

# Slack and prices during Covid-19: accounting for labor market participation \*

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...published unemployment rates during COVID have dramatically understated the deterioration in the labor market.

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J. Powell speech “*Getting Back to a Strong Labor Market*” February 10, 2021.

Changes in labor force participation contain important information about the strength of the labor market that is not captured in the unemployment rate.

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L. Brainard speech “*How Should We Think about Full Employment in the Federal Reserve’s Dual Mandate?*” February 24, 2021.

## Abstract

Strong labor force participation cyclicity during the Covid-19 pandemic has put further into question the capacity of standard Phillips Curve (PC) models to fully capture labor market cyclical conditions. In this paper, we jointly estimate natural unemployment and participation rates (i.e. compatible with constant inflation) through an augmented PC informed by structural labor market flows across employment, unemployment and inactivity. Focusing on Italy we find that, during the pandemic: i) natural unemployment has remained unchanged, while natural participation has declined slightly, mostly due to a rise in retirement flows driven by a temporary reduction in pension eligibility rules; ii) virtually all slack was accounted for by the participation margin, which added significant downward pressures to inflation dynamics.

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# 1 Introduction

Departing from the standard assumption of fixed labor force participation, a growing empirical literature analyzes the cyclicity of the activity rate and its implications for labor market dynamics: Elsby et al. (2015) for example find that the participation margin accounts for one third of the cyclical fluctuation of the unemployment rate in the USA.<sup>1</sup> Moreover, it is standard in macroeconomics to use Phillips curve (PC) models to interpret price dynamics in relation to labor market slack, usually captured by the unemployment rate or some transformation of it. However if the participation margin provides additional information on labor market conditions, neglecting it may lead to an incorrect assessment of the actual state of the economy and inflation drivers.

During the Covid crisis, advanced economies experienced the largest drops in labor force participation on records.<sup>2</sup> During the spring of 2020, participation rates dropped by about 2.5 percentage points in the USA and the euro area (Figure 1). As a result, the unemployment rate declined or rose only modestly compared to what would have happened absent any change in labor force participation. For example, without the drop in the activity rate, the increase in the unemployment rate at the peak would have been 3 percentage points higher in the USA and in the euro area; in the latter, the drop in labor supply fully offset the decrease in employment in the first months of the pandemic, leaving the unemployment rate constant. Obviously, models assessing labor market slack only based on unemployment dynamics would have thus failed to adequately capture the full extent of the deterioration of cyclical conditions.

Starting from this fact, in this paper we provide an assessment of labor market slack in Italy based on both the unemployment and the participation margin. To do so, we employ the model presented in D'Amuri et al. (2021) that in turn generalizes Crump et al. (2019) by explicitly taking into account movements into and out of the labor force. The participation margin can provide useful information on total labor market slack: a participation rate that is below its natural level is an indication that the economy is running below potential, for instance because some inactive workers may have temporarily exited from the labor market waiting for better employment opportunities. A Phillips curve model featuring both an unemployment and a participation gap provides a measure of total labor market slack that properly takes into account also temporary movements into and out of activity, a feature that makes such model particularly attractive during the pandemic.

Estimates are obtained in two steps. First, using the flow-based model of unemployment dynamics proposed by Shimer (2012) along with an unobserved component model, we retrieve the *structural* participation and unemployment rates, obtained by evaluating

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<sup>1</sup>Cajner et al. (2021), exploiting exogenous local business cycle shocks, also provide evidence for the cyclicity of the labor force participation rate in the USA.

<sup>2</sup>Analyzing a wide array of survey data, Balgova and Pestel (2021) Coibion et al. (2020), Forsythe et al. (2020), Hensvik et al. (2021) confirm the strong labor force participation cyclicity during the Covid crisis.

at the steady state the trend components of labor market flows between employment, unemployment and inactivity for six demographic cells defined by gender and age. Such rates are only determined by structural factors (demography and changes in the labor market environment: preferences, institutions, matching technology). Second, we use such structural rates as anchors in the estimation of the *natural* (i.e. coherent with stable inflation) unemployment and participation rates through a forward-looking Phillips Curve.

The analysis of the flows reveals that transitions into inactivity from both unemployment and employment raised substantially during the Covid crisis. While the former increased for all demographic groups, the latter increased in particular for mature (55-64) workers, interrupting a long-term declining trend that was fostered by reforms restricting public pension eligibility (D’Amuri et al., 2021). After distinguishing the structural component of these changes in labor market flows and comparing the pre-Covid (2019) projections for structural unemployment and participation rates with their actual 2020 evolution, overall we find no sizable impact of the Covid recession on structural unemployment, and a slight decrease in structural participation (0.24 percentage points in 2020q3-4). Such a decrease is present in all demographic groups but it is larger for mature (55-64) workers; the aggregate effect, indeed, is mostly determined by the behaviour of the elderly. Additional evidence suggests that the drop in participation of older workers is mostly driven by an increase in retirement probability, made possible by a three-year temporary reduction in pension eligibility requirements (so called “quota 100”) that entered into force in 2019. Indeed we find that retirement flows: i) started increasing already in 2019 and did not further accelerate afterwards; ii) increased the most in sectors such as public administration, whose workers – characterized by more stable careers – benefited more from the reform. We conclude that the majority of these retirements would have occurred irrespective of the pandemic.

We then ask whether the cyclical movements of the participation margin provide relevant information for overall economic conditions, thus contributing to shape price dynamics. To address this issue we estimate a Phillips curve model in which inflation depends not only on the unemployment gap – the standard measure employed in the literature – but also on a participation gap. Our estimates confirm the sizable role of the participation gap to overall slack in the five years preceding the health crisis (D’Amuri et al., 2021). Moreover, we find that such contribution became more sizable in the first two quarters of 2020, while the unemployment gap turned negative due to the fall in labor supply, bringing headline unemployment figures below their natural level. Our augmented PC model implies that in 2020 total slack subtracted 0.4 percentage points to price and wage dynamics; according to an otherwise identical model not including the participation margin, such effect would have been almost nihil. The augmented model outperforms the standard one also from an *ex-ante* perspective: when computing inflation forecasts conditional on our measures of labor market slack, we confirm the importance of the

participation gap, that widened in 2020 thus adding downward pressures on inflation.

To the best of our knowledge, our work is the first to gauge the impact of the Covid crisis on *natural* unemployment and participation rates, contributing to the recent literature on labor market dynamics during the pandemic (Balgova and Pestel, 2021; Coibion et al., 2020; Forsythe et al., 2020; Hensvik et al., 2021; Şahin et al., 2021). Our approach, described more in detail in D’Amuri et al. (2021), builds on the large literature on the flow-based analysis of labor market dynamics (Choi et al., 2015; Crump et al., 2019; Elsby et al., 2019; Fujita and Ramey, 2009; Gomes, 2012; Petrongolo and Pissarides, 2008; Shimer, 2012, among others). More in general, our results are relevant for the literature proposing alternative labor market slack measures (Abraham et al., 2020; Bell and Blanchflower, 2013; Gordon, 2013) or focusing on the impact of labor supply fluctuations on cyclical dynamics (Strand and Dernburg, 1964; Garibaldi and Wasmer, 2005; Pries and Rogerson, 2009; King, 2011; Kudlyak and Schwartzman, 2012; Elsby et al., 2015; Krusell et al., 2017, 2020; Lalé, 2013). Moreover, our evidence that participation is cyclical is an important result also for other models in the literature, like for instance search and matching models, which usually assume that participation is fixed (few exceptions are Krusell et al., 2017 and Cairó et al., 2021). In particular, our findings suggest that measuring labour market tightness only based on unemployment and assuming that labour supply is exogenous would bias the estimation of the matching function and of matching efficiency (as also pointed out by Barnichon and Figura, 2015 and Hall and Schulhofer-Wohl, 2018), and that this bias varies along the cycle, therefore changing the interpretation of movements in the Beveridge curve, for instance. Finally, we contribute to the extensive literature on Phillips curve estimation (see Coibion and Gorodnichenko, 2015; Ball and Mazumder, 2019; Stock and Watson, 2020; Del Negro et al., 2020 for recent discussions), showing that the participation margin provides relevant and autonomous information on economic slack and contributes to explaining inflation dynamics.

The rest of the paper is organized as follows. Section 2 defines the concepts of *structural* and *natural* participation and unemployment rates. Sections 3 and 4 respectively present and discuss estimates of the structural and natural rates. Section 5 concludes.

## 2 Definitions

Following the taxonomy that has recently been proposed by Crump et al. (2020) for the unemployment rate, extended to participation rates by D’Amuri et al. (2021), we distinguish two concepts: i) the *structural* (or trend) unemployment and participation rates; these are the rates expected to prevail after adjusting to business cycle shocks. They are determined by purely structural (non-monetary) factors, like structural reforms or changes in the socio-demographic or sectoral and occupational composition in the labor market, and ii) the *natural* unemployment and participation rates, that are the rates coherent with constant inflation; they connect the real and the nominal side of the

economy.

As in D'Amuri et al. (2021), we decompose the unemployment rate and the participation rate as follows:

$$u_t = \bar{u}_t + \underbrace{(u_t - u_t^*)}_{x_t^u} + \underbrace{(u_t^* - \bar{u}_t)}_{z_t^u}, \quad (1)$$

$$p_t = \bar{p}_t + \underbrace{(p_t - p_t^*)}_{x_t^p} + \underbrace{(p_t^* - \bar{p}_t)}_{z_t^p}, \quad (2)$$

where  $u_t$  and  $p_t$  are the actual unemployment and activity rates;  $\bar{u}_t$  and  $\bar{p}_t$  are the structural (or trend) unemployment and activity rates,  $u_t^*$  and  $p_t^*$  are the natural unemployment and activity rates and  $x_t^u = (u_t - u_t^*)$  and  $x_t^p = (p_t - p_t^*)$  are the unemployment and participation gaps.  $z_t^u = (u_t^* - \bar{u}_t)$  and  $z_t^p = (p_t^* - \bar{p}_t)$  are the gaps between the natural and the structural rates. A wedge between the two can arise because of transitory factors relevant for price dynamics, like temporary labor market policies that affect wages or variations in firms markups.

We derive structural rates by extracting the trend components from labor market flows and evaluating them at the steady state (Section 3). Natural rates are instead estimated within the context of a Phillips curve framework (Section 4), using  $\bar{u}$  and  $\bar{p}$  to discipline  $u^*$  and  $p^*$  by assuming that the natural rates converge to the structural ones in the long-run.

## 3 Structural unemployment and activity rates

### 3.1 Estimation of the structural rates

The estimation procedure for the structural rates involves four steps.<sup>3</sup> First, we use the Italian Labour Force Survey micro data to estimate labor market flows between the three labor market states (employment  $E$ , unemployment  $U$  and inactivity  $N$ ) over the 1984–2020q4 period for six demographic groups defined by three age classes (15–34, 35–54 and 55–64) and gender.<sup>4</sup> In this way, we obtain six underlying hazard rates for each group  $g$ :

$$\left\{ f_{g,t}^{NU}, f_{g,t}^{NE}, f_{g,t}^{EU}, f_{g,t}^{EN}, f_{g,t}^{UE}, f_{g,t}^{UN} \right\}_{t=1984,q1}^{2020q4},$$

where  $f_{g,t}^{XY}$  is the transition rate from state  $X$  to state  $Y$  for demographic group  $g$  at time  $t$ .

Second, we decompose each labor market flow (in each demographic cell) into a

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<sup>3</sup>For a full description of the estimation procedure, as well as of the robustness of our technique, see also D'Amuri et al. (2021).

<sup>4</sup>Following the existing literature (Barnichon and Mesters, 2018, Elsby et al., 2015 and Shimer, 2012), we make some adjustments: i) we make them consistent with the dynamics of the stocks (*margin error correction* - MEC) and ii) we derive continuous-time flow rates from discrete time transition probabilities, in order to account for the possibility of multiple transitions taking place within the observation window (*temporal aggregation correction* - TAC). See Appendix A for details.

stochastic trend and a stationary cyclical component, using an unobserved component model which jointly takes into account GDP dynamics.<sup>5</sup> As outcome of this second step we obtain the trend components of the flow rates ( $\bar{f}_{g,t}^{XY}$ ), which are then used in the next step to compute the structural unemployment and activity rates.

Third, to obtain the structural rates, we rely on the notion of flow-consistent rates (as in Shimer, 2012). Let  $U_{g,t}$ ,  $E_{g,t}$  and  $N_{g,t}$  be the relevant stocks of unemployment, employment and inactive population for demographic group  $g$  at time  $t$ . The evolution of the stocks over time depends on the hazard rates through the following differential equations:

$$\dot{U}_{g,t} = f_{g,t}^{EU} E_{g,t} + f_{g,t}^{NU} N_{g,t} - (f_{g,t}^{UE} + f_{g,t}^{UN}) U_{g,t}, \quad (3)$$

$$\dot{E}_{g,t} = f_{g,t}^{UE} U_{g,t} + f_{g,t}^{NE} N_{g,t} - (f_{g,t}^{EU} + f_{g,t}^{EN}) E_{g,t}, \quad (4)$$

$$\dot{N}_{g,t} = f_{g,t}^{UN} U_{g,t} + f_{g,t}^{EN} E_{g,t} - (f_{g,t}^{NU} + f_{g,t}^{NE}) N_{g,t}. \quad (5)$$

Under the assumption of constant transition rates, we can use (3), (4) and (5) to solve for the steady-state levels of  $U_g^*$ ,  $E_g^*$  and  $N_g^*$ , by setting  $\dot{U}_{g,t} = \dot{E}_{g,t} = \dot{N}_{g,t} = 0$ . In order to obtain the trend unemployment and participation rates, we evaluate equations (3)-(5) in steady state plugging-in the estimated trend components of the flows,  $\bar{f}_{g,t}^{XY}$  (as in Tasci, 2012 and Crump et al., 2019). Let us then formally define the structural unemployment and participation rates as:

$$\bar{u}_{g,t} = \frac{\bar{U}_{g,t}^*}{\bar{U}_{g,t}^* + \bar{E}_{g,t}^*}, \quad \bar{p}_{g,t} = \frac{\bar{U}_{g,t}^* + \bar{E}_{g,t}^*}{\bar{U}_{g,t}^* + \bar{E}_{g,t}^* + \bar{N}_{g,t}^*}.$$

Plugging in the equilibrium values, and using the fact that total population is normalized to 1, we can solve for the structural unemployment rate  $\bar{u}_{g,t}$  and participation rate  $\bar{p}_{g,t}$  of each group  $g$  as a function of the structural rates  $\bar{f}_{g,t}^{XY}$ .

Finally, we compute weighted averages of the group-specific structural unemployment and activity rates to obtain the aggregate ones. The weights used for the participation rate ( $\omega_{g,t}^p$ ) represent the share of individuals belonging to group  $g$  at time  $t$  over the total population, such that  $\sum_g \omega_{g,t}^p = 1 \forall t$ .

$$\bar{p}_t = \sum_g \omega_{g,t}^p \bar{p}_{g,t}. \quad (6)$$

For the aggregation of group-specific unemployment rates, the weights are a combination of the group-specific weights in the total population (the  $\omega_{g,t}^p$  defined above) and the incidence of the group in the structurally active population.

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<sup>5</sup>See Appendix A for more details on the filtering technique.

$$\bar{u}_t = \sum_g \omega_{g,t}^p \underbrace{\frac{\bar{p}_{g,t}}{\bar{p}_t}}_{\bar{\omega}_{g,t}^u} \bar{u}_{g,t}, \quad (7)$$

where  $\bar{\omega}_{g,t}^u$  represents the share of structural active population (that is, the active population identified by the structural rates) accounted for by the specific group  $g$  at time  $t$ .

### 3.2 Estimation of the effect of Covid-19 on structural rates

The richness of our approach, which relies on detailed micro-level data for single demographic groups and takes into account labor force participation, provides the ideal setting for the estimation of the impact of the Covid-19 pandemic on structural unemployment and participation rates. First, our approach considers transitions between all three labor market states in a unitary framework, and not only flows into and out of employment. This allows us to detect the large observed spike in the flows between unemployment and inactivity. Two-state models neglecting the participation margin would interpret such flows as a genuine reduction in labor market slack. Second, our approach is able to capture cyclical and structural changes in participation for each demographic group. In this way, for instance, we are able to separately consider reductions in participation for older individuals, who may opt for early retirement schemes during recessions (OECD, 2013). These factors may have played an important role also in the current crisis, given the sizable fluctuations in the activity rate.

To gauge the impact of Covid-19 on the structural rates, we first need to compute counterfactual “No-Covid” structural unemployment and participation rates. These are obtained by deriving our best forecast of the structural rates based on the pre-Covid trends in labor market flows using only data until 2019q4. In particular, we project over 2020 each labor market flow within each demographic cell, following two different scenarios. The first assumes that each group-specific trend in the structural flows  $\bar{f}_{g,t}^{XY}$  will continue in the next year to follow the same dynamics as those registered on average in the previous five years (baseline projection); the second hypothesizes that the structural flow rates  $\bar{f}_{g,t}^{XY}$  would remain constant at their estimated level in 2019q4. This second scenario allows to isolate the effects of the ongoing changes in the demographic structure from those of variations in the rates within each demographic cell. We denote as  $\{\bar{u}_t^{PRE}\}$  and  $\{\bar{p}_t^{PRE}\}$  the paths of the structural unemployment and structural participation in place prior to the Covid crisis; we interpret them as the counterfactual evolution of the Italian labor market throughout 2020 absent the pandemic.

Then, we compare these counterfactual rates with what we get by applying our methodology on the full sample, hence including all the available observations in 2020.<sup>6</sup> We obtain  $\{\bar{u}_t^{POST}\}$  and  $\{\bar{p}_t^{POST}\}$ ; we normalize their levels in 2019 to be equal to those

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<sup>6</sup>The last available data point is 2020q4.

estimated in the pre-Covid period.<sup>7</sup> Finally, we compute the effect of the Covid crisis as the simple difference between the POST- and the PRE-series.

### 3.3 Results on labor market flows and structural rates

Figures D.1 to D.6 in the Appendix show the evolution between 2010q1 and 2020q4 of the observed transition rates between labor market states  $X$  and  $Y$  ( $f_{g,t}^{X,Y}$ ) and that of the estimated long-term trends in these rates ( $\bar{f}_{g,t}^{X,Y}$ ) for each demographic group  $g$ .<sup>8</sup> Three patterns emerge from the Figures, that are peculiar to this Covid recession. First, the Covid recession appears to have generated a very large spike in the flows from unemployment to inactivity (UN) for all demographic groups; this is consistent with the observed drop in unemployment and the contemporaneous increase in inactivity.<sup>9</sup> Second, there are little changes in the flows between employment and unemployment (EU and UE). This contrasts with previous recessions, usually characterized by a spike in the flow between employment and unemployment and by an increased difficulty for unemployed individuals to find a new job. The modest effect on job separations during this Covid recession could be explained by some policies enacted in these months by the Italian Government, which - as in many other European countries (OECD, 2020) - extended the coverage of Short Time Work schemes, increased their duration and abolished any form of employers' burden sharing or experience rating. Furthermore, the Government introduced a ban on dismissals for permanent workers (see Carta and De Philippis, 2021a). As a result, the flows out of employment are mainly concentrated among the youth who are more likely to be employed with temporary contracts, uncovered by short time work schemes once they expire. The third fact that emerges is an increase in flows from employment directly to inactivity (EN) concentrated among the elderly, in stark contrast with a long-term declining pattern. Nevertheless, such development seems to be favored by a temporary reduction in pension eligibility requirements for years 2019-2021 (the so called "quota 100"), that was already in place before the pandemic.<sup>10</sup> Indeed, we find that: i) a similar increase in flows from employment into inactivity among the elderly was in place already in 2019 and continued during 2020; ii) the increase in retirement flows was most pronounced among public employees more likely to be benefiting by the temporary reduction in pension eligibility requirements. More details and additional evidence are provided in Appendix C.

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<sup>7</sup>As we want to avoid that our filtering technique changes the estimation for the period prior to the reform, for each subgroup we define an adjustment factor  $adj_g^x = \bar{x}_{g,2019q4}^{PRE} - \bar{x}_{g,2019q4}^{POST*}$ , and construct our final POST-series accordingly:  $\bar{x}_{g,t}^{POST} = \bar{x}_{g,t}^{POST*} + adj_g^x$  for  $x \in \{u, p\}$  and  $t \in [2020q1 - q4]$ , where  $\bar{x}_{g,t}^{POST*}$  refers to the non-adjusted series.

<sup>8</sup>Figures D.7 to D.12 show trend hazard rates for the entire sample (1984q1-2020q4).

<sup>9</sup>This sudden retreat from the labor market, observed in all advanced economies, has been driven by a mix of factors: decreased number of job postings during the pandemic, fears of infections (reducing the willingness to engage in activities at risk of contagion, reduced mobility).

<sup>10</sup>Article 14 of the Decree Law 4/2019 gave the possibility to retire with no penalties to individuals reaching age 62 with 38 years of accrued social security contributions during the three year interval 2019-2021; moreover, it froze the indexation mechanism to life expectancy for old-age public pensions.

Overall, Figures D.1 to D.6 suggest that the Covid crisis did not have large effects on structural transition rates, since a large portion of the changes observed in 2020 can be attributed to cyclical conditions.

Then, the structural transition rates are used to compute the structural unemployment and participation rates in each demographic cell, which are then combined so to obtain the aggregate rates, as described in Section 3.1. Figure 2 plots the estimated aggregate structural unemployment rate for the years 2015-2020.<sup>11</sup> The structural unemployment rate was essentially flat in the years before the Covid crisis: between 2015 and 2019 its value is estimated at around 9%, slightly below the level of the observed unemployment rate. The flat dynamics observed starting from 2015 is due to the offsetting of two countervailing forces: on the one hand, the downward pressure provided by demographics (due to the greater weight of the elderly and the smaller weight of the youth, characterized respectively by very low and very high trend unemployment); on the other hand, the upward pressure from the increasing trend unemployment in most demographic groups (see also D’Amuri et al., 2021).<sup>12</sup> Our estimates indicate that the outbreak of the Covid-19 pandemic did not have a significant impact on these underlying forces and hence on the structural unemployment rate, which continued to remain basically flat.

The small impact of the pandemic on structural unemployment is confirmed also at the group level. Figure 3 displays the evolution of the group-specific structural unemployment rates, comparing those estimated with the post-Covid data points (solid yellow line) with those obtained under the two counterfactual scenarios. Overall, the within-group changes are very small for all demographic groups: the largest increase is observed among young women (0.07 percentage points between 2019q4 and 2020q4), the smallest increase among prime age women (0.02 percentage points in the same period). Moreover, the demographic groups for which the Covid crisis generated the smallest increase in  $\bar{u}_t^g$  (middle-aged individuals) are those whose structural activity rate is larger, and therefore those who matter the most for the aggregate structural unemployment rate.

As for the structural participation rate, Figure 4 reveals that it was increasing until 2018q4 and started to slowly decrease already in 2019, before the onset of the Covid crisis.<sup>13</sup> Moreover, we estimate that the structural component was above the observed participation rate already before the health crisis. This happened because our model interpreted the decrease in the actual participation rate of prime-age men and of the youth during the years before the pandemic mainly as cyclical, while it identified the increase in the participation rate of the elderly as structural (see D’Amuri et al., 2021 for a detailed discussion of this result).

The Covid crisis induced a slight decrease in structural participation. Compared to its counterfactual “No-Covid” evolution, structural participation in 2020q4 was lower by between 0.15 and 0.26 percentage points, depending on the scenario we consider. The

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<sup>11</sup>Figure D.13 in the Appendix reports our estimates for the entire sample, starting from 1984q1.

<sup>12</sup>See Figures D.15 and D.16 in the Appendix for more details

<sup>13</sup>Figure D.14 shows the evolution of  $\bar{p}_t$  for the entire sample period, 1984q1-2020q4.

drop in  $\bar{p}_t^g$  affected all demographic groups (Figure 5), but it was larger among the elderly (-0.23 pp among women aged 55-64, -0.21 among men aged 55-64) and to a lesser extent also among the youth (-0.11 percentage points among men aged 15-34, -0.14 percentage points among women aged 15-34). As explained before, this relatively larger decrease in the structural participation rate of the elderly is related to their choice of opting for early retirement schemes, favored already in 2019 by the temporary reduction in pension eligibility requirements. Since retirement flows show little cyclicity in the past, the observed drop in participation is interpreted as structural in our model.

## 4 The impact of Covid-19 on $u^*$ and $p^*$

In this Section we ask whether the participation margin, beyond offering valuable insights on labor market dynamics, is also relevant from a macroeconomic perspective. In particular, we ask whether it provides additional information on overall economic slack that can be useful to explain price and wage dynamics. Indeed the cyclicity of labor market participation does not imply *per se* that it adds relevant information for other outcomes of interest at the macro level. If, for instance, the unemployment and the participation gaps were perfectly correlated, adding the latter to economic models would provide very little additional information.

In the spirit of Crump et al. (2020) and D’Amuri et al. (2021), we employ a Phillips curve framework that includes both an unemployment and a participation gap, and that is informed by the structural rates calculated as in Section 3. We then compare our estimates with a standard model based only on the unemployment gap. This approach allows us to estimate the so-called *natural* unemployment and participation rates ( $u^*$  and  $p^*$ , respectively), namely those consistent with stable inflation absent supply shocks.

### 4.1 The augmented Phillips Curve

We use a rich state-space model where the main equation is a generalized version of the Phillips Curve: price inflation depends negatively on current and future unemployment gaps ( $x_t^u = u_t - u_t^*$ ) and positively on the present discounted value of current and future participation gaps ( $x_t^p = p_t - p_t^*$ ). We assume that inflation expectations follow a time-varying trend ( $\pi_t^*$ ), pinned down using short- and long-run inflation expectations derived from Consensus Forecasts. This trend represents the stable inflation path when both the unemployment and the participation gaps are closed. Formally, we estimate the following equation, where the dependent variable is the price inflation gap, that is the difference between realized price inflation and the estimated trend:

$$\pi_t - \pi_t^* = \gamma (\pi_{t-1} - \pi_{t-1}^*) - \gamma \sigma_{\pi^*} \epsilon_t^{\pi^*} - \kappa^u E_t \sum_{T=t}^{\infty} \beta^{T-t} x_T^u + \kappa^p E_t \sum_{T=t}^{\infty} \beta^{T-t} x_T^p - \beta \frac{1 - \rho_a}{1 - \beta \rho_a} \Delta a_t, \quad (8)$$

where  $\gamma$  captures inflation inertia, and  $\kappa^u$  and  $\kappa^p$  denote the reaction of inflation to the present discounted value of future unemployment and participation gaps, respectively. Notice that we expect inflation to depend negatively on unemployment gaps and positively on participation gaps.  $\epsilon_t^{\pi^*}$  indicates shocks to the inflation trend and hence to long-term inflation expectations which effectively identify it; such shock can thus be interpreted as a measure of (de)anchoring of professional forecasters' expectations to a given inflation target.  $\Delta(a_t)$  follows an AR(1) process and represents supply factors (e.g. productivity), which affect price inflation (here measured by the y-o-y growth rate of the HICP<sup>14</sup>) beyond the demand ones captured by the unemployment gap. We further assume that the inflation trend follows a random walk and the unemployment and participation gaps are represented by AR(2) processes. Moreover, the rational expectations hypothesis implies that short- and long-term inflation expectations are consistent with the forward iteration of eq. (8) with a margin of error.

We can estimate the unemployment and the participation gaps using the decomposition of the realized unemployment and participation rates described in Section 2:

$$u_t = x_t^u + z_t^u + \bar{u}_t \quad (9)$$

$$p_t = x_t^p + z_t^p + \bar{p}_t \quad (10)$$

where  $z_t^u = u_t^* - \bar{u}_t$  is the deviation of the natural unemployment rate from the structural unemployment rate and  $z_t^p = p_t^* - \bar{p}_t$  is the deviation of the natural participation rate from the structural participation rate. We assume that both  $z_t^u$  and  $z_t^p$  follow an AR(1) process:

$$z_t^u = \rho_{z^u} z_{t-1}^u + \sigma_{z^u, \varsigma} \sigma_{\varsigma} \epsilon_t^{z^u} \quad (11)$$

$$z_t^p = \rho_{z^p} z_{t-1}^p + \sigma_{z^p, \varsigma} \sigma_{\varsigma} \epsilon_t^{z^p}. \quad (12)$$

Equations (11-12) imply that  $u^*$  and  $p^*$  converge to their respective structural rates  $\bar{u}_t$  and  $\bar{p}_t$  in the long-run; however, in the short-run, deviations are allowed with degrees of persistence  $\rho_{z^u}$  and  $\rho_{z^p}$ . Since  $\sigma_{\varsigma}$  represents the volatility of inflation due to supply shocks<sup>15</sup>,  $\sigma_{z^u, \varsigma}$  and  $\sigma_{z^p, \varsigma}$  can be interpreted as the signal-to-noise ratios, that is the volatility of the unobserved states  $u_t^*$  and  $p_t^*$  relative to inflation. Notice that, from the perspective of the Phillips curve model, the trend unemployment and participation rates are exogenous

<sup>14</sup>Our findings are robust to the use of core inflation instead of the HICP. Results are available upon request.

<sup>15</sup>If we define  $\varsigma_t = -\beta \frac{1 - \rho_a}{1 - \beta \rho_a} \Delta a_t = \rho_a \varsigma_{t-1} + \sigma_{\varsigma} \epsilon_t^{\varsigma}$ , inflation is affected by shocks of volatility  $\sigma_{\varsigma}$ .

observable inputs; for this reason, the shocks moving  $z_t^u$  and  $z_t^p$  are fully reflected in the natural unemployment and participation rates. Equations (8) to (12) together with the others described in Appendix B allow us to jointly estimate the parameters of the Phillips curve,  $u^*$  and  $p^*$ . More specifically, the observable variables are inflation, the unemployment rate, the participation rate, and inflation expectations. The unobserved state variables, which are estimated together with the model parameters through the Kalman filter, include the natural unemployment and participation rates, the inflation trend and the proxy for supply-type inflation pressures.

In order to use all the available information, our baseline model further includes the q-o-q growth rate of negotiated wages ( $\pi_t^w$ ), assuming that wage and price inflation are tied by the following relationship:  $\pi_t^w = \pi_t + \Delta a_t$ . We further consider that real wages grow at rate  $g_w$ . We thus add to the model another measurement equation:

$$\pi_t^w = g_w + \pi_t + \Delta a_t + oe_t^w$$

where  $oe_t^w$  is an i.i.d. normally distributed measurement error. The unemployment and the participation gaps have the same impact on both wages and prices which both help to identify the Phillips curve coefficients.<sup>16</sup>

We estimate the model with Bayesian techniques using Italian data over the period 1996Q1-2020Q4.<sup>17</sup> We use inflation expectations 2 and 6 quarters ahead.

## 4.2 Results

The prior and the posterior estimates of the model parameters are described in Table 1 and compared to those obtained from an analogous Phillips curve including only the unemployment gap.

The inflation process displays a moderate degree of inertia (the median estimate of  $\gamma$  is 0.4). The deviations of  $u^*$  and  $p^*$  from their respective long-run trends are highly auto-correlated, as  $\rho_{z^u}$  and  $\rho_{z^p}$  are close to 1. The median estimate of the signal-to-noise ratio is substantially higher for  $p^*$  (the median estimate for  $\sigma_{z^p, \varsigma}$  is 0.41) than for  $u^*$  (the median estimate of  $\sigma_{z^u, \varsigma}$  is 0.16), implying larger deviations of  $p^*$  from its long-run trend.

Let us now turn to the most interesting parameters, those capturing the reaction of prices and wages to the unemployment and participation gaps.  $\kappa^u$ , the coefficient on the discounted sum of future unemployment gaps, is relatively small (the median is 0.007); however, the implied overall reaction to the current and lagged unemployment gap ( $K^u$ ) is substantial (the median is 0.095), in line with the estimates of Eser et al. (2020) for the euro area.<sup>18</sup> Interestingly, the median estimates of  $\kappa^u$  and  $K^u$  in the augmented

<sup>16</sup>Compared to the specification used in D'Amuri et al. (2021), we neglect the information provided by other wage measures, like wage per hour and full time equivalent wage in the private sector, because of their high variation during the Covid-19 period due to composition effects.

<sup>17</sup>The choice of the sample period is motivated by data availability, since national accounts are released from 1995 onwards.

<sup>18</sup> $K^u$  and  $K^p$  denote the overall coefficients on current and lagged unemployment and participation

model are somewhat higher than those obtained with a Phillips curve including only the unemployment gap. The estimated median reaction of inflation to the participation gap is higher than the effect of the unemployment gap (the median estimates of  $\kappa^p$  and  $K^p$  are 0.07 and 0.29, respectively). However we will see that, according to our estimates, the unemployment gap is generally larger than the participation gap. As a consequence, a higher PC coefficient does not mean – *per se* – that the participation gap is a more relevant margin for explaining inflation dynamics.

To study the contribution of the two gaps to price dynamics, we compute the historical decomposition of the estimated inflation gap, namely the dependent variable of the Phillips curve (Figure 6). We find that the participation gap (purple bars) accounts for about 40% of the contribution of total slack (algebraic sum of purple and yellow bars) over the period 2015Q1–2019Q4. This contribution has become even more sizable and stubbornly negative in 2020, especially in the first two quarters, when the unemployment gap provided a positive contribution. While the behaviour of the unemployment gap may appear counter-intuitive, it depends on the fall in the observed unemployment rate due the dramatic but temporary reduction in labor force participation. Our model implies that in 2020, total slack subtracted on average 0.4 percentage points to price and wage dynamics. In the alternative standard model which neglects the participation margin, the contribution of unemployment gap – here capturing overall labor market slack – is almost nihil and the bulk of inflation is explained by other factors (Appendix Figure D.17).

Figures 7 and 8 plot the natural unemployment and participation rates estimated through the baseline Phillips curve regression including both the unemployment and the participation gap.<sup>19</sup>

We notice that the median estimate of  $u^*$  is very smooth and well anchored to the trend unemployment rate.  $p^*$  follows more closely the observed participation rate but significantly deviates from it in several periods. Both the unemployment and the participation gap consistently point to a substantial degree of labor market slack from 2015 until the end of 2019 (Figure 9, where the participation gap is reported on a reverse scale so that positive values signal a slack labor market, likewise the unemployment gap). The two measures, however, diverge at the outbreak of the Covid-19 epidemic.

The results of our baseline augmented Phillips curve can be compared to those derived from the standard model including only the unemployment gap. To compare these different models we combine the unemployment and participation gaps obtained in our baseline setup to obtain a measure of total slack (see Erceg and Levin, 2014 for a similar decomposition):  $e - e^* = (1 - u)(p - p^*) - p(u - u^*)$ . Results are shown in Figure 10, where the measure of total slack derived by our augmented specification is divided by the actual participation rate to make it comparable with the unemployment gap. The gap estimated under our baseline augmented model lies fairly close to the unemployment

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gaps, respectively:  $K^u = \kappa^u(\omega_{\pi,1}^u + \omega_{\pi,2}^u)$ ,  $K^p = \kappa^p(\omega_{\pi,1}^p + \omega_{\pi,2}^p)$ .

<sup>19</sup>Figure D.18 further shows that the inflation trend is precisely estimated and follows very closely the long-term inflation expectations.

gap obtained under a standard specification, but also displays some notable differences, especially in the Covid period. Thanks to the inclusion of the participation margin our model detects a significant amount of slack in 2020, while the standard specification based only on the unemployment gap gives instead a more optimistic interpretation of the labor market dynamics after the outbreak of the pandemic.

At first sight our slack measure appears to better account for the cyclical conditions, especially in 2020. We further validate this result by asking which estimated measure of slack can better explain observed price dynamics. In the spirit of Bańbura et al. (2015), we compute inflation forecasts from 2019Q4 onward conditional on our estimated measures of slack. We find that our baseline augmented model which explicitly takes into account the participation gap outperforms the specification based solely on the unemployment gap (Figure 11). Indeed, the negative participation gap in 2020 crucially adds to overall slack, putting downward pressures on inflation.

## 5 Conclusions

During the first year of the pandemic, the strong pro-cyclicality of the labor force participation rate has dampened the cyclical response of the unemployment rate, compared to what we would have observed if labor supply were fixed. This impairs the capacity of standard Phillips Curve models, that use the unemployment gap as the main explanatory variable, to provide a reliable measure of labor market slack.

In this paper we overcome this limitation by exploiting the model presented in D’Amuri et al. (2021), which estimates a forward-looking Phillips Curve that includes both a participation and an unemployment gap and is informed by structural labor market flows between three labor market states (employment, unemployment and inactivity).

We focus on Italy, which is one of the countries where participation was most affected by the Covid recession, and where therefore the response of unemployment was particularly confounded by contemporaneous cyclical changes in the activity rate.

When analyzing labor market flows between employment, unemployment and inactivity, we find that – to understand what happened during the Covid recession – it is crucial to use models that consider three rather than two labor market states (and therefore not only flows into and out of employment but also those into and out of the labor force). Indeed, the Covid crisis was peculiar since it was characterized by a very large spike in the flows from unemployment to inactivity for all demographic groups.

Our results indicate that during the pandemic structural unemployment remained unchanged; instead, the structural participation rate slightly declined, mostly due to an increase in the probability of opting for early retirement among the elderly, which however was part of a tendency in place even before the pandemic. Moreover, we find that accounting for the cyclical changes in the participation margin is crucial to obtain a reliable estimate of labor market slack, particularly so in 2020. This has important

macroeconomic implications, as confirmed by the significant impact of our augmented measure of labor market slack on price dynamics.

These results underline the importance of duly taking into account labor force participation dynamics when gauging the cyclical conditions of the labor market: neglecting changes in the participation gap, for instance, would underestimate the amount of slack in the labor market and overestimate expected price growth during the pandemic. Overall, we show that explicitly considering the participation margin delivers a better understanding of the way and the extent to which labor markets respond to the cycle. Our results are therefore also important for the design of various types of labor market models in the literature, like for instance search and matching models. We point out that measuring labor market tightness only based on unemployment and assuming that labor force participation is fixed would bias the estimation of the matching function and of matching efficiency, and that this bias varies along the cycle. Finally, we want to point out that the analysis of the intensive margin response (hours worked per employed), whose contribution in measuring labor market slack – also during the pandemic – has been highlighted in many recent works (Brandolini and Viviano, 2016; Bulligan et al., 2019; Faberman et al., 2021), clearly constitutes a promising avenue for future research but is beyond the scope of this paper.

## References

- Abraham, K. G., J. C. Haltiwanger, and L. E. Rendell (2020). How Tight is the U.S. Labor Market? *Brookings Papers on Economic Activity Conference Draft*.
- Balgova, M., S. T. C. Z. and N. Pestel (2021). Job Search during a Pandemic Recession: Survey Evidence from the Netherlands. IZA DP 14180, National Bureau of Economic Research, Inc.
- Ball, L. and S. Mazumder (2019). A Phillips Curve with Anchored Expectations and Short-Term Unemployment. *Journal of Money, Credit and Banking* 51(1), 111–137.
- Barnichon, R. and A. Figura (2015). Labor market heterogeneity and the aggregate matching function. *American Economic Journal: Macroeconomics* 7(4), 222–49.
- Barnichon, R. and G. Mesters (2018). On the demographic adjustment of unemployment. *Review of Economics and Statistics* 100(2), 219–231.
- Bañbura, M., D. Giannone, and M. Lenza (2015). Conditional forecasts and scenario analysis with vector autoregressions for large cross-sections. *International Journal of Forecasting* 31(3), 739–756.
- Bell, D. N. and D. G. Blanchflower (2013). Underemployment in the UK Revisited. *National Institute Economic Review* 224, F8–F22.
- Brandolini, A. and E. Viviano (2016, June). Behind and beyond the (head count) employment rate. *Journal of the Royal Statistical Society Series A* 179(3), 657–681.
- Bulligan, G., E. Guglielminetti, and E. Viviano (2019). Adjustment Along the Intensive Margin and Wages: Evidence from the Euro Area and the US. *Bank of Italy, mimeo*.
- Cairó, I., S. Fujita, and C. Morales-Jimenez (2021). The cyclicity of labor force participation flows: The role of labor. *Review of Economic Dynamics*.
- Cajner, T., J. Coglianesi, and J. Montes (2021). The Long-Lived Cyclicity of the Labor Force Participation Rate. *Finance and Economics Discussion Series; Board of Governors of the Federal Reserve System* (47).
- Carta, F., F. D’Amuri, and T. von Wachter (2021). Workforce Aging, Pension Reforms, and Firm Outcomes. *NBER Working Paper* (28407).
- Carta, F. and M. De Philippis (2021a). The impact of the Covid-19 shock on labour income inequality: evidence from Italy. *Questioni di Economia e Finanza (Occasional Papers)* 606, Bank of Italy.
- Carta, F. and M. De Philippis (2021b). Working Horizon and Labour Supply: the Effect of Raising Retirement Age on Middle-aged Individuals. *Tem di Discussione* 1314, Bank of Italy.

- Choi, S., A. Janiak, and B. Villena-Roldán (2015). Unemployment, Participation and Worker Flows over the Life-cycle. *The Economic Journal* 125(589), 1705–1733.
- Coibion, O. and Y. Gorodnichenko (2015, January). Is the Phillips Curve Alive and Well after All? Inflation Expectations and the Missing Disinflation. *American Economic Journal: Macroeconomics* 7(1), 197–232.
- Coibion, O., Y. Gorodnichenko, and M. Weber (2020, April). Labor Markets During the Covid-19 Crisis: A Preliminary View. Nber working papers, National Bureau of Economic Research, Inc.
- Crump, R., S. Eusepi, M. Giannoni, and A. Sahin (2019). A unified approach to measuring  $u^*$ . *Brookings Papers on Economic Activity*.
- Crump, R. K., C. J. Nekarda, and N. Petrosky-Nadeau (2020). Unemployment Rate Benchmarks. Finance and Economics Discussion Series (FEDS) 72, FED.
- D’Amuri, F., M. De Philippis, E. Guglielminetti, and S. L. Bello (2021). Natural unemployment and activity rates: Flow-based determinants and implications for price dynamics. *Questioni di Economia e Finanza (Occasional Papers)*, 599, Bank of Italy.
- Del Negro, M., M. Lenza, G. E. Primiceri, and A. Tambalotti (2020). What’s Up with the Phillips Curve? *Brookings Papers on Economic Activity*, 301–357.
- Elsby, M., B. Hobijn, F. Karahan, G. Koşar, and A. Şahin (2019). Flow Origins of Labor Force Participation Fluctuations. In *AEA Papers and Proceedings*, Volume 109, pp. 461–64.
- Elsby, M. W., B. Hobijn, and A. Şahin (2015). On the Importance of the Participation Margin for Labor Market Fluctuations. *Journal of Monetary Economics* 72, 64–82.
- Erceg, C. J. and A. T. Levin (2014). Labor Force Participation and Monetary Policy in the Wake of the Great Recession. *Journal of Money, Credit and Banking* 46(S2), 3–49.
- Eser, F., P. Karadi, P. R. Lane, L. Moretti, and C. Osbat (2020, May). The Phillips Curve at the ECB. Working Paper Series 2400, European Central Bank.
- Faberman, R., A. Mueller, and A. Şahin (2021). The Aggregate Hours Gap during the Covid-19 Pandemic. *mimeo*.
- Forsythe, E., L. B. Kahn, F. Lange, and D. G. Wiczer (2020, November). Searching, Recalls, and Tightness: An Interim Report on the COVID Labor Market. NBER Working Papers 28083, National Bureau of Economic Research, Inc.
- Fujita, S. and G. Ramey (2009). The Cyclicalities of Separation and Job Finding Rates. *International Economic Review* 50(2), 415–430.

- Garibaldi, P. and E. Wasmer (2005). Equilibrium Search Unemployment, Endogenous Participation, and Labor Market Flows. *Journal of the European Economic Association* 3(4), 851–882.
- Gomes, P. (2012). Labour Market Flows: Facts from the United Kingdom. *Labour Economics* 19(2), 165–175.
- Gordon, R. J. (2013, August). The Phillips Curve is Alive and Well: Inflation and the NAIRU During the Slow Recovery. Working Paper 19390, National Bureau of Economic Research.
- Hall, R. E. and S. Schulhofer-Wohl (2018, January). Measuring job-finding rates and matching efficiency with heterogeneous job-seekers. *American Economic Journal: Macroeconomics* 10(1), 1–32.
- Hensvik, L., T. L. Barbanchon, and R. R. (2021). Job Search during the Covid-19 Crisis. *Journal of Public Economics* (194).
- King, T. B. (2011). Variable Participation and Cyclical Unemployment. *Available at SSRN 1868930*.
- Krusell, P., T. Mukoyama, R. Rogerson, and A. Sahin (2020). Gross Worker Flows and Fluctuations in the Aggregate Labor Market. *Review of Economic Dynamics forthcoming*.
- Krusell, P., T. Mukoyama, R. Rogerson, and A. Şahin (2017, November). Gross worker flows over the business cycle. *American Economic Review* 107(11), 3447–76.
- Kudlyak, M. and F. F. Schwartzman (2012). Accounting for Unemployment in the Great Recession: Nonparticipation Matters. *Federal Reserve Bank of Richmond Working Paper* (12-04).
- Lalé, E. (2013). Understanding Fluctuations in the Ins and Outs of the Labor Force. *Available at SSRN 2534941*.
- OECD (2013). All in it together? The experience of different labour market groups following the crisis. OECD Employment Outlook 606, OECD Publishing.
- OECD (2020). Job Retention Schemes during the Covid-19 Lockdown and Beyond. OECD Policy Responses to Coronavirus (Covid-19).
- Petrongolo, B. and C. A. Pissarides (2008). The Ins and Outs of European Unemployment. *American Economic Review* 98(2), 256–62.
- Pries, M. and R. Rogerson (2009). Search Frictions and Labor Market Participation. *European Economic Review* 53(5), 568–587.

- Shimer, R. (2012). Reassessing the Ins and Outs of Unemployment. *Review of Economic Dynamics* 15(2), 127–148.
- Stock, J. H. and M. W. Watson (2020). Slack and cyclically sensitive inflation. *Journal of Money, Credit and Banking* 52(S2), 393–428.
- Strand, K. and T. Dernburg (1964). Cyclical Variation in Civilian Labor Force Participation. *The Review of Economics and Statistics* 46, 378–391.
- Tasci, M. (2012). The Ins and Outs of Unemployment in the Long run: Unemployment Flows and the Natural Rate. Koç University-TÜSİAD Economic Research Forum Working Paper Series.
- Şahin, A., M. Tasci, and J. Yan (2021). Unemployment in the Time of Covid-19: A Flow-Based Approach to Real-time Unemployment Projections. NBER Working Papers 28445, National Bureau of Economic Research, Inc.

# Tables and Figures

Table 1: Parameter estimates

	Dist.	Prior		Augmented PC			Standard PC (UGAP only)		
		Mean	Std	Median	5%	95%	Median	5%	95%
$a_{x^u,1}$	Gamma	1.25	0.200	0.857	0.685	1.07	0.796	0.684	0.944
$a_{x^u,2}$	Normal	0.000	1.00	0.073	-0.165	0.264	0.150	-0.006	0.259
$\kappa^u$	Normal	0.150	0.100	0.007	0.000	0.029	0.001	-0.003	0.008
$\gamma$	Beta	0.500	0.265	0.369	0.274	0.466	0.407	0.279	0.511
$\rho_{z^u}$	Beta	0.950	0.035	0.959	0.894	0.988	0.953	0.894	0.987
$\rho_a$	Beta	0.500	0.200	0.431	0.342	0.499	0.433	0.335	0.558
$\sigma_{x^u}^2$	InvGamma	0.112	0.000	0.220	0.168	0.287	0.216	0.163	0.280
$\sigma_{\zeta}^2$	InvGamma	1.00	0.000	0.222	0.175	0.286	0.229	0.182	0.292
$\sigma_{\pi^*}^2$	InvGamma	0.112	0.000	0.020	0.012	0.035	0.019	0.011	0.034
$\sigma_{z^u, \zeta}$	InvGamma	0.150	0.050	0.158	0.096	0.372	0.146	0.090	0.406
$g_w$	Normal	0.400	0.050	0.368	0.305	0.439	0.377	0.298	0.463
$K^u$	–	–	–	0.095	0.003	0.221	0.016	-0.059	0.098
$a_{x^p,1}$	Gamma	1.25	0.200	0.795	0.662	0.965	–	–	–
$a_{x^p,2}$	Normal	0.000	1.00	-0.028	-0.172	0.153	–	–	–
$\kappa^p$	Normal	0.150	0.100	0.072	0.010	0.178	–	–	–
$\rho_{z^p}$	Beta	0.950	0.035	0.973	0.931	0.990	–	–	–
$\sigma_{x^p}^2$	InvGamma	0.112	0.000	0.174	0.119	0.240	–	–	–
$\sigma_{z^p, \zeta}^p$	InvGamma	0.300	0.100	0.413	0.289	0.569	–	–	–
$K^p$	–	–	–	0.288	0.071	0.531	–	–	–

**Note:** Note: the table shows the prior and the posterior estimates of the parameters of the main model (Augmented PC) and of a standard model including the unemployment gap only (Standard PC - UGAP only).

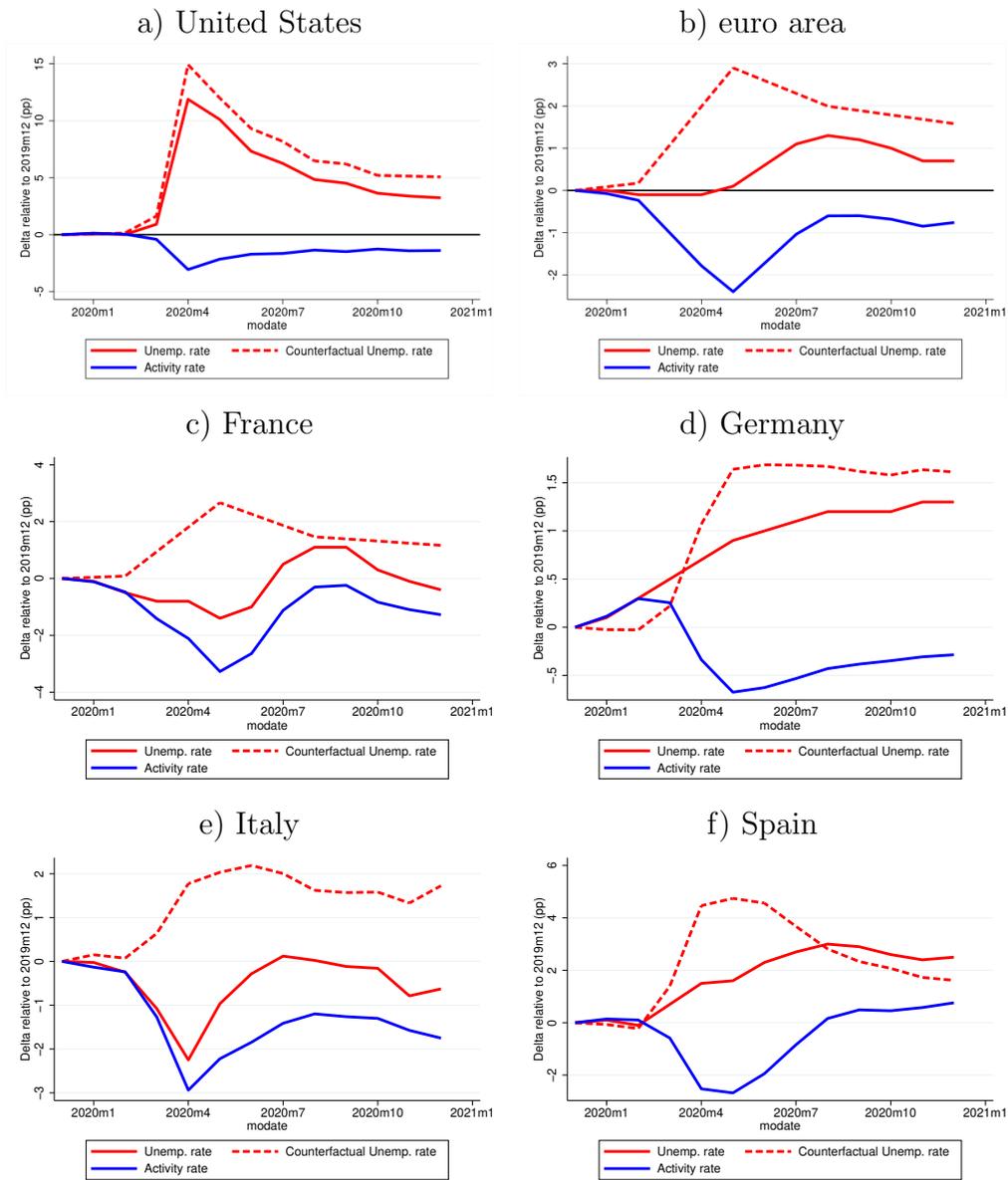


Figure 1: Unemployment and participation rates during the Covid crisis

**Source:** Eurostat, National statistical offices, FRED economic data. **Note:** Monthly rates from 2019m12 to 2020m12. For France and the euro area monthly data are obtained by interpolating quarterly data. Counterfactual unemployment is computed as if participation remained fixed at the 2019m12 level, and all changes in employment are reflected into changes in unemployment.

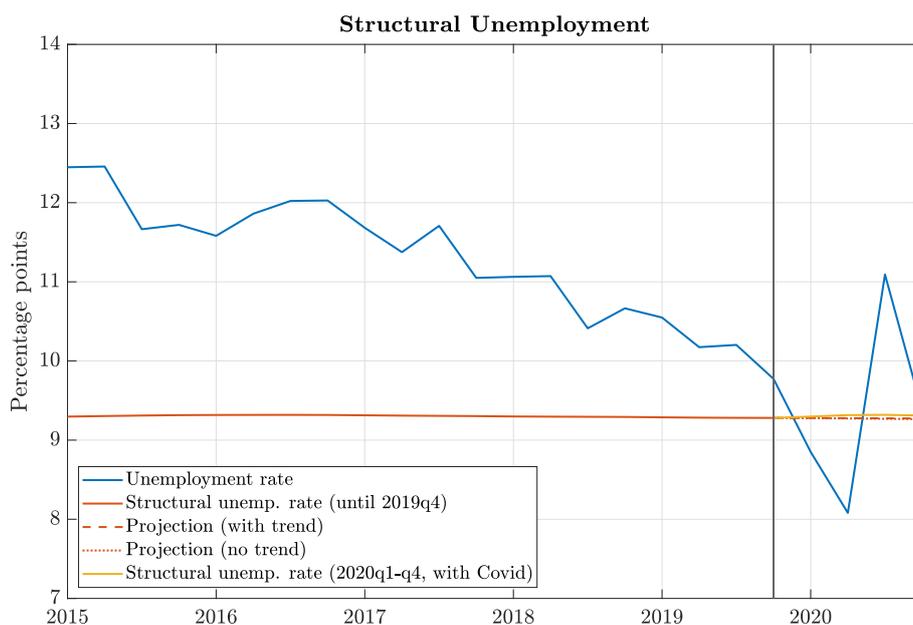


Figure 2: Structural Unemployment rate ( $\bar{u}_t$ )

**Note:** The figure plots the quarterly unemployment rate of the population 15–64 (blue line) and the estimated trend unemployment rate (red line) for the years 2015q1–2020q4 (for the entire estimation period see Figure D.13 in the Appendix). The dashed red line represents the projection of the trend unemployment rate, assuming that the long-term trends in labor market flows will follow the same dynamics as those observed between 2015 and 2019; the dotted yellow line represents the projection of the trend activity rate, assuming that the labor market flows will remain at the same levels as those observed in 2019; the solid yellow line represents the trend unemployment rate, when we include also information about the flows until 2020q4.

## Structural Unemployment

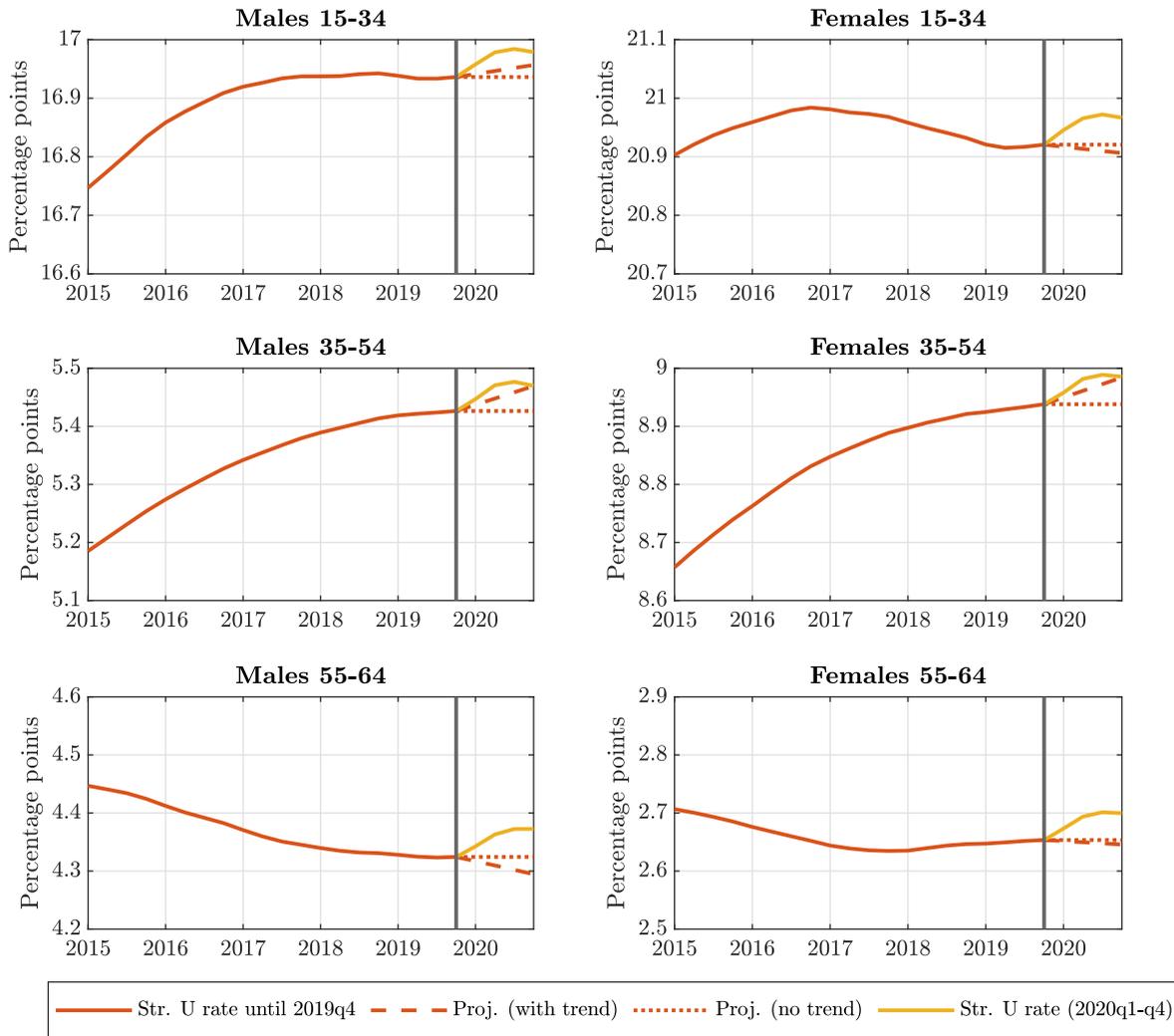


Figure 3: Structural Unemployment rate ( $\bar{u}_t$ ), by demographic cell

**Note:** The figure plots for each cell in the population 15–64: i) the estimated trend unemployment rate (red line) for the years 2015q1–2019q4; ii) the projection of the trend unemployment rate, assuming that the long-term trends in labor market flows will follow the same dynamics as those observed between 2015 and 2019 (dashed red line); iii) the projection of the trend unemployment rate, assuming that the labor market flows will remain at the same levels as those observed in 2019 (dotted red line); iv) the trend unemployment rate, when we include also information about the flows until 2020q4 (solid yellow line).

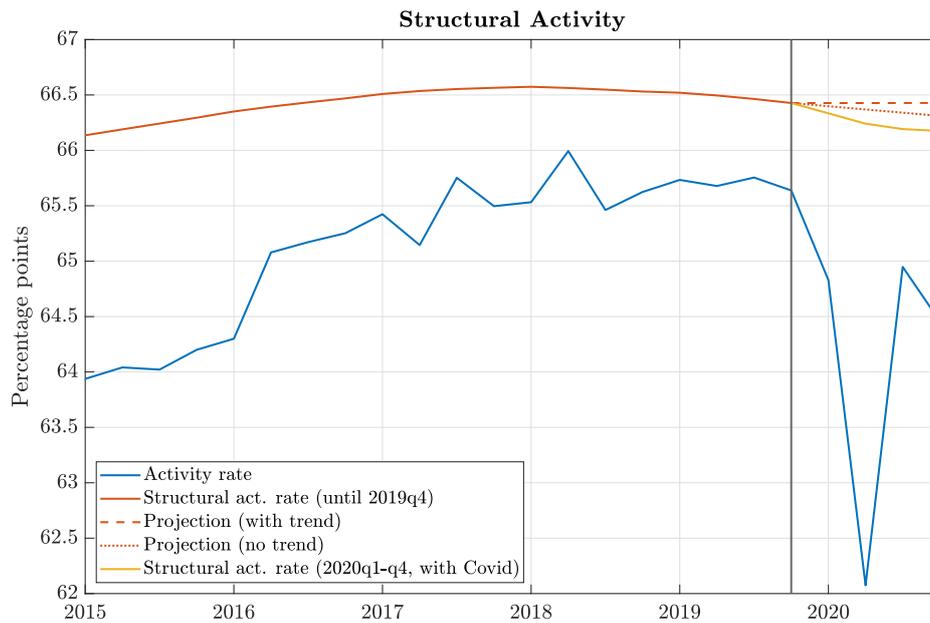


Figure 4: Structural Activity rate ( $\bar{p}_t$ )

**Note:** The figure plots the quarterly activity rate of the population 15–64 (blue line) and the estimated trend activity rate (red line) for the years 2015q1–2020q4 (for the entire estimation period see Figure D.14 in the Appendix). The dashed red line represents the projection of the trend activity rate, assuming that the long-term trends in labor market flows will follow the same dynamics as those observed between 2015 and 2019; the dotted yellow line represents the projection of the trend activity rate, assuming that the labor market flows will remain at the same levels as those observed in 2019; the solid yellow line represents the trend activity rate, when we include also information about the flows until 2020q4.

## Structural Activity

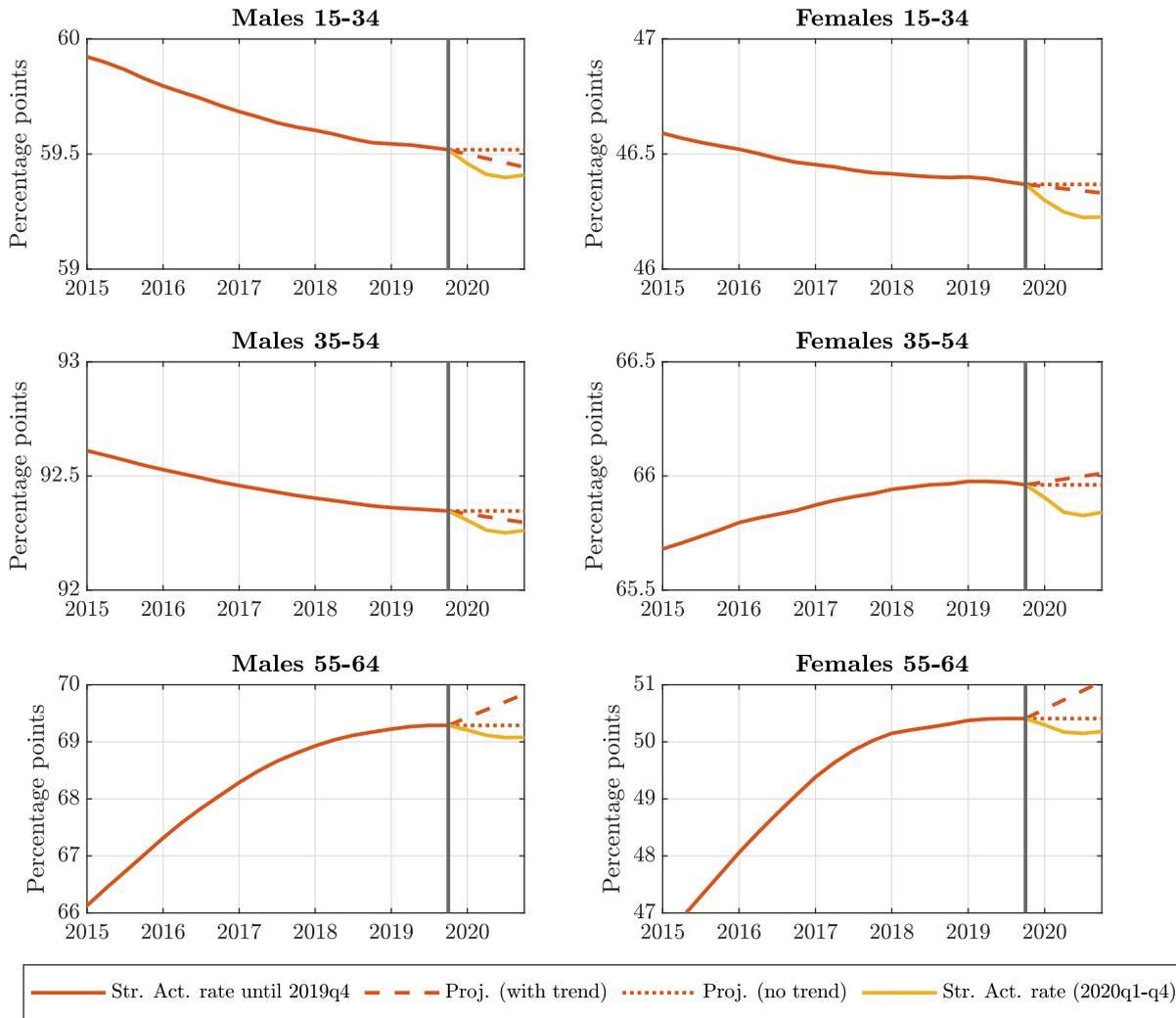


Figure 5: Structural Activity rate ( $\bar{p}_t$ ), by demographic cell

**Note:** The figure plots for each cell in the population 15–64: i) the estimated trend activity rate (red line) for the years 2015q1–2019q4; ii) the projection of the trend activity rate, assuming that the long-term trends in labor market flows will follow the same dynamics as those observed between 2015 and 2019 (dashed red line); iii) the projection of the trend activity rate, assuming that the labor market flows will remain at the same levels as those observed in 2019 (dotted red line); iv) the trend activity rate, when we include also information about the flows until 2020q4 (solid yellow line).

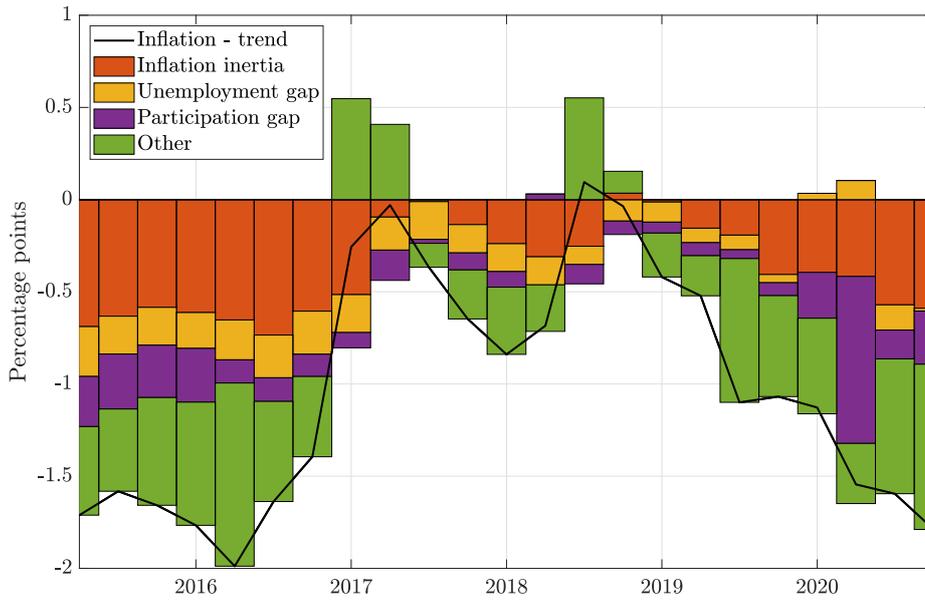


Figure 6: Historical decomposition of the inflation gap according to the augmented Phillips curve model (UGAP + PGAP)

**Note:** The solid line represents the historical evolution of median inflation gap (realized inflation - estimated trend inflation) and the colored bars the median contributions of the factors included in the baseline Phillips curve model. The model is estimated over the period 1996q1–2020q4.

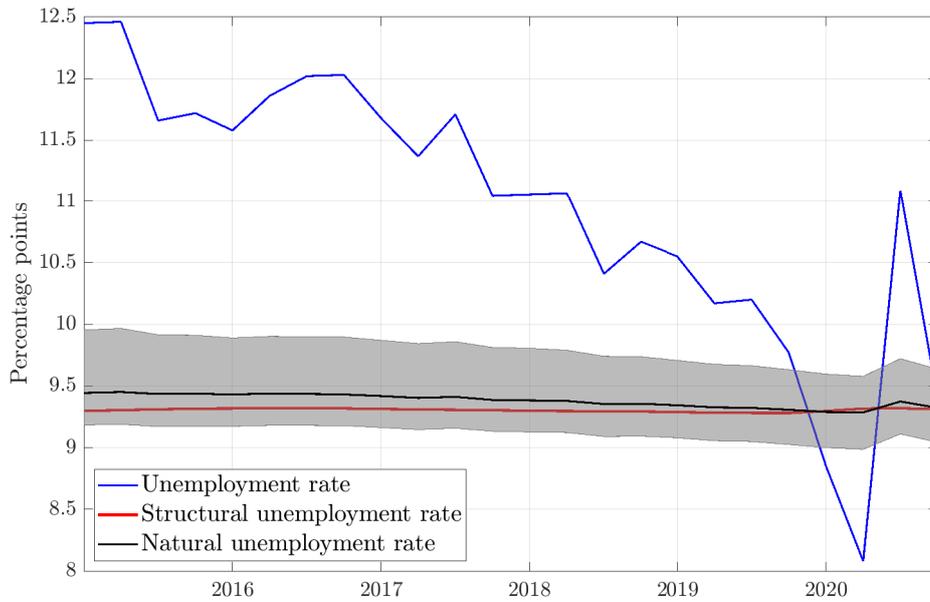


Figure 7:  $u^*$  estimated through the augmented Phillips curve model (UGAP + PGAP)

**Note:** Shading denotes the 68% credibility interval. The model is estimated over the period 1996q1–2020q4.

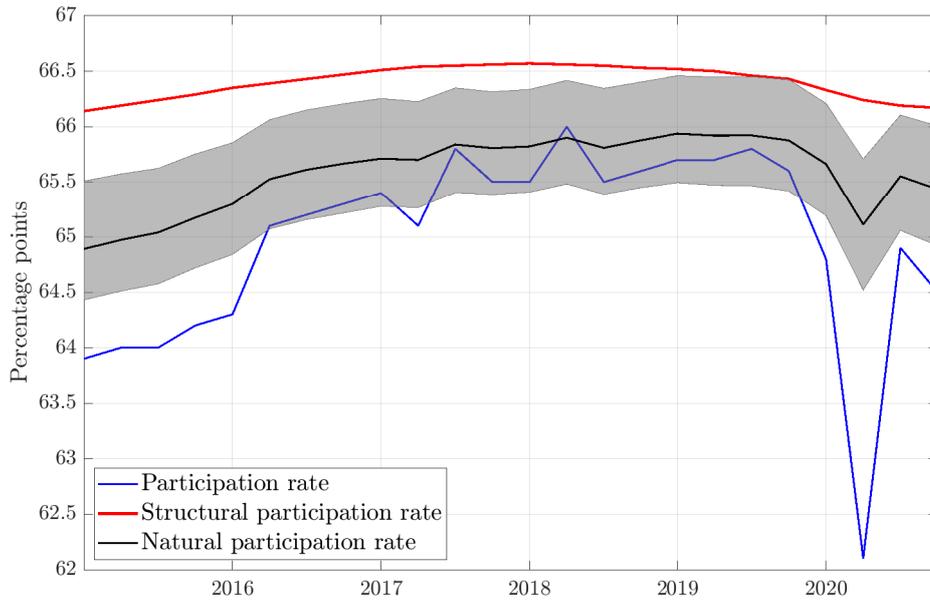


Figure 8:  $p^*$  estimated through the augmented Phillips curve model (UGAP + PGAP)

**Note:** Shading denotes the 68% credibility interval. The model is estimated over the period 1996q1–2020q4.

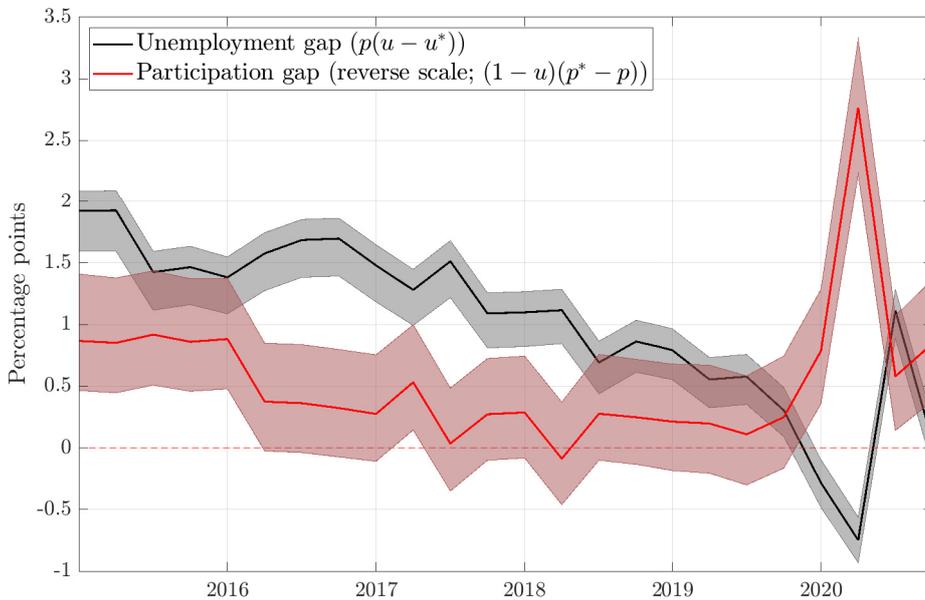


Figure 9: Unemployment and participation gaps estimated through the augmented Phillips curve model (UGAP + PGAP)

**Note:** Shading denotes the 68% credibility interval. The model is estimated over the period 1996q1–2020q4. Positive unemployment and participation gaps denote a slack labor market.

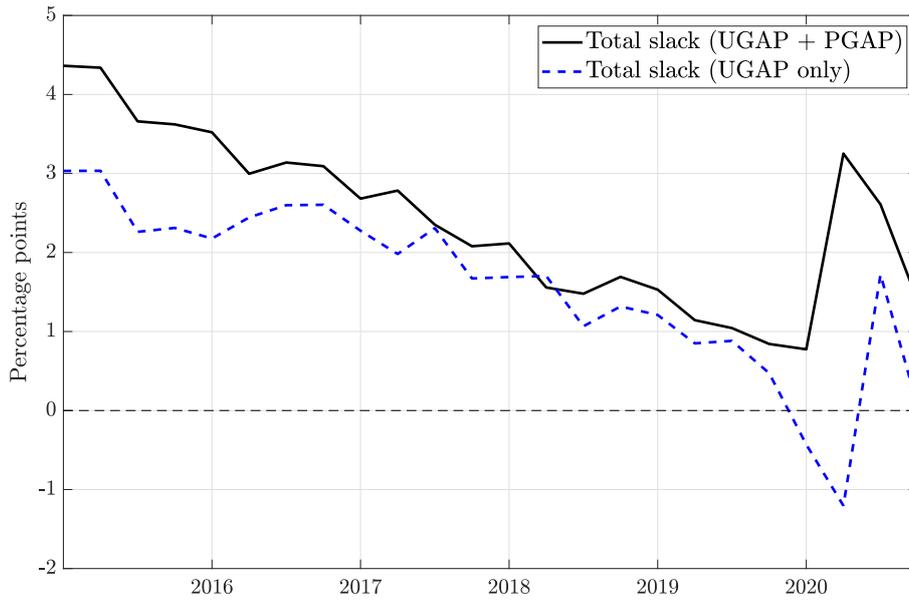


Figure 10: Comparison of estimates of total slack

**Note:** The black solid line represents the median employment gap estimated through the baseline augmented Phillips curve including both the unemployment and the participation gap. The blue dotted line refers to the standard model including only the unemployment gap. Total slack measures are rescaled to be comparable.

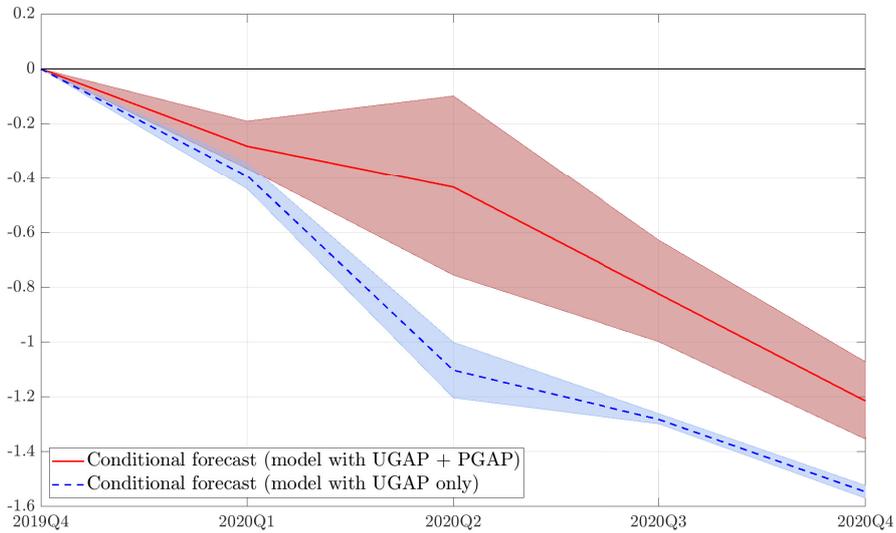


Figure 11: Conditional forecasts of inflation (actual - projection)

**Note:** The lines represent actual inflation minus its conditional forecast, either in the augmented model (red line) or in the standard PC based only on the unemployment gap (blue dashed line). The conditioning set includes labor market variables, that is actual, structural and natural unemployment and participation rates from 2020q1 till 2020q4. Shading denotes the 68% credibility interval.

# Appendix

## A Some details on the estimation of structural unemployment and activity rates

### Estimating the group-specific labor market transition rates

The estimation of the transition rates between employment ( $E$ ), unemployment ( $U$ ) and inactivity ( $N$ ) for each demographic group  $g$  (defined by gender and three age classes) follows closely D’Amuri et al. (2021). In particular, from 2004 onward, the construction of the six transition probabilities relies on panel data from the Labor Force Survey, which allows us to observe the same individual for consecutive quarters. In this way, we are able to directly construct transition probabilities by using the multiple individual observations. For the period prior to 2004, when the panel component is not available, we are able to extend the series back until 1984 relying on: (i) the observed changes in the relevant stocks of unemployment  $U_{g,t}$ , employment  $E_{g,t}$ , inactivity  $N_{g,t}$ ; (ii) the changes in the stocks of short-term unemployment  $U_{g,t}^{st}$  constructed using the retrospective question on unemployment duration, as in Shimer (2012); (iii) the changes in the stock of short-term employment  $E_{g,t}^{st}$ , constructed using the retrospective question on employment duration; and (iv) the flows from unemployment towards inactivity, estimated exploiting a question on the reason for being inactive to elicit information on the nature of the transition towards inactivity.

Following the existing literature (for instance Shimer, 2012, Elsby et al., 2015 and Barnichon and Mesters, 2018), We perform two important adjustments to the measured flows between the employment, unemployment and inactivity.

First, we make them consistent with the dynamics of the stocks (*margin error correction - MEC*). The inconsistency between transition probabilities estimated through individual-level data and the observed dynamics of the stocks is a well-known issue and may be due to a variety of reasons, mainly related to the turnover of individuals in the sample (for instance, people leaving the sample because of migration, death or not-responding or, conversely, new people entering the sample). In this respect we closely follow the correction proposed by Elsby et al. (2015) and Barnichon and Mesters (2018). Their proposed solution consists in finding the minimum adjustment to flows which makes them fully consistent with observed changes in the stocks. They show that this adjustment takes a very simple analytical form (see Appendix A.2 of Elsby et al., 2015 for details).

Second, we derive continuous-time flow rates from discrete time transition probabilities, in order to account for the possibility of multiple transitions taking place within the observation window (*temporal aggregation correction - TAC*). Due to the discrete time nature (quarterly, in our case) of our observations, the gross flows are in fact a series of snapshots of an individual’s labor market status. Upon observing an individual in state  $X$  at time  $t$  and state  $Y$  at time  $t + 1$ , we classify that as a movement from  $X$  to  $Y$  in

our transition matrix. In practice, that individual may have taken multiple transitions within the period, or could have transitioned to  $Y$  through state  $Z$ . This means that the gross transition probabilities provide estimates which may be not accurate of the actual underlying flows. By construction, this procedure misses some transitions and incorrectly includes others. A solution to this problem has been found by Shimer (2012), who shows that it is possible to back out the underlying flows in continuous time using a simple eigendecomposition of the Markov transition matrix in discrete time (see Appendix A.3 of Elsby et al., 2015 for details).

### Separating the trend from the cyclical component of the transition rates

Following Tasci (2012), we use an unobserved component model in which real log GDP  $y_t$  and the six labor market flows can be decomposed into a stochastic trend and a stationary cyclical component.<sup>20</sup> These components are not observed by the econometrician. Our model reads as follows:

$$y_t = \bar{y}_t + y_t^c,$$

$$f_{g,t}^j = \bar{f}_{g,t}^j + f_{g,t}^{j,c},$$

with the latter equation holding for each flow  $j \in \{NU, NE, EU, EN, UE, UN\}$  and each group  $g$ . The trend components are denoted by  $\bar{y}_t$  and  $\bar{f}_{g,t}^j$ , while  $y_t^c$  and  $f_{g,t}^{j,c}$  capture the cyclical movements. In turn, the stochastic trends are assumed to follow a random walk:

$$\bar{y}_t = \bar{y}_{t-1} + \epsilon_t^y,$$

$$\bar{f}_{g,t}^j = \bar{f}_{g,t-1}^j + \epsilon_{g,t}^j.$$

Instead, the cyclical component of log GDP follows an AR(2) process and affects the cyclical component of the flows as follows:

$$y_t^c = \phi_1 y_{t-1}^c + \phi_2 y_{t-2}^c + \epsilon_t^{y,c},$$

$$f_{g,t}^{j,c} = \rho_{1,g}^j y_t^c + \rho_{2,g}^j y_{t-1}^c + \epsilon_{g,t}^{j,c}.$$

All error terms are assumed to be drawn from Normal distributions with zero mean. Notice that all trend flows are jointly estimated but we do not allow for interactions between them to avoid overparameterization. For the same reason, we estimate the trends separately for each group  $g$ .

Fixing a group  $g$ , the statistical model to be estimated can be written in state space

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<sup>20</sup>We also replicate the estimation of trends using a standard HP(1600) filter. Relative to our baseline structural rates, those obtained via HP filter appear excessively volatile, following closely the actual series.

form. The measurement equation is given by:

$$\begin{bmatrix} y_t \\ f_{g,t}^{NU} \\ f_{g,t}^{NE} \\ f_{g,t}^{EU} \\ f_{g,t}^{EN} \\ f_{g,t}^{UE} \\ f_{g,t}^{UN} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \rho_1^{NU} & \rho_2^{NU} & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \rho_1^{NE} & \rho_2^{NE} & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & \rho_1^{EU} & \rho_2^{EU} & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & \rho_1^{EN} & \rho_2^{EN} & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & \rho_1^{UE} & \rho_2^{UE} & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & \rho_1^{UN} & \rho_2^{UN} & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \bar{y}_t \\ y_t^c \\ y_{t-1}^c \\ \bar{f}_{g,t}^{NU} \\ \bar{f}_{g,t}^{NE} \\ \bar{f}_{g,t}^{EU} \\ \bar{f}_{g,t}^{EN} \\ \bar{f}_{g,t}^{UE} \\ \bar{f}_{g,t}^{UN} \end{bmatrix} + \begin{bmatrix} 0 \\ \epsilon_{g,t}^{NU_c} \\ \epsilon_{g,t}^{NE_c} \\ \epsilon_{g,t}^{EU_c} \\ \epsilon_{g,t}^{EN_c} \\ \epsilon_{g,t}^{UE_c} \\ \epsilon_{g,t}^{UN_c} \end{bmatrix}. \quad (13)$$

Instead, the transition equation reads as follows:

$$\begin{bmatrix} \bar{y}_t \\ y_t^c \\ y_{t-1}^c \\ \bar{f}_{g,t}^{NU} \\ \bar{f}_{g,t}^{NE} \\ \bar{f}_{g,t}^{EU} \\ \bar{f}_{g,t}^{EN} \\ \bar{f}_{g,t}^{UE} \\ \bar{f}_{g,t}^{UN} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \phi_1 & \phi_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \bar{y}_{t-1} \\ y_{t-1}^c \\ y_{t-2}^c \\ \bar{f}_{g,t-1}^{NU} \\ \bar{f}_{g,t-1}^{NE} \\ \bar{f}_{g,t-1}^{EU} \\ \bar{f}_{g,t-1}^{EN} \\ \bar{f}_{g,t-1}^{UE} \\ \bar{f}_{g,t-1}^{UN} \end{bmatrix} + \begin{bmatrix} \epsilon_t^y \\ \epsilon_t^{y_c} \\ 0 \\ \epsilon_{g,t}^{NU} \\ \epsilon_{g,t}^{NE} \\ \epsilon_{g,t}^{EU} \\ \epsilon_{g,t}^{EN} \\ \epsilon_{g,t}^{UE} \\ \epsilon_{g,t}^{UN} \end{bmatrix}. \quad (14)$$

The unobserved components, along with the variance of the error terms, are estimated with the Kalman filter via Maximum Likelihood.<sup>21</sup> The filtered rates, as well as the raw time series of the hazard rates constructed in step 1, can be found in Figures D.1-D.6 and D.7-D.12).

The outcome of this second step are the structural components of the flow rates, which represent the building blocks of the structural unemployment and activity rate.

<sup>21</sup>We impose the following assumptions on the ratio between the variance of the trend and cyclical components:  $\sigma^y = \frac{\sigma_{\epsilon^y}}{\sigma_{\epsilon^{y_c}}} = 0.1$ ;  $\sigma^{EN} = \frac{\sigma_{\epsilon_g^{EN}}}{\sigma_{\epsilon_g^{EN_c}}} = 0.0045$ ,  $\sigma^j = \frac{\sigma_{\epsilon_g^j}}{\sigma_{\epsilon_g^{j_c}}} = 0.001$  for the other five flows, for all demographic groups.

## B Derivation of the natural unemployment and participation rates

Let us start by considering the standard price Phillips curve derived from the simple model in (Crump et al., 2019), which only depends on the unemployment gap:

$$\pi_t = -\kappa^u x_t^u + \beta \mathbb{E}_t \pi_{t+1} + \beta \mathbb{E}_t (\Delta a_{t+1} - \Delta a_t), \quad (15)$$

where the exogenous process  $a_t$  capture (log) productivity and mark-up shocks to firms. Assuming rational expectations, we can iterate forward equation (15) to obtain:

$$\pi_t = -\kappa^u \mathbb{E}_t \sum_{T=t}^{\infty} \beta^{T-t} x_T^u + \beta \mathbb{E}_t \sum_{T=t}^{\infty} \beta^{T-t} (\Delta a_{T+1} - \Delta a_T) \quad (16)$$

The process  $\Delta a_t$  is assumed to be AR(1):  $\Delta a_t = \rho_a \Delta a_{t-1} + \sigma_a \varepsilon_t^a$ . Hence,

$$\mathbb{E}_t (\Delta a_{t+1} - \Delta a_t) = -(1 - \rho_a) \Delta a_t$$

Replacing the previous expression in equation (16), we obtain:

$$\pi_t = -\kappa^u \mathbb{E}_t \sum_{T=t}^{\infty} \beta^{T-t} x_T^u - \beta(1 - \rho_a) \mathbb{E}_t \sum_{T=t}^{\infty} \beta^{T-t} \Delta a_T \quad (17)$$

By considering that  $\mathbb{E}_t \Delta a_T = \rho_a^{T-t} \Delta a_t$  and  $\sum_{T=t}^{\infty} (\beta \rho_a)^{T-t} = \frac{1}{1 - \beta \rho_a}$ , we get:

$$\pi_t = -\kappa^u \mathbb{E}_t \sum_{T=t}^{\infty} \beta^{T-t} x_T^u - \beta \frac{1 - \rho_a}{1 - \beta \rho_a} \Delta a_t \quad (18)$$

Let us further consider the existence of an exogenous inflation trend  $\pi_t^*$  which follows a RW:

$$\pi_t^* = \pi_{t-1}^* + \sigma_{\pi^*} \varepsilon_t^{\pi^*} \quad (19)$$

We assume that equation (18) holds for the inflation gap, that is the deviation between realized inflation  $\pi_t$  and  $\pi_t^*$ . Furthermore, the inflation gap displays some inertia, captured by the parameter  $\gamma$ :

$$\pi_t - \pi_t^* = \gamma (\pi_{t-1} - \pi_{t-1}^*) - \gamma \sigma_{\pi^*} \varepsilon_t^{\pi^*} - \kappa^u \mathbb{E}_t \sum_{T=t}^{\infty} \beta^{T-t} x_T^u - \beta \frac{1 - \rho_a}{1 - \beta \rho_a} \Delta a_t \quad (20)$$

By augmenting the model to take into account the effects of participation rate on inflation we finally get equation (8) in the main text:

$$\pi_t - \pi_t^* = \gamma (\pi_{t-1} - \pi_{t-1}^*) - \gamma \sigma_{\pi^*} \varepsilon_t^{\pi^*} - \kappa^u \mathbb{E}_t \sum_{T=t}^{\infty} \beta^{T-t} x_T^u + \kappa^p \mathbb{E}_t \sum_{T=t}^{\infty} \beta^{T-t} x_T^p - \beta \frac{1 - \rho_a}{1 - \beta \rho_a} \Delta a_t \quad (21)$$

We further assume that the the unemployment and the participation gaps follow an AR(2) process:

$$\begin{aligned}x_t^u &= a_{x^u,1}x_{t-1}^u + a_{x^u,2}x_{t-2}^u + \sigma_{x^u}\epsilon_t^{x^u} \\x_t^p &= a_{x^p,1}x_{t-1}^p + a_{x^p,2}x_{t-2}^p + \sigma_{x^p}\epsilon_t^{x^p}\end{aligned}$$

and we define

$$\varsigma_t = -\beta \frac{1 - \rho_a}{1 - \beta\rho_a} \Delta a_t = \rho_a \varsigma_{t-1} + \sigma_\varsigma \epsilon_t^\varsigma$$

Hence we can rewrite equation (21) as:

$$\pi_t - \pi_t^* = \gamma (\pi_{t-1} - \pi_{t-1}^*) - \gamma \sigma_{\pi^*} \epsilon_t^{\pi^*} - \kappa^u \omega_{\pi,1}^u x_t^u - \kappa^u \omega_{\pi,2}^u x_{t-1}^u + \kappa^p \omega_{\pi,1}^p x_t^p + \kappa^p \omega_{\pi,2}^p x_{t-1}^p + \rho_a \varsigma_{t-1} + \sigma_\varsigma \epsilon_t^\varsigma \quad (22)$$

where  $\omega_{\pi,1}^u = (1 - \beta(a_{x^u,1} + \beta a_{x^u,2}))^{-1}$ ,  $\omega_{\pi,2}^u = \beta a_{x^u,2} \omega_{\pi,1}^u$ ,  $\omega_{\pi,1}^p = (1 - \beta(a_{x^p,1} + \beta a_{x^p,2}))^{-1}$  and  $\omega_{\pi,2}^p = \beta a_{x^p,2} \omega_{\pi,1}^p$ .

Theoretically, the relationship between price and wage inflation is:

$$\pi_t^w = \pi_t + \Delta a_t$$

Hence wage inflation can be expressed as:

$$\pi_t^w = \pi_t^* + \gamma (\pi_{t-1} - \pi_{t-1}^*) - \gamma \sigma_{\pi^*} \epsilon_t^{\pi^*} - \kappa^u \omega_{\pi,1}^u x_t^u - \kappa^u \omega_{\pi,2}^u x_{t-1}^u + \kappa^p \omega_{\pi,1}^p x_t^p + \kappa^p \omega_{\pi,2}^p x_{t-1}^p - \frac{1 - \beta}{\beta(1 - \rho_a)} \varsigma_t$$

We further assume that wage inflation has its own specific growth rate  $g_w$ , so that the final equation becomes:

$$\begin{aligned}\pi_t^w &= g_w + \pi_t^* + \gamma (\pi_{t-1} - \pi_{t-1}^*) - \gamma \sigma_{\pi^*} \epsilon_t^{\pi^*} - \kappa^u \omega_{\pi,1}^u x_t^u - \kappa^u \omega_{\pi,2}^u x_{t-1}^u \\ &\quad + \kappa^p \omega_{\pi,1}^p x_t^p + \kappa^p \omega_{\pi,2}^p x_{t-1}^p - \frac{1 - \beta}{\beta(1 - \rho_a)} \varsigma_t + oe_t^w\end{aligned} \quad (23)$$

where  $oe_t^w$  denotes a normally distributed measurement error. Notice that, by plugging eq. (22) into (23) we obtain an alternative expression for wage inflation:

$$\pi_t^w = g_w + (\pi_t - \pi_t^*) + \pi_t^* - \frac{1 - \beta\rho_a}{\beta(1 - \rho_a)} \varsigma_t + oe_t^w$$

## B.1 State-space model

The model described above can be cast into a state-space form of the following type:

$$\mathbf{y}_t = \mathbf{M}_y \alpha_t + \mathbf{H} \mathbf{s}_t \quad (24)$$

$$\mathbf{s}_t = \mathbf{F} \mathbf{s}_{t-1} + \mathbf{G} \epsilon_t \quad (25)$$

where eq. (24) is the measurement equation and eq. (25) is the transition equation.

For simplicity, we start consider a model including only price inflation.  $\mathbf{y}_t$  is a vector of  $n_y = 5$  elements collecting the observed variables:  $\mathbf{y}_t = [u_t, p_t, \pi_t, \mathbb{E}_t \pi_{t+2Q}, \mathbb{E}_t \pi_{t+6Q}]$ , that is the unemployment rate, the participation rate, inflation, and short and medium-term inflation expectations.  $\alpha_t$  is a vector of exogenous variables:  $\alpha_t = [\bar{u}_t, \bar{p}_t]$ .  $\mathbf{s}_t$  is a vector of  $n_s = 11$  elements collecting the state variables:  $\mathbf{s}_t = [\pi_t - \pi_t^*, x_t^u, x_{t-1}^u, x_t^p, x_{t-1}^p, \varsigma_t, \pi_t^*, z_t^u, z_t^p, oe^{6Q}, oe^{2Q}]$ .  $x_t^u$  denotes the unemployment gap ( $x_t^u = u_t - u_t^*$ ),  $x_t^p$  the participation gap ( $x_t^p = p_t - p_t^*$ ),  $\varsigma_t = -\beta \frac{1-\rho_a}{1-\beta\rho_a} \Delta a_t$  is a transformation of the productivity shock,  $\pi_t^*$  is the inflation trend,  $z_t^u$  the difference between the natural and the structural unemployment rates ( $u_t^* - \bar{u}_t$ ),  $z_t^p$  the difference between the natural and the structural participation rates ( $p_t^* - \bar{p}_t$ ).  $oe^{6Q}$  and  $oe^{2Q}$  represent the observation errors on the medium and short-term inflation expectations, respectively.  $\varepsilon_t$  is a vector of shocks of dimension  $n_\varepsilon = 8$ :  $\varepsilon_t = [\epsilon_t^{x^u}, \epsilon_t^{x^p}, \epsilon_t^\varsigma, \epsilon_t^{\pi^*}, \epsilon_t^{z^u}, \epsilon_t^{z^p}, \epsilon_t^{oe^{6Q}}, \epsilon_t^{oe^{2Q}}]$ .

$$H_{n_y \times n_s} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & & & & & & & & & \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & & & & & & & & & \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & & & & & & & & & \\ F_{1,1}^{2Q} & F_{1,2}^{2Q} & F_{1,3}^{2Q} & F_{1,4}^{2Q} & F_{1,5}^{2Q} & F_{1,6}^{2Q} & 1 & 0 & 0 & 0 \\ 1 & & & & & & & & & \\ F_{1,1}^{6Q} & F_{1,2}^{6Q} & F_{1,3}^{6Q} & F_{1,4}^{6Q} & F_{1,5}^{6Q} & F_{1,6}^{6Q} & 1 & 0 & 0 & 1 \\ 0 & & & & & & & & & \end{bmatrix}$$

where  $F_{i,j}^A$  is the element of row  $i$  and column  $j$  of matrix  $F^A$ , as defined below.

$$\mathbf{M}_y = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}^T$$



$$\begin{aligned}
u_t &= x_t^u + z_t^u + \bar{u}_t \\
p_t &= x_t^p + z_t^p + \bar{u}_t \\
\pi_t &= (\pi_t - \pi_t^*) + \pi_t^* \\
\mathbb{E}_t \pi_{t+2Q} &= \pi_t^* + l'_\pi \underbrace{\left[ \frac{1}{2} \sum_{j=1}^{j=2} \tilde{F}^j \right]}_{F^{12Q}} \tilde{\mathbf{y}}_t + oe^{2Q} \\
\mathbb{E}_t \pi_{t+6Q} &= \pi_t^* + l'_\pi \underbrace{\left[ \frac{1}{6} \sum_{j=1}^{j=6} \tilde{F}^j \right]}_{F^{6Q}} \tilde{\mathbf{y}}_t + oe^{6Q}
\end{aligned}$$

with  $\tilde{\mathbf{y}}_t = [\pi_t - \pi_t^*, x_t^u, x_{t-1}^u, x_t^p, x_{t-1}^p, \varsigma_t]$ ,  $l'_\pi = [1, 0, 0, 0, 0]$  is a selection vector of the inflation equation and  $\tilde{F}$  denotes the first six rows and columns of matrix  $F$ .

When adding information from wages, we extend the model by adding a measurement equation:

$$\pi_t^{w^j} = g_w + (\pi_t - \pi_t^*) + \pi_t^* - \frac{1 - \beta \rho_a}{\beta(1 - \rho_a)} \varsigma_t + oe_t^{w^j}$$

where  $oe_t^{w^j}$  is the measurement error wage growth.

The transition equations read as follows:

$$\begin{aligned}
\pi_t - \pi_t^* &= \gamma (\pi_{t-1} - \pi_{t-1}^*) - \kappa^u (\omega_{\pi,1}^u a_{x^u,1} + \omega_{\pi,2}^u) x_{t-1}^u - \kappa^u \omega_{\pi,1}^u a_{x^u,2} x_{t-2}^u + \\
&\quad \kappa^p (\omega_{\pi,1}^p a_{x^p,1} + \omega_{\pi,2}^p) x_{t-1}^p + \kappa^p \omega_{\pi,1}^p a_{x^p,2} x_{t-2}^p + \rho_a \varsigma_{t-1} \\
&\quad - \kappa^u \omega_{\pi,1}^u \sigma_{x^u} \epsilon_t^{x^u} + \kappa^p \omega_{\pi,1}^p \sigma_{x^p} \epsilon_t^{x^p} + \sigma_\varsigma \epsilon_t^\varsigma - \gamma \sigma_{\pi^*} \epsilon_t^{\pi^*} \\
x_t^u &= a_{x^u,1} x_{t-1}^u + a_{x^u,2} x_{t-2}^u + \sigma_{x^u} \epsilon_t^{x^u} \\
x_{t-1}^u &= x_{t-1}^u \\
x_t^p &= a_{x^p,1} x_{t-1}^p + a_{x^p,2} x_{t-2}^p + \sigma_{x^p} \epsilon_t^{x^p} \\
x_{t-1}^p &= x_{t-1}^p \\
\varsigma_t &= \rho_a \varsigma_{t-1} + \sigma_\varsigma \epsilon_t^\varsigma \\
\pi_t^* &= \pi_{t-1}^* + \sigma_{\pi^*} \epsilon_t^{\pi^*} \\
z_t^u &= \rho_{z^u} z_{t-1}^u + \sigma_{z^u, \varsigma} \sigma_\varsigma \epsilon_t^{z^u} \\
z_t^p &= \rho_{z^p} z_{t-1}^p + \sigma_{z^p, \varsigma} \sigma_\varsigma \epsilon_t^{z^p} \\
oe^{6Q} &= \sigma_{oe^{6Q}} \epsilon_t^{oe^{6Q}} \\
oe^{2Q} &= \sigma_{oe^{2Q}} \epsilon_t^{oe^{2Q}}
\end{aligned}$$

## C Temporary (2019-2021) pension reform and retirement flows

In the main text we documented a fall in structural participation rates taking place in 2019 and 2020, driven mostly by a decrease in mature (55-64) workers' labor supply. Such a decrease coincided with a pension reform (so called "quota 100"), that temporarily softened pension eligibility requirements and suspended statutory retirement age indexation to life expectancy for the three year interval 2019-21. Even if an analysis of the effects of such reform on mature workers' labor supply is beyond the scope of this paper, in this section we check whether the fall in structural participation rates took place together with an increase in new pension claims.

In Figure D.19 we plot, for the 55-64 age group, the average transitions at one year interval from Employment to Non Employment (blue line) and from Employment to Pension (red line).<sup>22</sup> The two time series co-move over time, with the ratio of the latter over the former decreasing after 2012 (the year in which a major pension reform substantially increased pension eligibility requirements). An increase in Employment to Non Employment flows took place in 2019-2020, almost entirely attributable to the increase in Employment to Pension flows. Administrative data on new pension claims, covering employees only (black line), confirm the marked increase in retirements in 2019 and 2020.

We further assess whether such increase in employment to pension transitions can be coherent, in year 2020, with an increase in pension claims among employees in those sectors that were hardest hit by the recession (retail trade, hotels and restaurants). Figure D.20a shows that this does not seem to be the case, as no clear discontinuity in pension flows took place in those two sectors (as in any other sector) in 2020. If anything, the sectoral analysis suggests that the increase in pension flows was broad based and started already in 2019, when the pension reform was introduced.

Finally, we check whether bigger retirement flows in 2019 and 2020 could be due to a cohort size effect. As in Labor Force Survey data we lack the information on the exact age, since it is provided only in 5 year brackets, it could be that a larger cohort reaching Statutory Retirement Age in a given year could determine larger employment to pension flows. Figure D.21 shows that this is not the case, as cohorts crossing usual Retirement Age (60-63) in 2018 and 2019 have similar sizes.

We conclude that the increase in Employment to Non Employment flows during 2019 and 2020 for 55-64 workers can plausibly be attributed to the 2019 pension reform. As the reform is temporary, we thus would expect Employment to non Employment flows among 55-64 workers to fall again in the near future.

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<sup>22</sup>Flows from Non-Employment to Pension refer to non employed individuals who state to have claimed a pension in year  $t$  and that they were employed in year  $t - 1$ ; they are thus a subset of Employment to Non Employment transitions.

# D Additional Tables and Figures

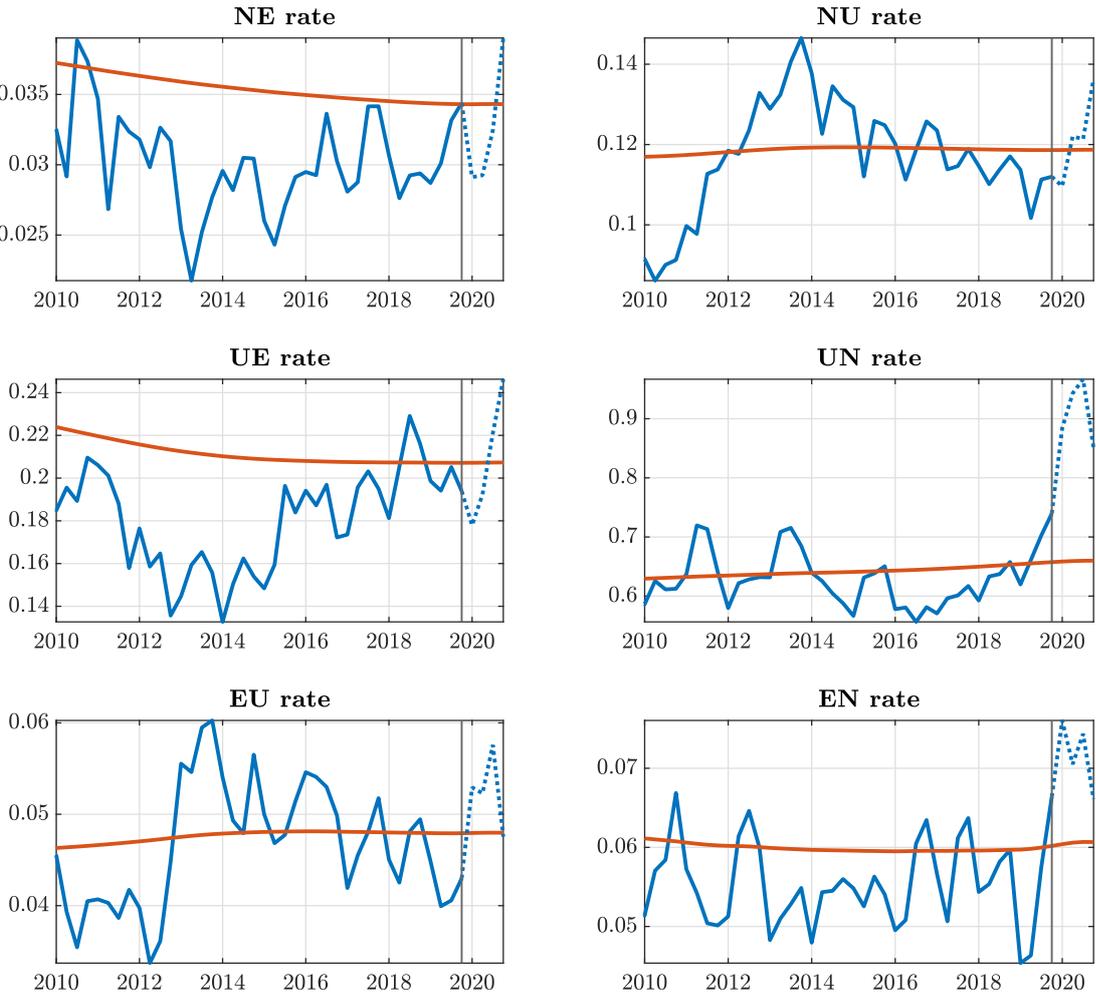


Figure D.1: Labor market flows, Women 15-34; 2010-2020

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the period 2010q1-2020q4 (trend hazard rates are estimated over the period 1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D’Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

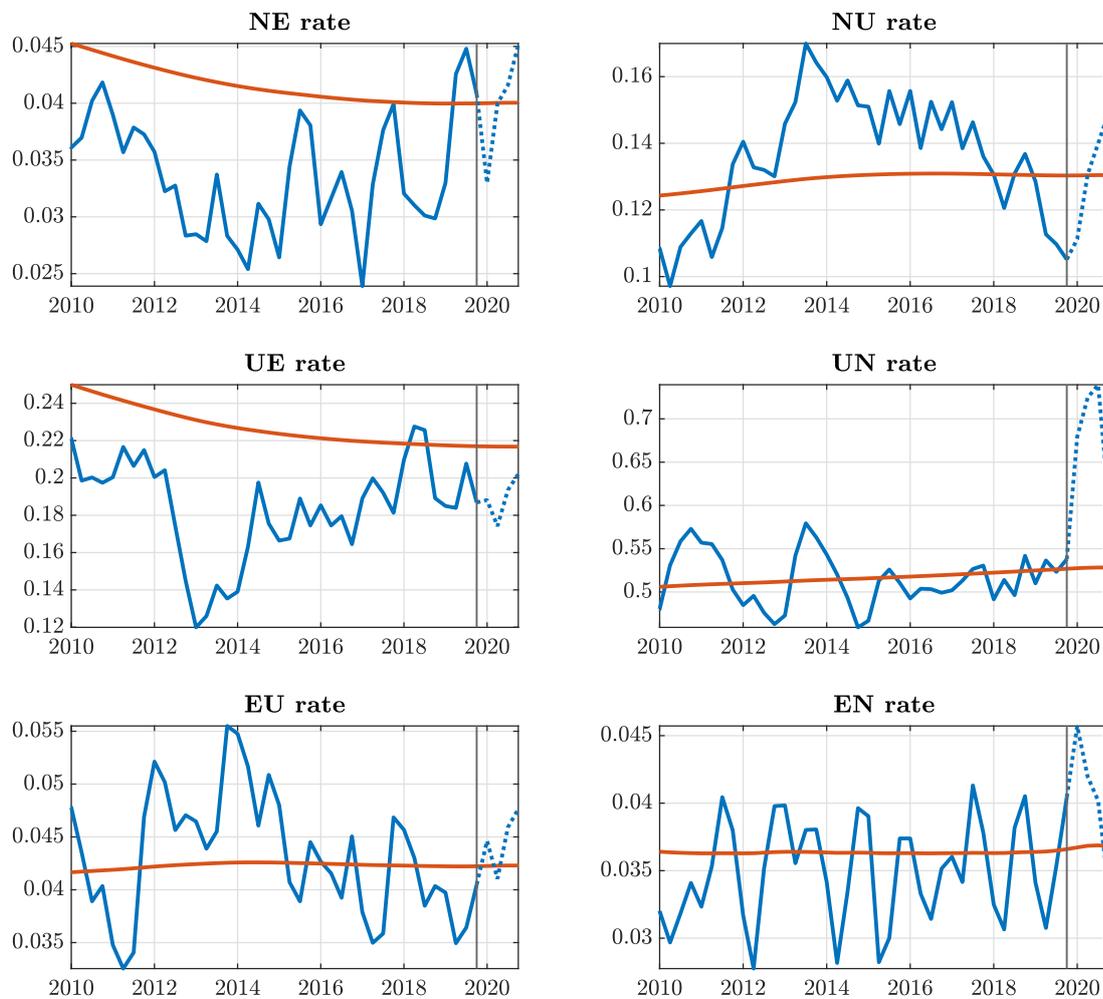


Figure D.2: Labor market flows, Men 15-34; 2010-2020

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the period 2010q1-2020q4 (trend hazard rates are estimated over the period 1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D'Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

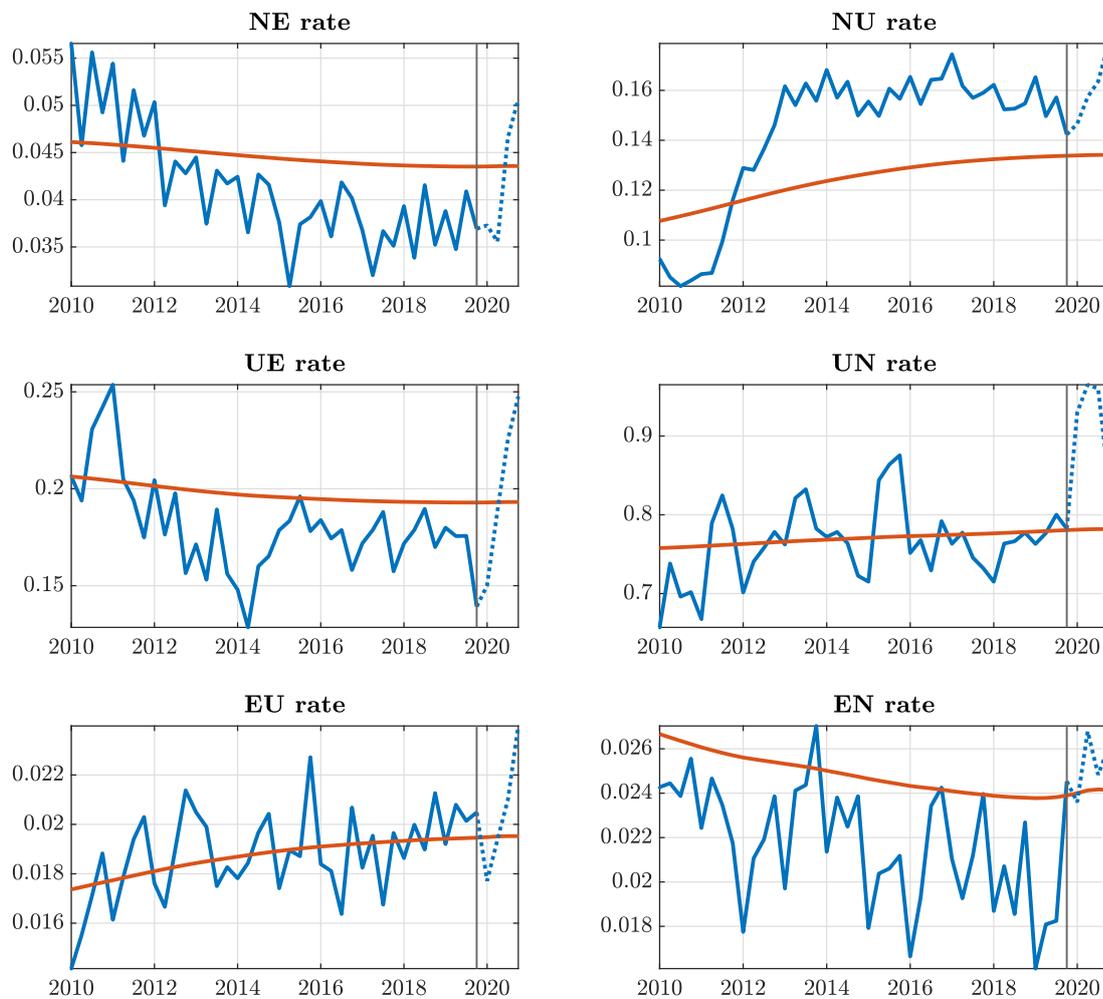


Figure D.3: Labor market flows, Women 35-54; 2010-2020

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the period 2010q1-2020q4 (trend hazard rates are estimated over the period 1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D'Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

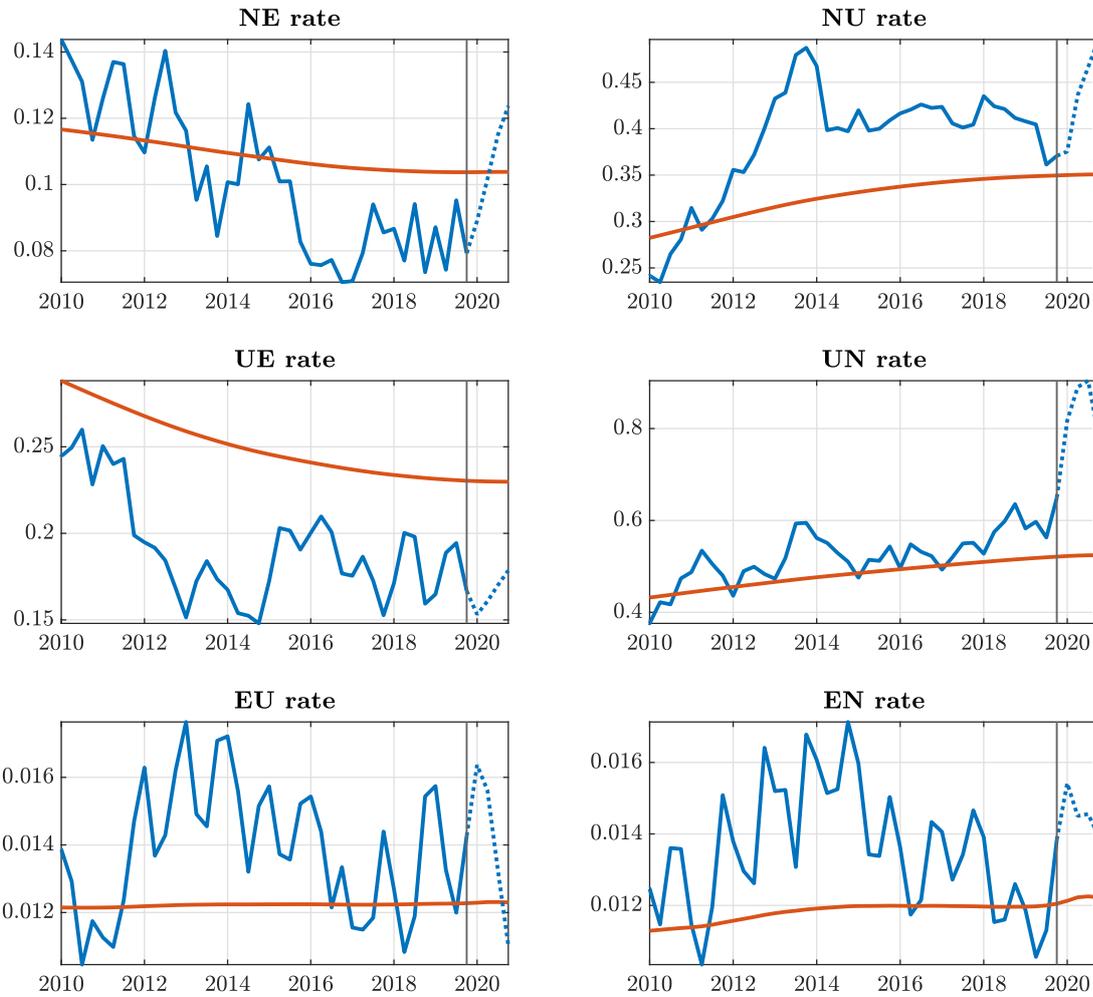


Figure D.4: Labor market flows, Men 35-54; 2010-2020

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the period 2010q1-2020q4 (trend hazard rates are estimated over the period 1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D'Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

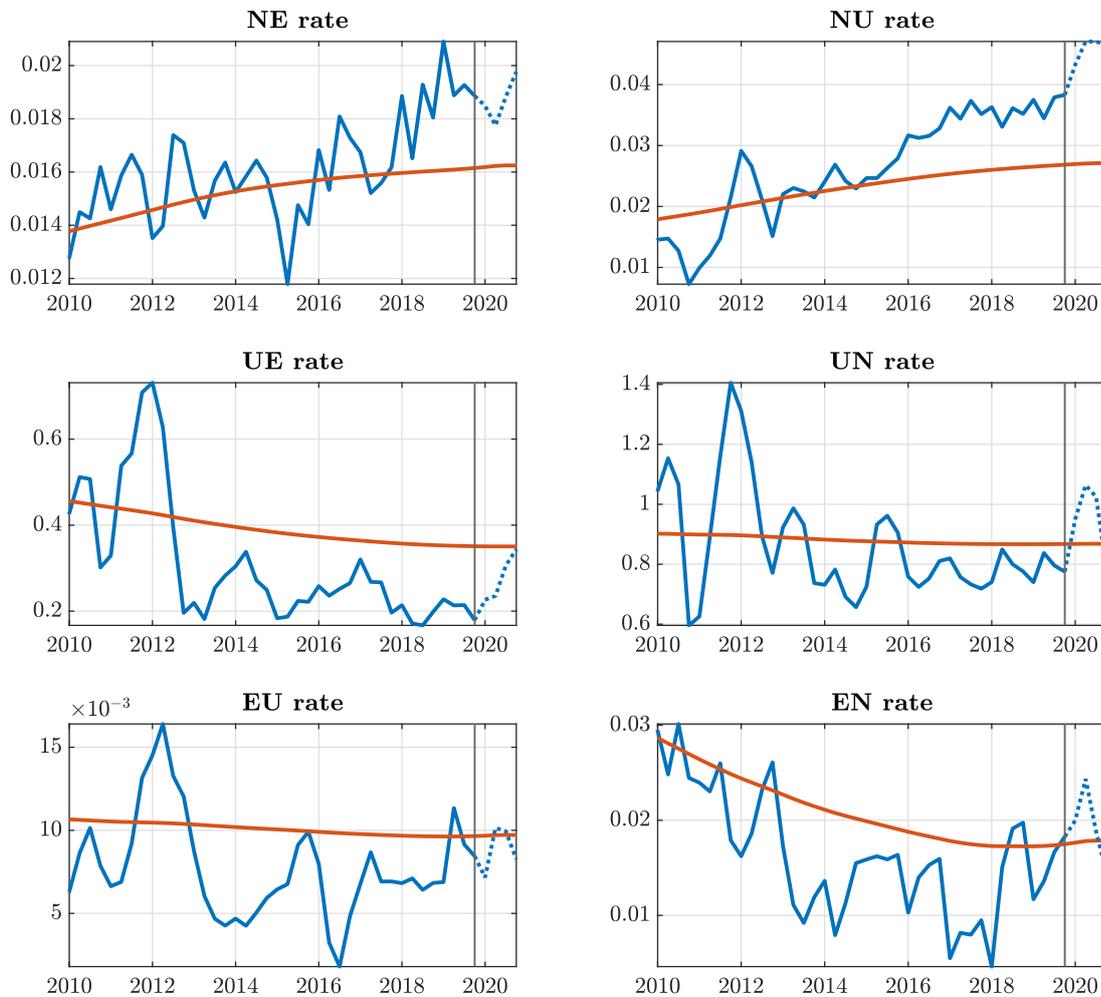


Figure D.5: Labor market flows, Women 55-64; 2010-2020

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the period 2010q1-2020q4 (trend hazard rates are estimated over the period 1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D’Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

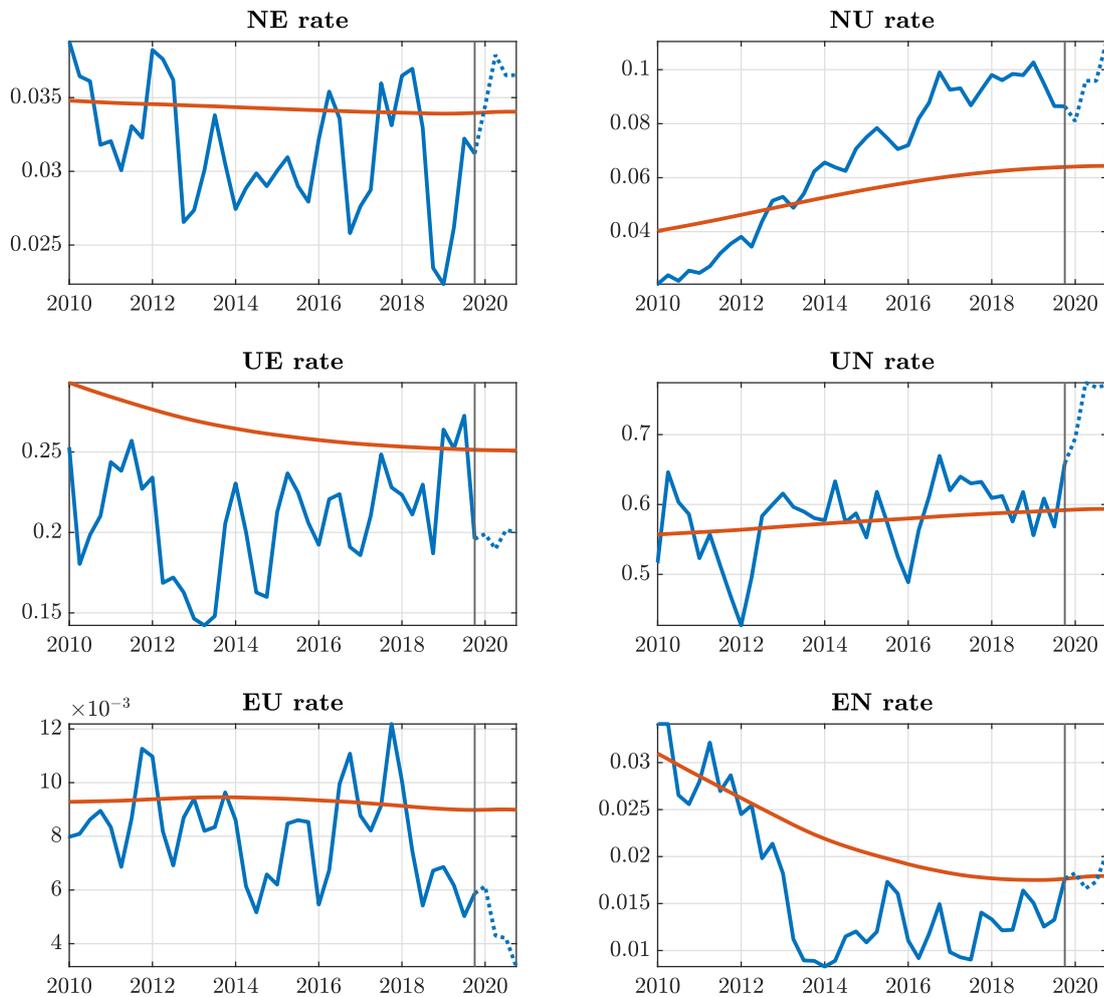


Figure D.6: Labor market flows, Men 55-64; 2010-2020

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the period 2010q1-2020q4 (trend hazard rates are estimated over the period 1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D’Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

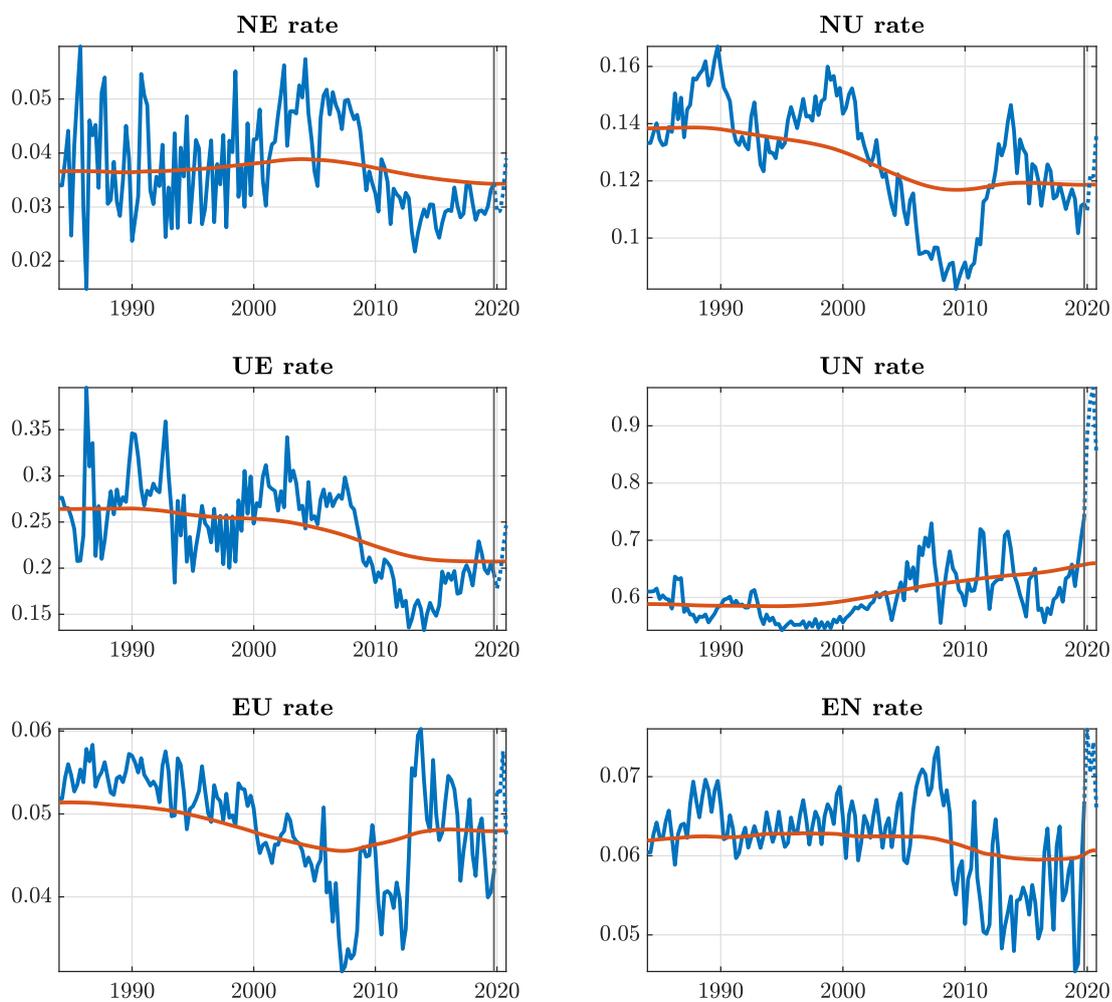


Figure D.7: Labor market flows, Women 15-34

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the full estimation period (1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D'Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

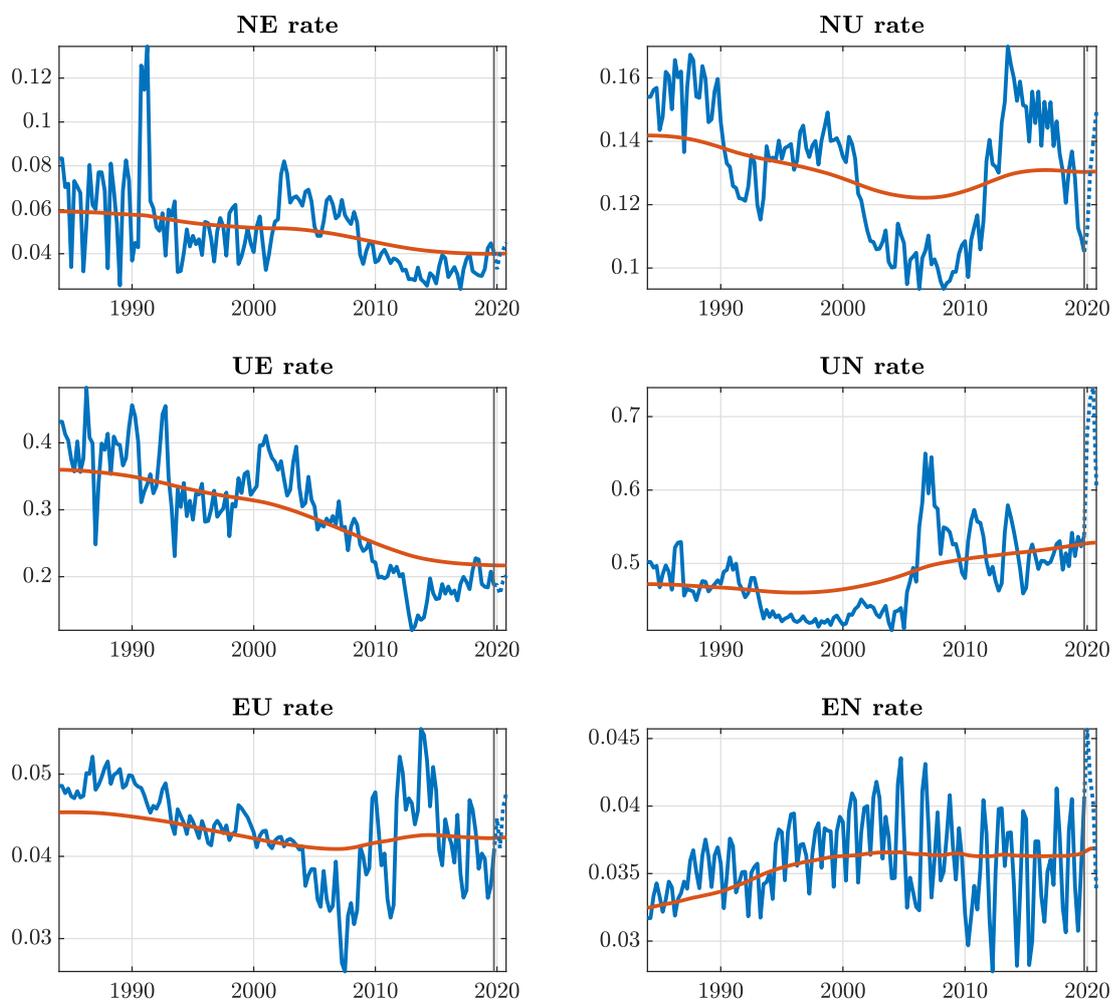


Figure D.8: Labor market flows, Men 15-34

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the full estimation period (1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D’Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

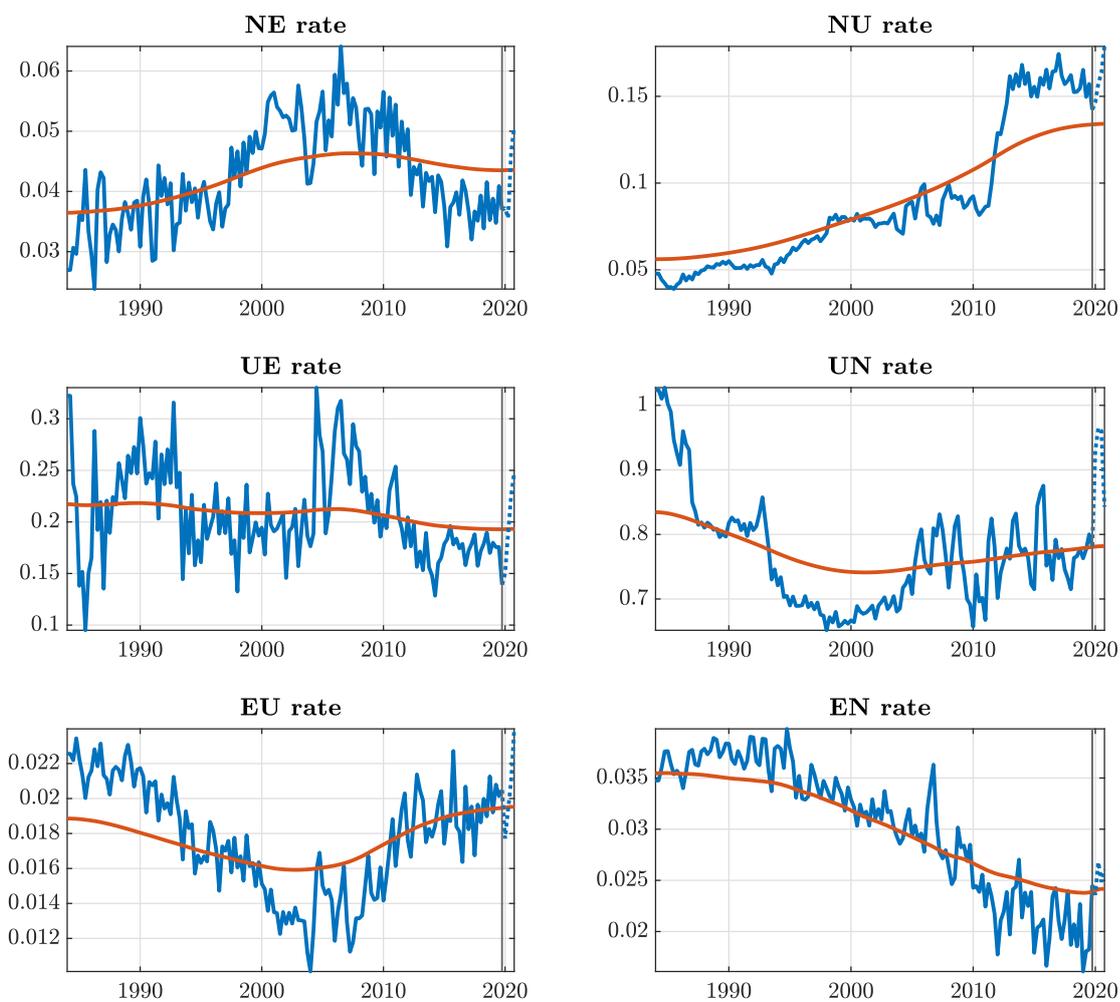


Figure D.9: Labor market flows, Women 35-54

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the full estimation period (1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D’Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

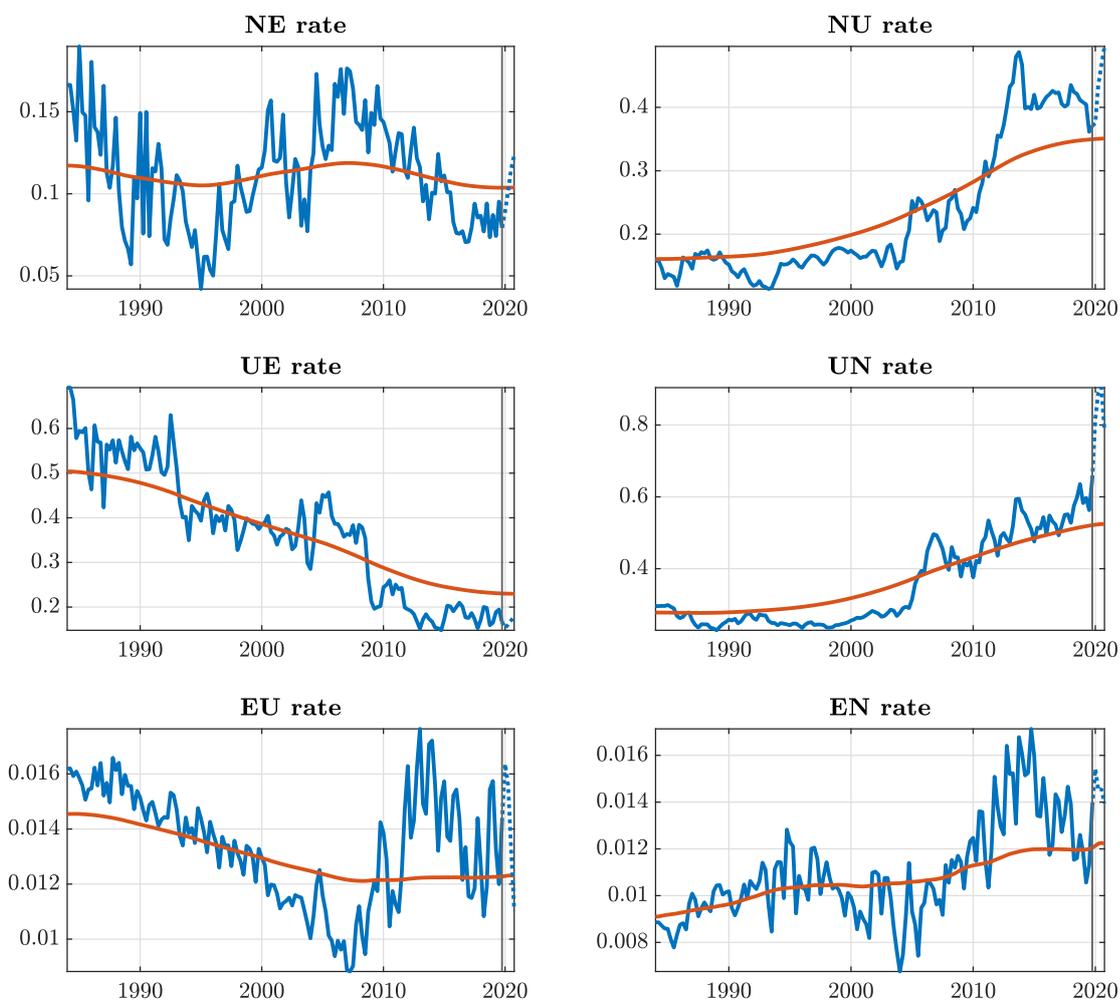


Figure D.10: Labor market flows, Men 35-54

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the full estimation period (1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D'Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

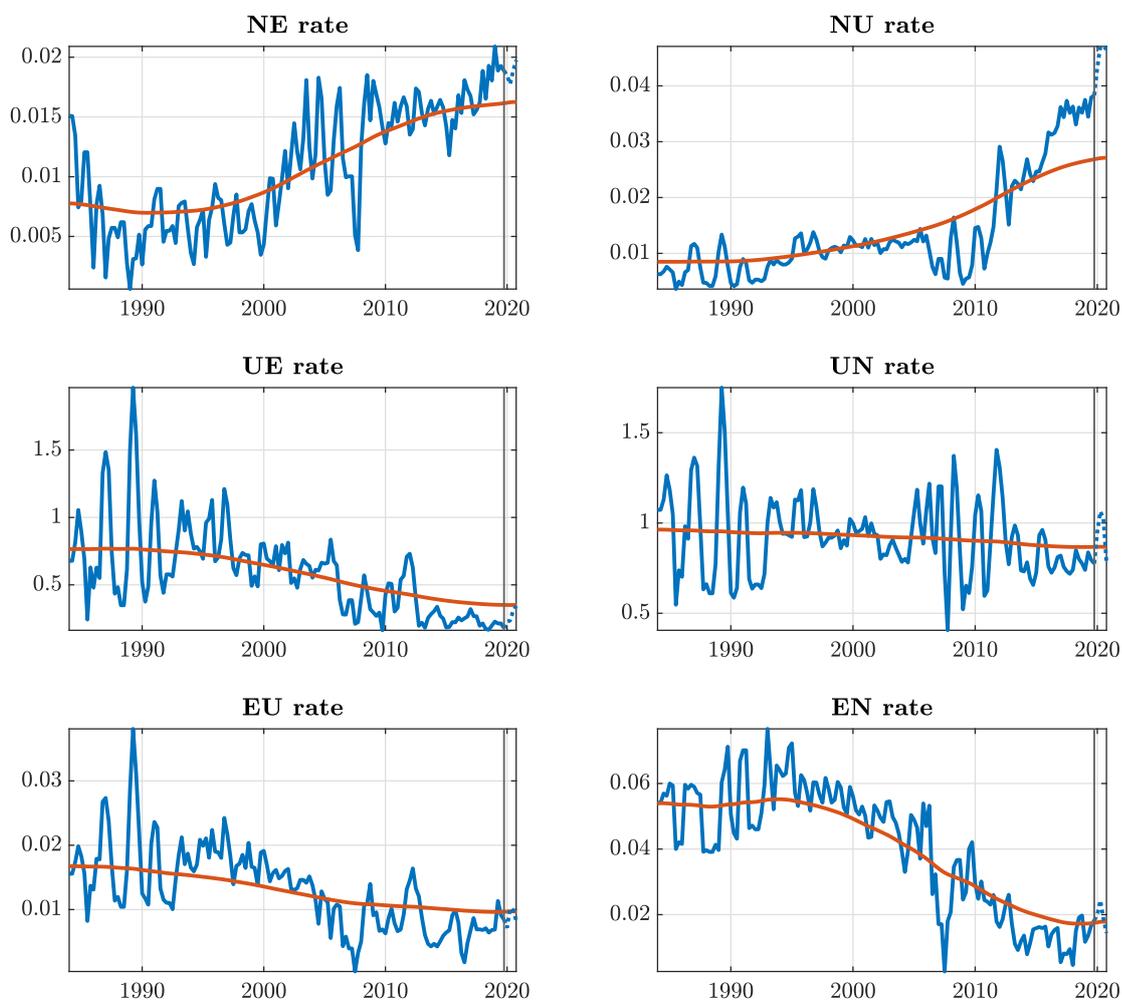


Figure D.11: Labor market flows, Women 55-64

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the full estimation period (1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D'Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

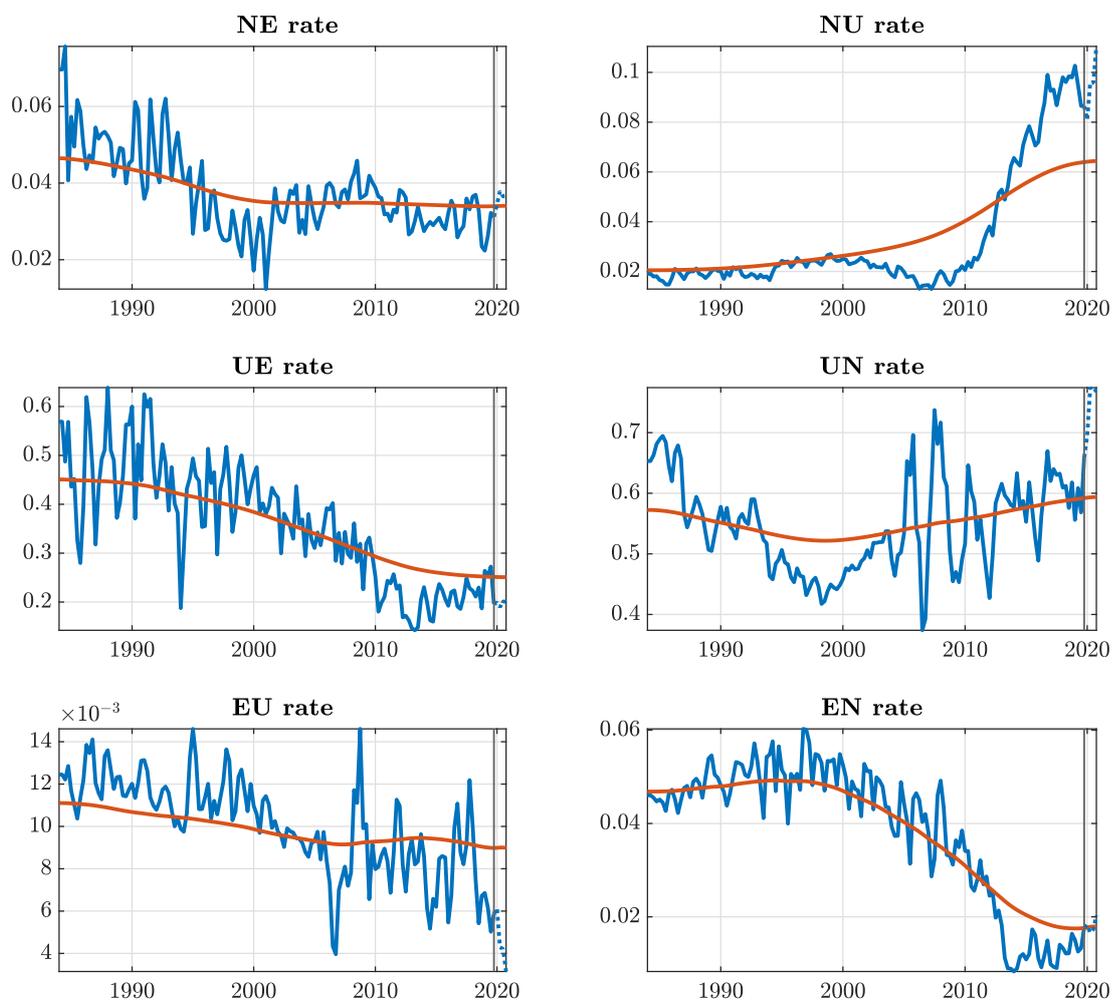


Figure D.12: Labor market flows, Men 55-64

**Note:** The figure plots the hazard rates (blue lines) and the trend hazard rates (red lines), for the full estimation period (1984q1-2020q4). The hazard rates are based on microdata from the Labour Force Survey and the trend rates are obtained via Kalman filter, as explained in D’Amuri et al. (2021). The dotted lines refer to the four quarters of 2020 (post Covid).

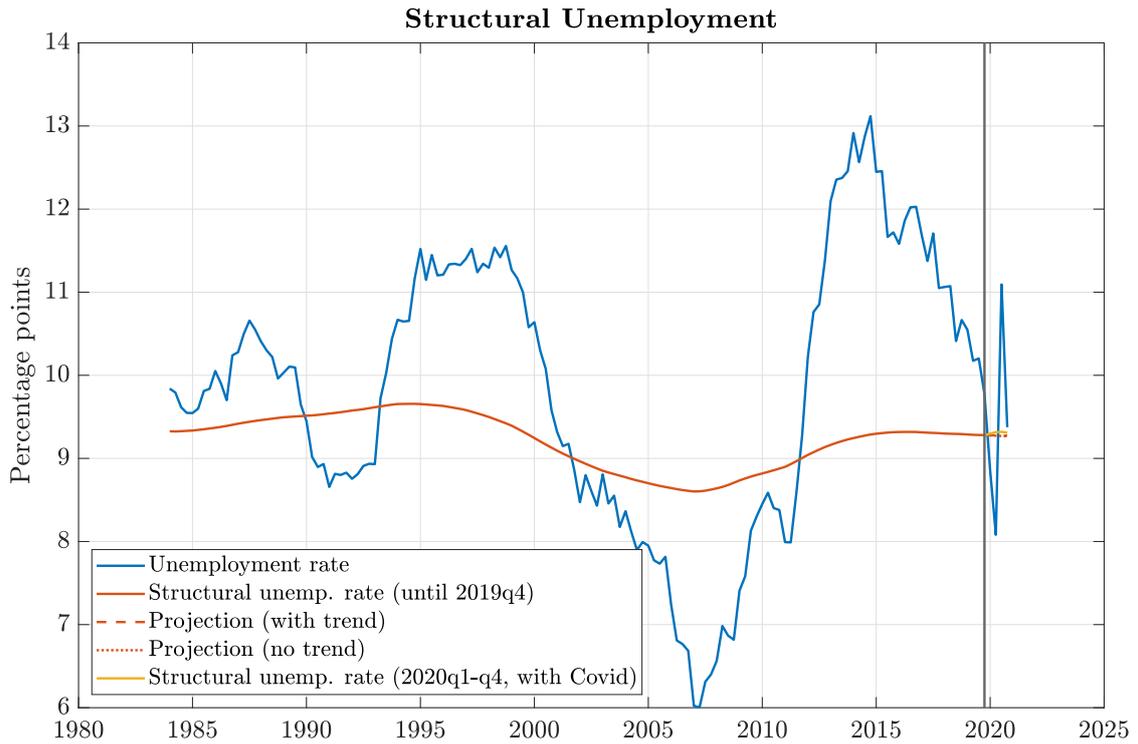


Figure D.13: Structural unemployment rate, full sample

**Note:** The figure plots the quarterly unemployment rate of the population 15–64 (blue line) and the estimated trend activity rate (red line) for the years 1984q1-2020q4.

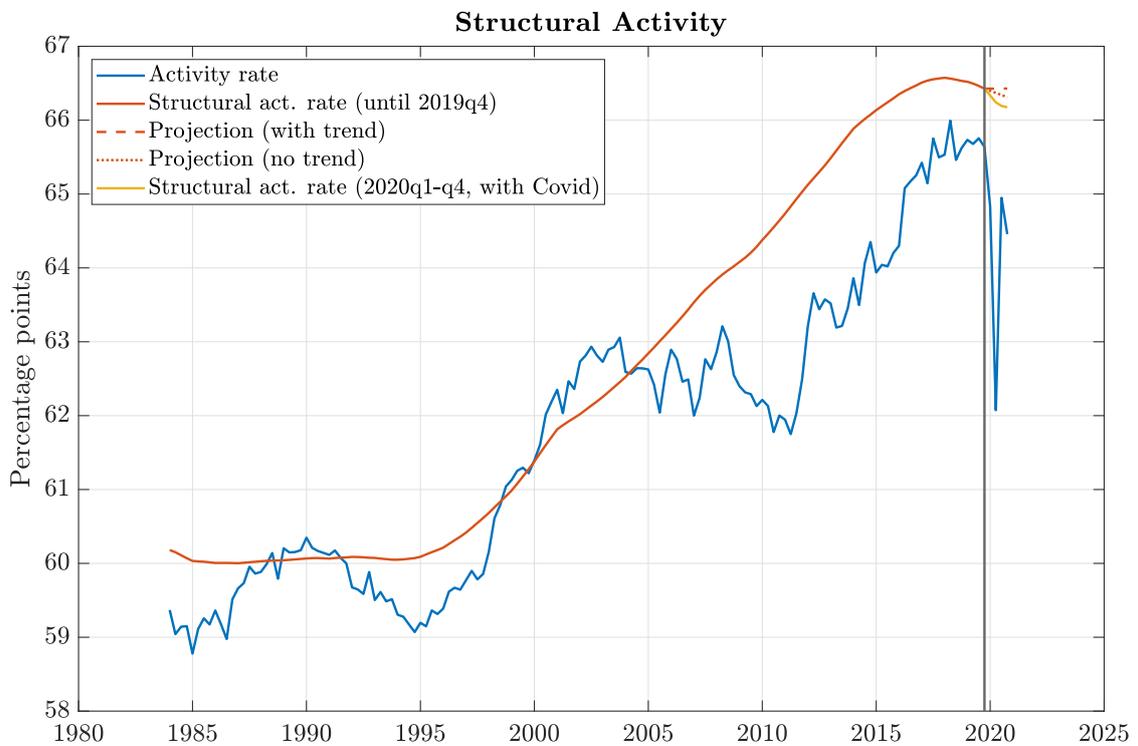


Figure D.14: Structural activity rate, full sample

**Note:** The figure plots the quarterly activity rate of the population 15–64 (blue line) and the estimated trend activity rate (red line) for the years 1984q1-2020q4.

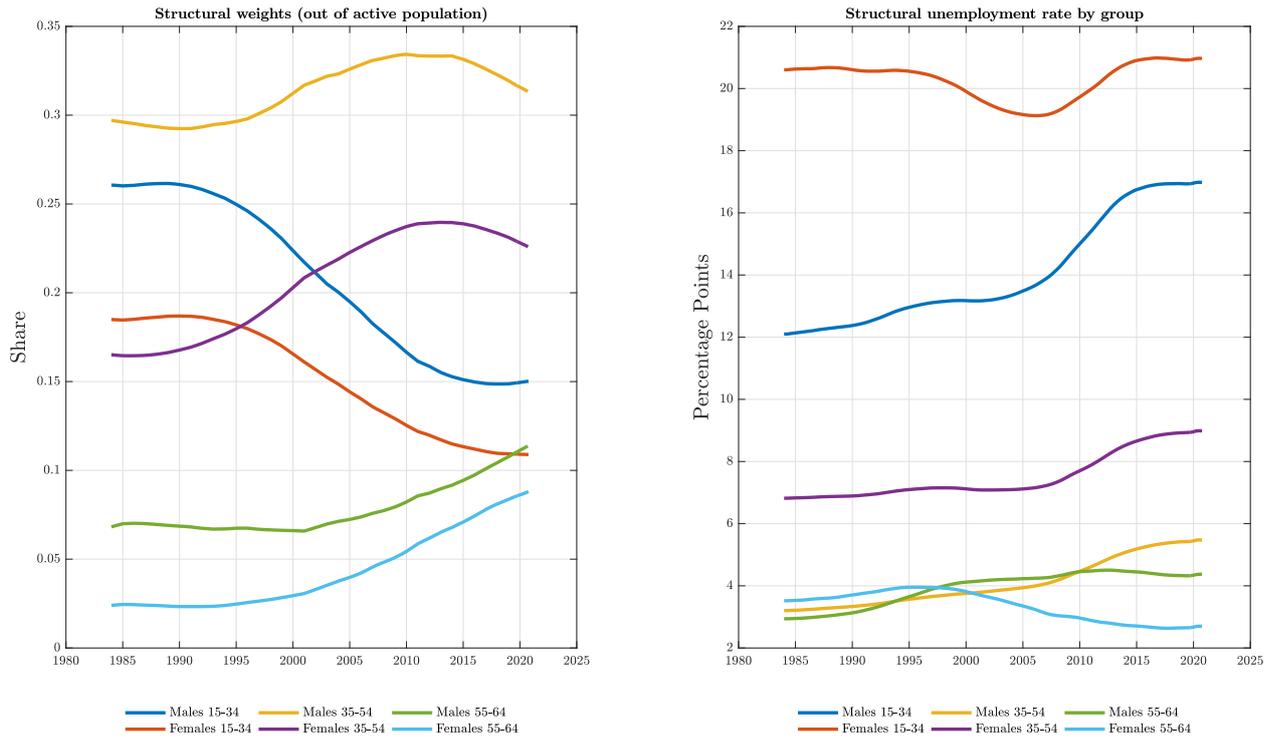


Figure D.15: Determinants of the structural unemployment rate

**Note:** The figure plots the evolution over time of the components of the structural unemployment rate (see Equation 7 in the paper) for the years 1984q1-2020q4.

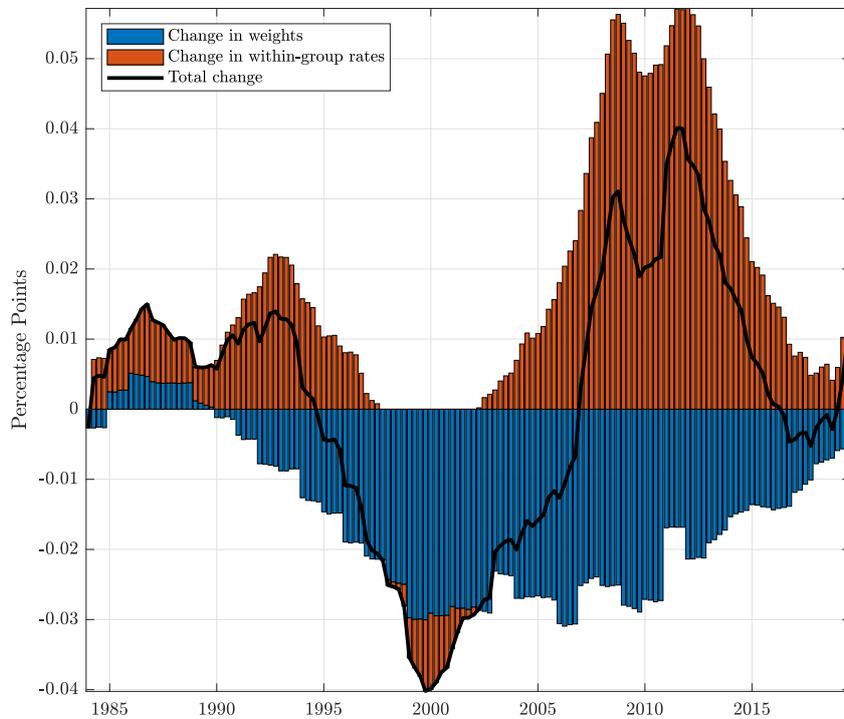


Figure D.16: Decomposition of the structural unemployment rate dynamics

**Note:** The figure plots the contributions to aggregate dynamics of the structural unemployment rate given by: group-specific weights and within dynamics (see Equation 7 in the paper) for the years 1984q1-2020q4.

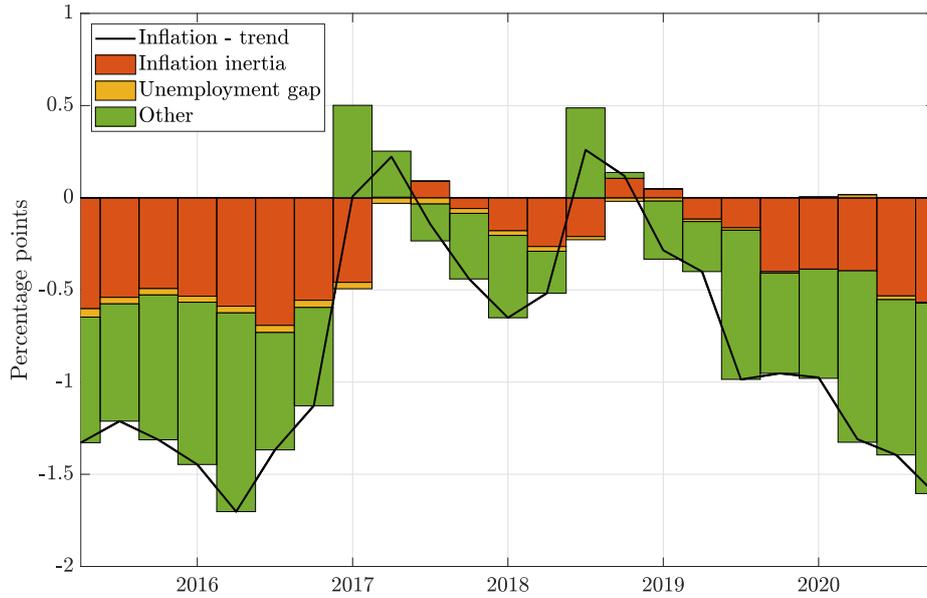


Figure D.17: Historical decomposition of the inflation gap in the model with UGAP only

**Note:** The solid line represents the historical evolution of median inflation gap (realized inflation - estimated trend inflation) and the colored bars the median contributions of the factors included in the Phillips curve model including only the unemployment gap. The model is estimated over the period 1996q1–2020q4.

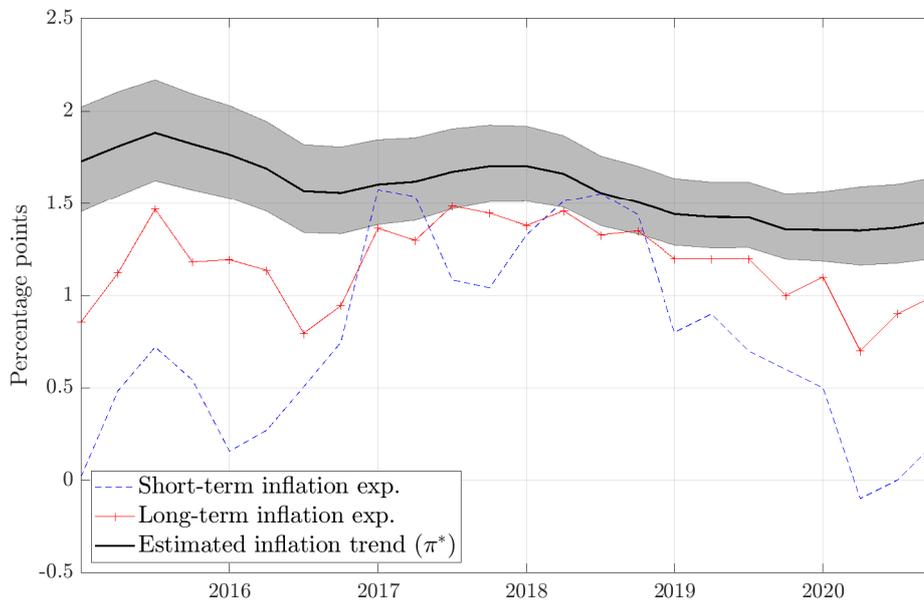


Figure D.18: Inflation trend estimated through the augmented Phillips curve model (UGAP + PGAP)

**Note:** Shading denotes the 68% credibility interval. The model is estimated over the period 1996q1–2020q4. Short-term expectations are inflation expectations 2 quarters ahead from Consensus Forecasts. Long-term expectations are inflation expectations 6 quarters ahead from Consensus Forecasts.

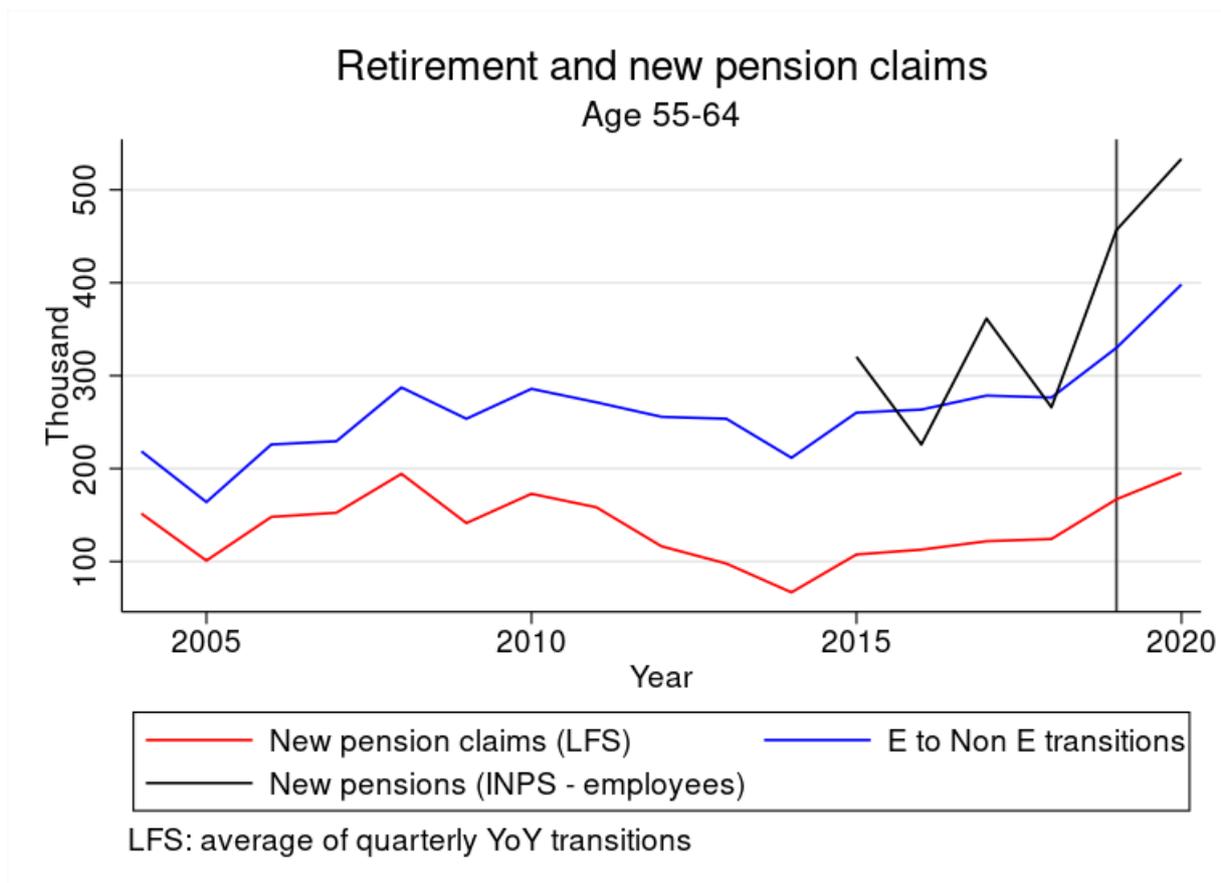


Figure D.19: Flows into retirement and new pension claims

**Note:** For LFS data, the figure plots average quarterly transitions relative to the same quarter in the previous year (from employment in year  $t$  to pension claimant in year  $t + 1$ ); for INPS: total of new pension claimants (employees). A major pension reform postponing significantly statutory retirement age took place in 2012 (Carta and De Philippis, 2021b; Carta et al., 2021); this reform was partially reversed in 2019, by Law 4/2019 that temporarily softened pension eligibility requirements for the three year interval 2019-21 and suspended statutory retirement age indexation to life expectancy.

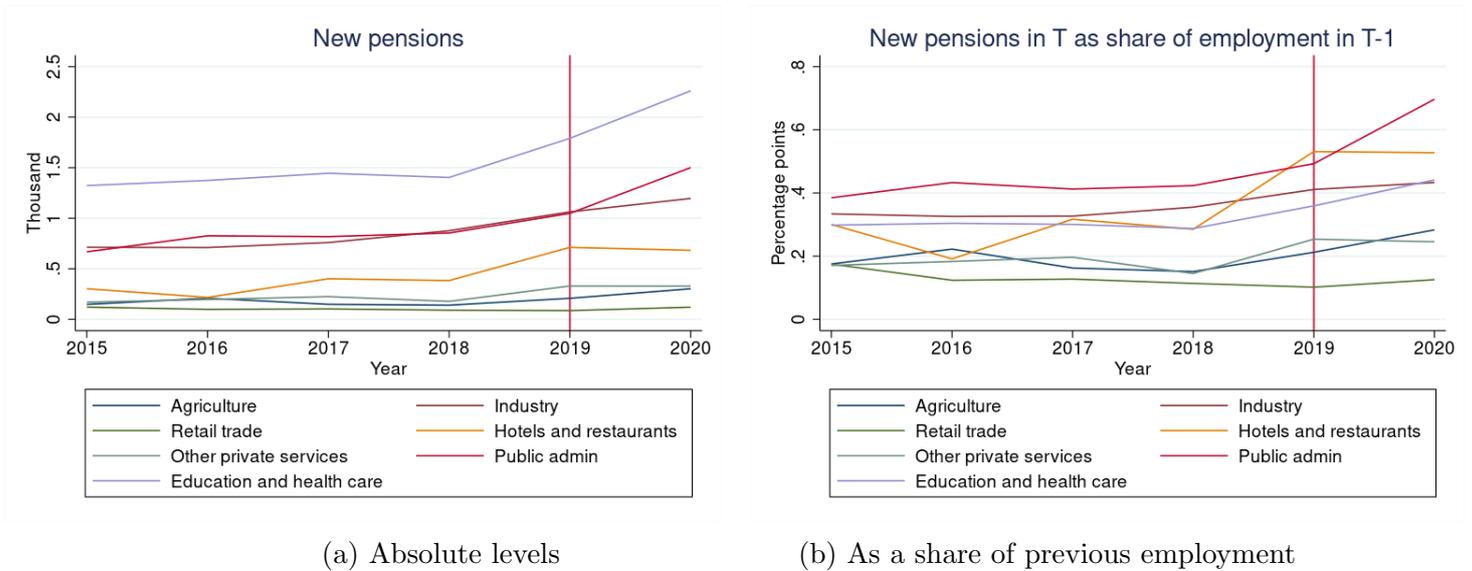


Figure D.20: New pension claims by sector

**Note:** The figure plots average quarterly transitions relative to the same quarter the previous year (from employment in year  $t$  to pension claimant in year  $t + 1$ ). A major pension reform postponing significantly statutory retirement age took place in 2012 (Carta and De Philippis, 2021b; Carta et al., 2021); this reform was partially reversed in 2019, that temporarily softened pension eligibility requirements for the three year interval 2019-21 and suspended statutory retirement age indexation to life expectancy.

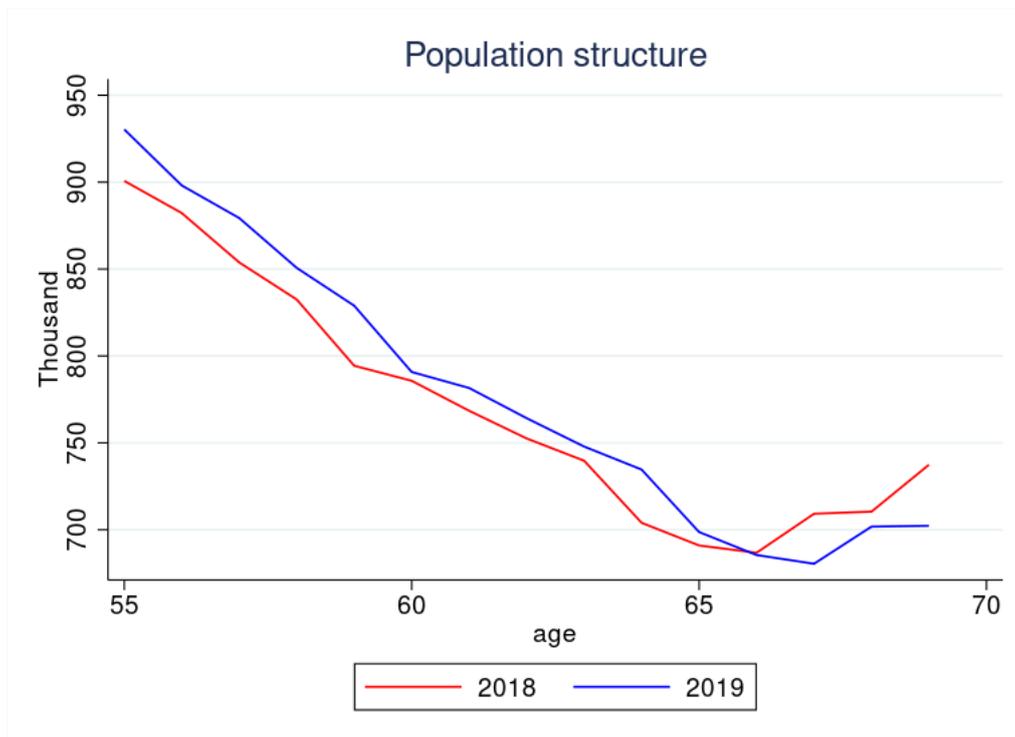


Figure D.21: 55-70 population in 2018 and 2019

Source: Istat.