (1) but female; (3) same as (1) but aged 17–29; (4) same as (1) but aged 50–59; (5) same as (1) but with 0–9 years of experience; (6) same as (1) but with 20–29 years of experience; (7) same as (1) but with 30+ years of experience; (8) same as (1) but blue collar; (9) same as (1) but manager; (10) same as (1) but in a firm with 1–16 full-year equivalent employees; (11) same as (1) but in a firm with 200+ full-year equivalent employees; (12) same as (1) but mover; (13) same as (1) but employed in Sicily; (14) same as (1) but employed in Campania; (15) same as (1) but employed in Latium; (16) same as (1) but employed in Veneto.

Figure 1: Annual inflation in Italy and in its main cities. The vertical bars denote recession years.

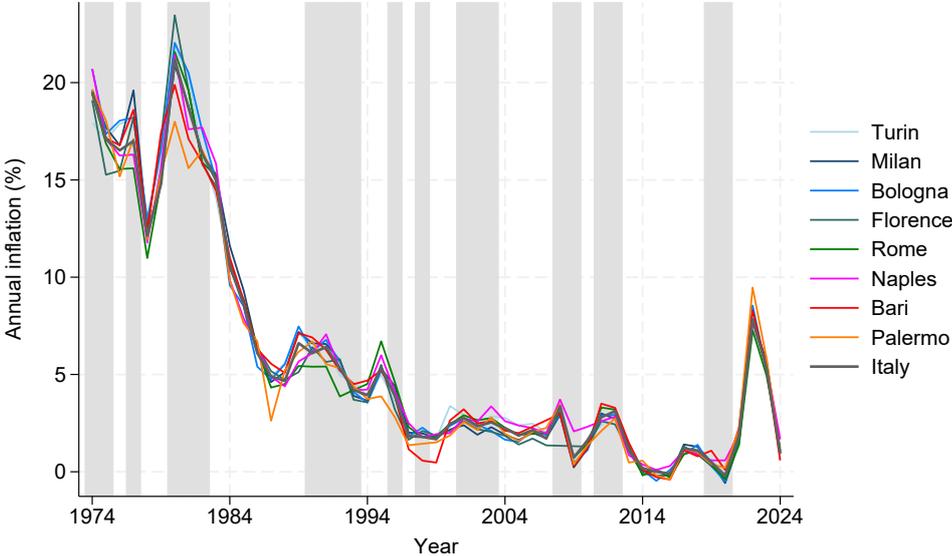


Figure 2: Histograms of nominal wage growth (females and males combined). The red line marks zero wage growth, while the green line marks wage growth equal to average inflation over the subperiod considered

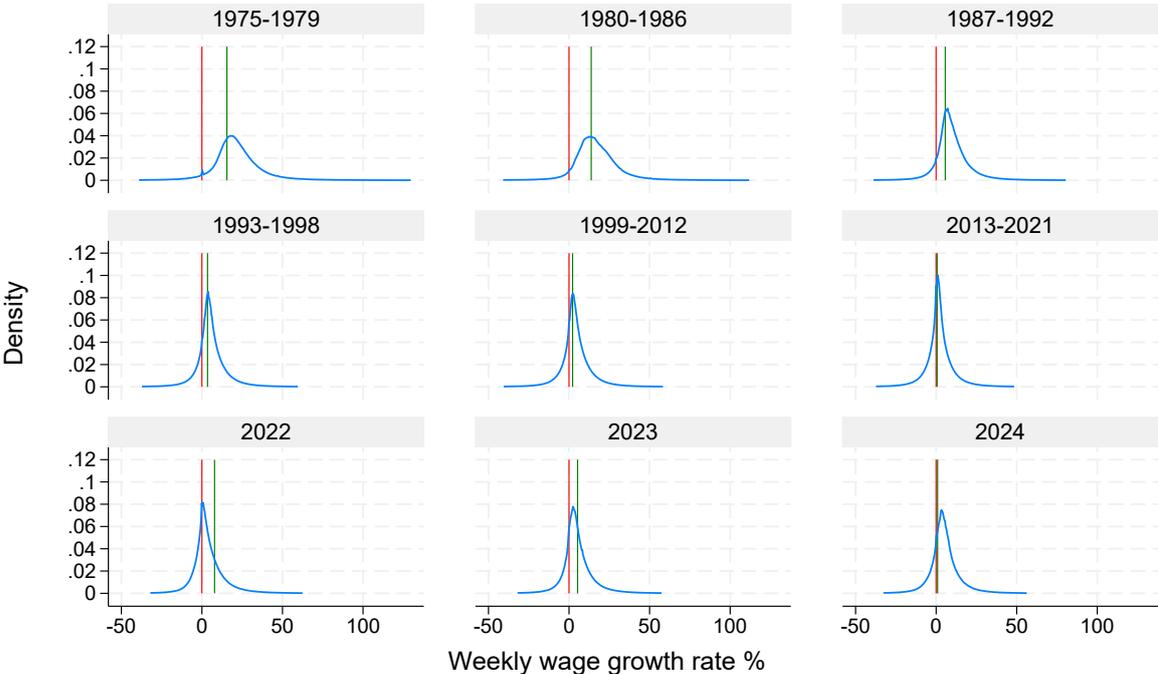


Figure 3: Annual inflation and fraction of workers with a nominal wage cut.

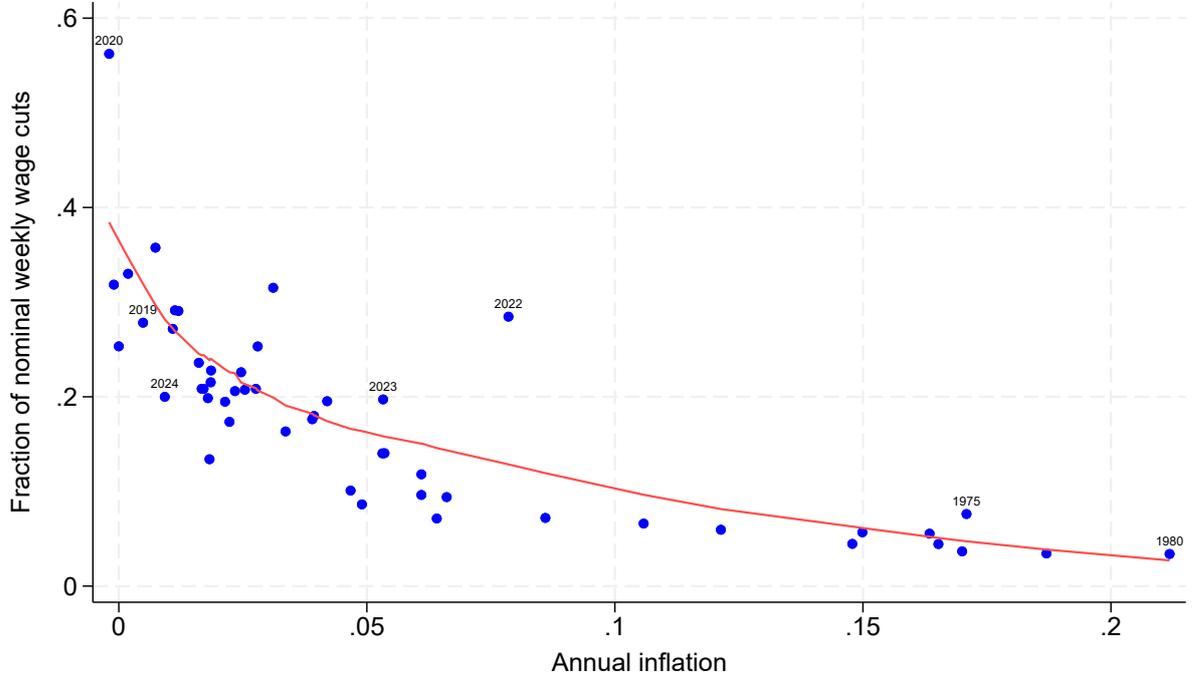


Figure 4: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by sex. 3-year uncentered running average. The vertical bars denote recession years.

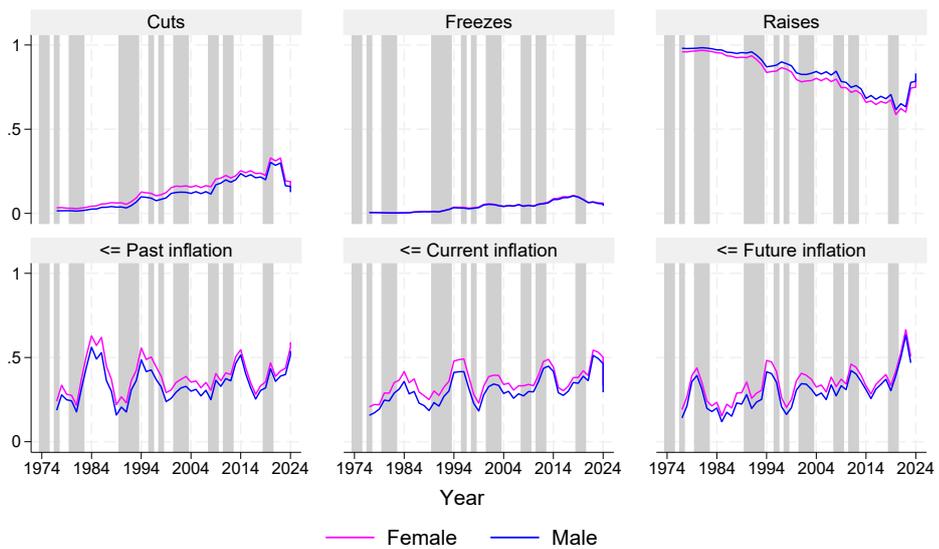


Figure 5: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by age group. 3-year uncentered running average. The vertical bars denote recession years.

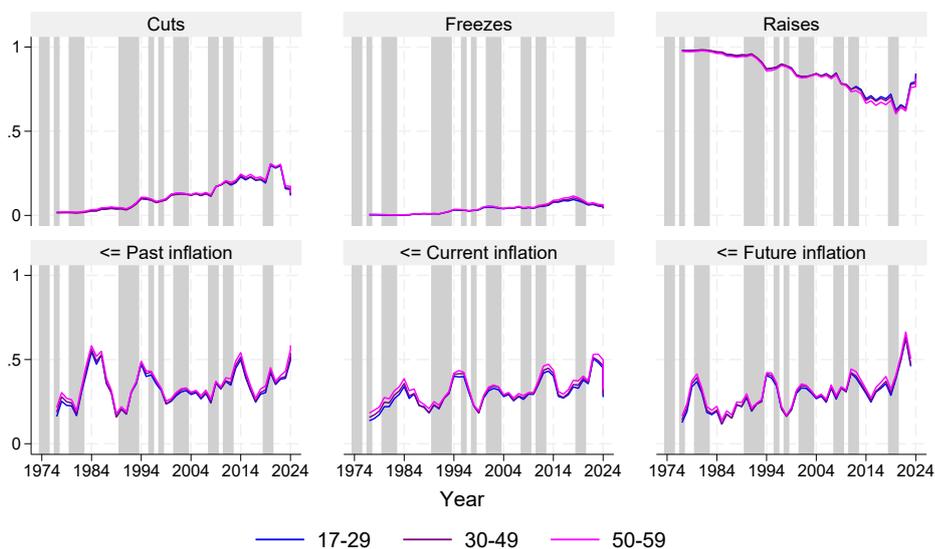


Figure 6: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by years of labor market experience. 3-year uncentered running average. The vertical bars denote recession years.

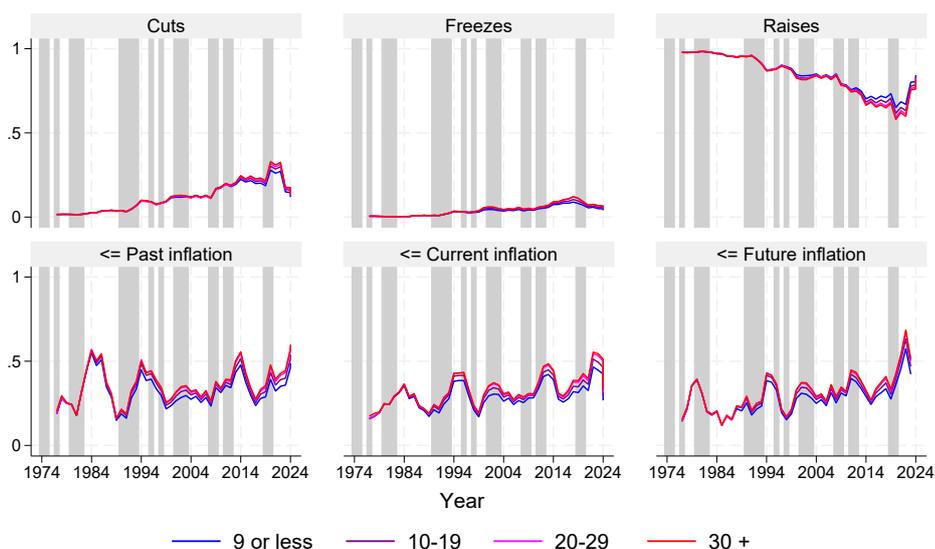


Figure 7: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by occupational category. 3-year uncentered running average. The vertical bars denote recession years.

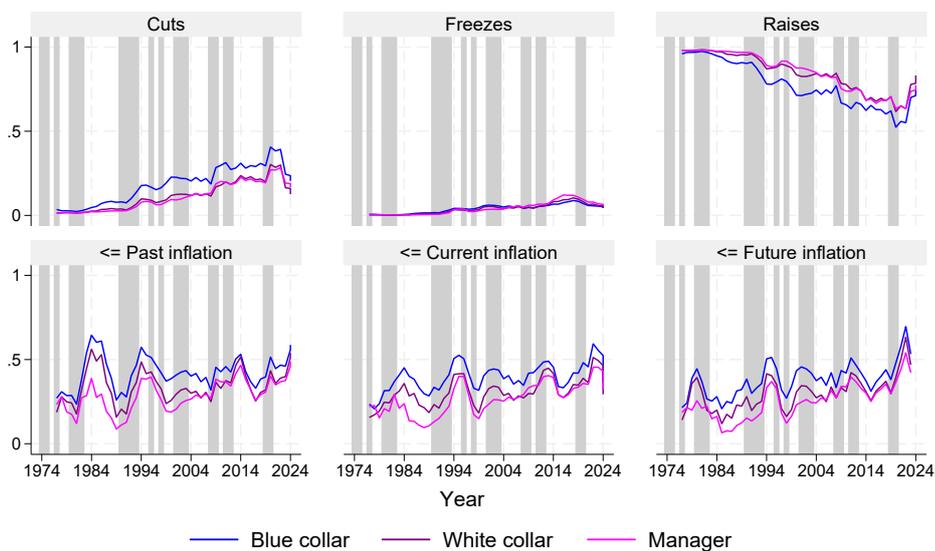


Figure 8: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by firm size. 3-year uncentered running average. The vertical bars denote recession years.

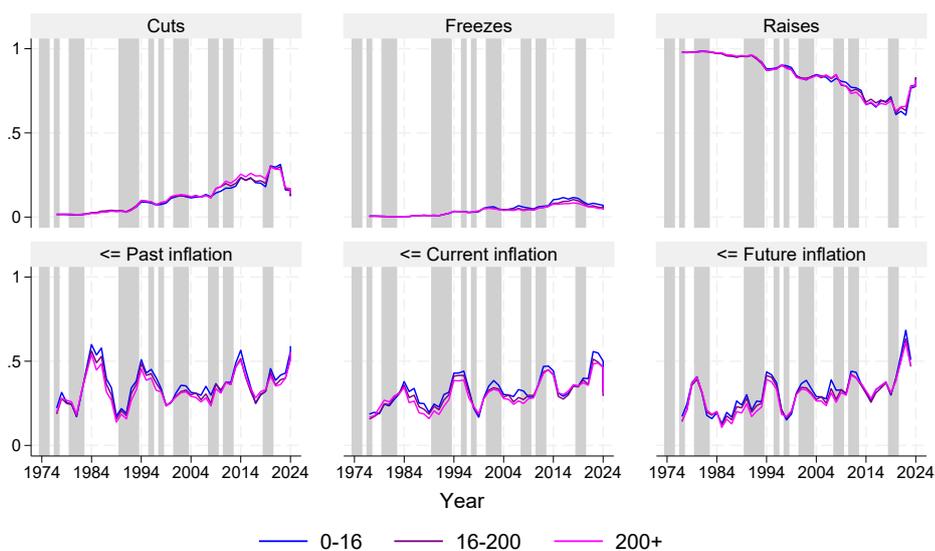


Figure 9: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by province of employment. 3-year uncentered running average. The vertical bars denote recession years.

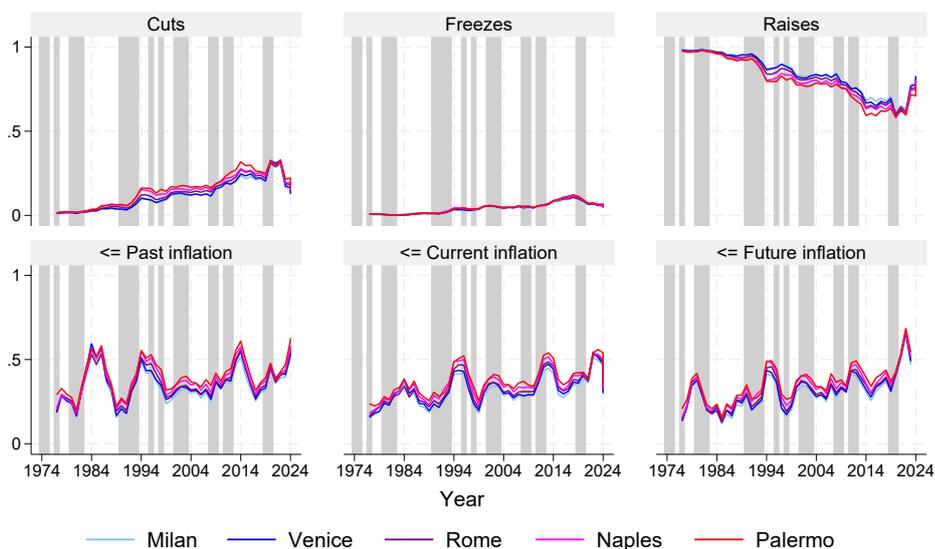


Figure 10: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation for movers and stayers. 3-year uncentered running average. The vertical bars denote recession years.

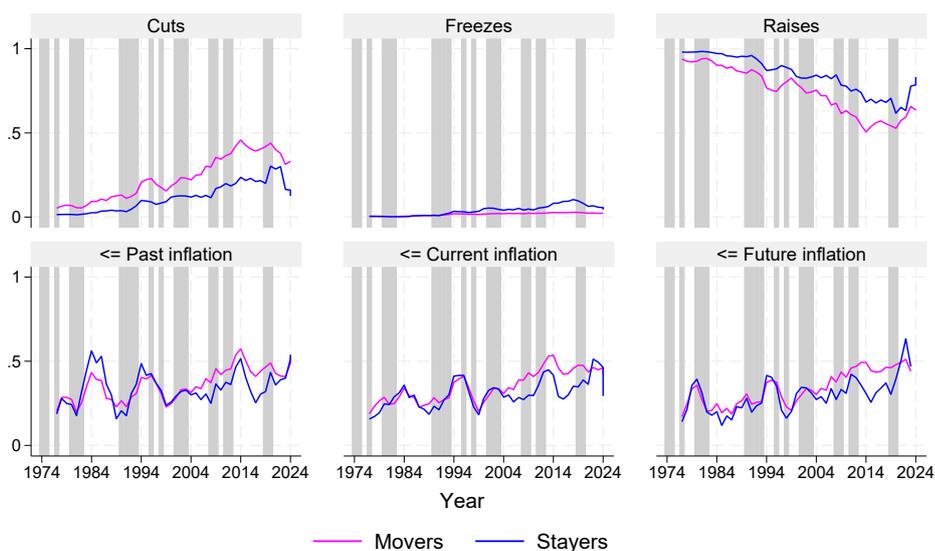


Figure 11: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by rank in terms of labor productivity. 3-year uncentered running average. The vertical bars denote recession years.

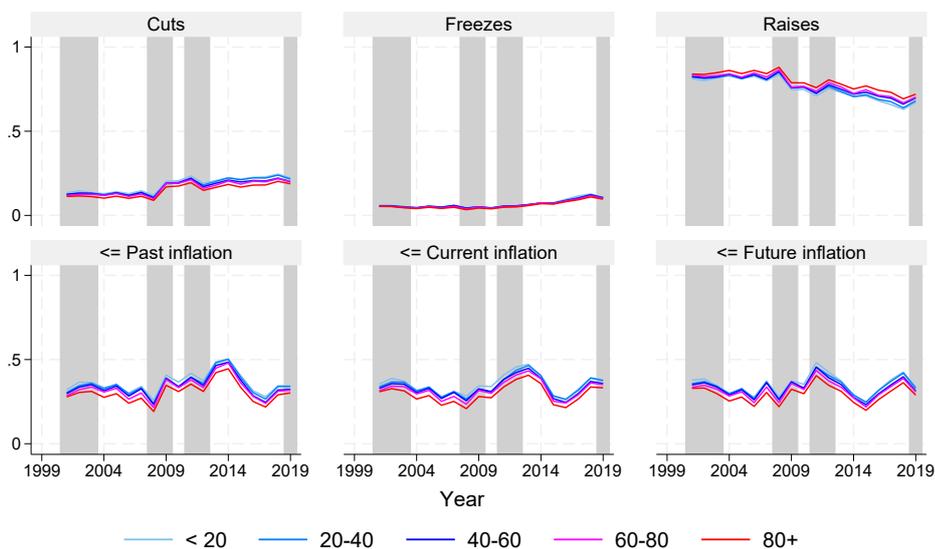


Figure 12: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by rank in terms of ROA. 3-year uncentered running average. The vertical bars denote recession years.

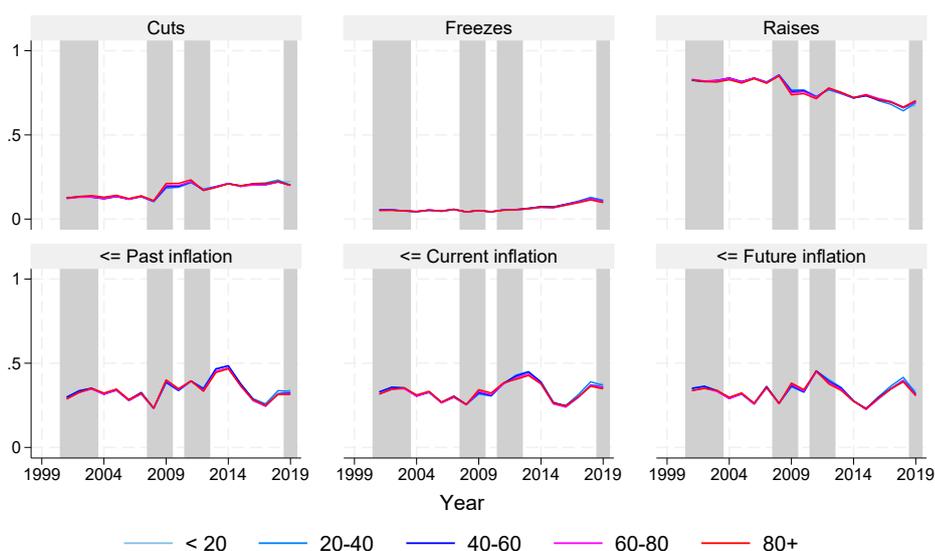


Figure 13: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by rank in the terms of leverage. 3-year uncentered running average. The vertical bars denote recession years.

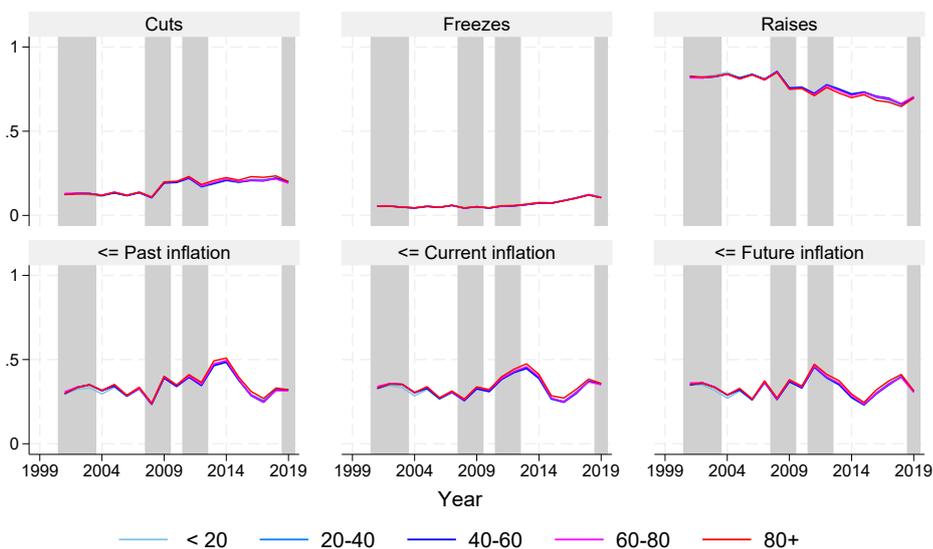


Figure 14: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by number of years of negative profits. 3-year uncentered running average. The vertical bars denote recession years.

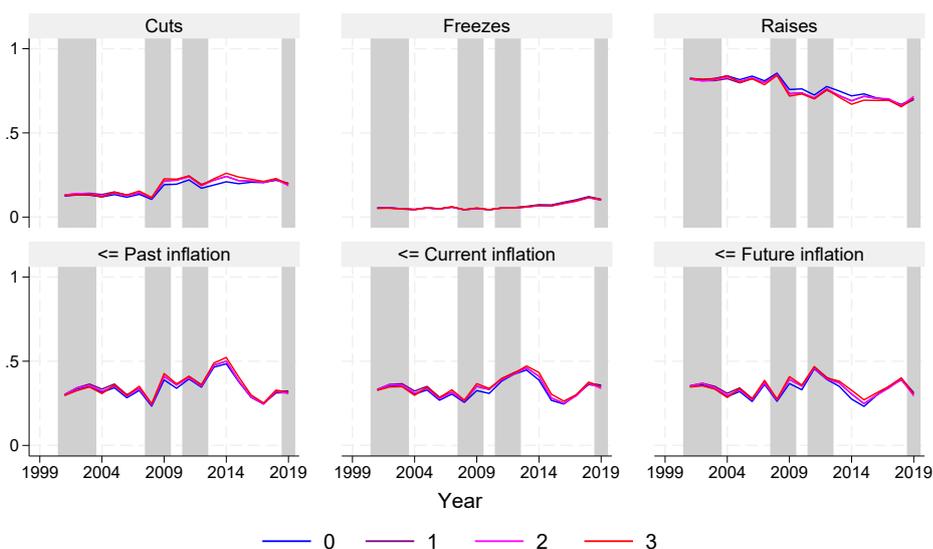


Figure 15: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by sector of activity. 3-year uncentered running average. The vertical bars denote recession years.

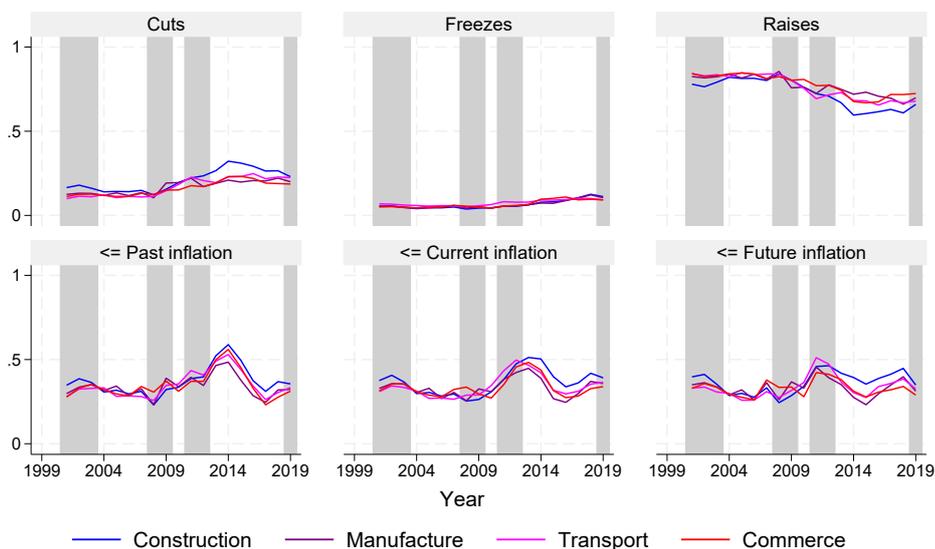


Figure 16: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by type of contract. 3-year uncentered running average. The vertical bars denote recession years.

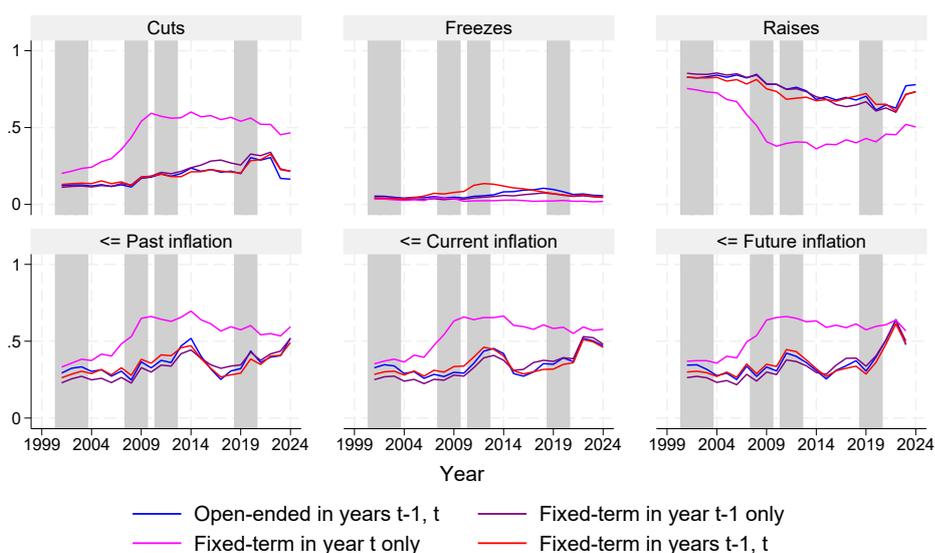


Figure 17: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by reason of switching job. 3-year uncentered running average. The vertical bars denote recession years.

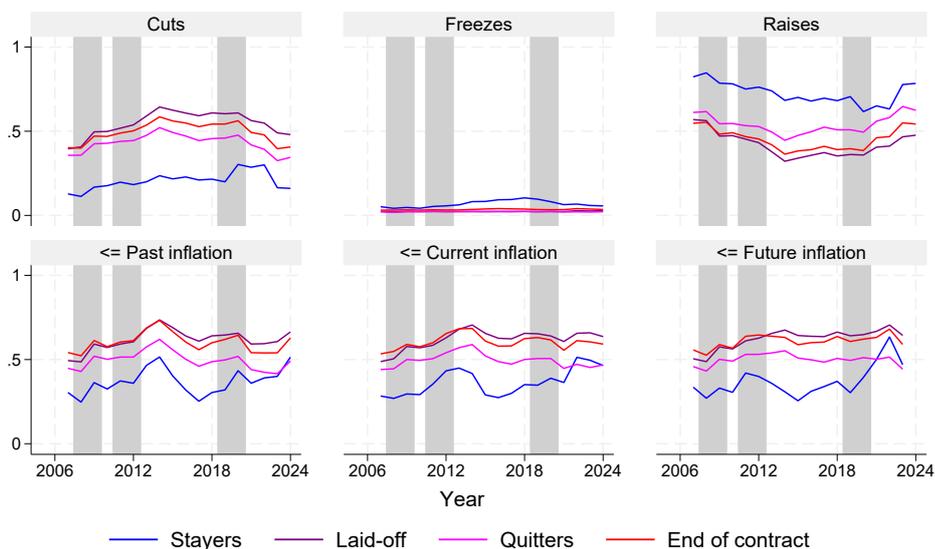


Figure 18: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation by contract renewal. 3-year uncentered running average. The vertical bars denote recession years.

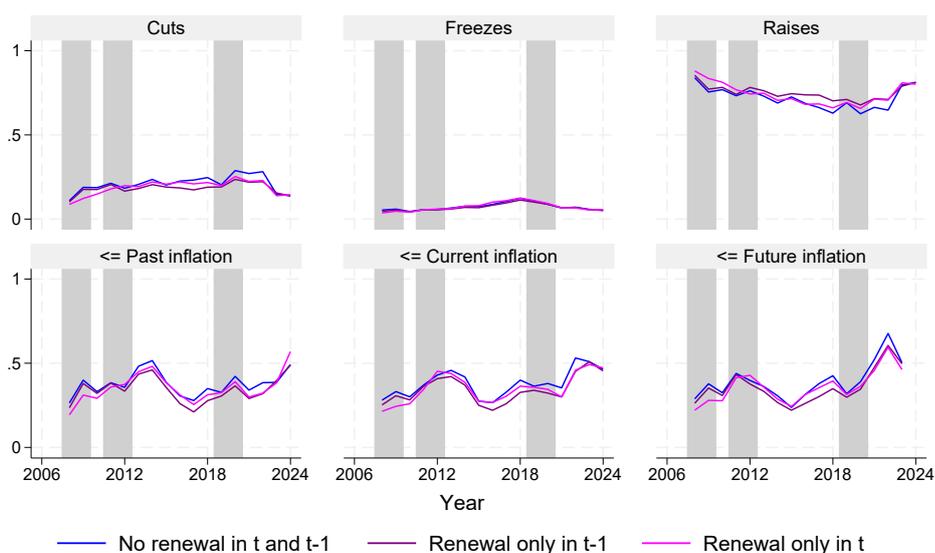


Figure 19: Estimated probabilities of nominal wage cuts, freezes, raises and that the nominal wage is lower or equal than past, current and future inflation in terms of type and occurring of notional events. 3-year uncentered running average. The vertical bars denote recession years.

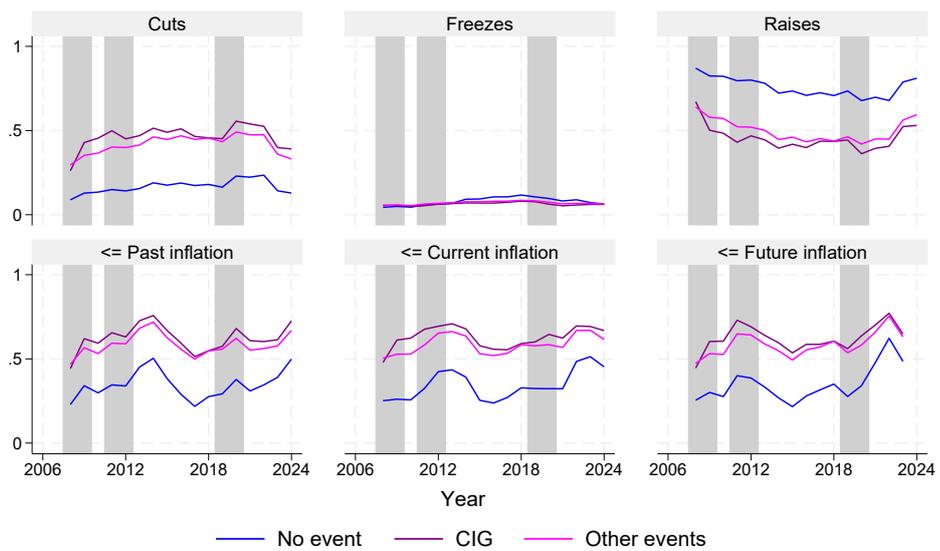
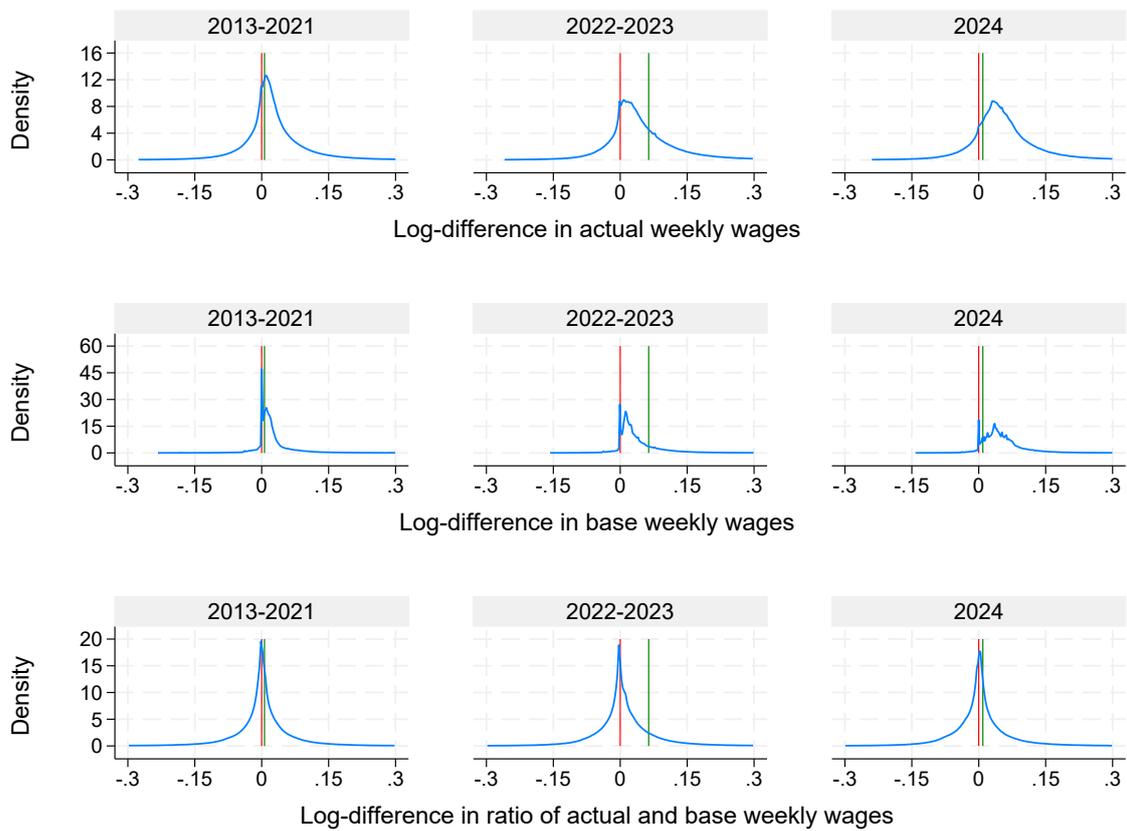


Figure 20: Histograms of actual nominal wage growth (top), base wage growth (middle) and difference between actual and base wage growth (bottom) for workers without notional events over a period of two consecutive years. The red line marks 0 while the green line marks average national inflation over the given subperiod.



A Measuring wage growth

For a job stayer, the individual-level relative wage change between year $t-1$ and year $t = 1975, \dots, 2024$ is simply $\dot{W}_{it} = W_{it}/W_{i,t-1} - 1$. We henceforth refer to \dot{W}_{it} as the (nominal) wage growth of worker i in year t , although it can be zero or even negative.

For a job changer, things are slightly more complicated. The easiest case is when a worker holds only one job in year $t-1$ and two jobs in year t , the first representing a continuation of the job held in the previous year, and the second a new job. For such worker,

$$W_{it} = W_{it}^{(1)}(1 - f_{it}) + W_{it}^{(2)}f_{it},$$

where f_{it} is the fraction of weeks spent in the new job that year. Hence

$$\frac{W_{it}}{W_{i,t-1}} = \frac{W_{it}^{(1)}}{W_{i,t-1}}(1 - f_{it}) + \frac{W_{it}^{(2)}}{W_{i,t-1}}f_{it},$$

that is,

$$\dot{W}_{it} + 1 = [\dot{W}_{it}^{(1)} + 1](1 - f_{it}) + [\dot{W}_{it}^{(2)} + 1]f_{it},$$

where $\dot{W}_{it}^{(s)} = W_{it}^{(s)}/W_{i,t-1} - 1$, $s = 1, 2$. Therefore

$$\dot{W}_{it} = \dot{W}_{it}^{(1)}(1 - f_{it}) + \dot{W}_{it}^{(2)}f_{it} = \dot{W}_{it}^{(1)} + \Delta\dot{W}_{it}f_{it}, \quad (5)$$

where $\Delta\dot{W}_{it} = \dot{W}_{it}^{(2)} - \dot{W}_{it}^{(1)}$, that is, wage growth is equal to wage growth in the previous job plus the difference in wage growth between the new and the previous job multiplied by the fraction of weeks spent on the new job. The term $\Delta\dot{W}_{it}$ measures the gain or loss in terms of wage growth from taking a new job in year t .

Instead of \dot{W}_{it} , the logit analyses in Sections 6 and 7 use $\dot{W}_{it}^{(2)}$ for movers.

B Data appendix

This appendix contains detailed information on all the data we use.

B.1 ISTAT

In addition to the price data discussed in Section 4.2, Istat is the source of our measures of local business and labor market conditions, namely real GDP growth, labor force participation and unemployment at the regional level.

Istat collects information on the regional level of employment and unemployment and on the regional population in the labor force by aggregating microdata from the Italian Labor Force Survey. We then obtain the regional unemployment rate by taking the ratio between the aggregate level of unemployment and the total number of people in the labor force.

Istat also provides information on the aggregate regional level of nominal GDP. However, data on nominal GDP are available on the Istat website only from 1995 onward. For the earlier period, we have been furnished of the data on nominal regional GDP by CRENOS, as mentioned in Section 4.2. Hence, a word of caution is needed in order to describe how we go from nominal GDP to real GDP.

Given that we observe a jump at the point in time (1995) in which we append the two series for each region, we make a correction in order to eliminate this discontinuity. First, we compute the ratio between the Istat regional nominal GDP in 1995 and the CRENOS regional nominal GDP in 1995. Then we simply apply this ratio to the CRENOS series.

Moreover, since we only have data on nominal GDP for the entire period, we first construct a price index by concatenating the FOI by region using 1995 as the base year. Next, we compute the real GDP in region r and year t as the ratio between the nominal GDP and the constructed price index in region r and year t . Finally, we compute the growth rate of the real GDP, $\dot{GDP}_{rt} = GDP_{rt}/GDP_{rt-1} - 1$.

B.2 INPS

This section provides additional detail on the three INPS archives that we managed to merge by exploiting the availability of unique identifiers at the individual worker and establishment/firm level.

The first archive is the “employment relations registry” (*Rapporti di Lavoro Annuali dei Dipendenti del Settore Privato Extra Agricolo*), namely the registry of all employment relations of non-agricultural private-sector employees. This archive covers the 1974–2024 period and contains detailed information (earnings, weeks worked, occupational category, establishment, firm identifier, etc.) on all employment relations held by a worker during a year. Specifically, it records the annual earnings, the annual weeks worked, the occupational category, and the province of employment of a worker.

Earnings before 2002 are expressed in Italian Liras (ITL) and have been converted to Euros (EUR) using the fixed exchange rate of 1,936.27 ITL per EUR. Annual earnings and annual weeks worked are the main variables of interest because they allow us to construct our wage growth measure. For each employment relation, actual earnings include base earnings, cost of living adjustments, overtime work, paid vacation, sick leave, bonuses, profit sharing payments, and the monetary value of in kind payments while do not include severance payment in case of separation. By annual weeks worked we instead mean the number of weeks in which the agent worked at least one day.

As mentioned in Section 4.1.3, we also distinguish between job stayers and job movers for the entire period. We define a job mover as a worker who in year t has two full-time employment relations with two different firms. The reason is that Italian labor laws prevent workers from having two full-time employment relations at the same time.²⁷ In our modeling exercises (except that in Section 7.2), we focus on workers whose unique job in the first year is the same as that of the second year (or of one of

²⁷Decreto legislativo 66/2003, art.4, <https://www.gazzettaufficiale.it/eli/id/2003/04/14/003G0091/sg>.

the two for movers). Thus, for movers, our measure of wage growth compares the wage in the second job of the second year (identified as the employment relation for which the firm identifier is different from that of the first year) with the wage of the first-year job.

In Section 7.3, we consider the cause of the end of the first employment relation, that is the one in which the firm identifier is equal to that of the first year. Unfortunately, we are only able to identify the reason for the end of an employment relation starting from 2005. First, we ignore the reason why an employment relation ended for a stayer who has two employment relations with the same firm, given that she did not actually switch job. Moreover, for some movers, the reason for which the first employment relation ended is missing. Typically, this case should be interpreted as if the employment relation did not end in that year. However, since we know that these workers actually changed job, we discard them and interpret this as missing information. On average, these discarded workers represent less than 1% of the working sample in Table 1 and around 18% of the movers. Given this further sample selection, movers represent on average 4.2% of the available workers for the analysis, that is, around 220,000 workers.

The INPS archives also contain information of the province on employment. Given that we are interested in long-run trends, we take into account that the administrative subdivision of Italy into provinces changed over the period we consider. In particular, before 2004, the province of Fermo in the Marche region was part of the province of Ascoli Piceno. Hence, we assign Ascoli Piceno to all workers whose province of employment is Fermo. For the same reason, we assign Milan to all workers whose province of employment is Monza. More complicated cases arise in the regions of Apulia and Sardinia. Since the Apulian province of Barletta-Andria-Trani was created in 2004 from municipalities belonging to the provinces of Bari and Foggia, we assign Bari to all workers whose province of employment is Foggia or Barletta-Andria-Trani. Finally, we assign to the Sardinian province of Cagliari all workers whose province of employment is not Sassari, as we cannot find a temporally homogeneous geographical division of Sardinian provinces at a finer level.

From the types of occupation described in Section 4, we construct a residual category which includes flight pilots, flight assistants, flight engineers, etc.

Using data on annual earnings and annual weeks worked, we rank workers according to their wages.²⁸ Finally, we measure firm size by the total number of full-year equivalent employees.²⁹

The second archive is the “workers registry” (*Anagrafica Lavoratori e Beneficiari Prestazioni*), which contains background information (date of birth, sex, etc.) on all workers present in the em-

²⁸ This raises the issue of which occupation to assign to a worker with more than one job in a given year. By convention, all time- and job-specific variables refer to the unique job in the initial year (year $t - 1$).

²⁹ If N_t is the total number of employees in year t according to the INPS dataset and f_{ijt} is the fraction of weeks that employee i spent working in firm j during that year, the size of firm j in year t is computed as $\sum_{i=1}^{N_t} f_{ijt}$, so each employee contributes a value of one if she worked full-year in firm j during year t , a value of zero if she did not have an employment relation with firm j in year t , and a value between zero and one otherwise.

ployment relations registry.

The third archive is the “establishment registry”, which covers the 1983–2024 period and contains information (number of employees, sector of activity, municipality and province of location, etc.) on all establishments in which a worker from the workers registry has been employed. Since we aim to combine these archives with the Cerved dataset, we collapse this information at the firm level. For a given firm in the Inps archive, the number of employees is the total across all establishments in the given firm. On the other hand, we assign to each firm the sector of activity corresponding to the establishment with the highest number of employees.

B.3 Cerved

Cerved (*Centro Elettronico Regionale Veneto Elaborazione Dati*) represents one of the main sources of information on Italian firms. It assembles and organizes the data that firms are required to provide to the Italian Chambers of Commerce and the Italian registry of firms. The resulting dataset contains balance-sheet information on the universe of all Italian private non-financial limited liability firms, with no restrictions on the number of employees. Cerved data are updated on a continuous basis. The version of the data available in the INPS archives covers the 1996–2018 period.

For a firm to be included in our matched INPS-Cerved sample, it must be present in both the INPS establishment archives and the Cerved data for three consecutive years. We also require that no relevant information is missing in any of the three years. The reason is that some of the indicators that we consider are extremely volatile, so we work with their uncentered 3-year moving averages. Within each industry, we then assign firms to five mutually exclusive and totally exhaustive classes corresponding to the quintiles of each measure.

The balance-sheet information that we consider includes the operational value added (*valore operativo aggiunto*),³⁰ the returns on assets (ROA), and the profits (*utile o perdita d’esercizio*). As a measure of leverage, we take the ratio between financial debt (*debiti finanziari*) and total assets (*totale attivo*). The measure of productivity that we consider is the ratio between the operational added value and the total number of workers, which is a proxy for the worker’s labor productivity.

B.4 CNEL

By law (DPR n.936 of December 30 1986) the parties who signed a labor contract must deposit it with CNEL (Consiglio Nazionale dell’Economia e del Lavoro). From the CNEL database, available at <https://www.cnel.it/Archivio-Contratti> we extracted the year in which each contract was signed or renewed and the signing parties (representatives of entrepreneurs and trade unions). These data have been matched with the INPS database which reports the contract applied to each worker. Since

³⁰ The operational value added can be negative, in which case we replace it with the labor costs to guarantee that the numerator of our productivity measure is non-negative.

reliable data from INPS are available only from 2005, also our series on the years in which contracts are signed or renewed starts from that period. The CNEL codes of contracts are different from the INPS codes, hence we used a conversion table available from INPS. Since 2021 INPS has decided to employ CNEL codes in its database. Since in the analysis we focus on the association between contract renewals and the probabilities of experiencing nominal or real wage cuts, we restricted the sample to those contracts that have been renewed periodically every three-four years.

C Additional tables and figures

Table C.1: Sample sizes (thousands of firms and workers) at each stage of the sample selection process in Section 4.3.

Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1998	1,241.1	966.1	423.3	343.0	751.3	128.1	214.9	210.1	84.4	3,749.7	2,809.2
2000	1,345.9	996.7	474.5	377.4	760.5	141.2	236.2	232.9	87.8	4,118.4	3,075.6
2002	1,479.8	1,097.4	528.1	411.7	823.7	148.1	263.7	262.1	93.4	4,481.4	3,337.3
2004	1,552.0	1,190.0	659.5	424.0	900.4	134.5	289.5	288.4	212.4	4,472.2	4,022.2
2006	1,620.7	1,241.8	710.9	548.3	923.9	230.4	317.9	317.4	317.3	4,513.2	4,513.1
2008	1,728.9	1,304.8	758.8	584.2	956.8	236.2	348.0	347.5	347.5	4,736.5	4,736.4
2010	1,712.2	1,355.0	792.4	624.1	979.6	248.6	375.4	375.0	375.0	4,782.2	4,782.2
2012	1,719.0	1,352.0	790.5	643.9	963.5	255.4	388.5	388.1	388.1	4,696.1	4,696.1
2014	1,617.2	1,311.6	794.9	640.6	923.4	252.4	388.2	387.9	387.8	4,641.1	4,641.1
2016	1,629.1	1,270.1	779.0	620.5	887.3	237.6	382.8	382.5	382.5	4,660.5	4,660.4
2018	1,644.3	1,310.7	666.7	431.6	971.2	92.1	339.6	339.3	339.3	4,463.8	4,463.7

- (1): Total number of firms in the original INPS data.
(2): Total number of firms in the INPS data in years $t - 2$, $t - 1$, and t .
(3): Total number of firms in the original Cerved data.
(4): Total number of firms in the Cerved data in years $t - 2$, $t - 1$, and t .
(5): Total number of firms only in the INPS data in years $t - 2$, $t - 1$, and t .
(6): Total number of firms only in the Cerved data in years $t - 2$, $t - 1$, and t .
(7): Total number of firms in both the INPS and Cerved data in years $t - 2$, $t - 1$, and t .
(8): Excluding firms with sector missing or labor productivity, roa or profits missing in either year $t - 2$, $t - 1$ or t among firms in (7).
(9): Excluding firms with leverage missing in year $t - 2$, $t - 1$ or t among firms in (8).
(10): Total number of workers among those in our 2 year panel of workers of year $t + 1$ covered by firms in (8).
(11): Total number of workers among those in our 2 year panel of workers of year $t + 1$ covered by firms in (9).

Table C.2: Average estimated probabilities of a nominal wage cut by subperiod. Breakdown by sex, age, experience and type of occupation.

Period	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cuts									
1975–1979	.016	.033	.019	.021	.017	.016	.018	.033	.016
1980–1986	.025	.043	.028	.033	.026	.024	.025	.049	.020
1987–1992	.042	.066	.046	.050	.042	.040	.042	.089	.032
1993–1998	.089	.117	.093	.098	.089	.087	.091	.172	.074
1999–2012	.147	.180	.148	.153	.143	.143	.148	.244	.143
2013–2021	.240	.264	.235	.248	.224	.248	.256	.324	.227
2022–2024	.153	.181	.146	.165	.141	.158	.166	.230	.184
1975–2024	.115	.141	.115	.123	.110	.115	.120	.183	.111
Freezes									
1975–1979	.005	.005	.003	.006	.005	.005	.005	.004	.006
1980–1986	.005	.005	.004	.005	.005	.005	.005	.007	.003
1987–1992	.012	.014	.012	.013	.012	.013	.013	.019	.008
1993–1998	.031	.035	.030	.033	.028	.032	.032	.040	.030
1999–2012	.049	.051	.047	.052	.044	.054	.055	.054	.051
2013–2021	.084	.087	.078	.093	.073	.094	.095	.071	.101
2022–2024	.053	.058	.049	.060	.047	.059	.061	.049	.063
1975–2024	.039	.041	.036	.042	.035	.043	.043	.040	.042
Raises									
1975–1979	.979	.961	.978	.972	.978	.979	.977	.962	.979
1980–1986	.970	.952	.968	.962	.969	.971	.970	.945	.978
1987–1992	.947	.920	.943	.938	.947	.949	.947	.891	.960
1993–1998	.882	.849	.879	.871	.885	.883	.879	.787	.900
1999–2012	.806	.768	.806	.797	.815	.806	.800	.702	.808
2013–2021	.678	.649	.687	.660	.704	.660	.650	.605	.674
2022–2024	.795	.761	.805	.777	.813	.784	.774	.720	.752
1975–2024	.848	.818	.849	.836	.856	.844	.839	.777	.849

- (1): Male, aged 30–49, experienced 10–19, white collar in $t - 1$ (+ other).
(2): Female, aged 30–49, experienced 10–19, white collar in $t - 1$ (+ other).
(3): Male, aged 17–29, experienced 10–19, white collar in $t - 1$ (+ other).
(4): Male, aged 50–59, experienced 10–19, white collar in $t - 1$ (+ other).
(5): Male, aged 30–49, experienced 0–9, white collar in $t - 1$ (+ other).
(6): Male, aged 30–49, experienced 20–29, white collar in $t - 1$ (+ other).
(7): Male, aged 30–49, experienced more than 30 years, white collar in $t - 1$ (+ other).
(8): Male, aged 30–49, experienced 10–19, blue collar in $t - 1$ (+ other).
(9): Male, aged 30–49, experienced 10–19, manager in $t - 1$ (+ other).

Table C.3: Average estimated probabilities of a nominal wage growth not exceeding past, current or future inflation by subperiod. Breakdown by sex, age, experience and type of occupation.

Period	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Not exceeding past inflation									
1975–1979	.243	.289	.219	.268	.246	.245	.253	.310	.210
1980–1986	.428	.501	.416	.450	.417	.436	.436	.511	.274
1987–1992	.233	.291	.233	.246	.215	.244	.242	.332	.149
1993–1998	.371	.439	.359	.381	.342	.388	.388	.474	.323
1999–2012	.325	.372	.316	.337	.302	.340	.346	.419	.300
2013–2021	.356	.387	.346	.375	.326	.377	.387	.420	.341
2022–2024	.509	.558	.489	.552	.458	.553	.568	.555	.459
1975–2024	.346	.397	.334	.364	.323	.361	.367	.428	.292
Not exceeding current inflation									
1975–1979	.190	.230	.170	.216	.193	.193	.200	.258	.179
1980–1986	.299	.365	.284	.326	.296	.304	.305	.391	.204
1987–1992	.227	.287	.226	.241	.209	.237	.237	.326	.146
1993–1998	.321	.384	.311	.333	.298	.333	.334	.428	.286
1999–2012	.330	.379	.321	.341	.306	.345	.352	.426	.303
2013–2021	.335	.365	.325	.354	.307	.354	.364	.406	.324
2022–2024	.396	.434	.383	.427	.363	.425	.437	.462	.386
1975–2024	.305	.354	.294	.323	.286	.318	.324	.392	.267
Not exceeding future inflation									
1975–1979	.290	.335	.270	.311	.289	.291	.295	.349	.208
1980–1986	.174	.217	.168	.194	.177	.176	.178	.250	.137
1987–1992	.229	.290	.228	.243	.210	.239	.239	.327	.141
1993–1998	.283	.339	.278	.295	.264	.292	.293	.392	.246
1999–2012	.330	.378	.322	.342	.306	.346	.353	.427	.299
2013–2021	.376	.404	.366	.397	.345	.397	.405	.443	.349
2022–2023	.397	.432	.387	.429	.359	.431	.442	.459	.372
1975–2023	.297	.342	.289	.314	.278	.309	.314	.381	.253

- (1): Male, aged 30–49, experienced 10–19, white collar in $t - 1$ (+ other).
(2): Female, aged 30–49, experienced 10–19, white collar in $t - 1$ (+ other).
(3): Male, aged 17–29, experienced 10–19, white collar in $t - 1$ (+ other).
(4): Male, aged 50–59, experienced 10–19, white collar in $t - 1$ (+ other).
(5): Male, aged 30–49, experienced 0–9, white collar in $t - 1$ (+ other).
(6): Male, aged 30–49, experienced 20–29, white collar in $t - 1$ (+ other).
(7): Male, aged 30–49, experienced more than 30 years, white collar in $t - 1$ (+ other).
(8): Male, aged 30–49, experienced 10–19, blue collar in $t - 1$ (+ other).
(9): Male, aged 30–49, experienced 10–19, manager in $t - 1$ (+ other).

Table C.4: Average estimated probabilities of a nominal wage cut by subperiod. Breakdown by firm-size, type of worker, province of employment.

Period	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cuts								
1975–1979	.016	.016	.019	.064	.019	.019	.017	.015
1980–1986	.025	.023	.022	.081	.039	.035	.029	.029
1987–1992	.042	.039	.036	.124	.068	.068	.052	.042
1993–1998	.089	.082	.090	.199	.158	.138	.111	.092
1999–2012	.147	.137	.151	.288	.192	.178	.161	.146
2013–2021	.240	.239	.256	.411	.283	.270	.262	.256
2022–2024	.153	.149	.164	.338	.207	.185	.174	.159
1975–2024	.115	.111	.119	.234	.153	.142	.129	.119
Freezes								
1975–1979	.005	.006	.005	.004	.008	.007	.009	.006
1980–1986	.005	.005	.005	.005	.006	.006	.006	.005
1987–1992	.012	.012	.012	.011	.014	.017	.014	.013
1993–1998	.031	.031	.033	.018	.041	.040	.038	.034
1999–2012	.049	.056	.047	.021	.054	.054	.053	.052
2013–2021	.084	.099	.074	.026	.096	.092	.088	.090
2022–2024	.053	.064	.050	.023	.065	.057	.056	.054
1975–2024	.039	.044	.036	.017	.045	.044	.042	.041
Raises								
1975–1979	.979	.978	.976	.928	.973	.975	.975	.980
1980–1986	.970	.973	.974	.913	.955	.958	.966	.966
1987–1992	.947	.950	.954	.861	.918	.915	.934	.946
1993–1998	.882	.890	.880	.778	.799	.821	.852	.877
1999–2012	.806	.810	.803	.684	.753	.767	.787	.804
2013–2021	.678	.664	.669	.555	.619	.637	.650	.654
2022–2024	.795	.790	.786	.630	.727	.758	.771	.788
1975–2024	.848	.847	.845	.744	.801	.814	.830	.841

- (1): Stayer in firm with 16-200 full-year equivalent employees in Milan in $t - 1$ (+ other).
(2): Stayer in firm with 1-16 full-year equivalent employees in Milan in $t - 1$ (+ other).
(3): Stayer in firm with 200+ full-year equivalent employees in Milan in $t - 1$ (+ other).
(4): Mover in firm with 16-200 full-year equivalent employees in Milan in $t - 1$ (+ other).
(5): Stayer in firm with 16-200 full-year equivalent employees in Palermo in $t - 1$ (+ other).
(6): Stayer in firm with 16-200 full-year equivalent employees in Naples in $t - 1$ (+ other).
(7): Stayer in firm with 16-200 full-year equivalent employees in Rome in $t - 1$ (+ other).
(8): Stayer in firm with 16-200 full-year equivalent employees in Venice in $t - 1$ (+ other).

Table C.5: Average estimated probabilities that nominal wage growth does not exceed past, current or future inflation by subperiod. Breakdown by firm-size, type of worker, province of employment.

Period	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Not exceeding past inflation								
1975–1979	.243	.267	.258	.264	.322	.257	.253	.241
1980–1986	.428	.454	.402	.331	.459	.437	.421	.444
1987–1992	.233	.258	.203	.258	.279	.282	.252	.237
1993–1998	.371	.384	.352	.351	.475	.445	.415	.389
1999–2012	.325	.342	.312	.376	.391	.372	.347	.336
2013–2021	.356	.378	.361	.457	.415	.397	.383	.383
2022–2024	.509	.552	.514	.501	.606	.559	.540	.526
1975–2024	.346	.368	.336	.366	.411	.387	.366	.359
Not exceeding current inflation								
1975–1979	.190	.203	.211	.240	.253	.211	.201	.183
1980–1986	.299	.316	.280	.278	.343	.327	.300	.315
1987–1992	.227	.249	.196	.259	.278	.278	.248	.231
1993–1998	.321	.325	.308	.329	.422	.396	.364	.336
1999–2012	.330	.350	.316	.378	.396	.381	.353	.341
2013–2021	.335	.355	.343	.451	.394	.377	.363	.359
2022–2024	.396	.423	.401	.447	.467	.435	.421	.407
1975–2024	.305	.323	.297	.349	.369	.350	.327	.317
Not exceeding future inflation								
1975–1979	.290	.316	.300	.282	.340	.293	.292	.276
1980–1986	.174	.175	.168	.208	.216	.206	.185	.186
1987–1992	.229	.252	.198	.260	.281	.281	.249	.236
1993–1998	.283	.285	.274	.308	.378	.354	.324	.298
1999–2012	.330	.351	.318	.376	.396	.380	.353	.342
2013–2021	.376	.393	.384	.467	.437	.420	.405	.399
2022–2023	.397	.429	.390	.406	.479	.436	.425	.410
1975–2023	.297	.313	.290	.338	.359	.341	.319	.308

- (1): Stayer in firm with 16-200 full-year equivalent employees in Milan in $t - 1$ (+ other).
(2): Stayer in firm with 1-16 full-year equivalent employees in Milan in $t - 1$ (+ other).
(3): Stayer in firm with 200+ full-year equivalent employees in Milan in $t - 1$ (+ other).
(4): Mover in firm with 16-200 full-year equivalent employees in Milan in $t - 1$ (+ other).
(5): Stayer in firm with 16-200 full-year equivalent employees in Palermo in $t - 1$ (+ other).
(6): Stayer in firm with 16-200 full-year equivalent employees in Naples in $t - 1$ (+ other).
(7): Stayer in firm with 16-200 full-year equivalent employees in Rome in $t - 1$ (+ other).
(8): Stayer in firm with 16-200 full-year equivalent employees in Venice in $t - 1$ (+ other).

Table C.6: Sample sizes (thousands of workers) at each stage of the sample selection process in Section 7.4.

Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2006	5,809.3	3,338.8	3,316.5	727.6	1,980.8	605.3	2.9
2007	5,743.4	3,289.7	3,267.4	618.4	694.1	1,951.0	3.9
2008	5,779.8	3,307.2	3,284.2	1,682.1	920.8	636.7	44.6
2009	5,771.1	3,274.5	3,251.0	1,990.8	308.1	949.8	2.3
2010	5,491.6	3,061.4	3,037.2	2,217.5	514.2	304.3	1.3
2011	5,500.4	3,102.1	3,077.8	1,932.6	641.7	501.9	1.6
2012	5,562.9	3,070.8	3,046.9	968.3	1,440.0	633.2	5.4
2013	5,314.6	2,937.0	2,913.3	935.3	585.6	1,386.7	5.8
2014	5,269.7	2,921.2	2,897.5	1,574.0	742.0	579.3	2.2
2015	5,192.9	2,912.0	2,889.0	1,658.0	485.2	714.1	31.7
2016	4,957.7	2,769.7	2,733.4	1,138.8	1,112.3	481.2	1.0
2017	5,251.3	2,920.2	2,879.2	1,153.5	557.8	1,159.4	8.5
2018	5,176.7	2,886.3	2,843.5	1,050.7	1,236.8	543.2	12.8
2019	5,228.5	2,880.9	2,831.0	1,136.1	408.8	1,284.3	1.8
2020	5,385.5	3,108.5	3,052.0	2,331.3	251.4	468.8	.4
2021	3,749.8	2,046.6	2,006.8	706.6	1,122.7	175.8	1.8
2022	5,116.7	2,703.2	2,597.6	513.0	376.8	1,696.9	10.9
2023	5,555.5	4,569.8	4,274.4	2,898.5	800.7	569.5	5.7
2024	5,423.8	4,457.8	4,166.8	3,420.8	3.1	742.8	.0

- (1): Working sample;
- (2): Excluding workers with at least one contract not in our selected CNEL frequently renewed contracts among workers in (1);
- (3): Excluding workers not covered by CGIL, CISL or UIL for the entire 2 year period among workers in (2);
- (4): Workers with no renewal in $t - 1$ and t among workers in (3);
- (5): Workers with contract renewal only in t among workers in (3);
- (6): Workers with contract renewal only in $t - 1$ among workers in (3);
- (7): Workers with contract renewal in both in $t - 1$ and t among workers in (3);

Table C.7: Mean, median (P50) and standard deviation (SD) of wage growth by the experience of a notional event.

Year	(1)			(2)			(3)			(4)		
	Mean	P50	SD	Mean	P50	SD	Mean	P50	SD	Mean	P50	SD
2006	.053	.038	.086	.087	.070	.095	.005	.008	.103	.044	.041	.112
2007	.051	.033	.091	.087	.065	.099	.005	.005	.106	.037	.031	.112
2008	.070	.059	.087	.100	.086	.098	.014	.021	.101	.049	.049	.112
2009	.028	.025	.084	.061	.052	.096	-.048	-.032	.110	-.014	-.002	.123
2010	.041	.032	.080	.085	.068	.097	-.010	-.001	.100	.030	.027	.116
2011	.034	.024	.077	.077	.060	.092	-.015	-.006	.095	.027	.023	.108
2012	.025	.021	.077	.061	.049	.090	-.027	-.015	.095	.002	.007	.105
2013	.027	.023	.074	.063	.051	.087	-.020	-.009	.091	.009	.013	.105
2014	.020	.011	.072	.055	.041	.085	-.025	-.016	.091	.010	.010	.101
2015	.031	.022	.072	.063	.048	.088	-.014	-.006	.088	.024	.021	.101
2016	.023	.014	.071	.054	.039	.084	-.021	-.014	.086	.010	.007	.098
2017	.026	.013	.073	.060	.042	.085	-.014	-.011	.086	.018	.012	.096
2018	.031	.018	.074	.062	.045	.085	-.011	-.008	.085	.019	.014	.092
2019	.031	.018	.075	.061	.044	.085	-.012	-.009	.086	.014	.011	.094
2020	.004	.003	.090	.033	.027	.099	-.053	-.046	.097	-.031	-.026	.110
2021	.046	.028	.089	.088	.070	.094	.006	-.001	.096	.051	.041	.109
2022	.046	.025	.093	.088	.064	.107	.011	-.000	.093	.038	.024	.111
2023	.055	.038	.089	.076	.058	.090	.011	.007	.097	.038	.031	.102

- (1): Without notional events in both year $t - 1$ and t ;
(2): With a notional event in year $t - 1$ only;
(3): With a notional event in year t only;
(4): With a notional event in both years $t - 1$ and t .

Table C.8: Sample sizes (thousands of workers) at each stage of the sample selection process in Section 7.5

Year	(1)	(2)	(3)	(4)	(5)	(6)
2006	5,809.3	4,462.6	601.1	37.1	554.2	9.9
2007	5,743.4	4,516.1	654.3	42.0	599.5	12.8
2008	5,779.8	4,453.4	711.4	113.2	567.8	30.4
2009	5,771.1	4,399.8	960.3	345.1	544.7	70.5
2010	5,491.6	3,982.4	621.5	116.9	484.9	19.6
2011	5,500.4	4,002.4	599.4	84.1	499.4	15.9
2012	5,562.9	4,137.6	669.6	162.1	477.0	30.6
2013	5,314.6	3,927.0	690.5	181.5	484.7	24.4
2014	5,269.7	3,765.0	568.3	79.9	475.3	13.0
2015	5,192.9	3,735.9	547.9	43.8	495.5	8.6
2016	4,957.7	3,677.5	525.8	31.5	488.5	5.9
2017	5,251.3	4,016.1	569.9	26.1	540.2	3.6
2018	5,176.7	3,995.8	602.3	37.4	556.6	8.3
2019	5,228.5	3,956.1	608.3	57.3	537.7	13.3
2020	5,385.5	3,978.5	1,886.9	1,095.9	489.3	301.7
2021	3,749.8	2,081.0	353.1	23.9	322.9	6.3
2022	5,116.7	3,348.7	1,058	37.4	996.7	23.9
2023	5,555.5	3,167.6	469.8	63.2	392.8	13.8
2024	5,423.8	3,980.3	651.6	106.7	521.2	23.7

(1): Working sample.

(2): Excluding workers with a notional event in year $t - 1$ among workers in (1).

(3): Workers with a notional event in year t among workers in (2).

(4): Only CIG workers among workers in (3);

(5): Only workers with other notional events among workers in (3);

(6): Workers with both CIG and other notional events among workers in (3).

Figure C.1: Annual inflation in Italy.

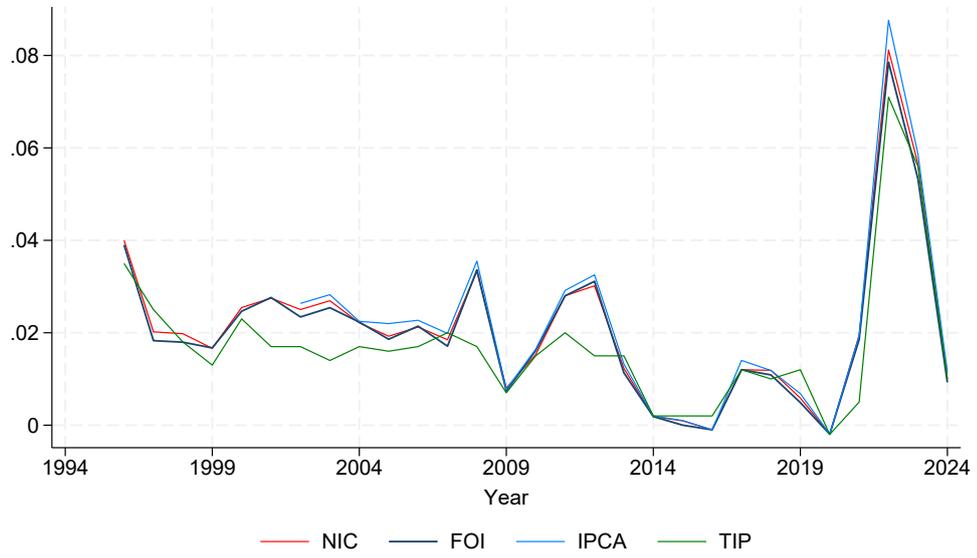


Figure C.2: Comparison of annual inflation in the main Italian cities,

