Patterns of labor market reforms: a regional approach to the Italian 'Jobs Act'

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After estimating the impact of wage subsidies and EPL reforms on open-ended employment, we single out which macro characteristics are responsible for the variability of the estimated effects at the regional level. We find that the impact of incentives is higher where GDP and VA per head are higher, and the informal economy is limited. Instead, we do not find any heterogeneity – and in most cases any impact – for the EPL component. We conclude that regions with a stronger economy benefitted more from subsidies, which might exacerbate territorial inequality.

Dopo aver stimato l'impatto di sussidi salariali e protezione dell'impiego sull'occupazione a tempo indeterminato, identifichiamo quali caratteristiche macro sono responsabili della variabilità regionale dell'impatto stimato. L'effetto degli incentivi è maggiore dove PIL e valore aggiunto pro-capite sono maggiori e l'economia informale è meno diffusa. Non emerge invece eterogeneità – e in molti casi nessun effetto – per la protezione dell'impiego. Pertanto, le regioni con un'economia più forte hanno beneficiato maggiormente dei sussidi, potenzialmente amplificando i divari territoriali.

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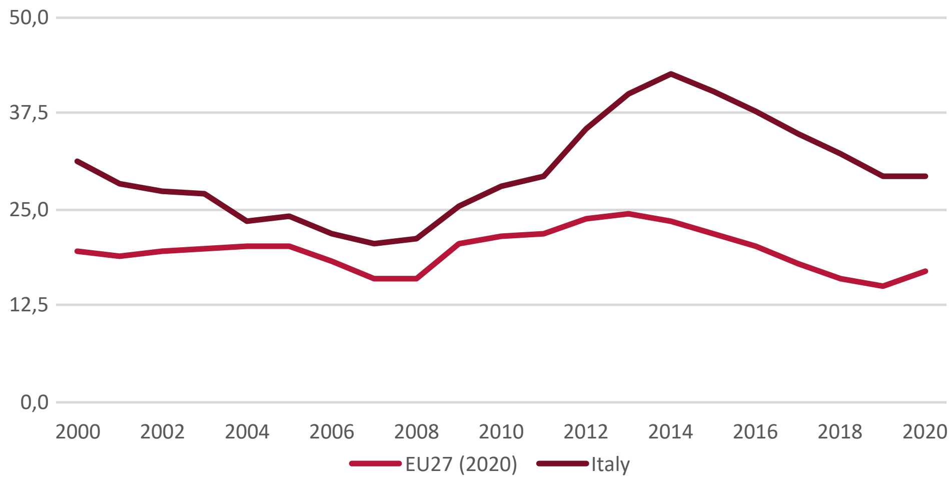
Introduction

For most countries, the last fifteen years have represented an unusually long period of economic turmoil, during which crises of different origins but with comparable impact have happened one after the other: those of sub-prime mortgages and sovereign debt hit first, followed more recently by the Covid-19 pandemic and the economic consequences of the war between Russia and Ukraine. The social impact has been momentous, and youths have been among those who paid the highest price. Although an incomplete and partial measure, the youth unemployment rate (Figure 1) provides some idea of what happened.

Under such pressure, the European Commission (Bekker 2017) and the OECD (2014) advised their members to reduce the employment protection gap between temporary and permanent workers, as a way to enhance the employment opportunities for the youth as well as their chances to get a more stable job. This strategy found favorable ground throughout the European Union (Eichhorst *et al.* 2017), and in particular where the public debt crisis created the political capital to enforce unprecedented reductions of the employment protection legislation (hereafter, EPL) governing open-ended contracts (Meardi 2014). To support this program, many countries paralleled a less

Figure 1. Youth (15-24) unemployment rate, EU27 and Italy



Source: Eurostat data

binding EPL with generous hiring subsidies (OECD 2010).

Italy – our case study – is largely reflected into this broad picture. First, it experienced a dramatic rise in youth unemployment (Figure 1). Second, its high public debt exposed the government to international pressure aimed at introducing deep labor market reforms (Sacchi 2015; 2018). Third, and more important, in 2015, under the Renzi government, a structural reform of the Italian labor market known as Jobs Act sharply reduced the firing costs for all new open-ended contracts signed in firms with more than fifteen employees. To further support the use of open-ended contracts, the Jobs Act was also coupled with a very generous hiring subsidy.

Specific institutional features of the two interventions, which we describe below and have been also exploited elsewhere (Deidda *et al.* 2021, Ardito *et al.* 2022; 2023; Sestito and Viviano 2018), allow to identify their impact on workers' perspectives of securing stable employment. Our specific contribution is to study how these impacts change across Italian regions, where the latter represent different socio-economic realms within a homogenous institutional context. To do so, we first estimate region-specific difference-in-differences (DiD) models of the impact of EPL reduction and of the hiring subsidy on the individual probability to get an open-ended contract. In a second step, we plug these estimated impacts as dependent variables of linear OLS models where the explanatory variables are the estimated principal components of a set of macroeconomic descriptors of the twenty Italian regions. Our results support the hypothesis of a heterogeneous impact of the hiring incentive, which appears higher in regions with (i) a stronger socio-economic and institutional fabric (as measured by per-head GDP and value added, informal economy and the take-up rate of the hiring incentives) and a (ii) more mature production process (*i.e.*, with a higher share of workers aged 50 or more and a lower propensity to innovate). Conversely, we do not find any heterogeneity – and in most cases any impact at all – for the EPL component of the reform under scrutiny. Breaking down reform impacts by gender reveals then that the bulk of the effect is carried by male workers.

Our paper proceeds as follows: the next section reviews the relevant literature, spanning from EPL to labor cost reductions. In section two we describe the institutional framework, and in section three the empirical strategy. Section four presents the data along with some descriptive statistics, while the main results are in section five. An ending section draws some concluding remarks. The article is completed with an annex on data construction, and one where the analysis is repeated by gender.

1. Review of the literature

Our contribution lies at the intersection of two well-established streams of literature. On the one hand, the implications of EPL on employment appear rather clear both theoretically and empirically. A less binding legislation on employment protection enhances workers' turnover (Kugler and Pica 2008). This may improve their allocation upon existing jobs (Berton *et al.* 2017; Rogerson 1987) but not the employment levels (Bentolila and Bertola 1990; Bertola 1990; Cazes 2013; OECD 2004). This picture becomes more complicated when we take into account that the level of EPL is usually not homogeneous within a labor market, as a consequence of the marginal nature of most labor market reforms during past decades, which deregulated the use of temporary contracts leaving EPL on open-ended jobs unaffected (Berton *et al.* 2012). Within this context, making open-ended contracts more flexible is expected to favor the inflows from temporary employment, and hence to reduce polarization (Boeri 2011; Dolado *et al.* 2002). This would turn beneficial to those groups of workers – women, non-nationals, and the youth – for whom persistence in temporary employment has been a negative bearing of partial reforms. However, Ardito *et al.* (2022) show that in this context firms (1) stabilize the workforce mainly through contract transformations of low-tenure and low-human-capital incumbent workers performing high-physical and low-intellectual tasks; (2) apply a cost-saving strategy that increases profits and decreases value added per head, so pointing to non-desirable side effects of these reforms.

Consistently with our focus, most of the empirical literature has focused on the youth, finding mixed results (Heckman and Pagés-Serra 2000; Kahn 2010; Noelke 2016). Another perspective, focusing on youths but more eccentric with respect to ours, is that of those who study the so-called *port-of-entry hypothesis*. In this case, rather than analyzing what happens to transitions from temporary to permanent employment when EPL on the latter is reduced, the authors exploit variations in EPL of (different types of) temporary contracts to assess the prediction that easier access to the labor market eventually favors, compared to longer search periods spent in unemployment, the access to stable employment. In this case too, the evidence is mixed: a recent and nice assessment of this literature is provided by Filomena and Picchio (2022).

The second stream of literature to which our article makes a reference is on hiring subsidies or, more in general, policies for labor cost reduction. The theory provides a clear prediction: a lower cost of labor raises its demand, and thus employment. Empirical evidence supports this view: Ciani and De Blasio (2015) find that monetary incentives to promote temporary workers have a large effect on the probability to get an open-ended job in Italy. Neumark and Grijalva (2017) exploit tax credits in the US, finding a positive effect on hires although not on net employment; similar results hold for Mexico (Bruhn 2020) and Sweden (Sjögren and Vikström 2015). Tax credits are studied also in Cahuc *et al.* (2019), who suggest instead that they have positive effects on net employment in France. Berson and Ferrari (2015) take a broader perspective and assess the issue of financing, suggesting that a tax on temporary employment to fund hiring subsidies for open-ended jobs performs better than other options. Earlier studies (*e.g.*, Martini and Trivellato 2011; Neumark 2013) do not affect this picture.

On the contrary, much less is known about the geographical heterogeneity of EPL and incentive effects, our focus here. Existing research takes advantage of international comparisons (*e.g.*, Cingano *et al.* 2010) and suffer in general from a limited capability to separate the effect of EPL from other institutions. Causal identification is indeed better granted with microdata on a single country where quasi-experimental conditions hold (Bentolila *et al.* 2019). The strategy we pursue here is hence to exploit country-specific labor market reforms combined with cross-regional differences, provided that regions bring a sufficient amount of socio-economic heterogeneity, as is the case in Italy. In this perspective, the literature – to the best of our knowledge – is void. Taking advantage of the same reforms under scrutiny here, Sestito and Viviano (2018) show that hiring subsidies account for 20% (80%) of the creation of (promotion to) permanent employment in Veneto, a large North-Eastern Italian region, in 2015, while EPL reduction accounts for a more limited 8%. Ardito *et al.* (2023) use data on Piedmont – another large Italian region, but in the North-West – and suggest that large firms are less sensitive than small ones to hiring incentives, unless combined with EPL reduction, and that there are heterogeneity effects among workers. Deidda *et al.* (2021) analyzed the introduction of the two mentioned reforms at the national level and showed that they had a positive impact on the share of new hires of youth with an open-ended contract over the total employment contracts registered in 2015, but no regional differences were analyzed. In all these cases regional comparisons are precluded.

2. Institutional framework

Our pre-treatment setting is defined by the so-called Fornero Law (Law 92/2012), following the name of the Labor Minister under the Monti Government. This setting provides workers with open-ended contracts employed in firms with more than 15 employees (those who used to benefit from the well-known article 18 of Law 300/1970, the Workers' Statute, amended exactly by Law 92/2012) with more generous protection against unfair individual dismissals than what happens in small firms. In the latter, in case of unfair dismissal and irrespective of the reason behind it, the employer holds the option to choose between initiating a new employment relationship with the wrongly discharged workers, or compensating them with up to fourteen monthly salaries, depending on tenure. Relevantly, as the new employment relationship is started and no option for reinstatement is envisaged, no compensation for foregone wages and social security contributions is due.

In medium and large firms, the compensation scheme depends on the alleged reason behind the layoff. When this is motivated under the disciplinary chapter, reinstatement is possible if the reason for layoff simply does not exist, or the relevant collective agreement rules that the case should be managed otherwise. The dismissed worker is also entitled to a minimum compensation of five monthly salaries on top of all foregone social security contributions. In all the other cases in which the judge rules illegitimate a layoff motivated by disciplinary reasons, dismissed workers benefit from a monetary compensation ranging from twelve to twenty-four monthly salaries. For layoffs motivated by an economic reason, instead, reinstatement is only allowed if the judge ascertains that the alleged reason does not exist. All the other cases entitle the worker to the monetary compensation described above.

According to many observers, Law 92/2012 failed to solve one of the major limitations of the Italian labor law, namely its high degree of uncertainty (Cavaletto and Pacelli 2014). The first of the reforms under scrutiny in this paper, which eventually resulted in an EPL reduction for workers employed in firms with more than fifteen employees, was aimed to overcome this problem. According to the Jobs Act[1], all new hires signed under open-ended contracts dating from March 7th, 2015 are subject to homogeneous EPL provisions that devoid judges of almost any discretionary power[2]. Reinstatement is limited to discriminatory layoffs and to cases where the alleged reason by the employer does not exist. In all the other cases wrongly discharged workers are entitled to a monetary compensation amounting to two months' wages for every year of seniority, with a minimum of four and a maximum of twenty-four monthly salaries. Rules in firms employing up to fifteen employees were left untouched.

The second government intervention we want to assess the impact of is defined in the Budget Law for 2015 (namely under article 118 of Law 190/2014). It introduced a generous hiring subsidy for all new open-ended relationships dating from January 1st, 2015, signed by workers who i) were not apprentices in the same firm, and ii) did not work under another open-ended contract during the previous six months. The incentive is a three-year 100% rebate on social security contributions, with a maximum of €8,060 per year.

Different temporal and sectional discontinuities of the two reforms, jointly with the absence of any further labor market intervention across the relevant thresholds, is what we take advantage of to apply a DiD approach, as we describe below.

3. Empirical strategy

We estimate both the effect of the hiring subsidy and of the reduced firing cost, adopting the following strategy. We focus on the probability of conversion from temporary to open-ended contracts within the same firm of employees hired with a fixed-term or an apprenticeship contract. Apprenticeships are not eligible for incentives, as discussed above, and they provide the control group to fixed-term employees. The latter are eligible for incentives, provided that they had no open-ended contracts in the previous

1 To be precise: Decree 23/2015 – as the EPL-dedicated part of a broader labor market reform called Jobs Act (Law 183/2014).
2 This specific aspect of the provision was then deemed against the Italian Constitution by the Supreme Court. Its effects take place after our period of analysis, though.

six months. Being incumbent in a given firm, it is also possible – with no threat of endogeneity – to compare firms subject to the article 18 reform (treated) to those not subject (controls), *i.e.*, firms above or below the 15-employee threshold[3], as discussed above. So, in the same model, we estimate the causal effects of both the incentives and the deletion of article 18 of the labor code, and their eventual interaction. In doing so, we replicate the strategy presented in Sestito and Viviano (2018).

It is a short-run approach, as it focuses on the first six months of 2015. After that period, issues linked to the dynamic selection of the eligible and non-eligible groups would appear (see Ardito *et al.* 2023, demanding a non-linear duration model that is beyond the scope of the present study. We implement a linear probability model to estimate the probability of conversion to a permanent contract π_{pwym} for a worker p that in the previous semester was employed with a temporary contract (w=1) or an apprenticeship one (w=0), in a firm g that is above (g=1) or below (g=0) the 15-employee threshold, in the year y (2013 to 2015), month m (up to June 2015), specified as follows:

$$\pi_{pwym}=\gamma_p+\gamma_g+\gamma_w+\gamma_y+\gamma_m+\beta D_{(w=1)(y\geq 2015)}+\delta D_{(g=1)(y\geq 2015)(m\geq March)} +\eta D_{(w=1)(y\geq 2015)} D_{(g=1)(y\geq 2015)(m\geq March)}+\varepsilon_{pwym} \quad (1)$$

Where γ_p, γ_g, γ_w, γ_y, γ_m are fixed effects for the corresponding characteristics; $D_{(w=1)(y\geq 2015)}$ is the indicator variable for person-month events taking place after January 2015 for eligible individuals, *i.e.*, β is the difference-in-differences coefficient of interest to estimate the causal effect of the subsidies; $D_{(g=1)(y\geq 2015)(m\geq March)}$ is the indicator variable for person-month events taking place after March 2015 in firms with more than 15 employees, *i.e.*, δ is the difference-in-differences coefficient of interest to estimate the causal effect of the Jobs Act's reduction of firing costs; $D_{(g=1)(y\geq 2015)(m\geq March)}$ is the interaction between the previous two variables, *i.e.*, η is the coefficient of interest in this case; ε_{pwym} is the error term. To estimate equation (1) we generate a person/month dataset, *i.e.*, each record presents the situation of each person in a given month.

The main interest of the present exercise is to estimate the model separately for each administrative region in Italy. This generates a set of three estimated coefficients of interest ($\hat{\beta}_r$, $\hat{\delta}_r$ and $\hat{\eta}_r$, where r={1,...,20}) for each of the twenty Italian regions. Studying the heterogeneity of these coefficients, *i.e.*, the reasons why the impact of EPL reduction and hiring incentives may have been different across regions, is the specific goal of the second step of our analysis. All regions indeed face the same institutional environment, but quite different economic settings with respect to sectors, infrastructures, and legality enforcement. All such macro socio-economic drivers are quite correlated with each other; furthermore, the very limited number of observations (twenty for each estimated coefficient) prevents the option to regress the set {$\hat{\beta}_r$, $\hat{\delta}_r$, $\hat{\eta}_r$} directly on them. We need therefore to reduce the number of drivers to save on degrees of freedom, trying to minimize the loss of variance explained by the socio-economic drivers. One possible solution, which we adopt, is to perform a Principal Component Analysis (PCA), which provides orthogonal components summing up the information of several – correlated – macro variables.

To be more precise, through PCA, the total variance represented in the set of socio-economic drivers we choose (see section five) is rearranged in uncorrelated principal components. The estimated principal components are then sorted by decreasing share of covered variance and, for the sake of efficiency, only the first $K'<K$ components are used in second-step estimation as explanatory variables of {$\hat{\beta}_r$, $\hat{\delta}_r$, $\hat{\eta}_r$}, under the criterium that a large share of socio-economic variance is represented. In fact, as we will see below, the first four components already cover nearly 90% of the total variance. In symbols, our second-step estimation reads:

$$\hat{\varphi}_r = \xi_0 + \sum_{1}^{K'} \xi_k X_{kr} + \epsilon_r \quad 2)$$

where $\hat{\varphi}_r$ is one of the estimated vectors {$\hat{\beta}_r$, $\hat{\delta}_r$, $\hat{\eta}_r$}, ξ_0 is a constant term and X_{kr} are (the predicted scores of) the principal components retained in the models.

Studying graphically the factor loadings, *i.e.*, the 'bearing' of the original socio-economic drivers on the components with a significant impact on $\hat{\varphi}_r$ according to equation (2), we will be able to identify the macroeconomic features that determine regional heterogeneity in the estimated impacts {$\hat{\beta}_r$, $\hat{\delta}_r$, $\hat{\eta}_r$}.

3 We are not able here, due to data limitations, to reproduce the exact threshold measure computed in Ardito *et al.* (2023).

4. Data

The dataset we use is built elaborating on two datasets derived from administrative sources. The first is LoSaI (Longitudinal Sample INPS), a sample of individual work histories extracted from the records of the Italian National Social Security Institution, INPS. The second is CICO (Campione Integrato Comunicazioni Obbligatorie), a sample of work relations of employees, extracted from SISCO (Sistema Informativo Statistico delle Comunicazioni Obbligatorie). We merge LoSai and CICO in a probabilistic way in order to add to the LoSaI archive a variable that is crucial for our exercise and that LoSaI does not record: the region of work. Annex A1 details the characteristics of the two datasets and the matching procedure is published in a public repository[4]. We then select the records according to the provisions of the law: we exclude domestic workers hired by households, public sector workers and those in the

Table 1. Macro drivers, summary statistics, 2015

Region	Take-up rate	University	Female	Non-regular employees	Non-reg. VA	Over 50	Manufacturing	Health & Edu.	Non-EU	Innovation	P.c. GDP	P.c. VA
Val D'Aosta	0.633	0.096	0.406	0.096	0.044	0.255	0.155	0.069	0.080	5.6	36590.1	32808.3
Piemonte	0.697	0.138	0.408	0.102	0.040	0.277	0.384	0.058	0.072	9.0	28921.5	25955.5
Liguria	0.631	0.130	0.373	0.116	0.044	0.255	0.167	0.052	0.088	36.1	30320.6	27124.0
Lombardia	0.592	0.163	0.407	0.104	0.036	0.239	0.295	0.040	0.109	7.9	36583.4	32713.2
Veneto	0.652	0.120	0.419	0.090	0.037	0.245	0.387	0.039	0.113	8.1	30868.5	27690.3
Trentino-Alto Adige	0.609	0.102	0.411	0.094	0.040	0.244	0.221	0.044	0.111	9.5	39706.4	35646.1
Friuli-Venezia Giulia	0.708	0.135	0.409	0.100	0.039	0.270	0.381	0.061	0.119	8.4	29588.2	26606.1
Emilia-Romagna	0.644	0.146	0.445	0.098	0.040	0.271	0.351	0.056	0.123	10.6	33622.1	30157.0
Toscana	0.613	0.134	0.436	0.108	0.045	0.266	0.324	0.050	0.119	7.4	29519.1	26454.8
Marche	0.698	0.135	0.431	0.104	0.046	0.269	0.446	0.055	0.108	6.4	25703.1	23251.7
Umbria	0.733	0.123	0.423	0.132	0.057	0.256	0.313	0.053	0.093	7.3	24277.7	21949.8
Lazio	0.720	0.184	0.397	0.155	0.053	0.329	0.090	0.045	0.065	10.7	32283.9	28992.1
Abruzzo	0.689	0.121	0.377	0.148	0.058	0.254	0.337	0.050	0.088	5.8	23908.1	21656.8
Molise	0.704	0.123	0.402	0.152	0.063	0.256	0.201	0.104	0.060	11.1	19433.6	17730.9
Campania	0.680	0.108	0.337	0.193	0.085	0.239	0.194	0.071	0.055	7.0	17880.2	16088.8
Basilicata	0.738	0.099	0.340	0.140	0.056	0.246	0.253	0.083	0.039	3.6	21205.7	19450.2
Puglia	0.693	0.097	0.374	0.161	0.071	0.244	0.202	0.073	0.042	5.6	17456.7	16041.4
Calabria	0.691	0.115	0.370	0.220	0.098	0.221	0.117	0.087	0.046	4.2	16373.3	14826.1
Sicilia	0.692	0.098	0.354	0.187	0.078	0.232	0.132	0.106	0.037	7.3	17121.6	15439.0
Sardegna	0.740	0.106	0.414	0.156	0.054	0.255	0.120	0.098	0.024	7.2	20308.1	18428.3

Source: Istat, CGIA and CICO-LoSaI merged data. Notes: innovation expenditure is in thousands of Euros. Innovation, GDP and Value Added are in 2015 Euros

4 See https://bit.ly/40Jp94P.

agricultural sector, who are not subject to the policy measures under scrutiny. In addition, we exclude job transitions in the tourism sector, due to its high seasonality. Finally, the contracts considered are fixed-term dependent contracts and apprenticeships. The final dataset includes around 947,549 work relations involving 543,825 workers and almost 338,824 firms. As we explained above, we also use macroeconomic data at the regional level. They are mostly drawn from the National Statistical Office data (Istat: per-capita GDP and value added; the share of female, high-educated, non-EU and over-50 workers among dependent employees of the private sector; also, the share of dependent employees in the manufacturing sector and that in healthcare and education, again excluding the public administration; per-employee expenditure in innovation activities in private firms sized ten or more), but also from our merged CICO-LoSaI data (the take-up rate of the hiring incentive) and the Statistical Office of the Craftsmen and Small Business Association (CGIA: share of non-regular employment on total employment and share of non-regular value added on total value added). All these descriptors are tracked in 2015, *i.e.*, the year in which both the reforms under scrutiny were enforced and the year to which our analysis refers (the first semester of 2015). Table 1 presents some summary statistics on the macro drivers.

5. Results

First, we estimate equation (1) separately for each of the twenty Italian administrative regions (Table 2, columns 1-3). We also estimate the same model excluding very small firms (1-5 employees) and larger ones (more than 30 employees) in order to focus on a more homogeneous group of firms and further reduce issues of unobserved heterogeneity, but also to provide the readers with a closer look at SMEs (Table 2, columns 4-6). It emerges a relevant heterogeneity by region, both in the complete and even more in the selected sample. In general, incentives ($\hat{\beta}_r$) have a positive and significant effect on contract transformations within the firm, although not in all regions. Reduced firing costs ($\hat{\delta}_r$) mostly show a non-significant impact, instead. However, when interacted to incentives ($\hat{\eta}_r$) they usually (but not always) display a negative and significant effect in the sample including all firms, while it becomes generally non-significant in the selected sample. When split by gender (Annex A2, Tables A2.1- A2.2), our analysis reproduces the same narrative.

Size and significance of the estimated effects vary across regions following a pattern that is not immediately clear. To shed more light on this we perform a PCA to identify the main drivers of the socio-economic differences among regions. Twelve components are identified, but as Figure 2 shows, the first five components already cover more than 90% of the variance in the drivers. Since component 5 will turn out to be non-significant in any of the regressions described below (Table 3), however, we stop with components 1-4[5].

In order to give an economic meaning to the significant components, in Figure 3 we compare them through their factor loadings, as a way to understand which of the socio-economic drivers described above have a heavier bearing on them. Component 1 (representing 68% of total variance) captures the regions with high GDP and value added per capita, and low non-regular economic activity. Component 2 (13%) is driven by regions with a high take-up rate, a high share of workers aged 50 or more, and a low per-employee expenditure on innovation activity. Component 3 (12%) has instead a relatively higher per-employee expenditure in innovation and a low share of employees in the manufacturing sector. The way component 4 qualifies is less clear-cut – and the share of covered variance rather small (around 6%); however, one may argue that some higher shares of manufacturing workers and of non-regular economic activity are present.

Socio-economic drivers are: per-capita GDP and value added; share of female, high-educated, non-EU and over-50, manufacturing, health&education workers among dependent employees of the private sector; per-employee expenditure in innovation activities in private firms sized ten or more; take-up rate of the hiring incentive; share of non-regular employment on total employment and share of non-regular value added on total value added.

We are now in a position to turn to the analysis of the determinants of the regional variability of the estimated impacts of the reforms under scrutiny. The dependent variables of model in equation (2)

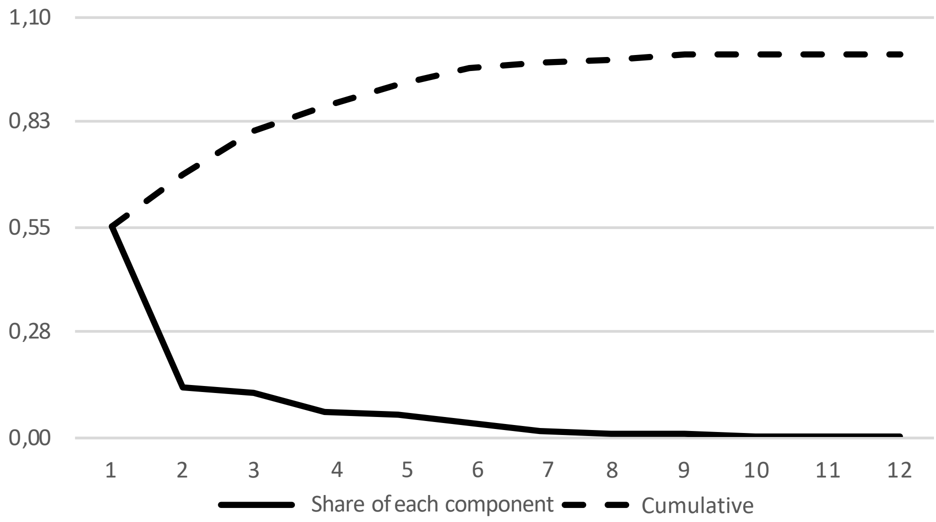
5 Estimates of equations (2) including component 5 among the regressors do not alter the results and are available upon request.

Table 2. Estimates from model (1): impacts of hiring incentives, EPL reduction and interaction

	Full sample			Firms sized 6-30		
Region	**Hiring incentive**	**EPL reduction**	**Interaction**	**Hiring incentive**	**EPL reduction**	**Interaction**
Val D'Aosta	0.007 0.007	0.016 0.024	-0.013 0.024	0.003 0.016	0.060 0.061	-0.057 0.062
Piemonte	**0.021***** 0.003	**-0.013***** 0.004	**-0.008**** 0.004	**0.042***** 0.006	-0.007 0.007	0.003 0.010
Liguria	**0.015***** 0.004	0.011 0.008	**-0.020***** 0.008	**0.027***** 0.008	0.012 0.014	-0.010 0.017
Lombardia	**0.023***** 0.002	**-0.012***** 0.003	**-0.009***** 0.002	**0.044***** 0.004	**-0.010**** 0.005	**0.011*** 0.006
Veneto	**0.013***** 0.002	-0.003 0.003	**-0.006*** 0.003	**0.021***** 0.004	-0.007 0.005	**0.016**** 0.007
Trentino-Alto Adige	0.007 0.004	0.001 0.006	0.004 0.006	**0.013*** 0.007	0.019 0.014	-0.018 0.014
Friuli-Venezia Giulia	**0.017***** 0.005	-0.008 0.007	-0.011 0.007	**0.030***** 0.010	0.011 0.020	-0.003 0.023
Emilia-Romagna	**0.017***** 0.002	-0.003 0.003	**-0.008**** 0.003	**0.032***** 0.004	-0.005 0.005	0.002 0.007
Toscana	**0.019***** 0.003	-0.004 0.004	**-0.009**** 0.004	**0.028***** 0.005	0.002 0.008	-0.008 0.010
Marche	**0.018***** 0.004	-0.002 0.006	-0.007 0.006	**0.020***** 0.007	0.001 0.011	0.012 0.015
Umbria	**0.024***** 0.006	-0.009 0.008	-0.013 0.009	**0.043***** 0.013	-0.004 0.018	-0.011 0.025
Lazio	**0.023***** 0.003	-0.003 0.004	**-0.017***** 0.004	**0.037***** 0.005	0.002 0.007	-0.010 0.009
Abruzzo	**0.021***** 0.004	0.010 0.008	**-0.023***** 0.008	**0.023***** 0.008	0.009 0.018	0.007 0.021
Molise	-0.004 0.020	-0.029 0.023	0.023 0.022	-0.024 0.037	-0.035 0.029	0.026 0.031
Campania	**0.015***** 0.004	-0.001 0.005	**-0.010**** 0.005	**0.024***** 0.007	-0.001 0.012	-0.007 0.013
Basilicata	**0.027**** 0.010	0.019 0.017	**-0.037**** 0.016	0.018 0.017	0.002 0.033	-0.025 0.035
Puglia	**0.011***** 0.004	-0.005 0.005	-0.006 0.005	**0.019***** 0.006	0.002 0.014	-0.009 0.015
Calabria	0.006 0.008	0.000 0.011	-0.008 0.011	0.021 0.016	-0.028 0.035	0.021 0.036
Sicilia	**0.015***** 0.003	-0.004 0.005	**-0.012**** 0.005	**0.019***** 0.007	-0.005 0.010	-0.001 0.012
Sardegna	0.005 0.009	-0.007 0.011	0.000 0.011	0.010 0.018	-0.023 0.017	0.023 0.019

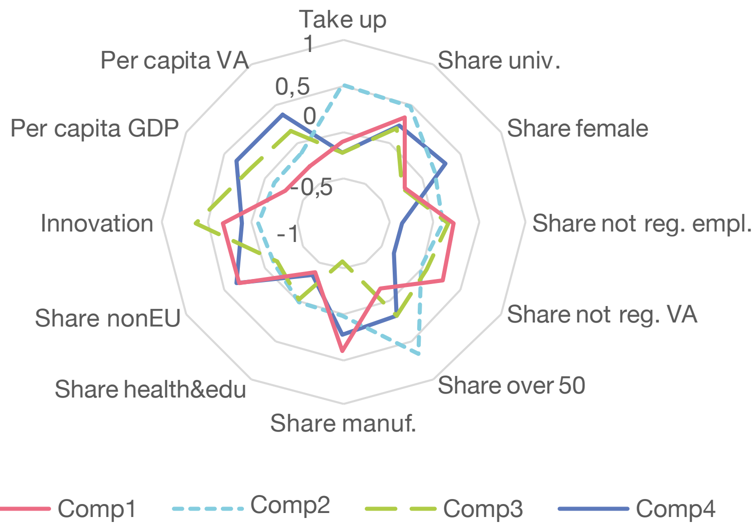
Notes: robust standard errors in second lines; *** 1% significant; ** 5% significant; * 10% significant.
Source: own computations on CICO-LoSaI merged data

Figure 2. Share of variance captured by the principal components



Source: own computations on Istat, CGIA and CICO-LoSaI merged data

Figure 3. Factor loadings of components 1-4



Source: own computations on Istat, CGIA and CICO-LoSaI merged data

will be from both the full and the reduced-sample estimates from Table 2, and $\hat{\eta}_r$ from the full sample only. All the other vectors of impact estimates, indeed, are zero-inflated, and results are likely to be driven by the behaviour of single regions. Table 3 displays the estimates of equation (2). Three messages emerge. First, regression of the interaction coefficient $\hat{\eta}_r$ on components 1-4 returns very limited information: only component 3 appears significant, but only at 10%; R-squared is low and the F-statistics does not fully ensure that the estimated model is different from one with no regressors at all. For these reasons, we will focus on the results about $\hat{\beta}_r$. Second, components 2 (high take-up rate, high share of mature workers, low innovation) and 4 (non-regular economic activity, manufacturing sector) appear relevant to explain the heterogeneity in the impact of the hiring incentives, on both the full and the reduced samples. Third, with firms sized 6-30 also component 1 (high per capita GDP and VA, low non-regular economic activity) emerges as a relevant source of heterogeneity. The evidence from the SMEs sample – more reliable as far as the

Table 3. Estimates from model (2)

	$\hat{\beta}_r$ (incentive), full sample	$\hat{\delta}_r$ (interaction), full sample	$\hat{\beta}_r$ (incentive), firms 6-30
Component 1	0.0009 0.266	0.0003 0.732	**0.0031***** 0.007
Component 2	**0.0028***** 0.003	-0.0008 0.274	**0.0037**** 0.012
Component 3	-0.0010 0.215	**-0.0023*** 0.087	0.0006 0.757
Component 4	**0.0050***** 0.004	0.0025 0.260	**0.0083***** 0.000
R-squared	0.4599	0.1391	0.6138
F-statistics (Prob > F)	**7.85***** (0.0013)	**3.29**** (0.0399)	**12.98***** (0.0001)
Observations	20		

Notes: p-values from robust standard errors in second lines; *** 1% significant; ** 5% significant; * 10% significant.
Source: own computations on Istat, CGIA and CICO-LoSaI merged data

estimation of the impacts of the reforms (Model 1, Table 2) is concerned, as it further reduces the room for unobserved heterogeneity – may therefore appear partially contradictory, in as much as while component 1 captures a low share of non-regular economic activity, component 4 does the opposite. However, once one considers that component 4 only captures 6% of total variance – with component 1 capturing almost 70% – and that the loading of component 1 towards a low share of non-regular economic activity is relatively much more pronounced than the loading of component 4 towards a high share, one may deem component 1 to be dominant.

All in all, therefore, we can conclude that the impact of hiring incentives on the probability to switch from temporary to open-ended employment has been larger in regions characterized by a stronger socio-economic and institutional fabric (high per-capita GDP and VA, low share of non-regular economic activity, high take-up rate of the incentives) and more mature production processes (lower per-employee innovation expenditure, higher share of workers aged 50 or more).

The analysis by gender (Annex A2, Table A2.3), eventually, lets us enrich the picture with two more messages. First, the evidence depicted so far is brought by male workers. On the one hand, indeed, regressions of $\hat{\beta}_r$ (*i.e.*, the regional impacts of the hiring incentives) on the four main principal components, closely mirror those reported in Table 3 when the $\hat{\beta}_r$ are estimated on the subsample of male workers only (Table A2.3, upper panel). On the other hand, the same regressions for the subsamples of female workers (Table A2.3, lower panel) generally display lower R-Squared and F-Statistics (to the point of non-significance in the subsamples of SMEs), as well as non-significance of the ξ_k parameters estimated from model (2). Second, for male workers only model (2) shows some explanatory power also for the interaction effects $\hat{\eta}_r$ in the full sample with no firm-size restrictions. More precisely, the interaction effect of the hiring incentives with the reduced EPL tends to be lower (*i.e.*, more negative) where components 3 (high per-employee innovation expenditure, low share of manufacturing workers) and 4 (non-regular economic activity) are more present. In other words, the combination of hiring incentives and weaker employment protection reduces the positive effects of the incentives on contract transformation more in regions with high non-regular economic activity, high innovation expenditure and a low share of manufacturing workers.

We are now in a position to draw some concluding remarks.

Concluding remarks

This paper contributes to the existing literature on wage subsidies, EPL reforms and their interaction focusing on regional disparities within the same country. The interest of the exercise relies on highlighting different reactions to the same reforms of the same institutional framework, depending on local economic and social conditions. After estimating the short-run causal effect of the mentioned reforms in each administrative region, we focus separately on the estimated impacts of hiring incentives, decreased EPL and their interaction to single out to which macro measures at the regional level can their variability be attributed. As many regional characteristics might be relevant, and acknowledging that they are quite correlated, we perform a principal component analysis and then regress each of the estimated impacts on the components. In this way, several patterns emerge. The impact of incentives on generating permanent contract relationships is higher in regions with a stronger socio-economic and institutional fabric (as measured by per-head GDP and value added, informal economy and the take-up rate of the hiring incentives) and a more mature production process *(i.e.*, with a higher share of workers aged 50 or more and a lower propensity to innovate). Reduced firing costs are never significant as a direct impact, and seldom significant (negative) when interacted to wage incentives. Hence in this case no detectable pattern across regions emerges. The analysis by gender highlights that the bulk of the effects in terms of hiring incentives is carried by male workers, for whom some potential role of socio-economic regional heterogeneity emerges also in explaining the interaction effects of incentives with (reduced) employment protection; indeed, such interaction reduces the probability to get an open-ended contract more where non-regular economic activity and manufacturing are more present, and innovation widespread. All in all, we can conclude that regions where the economy is stronger are also those benefiting more from generous wage subsidies. This pattern might exacerbate inequality across territories, a quite serious problem already present in Italy. Territorial disparities are linked to several dimensions of social exclusion, as discussed for the UK in Amin (2022), and policies should be more aware of these unintended side effects of interventions.

Annex A1. Data

This annex describes the construction and validation of the dataset on which the econometric analysis is run. The procedure to implement the probabilistic matching between LoSaI and CICO is published in a public repository[6]. As a first step, it is important to give an account of the potentiality of the existing data in providing a source of information suitable for our analysis, which is directed to the evaluation of the impact of hiring incentives and reduced firing costs on young workers' probability of obtaining permanent contracts (Table A1.1). The two data sources, CICO and LoSaI, are disseminated by the Ministry of Labor and Social Policies[7] but are built on different archives. CICO is structured as a register of employment relations and is a 48-date sample of the compulsory notifications that employers, public and private, send to the Ministry of Labor and Social Policies, to which a sample of autonomous workers is added. As far as our study is concerned, the source includes detailed information on hiring incentives since 2011. On the base of the available information, we can identify individuals eligible for such incentives by looking at previous work episodes, which are included in the sample as the sampling procedure is done at the individual level. However, contract transformations from temporary to permanent contracts are not recorded and cannot be identified either. On the contrary, the region where the job is performed+ is documented. Further information on the characteristics of the employment relationship is occupation, qualification, part-time and reason for termination. Half of the sample presents wages, the nominal wage communicated at the beginning of the contract. Individual characteristics are rich: gender, year of birth, education, qualification, citizenship, region of residence**.** The database does not include firm size information and therefore it is not possible to identify the set of firms affected by the changes in employment protection legislation.

Let's now consider the LoSaI dataset. The archive has an event structure. A new event is a change in the employment relationship that is relevant for social security, for instance, a change of contract type, job title, contract, qualification, work area, and so on. Therefore, the database has a panel structure and for each employment relationship there may be more records in the same year. Transformations to permanent contracts can be clearly identified as a new event is generated when the contract type is changed. A date of transformation can also be estimated on the base of the actual days of work that are registered for each episode, given the contract starting date. The database includes detailed information on the hiring incentives**,** in particular a variable that allows to identify the recipients of the latest social security contribution reliefs,

6 See https://bit.ly/40Jp94P.

7 See https://bit.ly/3JUAW9C.

Table A1.1. Summary of the available information in CICO and LoSaI

Characteristics	CICO Variable	LoSaI Variable
Beginning of work relation (day)	Rapporto_DataInizio	Data_assunzione
End of work relation	dtCessazioneEffettiva	Data_cessazione
Type of job contract	codTipoContratto	Tipo_contratto
Region of work	codRegioneLavoro	-
Salary	RetrMese_INPS (estimated)	Retribuzione_imponibile (final)
Type of incentive	codAgevolazione (up to 2012)	Tipo_politica
Qualification	codQualificaProfessionale	Qualifica
Contract trasformation	-	Not present but inferable
Cause of termination	codMotivoCessazioneCO	Motivo_cessazione
Sex	codGenere	SESSO
Age	AnnoNascita	ANNO_NASC
Education	codTitoloStudio	-
Citizenship	codCittadinanza	-
Region of living	codRegioneDomicilio	REGIONE
Firm identifier	cf_datore_crip	ID_AZIENDA
Year	-	ANNO
Firm size	-	CLASS_DIM
Sector of economic activity	-	ATECO07_2_CALC

Source: own representation

separating the three-year incentive established in 2015 (Tipo_politica == 51), the two-year hiring incentive that was then established in 2016 (Tipo_politica == 52, out of the scope of the present analysis) and other forms of hiring subsidies (Tipo_politica == 5).

The whole sample has information on wages, which are actual wages on which social security contributions are calculated. Additional information about the employment relationship is qualification, part-time, reason for hiring and reason for termination. The individual characteristics available are gender and year of birth. The database includes information on the size of the firm, organized in classes. Therefore, in addition to the perfect identification of actual and potential recipients of hiring incentives, the information is sufficient to identify the firm exposed to the changes in employment protection legislation. Unfortunately, two fundamental aspects are not covered and impinge on the possibility of fully relying on LoSaI: the region of work and education.

The strategy that we design to solve this issue is the following. We use LoSaI as the master dataset because it includes the possibility to identify employment relationships that are eligible for incentives, those incentivized and firm size, expressed as the number of employees. In addition, actual wages can be calculated. Nonetheless, LoSaI misses two important dimensions, namely the region where the job is localized and the highest education level achieved by the worker. Our strategy is to enrich LoSaI with CICO, which registers these dimensions. We opt for a probabilistic matching on individual work relationships on the sample of overlapping reference populations, while residually imputing the region of residence as the region of work for the remaining subset.

Data construction

Each dataset is elaborated and restructured as a panel of work relations uniquely identified by a worker identifier, a firm identifier (both consistent within each source, but not across them) and the start date of the employment relationship. The variables of the two datasets are harmonized. Then we move to the next stage which requires matching each individual in the LoSaI database to a single individual in CICO. In order to describe the method followed in the matching, we present an example. First, we implement a many-to-many matching over the following set of characteristics:

Table A1.2. Example of match and potential issues, drawn from the subsample 2012-2014

index	Id_losai	id_wr_losai	Id_cico	Start_date
1	L1	1	C1	28/05/2012
2	L1	2	C2	06/09/2012
3	L1	3	C1	03/12/2013
4	L1	3	C3	03/12/2013
5	L1	4	C1	09/12/2013
6	L1	4	C4	09/12/2013
7	L1	5	C5	01/04/2014
8	L1	6	.	05/05/2014
9	L1	7	C6	03/11/2014
10	L1	7	C7	03/11/2014
11	L1	7	C1	03/11/2014
12	L1	7	C8	03/11/2014

Source: LoSaI and CICO statistically integrated sample

- Work relation starting date (DD/MM/YYYY)
- Region of residence (21 NUTS2 region)
- Year of birth
- Sex
- Contract (Permanent or temporary)
- Time schedule (Full-time, part-time)

The many-to-many procedure allows more than one record in the using file (CICO) to be matched to the same record in the master file (LoSaI) and vice versa. An example is given in Table A1.2, where individual X in LoSaI is matched with 8 individuals in CICO.

The third work relation (id_wr_losai==3) is matched to two records in CICO, associated to id_cico C3 and C1. The latter is present three more times in the career, associated with id_wr_losai 1, 4 and 7. In the first case the match is perfect, while in the others more than one work relation is found. The work relations id_wr_losai 2 and 5 are associated with other CICO ids, while id_rl_losai is not associated with any CICO work relation. Therefore, the individual id_cico C1 is associated to the id_losai L1 in five out of seven valid cases.

We build an indicator to quantify the quality of the match. We measure the precision of the match between LoSaI and CICO at the individual level. For each individual in LoSaI, we count the number of observed work relations and the number of corresponding CICO individuals. The indicator is calculated as the number of recurrences of a CICO id over the total number of work relations observed for each individual in LoSaI:

$$PrecisionLoSai_{ij} = \frac{numberofmatches(idLoSai_j, idCico_{ij})}{numberofworkrelationsforidLoSai_j}$$

In the example presented above the id_cico with the highest number of matches is C1, with 4 matches on 7 work relations and a precision of 0.5714. The lowest possible precision (0) corresponds to the missing case, while the average precision is 0.1746 and informs us that we observe many low-volume matches with a high number of id_cico.

The single procedure on the whole sample is repeated iteratively. At each repetition, the individuals in LoSaI and CICO with precision 1 are excluded. The next iteration features a reduced set of individuals in both datasets and allows to use the same criterion to identify new full-precision matches. After a certain number of repetitions, no matches survive. In this case, we need to vary the parameters of the match, namely the list of features over which we perform the match and the threshold of precision. We opt for changing both parameters subsequently: for each level of precision (1, 0.75 and 0.5) we loop over four different keys, presented in Table A1.4, so that once we end iterating on the key for a level of precision, we lower the precision threshold and repeat the procedure over the same set of keys.

Validation

We use official INPS publications as a benchmark to assess the quality of our dataset in representing

Table A1.3. Summary measures of the precision of the match of L1, subsample 2012-14

Id_losai	Id_cico	Number of matches	id_wr_ losai_max	Precision	Precision min	Precision max	Precision avg
L1	C1	4	7	0.571429	0	0.571429	0.174603

Source: LoSaI and CICO statistically integrated sample

Table A1.4. Sets of keys used for matching

	Key
1	rapporto_datainizio [Work_relation_start_date], regione_abitazione [region_of_residence], codgenere [sex], annonascita [year of birth], contratto [permanent/ temporary], fulltime [fulltime/part-time]
2	rapporto_datainizio, codgenere, annonascita, contratto, fulltime
3	rapporto_datainizio_s, codgenere, annonascita, contratto, fulltime
4	rapporto_datainizio_m, codgenere, annonascita, contratto, fulltime

Note: rapporto_datainizio_s and rapporto_datainizio_m refer to the start date, coded to weekly bins or monthly bins respectively. The rationale is that we let the constraint be gradually less stringent by widening the time window on which work relations are matched.

Source: own representation

Table A1.5. New permanent contracts and conversions of temporary in 2015. Highlighted cells report computed values

	Hires				Conversions				Total			
	Our database		INPS		Our database		INPS		Our database		INPS	
	n	N	n	N	N	N	n	N	n	N	n	N
Total number of incentivized work relations	76,557	1,158,930	74,765	1,121,469	29,573	443,595	27,022	405,326	106,835	1,602,525	101,786	1,526,795
Total number of new work relations	148,598	2,328,495	130,545	1,958,181	39,231	588,465	35,585	533,770	194,464	2,916,960	166,130	2,491,951
% incentivized work relation on total		50%		57%		75%		76%		55%		61%

Source: LoSaI and CICO statistically integrated sample and INPS (2018)

stocks of workers affected by the hiring incentive. As we have seen above, the origin of our master database is LoSaI, which is a sample of social security records, simply restructured from a person-event structure to a work-relations structure. The subsequent enrichment of the information by means of statistical matching does not modify it. Therefore, having our sample the same theoretical reference population of the data used by INPS for the annual report 2018 (Inps 2018: Table 1.28, pages 67-68), we replicated their reported results. More specifically, we focused on the phenomena of interest, *i.e.*, contract activations, conversion, and incentives in 2015. Considering that LoSaI is a sample while INPS data are the whole population, we provide computed values for the population and a 24-dates sample respectively. Sample and population figures are then directly comparable. The comparison is presented in Table A1.5. The table reports the number of permanent contracts activated in 2015, except for apprentices, separating new hires and conversions from temporary contracts. We further compute the number of incentivized work relations in the group identified above and its prevalence. The table clearly shows that our attempt correctly estimates the number of incentivized work relations among new hires while overestimating the number of new activations. On the contrary, conversions are correctly estimated both in the number of incentivized and total numbers.

Annex A2. Analysis by gender

Table A2.1. Estimates from model (1): impacts of hiring incentives, EPL reduction and interaction; males only

	Full sample			Firms sized 6-30		
Region	**Hiring incentive**	**EPL reduction**	**Interaction**	**Hiring incentive**	**EPL reduction**	**Interaction**
Val D'Aosta	-0.004 0.009	0.024 0.026	-0.005 0.027	-0.015 0.022	0.068 0.065	-0.054 0.065
Piemonte	**0.024***** 0.004	**-0.015***** 0.005	**-0.009*** 0.005	**0.051***** 0.008	-0.003 0.010	-0.012 0.013
Liguria	**0.015***** 0.005	0.010 0.011	**-0.020*** 0.011	**0.029***** 0.011	0.018 0.021	-0.024 0.024
Lombardia	**0.026***** 0.003	**-0.012***** 0.004	**-0.010***** 0.003	**0.050***** 0.005	**-0.010*** 0.006	**0.016*** 0.008
Veneto	**0.017***** 0.003	0.000 0.004	**-0.009**** 0.004	**0.026***** 0.005	-0.003 0.007	0.014 0.010
Trentino-Alto Adige	0.005 0.006	0.005 0.008	0.007 0.008	0.007 0.008	0.028 0.020	-0.018 0.022
Friuli-Venezia Giulia	0.026*** 0.006	-0.006 0.009	-0.013 0.009	0.041*** 0.013	0.009 0.020	-0.003 0.025
Emilia-Romagna	**0.020***** 0.003	-0.001 0.004	-0.007 0.004	**0.041***** 0.005	0.002 0.007	0.003 0.010
Toscana	**0.024***** 0.004	-0.003 0.006	**-0.013**** 0.006	**0.033***** 0.007	-0.004 0.011	-0.006 0.013
Marche	**0.019***** 0.005	**-0.014*** 0.007	0.001 0.007	**0.020**** 0.010	-0.004 0.013	0.021 0.019
Umbria	**0.026***** 0.008	-0.007 0.010	-0.012 0.011	**0.046***** 0.017	-0.003 0.023	-0.004 0.033
Lazio	**0.024***** 0.004	-0.005 0.005	**-0.012**** 0.005	**0.042***** 0.006	0.003 0.009	-0.011 0.012
Abruzzo	**0.022***** 0.006	0.008 0.010	**-0.022**** 0.010	**0.034***** 0.012	0.018 0.033	-0.004 0.037
Molise	0.005 0.031	-0.036 0.033	0.027 0.033	-0.008 0.044	-0.039 0.036	0.031 0.041
Campania	**0.011**** 0.005	0.000 0.006	**-0.011*** 0.006	**0.017*** 0.010	-0.011 0.013	-0.003 0.014
Basilicata	**0.032**** 0.014	0.006 0.019	-0.026 0.018	0.031 0.023	0.007 0.042	-0.052 0.044
Puglia	**0.014***** 0.005	-0.003 0.006	-0.005 0.006	**0.015**** 0.007	0.003 0.013	-0.008 0.015
Calabria	0.007 0.011	0.006 0.015	-0.010 0.015	0.019 0.022	-0.034 0.046	0.060 0.049
Sicilia	**0.017***** 0.004	-0.005 0.006	-0.010 0.006	**0.015*** 0.008	-0.016 0.012	0.020 0.014
Sardegna	0.007 0.011	-0.002 0.016	-0.005 0.016	0.023 0.018	-0.015 0.019	0.008 0.022

Notes: robust standard errors in second lines; *** 1% significant; ** 5% significant; * 10% significant.
Source: own computations on CICO-LoSal merged data

Table A2.2. Estimates from model (1): impacts of hiring incentives, EPL reduction and interaction; females only

	Full sample			Firms sized 6-30		
Region	**Hiring incentive**	**EPL reduction**	**Interaction**	**Hiring incentive**	**EPL reduction**	**Interaction**
Val D'Aosta	**0.024**** 0.011	**-0.082*** 0.045	0.068 0.045	**0.028*** 0.015	-0.010 0.032	N.a.
Piemonte	**0.018***** 0.004	**-0.010*** 0.006	-0.007 0.006	**0.030***** 0.009	-0.015 0.011	0.025 0.015
Liguria	**0.016***** 0.006	0.013 0.010	**-0.019*** 0.010	**0.025**** 0.010	0.005 0.015	0.009 0.021
Lombardia	**0.019***** 0.003	**-0.011***** 0.004	**-0.006*** 0.004	**0.033***** 0.006	-0.008 0.008	0.005 0.010
Veneto	**0.009***** 0.003	-0.007 0.005	0.000 0.005	**0.014**** 0.006	**-0.015**** 0.007	**0.022**** 0.009
Trentino-Alto Adige	**0.013*** 0.007	-0.006 0.009	0.004 0.009	**0.022*** 0.012	0.004 0.014	-0.010 0.014
Friuli-Venezia Giulia	0.003 0.009	-0.012 0.013	-0.006 0.012	0.007 0.019	0.081 0.096	-0.071 0.097
Emilia-Romagna	**0.013***** 0.003	-0.006 0.005	**-0.009*** 0.005	**0.019***** 0.007	**-0.021***** 0.006	0.008 0.008
Toscana	**0.013***** 0.004	-0.006 0.005	-0.003 0.006	**0.023***** 0.006	0.009 0.013	-0.011 0.013
Marche	**0.017***** 0.005	0.021 0.013	**-0.027**** 0.013	**0.023**** 0.010	0.009 0.025	-0.005 0.028
Umbria	**0.023**** 0.010	-0.012 0.015	-0.015 0.015	**0.045**** 0.019	-0.004 0.032	-0.022 0.040
Lazio	**0.023***** 0.004	0.000 0.006	**-0.022***** 0.006	**0.031***** 0.007	0.000 0.011	-0.008 0.013
Abruzzo	**0.022***** 0.006	0.012 0.012	**-0.025**** 0.012	**0.010**** 0.005	-0.004 0.005	**0.021*** 0.013
Molise	-0.019 0.025	-0.009 0.023	0.012 0.019	-0.049 0.062	-0.005 0.035	-0.010 0.026
Campania	**0.022***** 0.005	-0.001 0.008	-0.010 0.008	**0.036***** 0.010	0.019 0.024	-0.018 0.026
Basilicata	0.020 0.015	0.053 0.038	**-0.066*** 0.037	-0.001 0.023	-0.032 0.025	0.047 0.040
Puglia	0.006 0.007	-0.008 0.011	-0.007 0.011	**0.027***** 0.010	-0.005 0.054	-0.006 0.054
Calabria	0.004 0.010	-0.012 0.016	-0.002 0015	0.020 0.020	-0.014 0.017	-0.019 0.014
Sicilia	**0.010*** 0.006	-0.003 0.009	-0.013 0.008	**0.024**** 0.011	0.020 0.020	**-0.043**** 0.020
Sardegna	-0.001 0.014	-0.019 0.011	0.013 0.012	-0.045 0.068	-0.058 0.056	0.065 0.058

Notes: robust standard errors in second lines; *** 1% significant; ** 5% significant; * 10% significant.
Source: own computations on CICO-LoSaI merged data

Table A2.3. Estimates from model (2), by gender

	$\hat{\beta}_r$ (incentive), full sample	$\hat{\delta}_r$ (interaction), full sample	$\hat{\beta}_r$ (incentive), firms 6-30
	Males		
Component 1	0.0013 0.177	**-0.0007*** 0.097	**0.0041***** 0.001
Component 2	**0.0031***** 0.005	-0.0003 0.638	**0.0058***** 0.005
Component 3	**-0.0019*** 0.070	**-0.0026***** 0.003	-0.0004 0.848
Component 4	**0.0050**** 0.014	**-0.0045***** 0.008	**0.0102***** 0.000
R-squared	0.4527	0.5216	0.6964
F-statistics (Prob > F)	**5.43***** (0.0066)	**31.79***** (0.000)	**15.48***** (0.000)
	Females		
Component 1	**0.0016**** 0.042	0.0003 0.853	0.0015 0.220
Component 2	0.0005 0.721	**-0.0029**** 0.029	-0.001 0.947
Component 3	0.0016 0.256	-0.0003 0.908	0.0023 0.322
Component 4	0.0017 0.583	-0.0015 0.692	0.0027 0.446
R-squared	0.2661	0.0566	0.1518
F-statistics (Prob > F)	**2.58*** (0.0802)	**3.70**** (0.0273)	1.11 (0.3863)
Observations		20	

Notes: p-values from robust standard errors in second lines; *** 1% significant; ** 5% significant; * 10% significant.
Source: own computations on Istat, CGIA and CICO-LoSaI merged data

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