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

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ABSTRACT

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 in highlighting different reactions to the same reforms of the same institutional framework, depending on local economic and social conditions. After estimating the 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 which macro characteristic at the regional level is responsible for their variability. Through a principal component analysis, we highlight that the impact of incentives on generating permanent contract relationships is higher in regions where GDP and VA per head are higher and where informal economy is limited; where a larger share of older workers and of take up rate of the incentive is present, where manufacturing and innovative activity are more present. Finally, we do not find any heterogeneity – and in most cases any impact at all – for the EPL component of the reform under scrutiny. All in all, we can conclude that regions where the economy is stronger are also those benefitting more of generous wage subsidies. This pattern might exacerbate inequality across territories, a quite serious problem already present in Italy.

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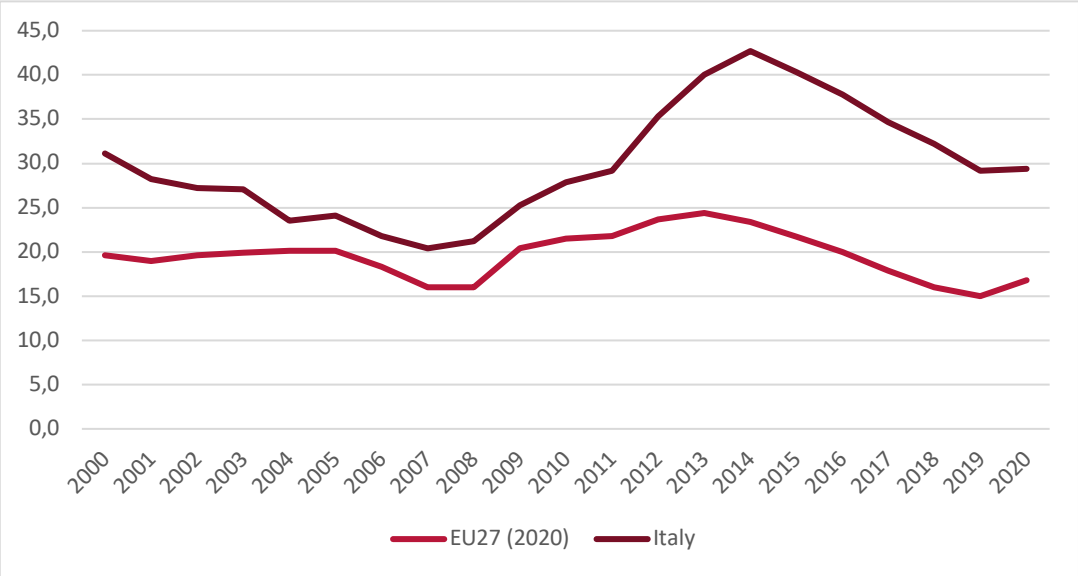
1. Introduction

For most countries, the last fifteen years represented an unusually long period of economic turmoil, during which crises of different origins but with comparable impact happened one after the other: those of sub-prime mortgages and of the 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.

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



Source: Eurostat data

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 grounds in all 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 binding EPL with generous hiring subsidies (OECD, 2010).

Italy – our case study here – widely mirrors 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., 2019; 2022; Sestito and Viviano, 2018), allow to identify their impact on workers' perspectives to get a stable employment. Our specific contribution here 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 i) with a high share of mature workers and a high take-up rate of the incentive, and ii) where the share of non-regular employment is larger. Narrowing our focus on firms sized 6 to 30, in order to reduce the room for unobserved heterogeneity in the DiD step of our analysis, a third group of regions – with high per-capita GDP – emerges for a higher impact of the hiring incentive. Conversely, we do not find any heterogeneity – and in most cases any impact at all – for the EPL component of the reform under scrutiny.

Our paper proceeds as follows: next section reviews the relevant literature, spanning from EPL to labour cost reductions. In section three we describe the institutional framework, and in section four the empirical strategy. Section five presents the data along with some descriptive statistics, while main results are in section six. Section seven draw some concluding remarks. The article is completed by an annex on data construction.

2. Review of the literature

Our contribution lays at the intersections 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 complicates if we take into account that the level of EPL is usually not homogeneous within a same labour market, as a consequence of the marginal nature of most labour market reforms during past decades, that 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 favour the inflows from temporary employment, and hence to reduce polarization (Boeri, 2011; Dolado et al., 2002). This would turn beneficial in particular 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 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, focussing on youths but more eccentric with respect to ours, is taken by those who study the so-called *port-of-entry hypothesis*. In this case, rather than analysing what happens to transitions from temporary to permanent employment when EPL on the latter is reduced, authors exploit variations in EPL of (different types of) temporary contracts to assess the prediction that an easier access to the labour market eventually favours, 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 (2021).

The second stream of literature to which our article makes a reference is on hiring subsidies or, more in general, policies for labour cost reduction. The theory provides a clear prediction: a lower cost of labour raises its demand, and so 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 geographical heterogeneity of EPL and incentive effects, our focus here. Research that takes advantage of international comparisons – although existing (e.g., Cingano et al., 2010) – suffers 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 labour 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. (2019) 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) analysed 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 analysed. In all these cases regional comparisons are precluded.

3. Institutional framework

Our pre-treatment setting is defined by the so-called “Fornero Law” (Law 92/2012), following the name of the Labour 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 a more generous protection against unfair individual dismissals than what happens in small firms. In the latter, in cases of an 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 worker, or to compensate her 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 under disciplinary reasons, the dismissed workers benefit from a monetary compensation ranging from twelve to twenty-four monthly salaries. For layoffs motivated under 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 of the monetary compensation described above.

According to many observers, Law 92/2012 failed to solve one of the major limitations of the Italian labour law, namely its high degree of uncertainty (Cavaletto and Pacelli, 2014). The first of the reforms under scrutiny in this paper, that 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 from 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 of wage 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 subsidies 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 labour market intervention across the relevant thresholds, is what we take advantage of to apply a DiD approach, as we describe below.

[1] To be precise: Decree 23/2015 – as the EPL-dedicated part of a broader labour 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.

4. Empirical strategy

In order to be able to estimate both the effect of the hiring subsidy and of the reduced firing cost, we adopt the following strategy. We focus on the probability of conversion from temporary to open-ended contract 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 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 the article 18 of the labour 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 focusses 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., 2019), demanding a non-linear duration model that is beyond the scope of the present exercise.

The estimation strategy is based on a linear probability model to estimate the probability of conversion to permanent contract π_{pwym} for a worker p that in 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 year y (2013 to 2015), month m (up to June 2015), specified as follows:

$$\pi_{pwym} = \gamma_p + \gamma_g + \gamma_w + \gamma_y + \gamma_m + \beta \mathrm{D}_{(\mathrm{w}=1)(\mathrm{y}\geq 2015)} + \delta D_{(g=+15)(y\geq 2015)(m\geq March)} + \eta \mathrm{D}_{(\mathrm{w}=1)(\mathrm{y}\geq 2015)} D_{(g=+15)(y\geq 2015)(m\geq March)} + \varepsilon_{pwym} \quad (1)$$

Where $\gamma_p, \gamma_g, \gamma_w, \gamma_y, \gamma_m$ are fixed effects for the corresponding characteristics; $D_{(\mathrm{w}=1)(\mathrm{y}\geq 2015)}$ 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; $D_{(g=+15)(y\geq 2015)(m\geq March)}$ 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; $\mathrm{D}_{(\mathrm{w}=1)(\mathrm{y}\geq 2015)} D_{(g=+15)(y\geq 2015)(m\geq March)}$ 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

[3] We are not able here, due to data limitations, to reproduce the exact threshold measure computed in Ardito et al. (2019).

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 $r = \{1, \dots, 20\}$) 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 among 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 in order to save on degree 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), that 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 K 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 total variance. In symbols, our second-step estimation reads:

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

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 $\{\hat{\beta}_r, \hat{\delta}_r, \hat{\eta}_r\}$.

5. 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). The Annex details the characteristics of the two datasets.

We merge LoSai and CICO in a probabilistic way (see the Annex for details) 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. 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 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 apprenticeship. 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 (first semester of 2015). Table 1 presents some summary statistics on the macro drivers.

Table 1 Macro drivers, summary statistics, 2015.

Region	Take-up	University	Female	Non-reg. empl.	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.

6. Results

First, we estimate equation (1) separately for each of the twenty Italian administrative regions (Table 2, columns 1-3). As a robustness exercise 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 (Table 2, columns 4-6). It emerges a relevant heterogeneity by region, both in the complete and 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 ($\hat{\delta}_r$) 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.

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 2shows, 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, however, we stop with components 1-4.[4]

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

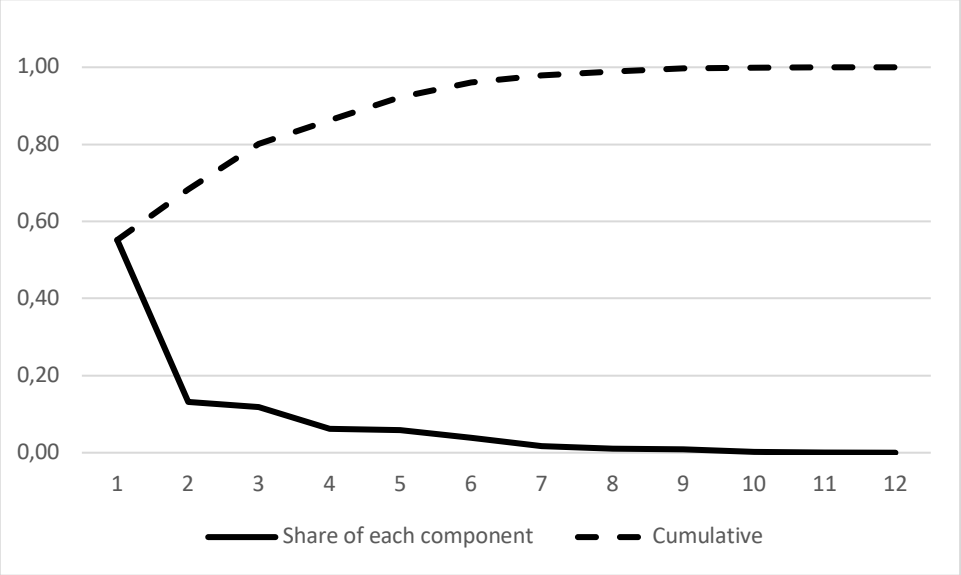
	Full sample			**Firms sized 6-30**		
	Hiring incentive	*EPL reduction*	*Interaction*	*Hiring incentive*	*EPL reduction*	*Interaction*
Val D'Aosta	0.007 0.007	0.016 0.024	-0.013 0.024	0.003 0.016	0.060 0.061	-0.057 0.062
Piemonte	**0.021***** 0.003	**-0.013***** 0.004	**-0.008**** 0.004	**0.042***** 0.006	-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

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

Marche	**0.018*** **	-0.002	-0.007	**0.020*** **	0.001	0.012
	0.004	0.006	0.006	0.007	0.011	0.015
Umbria	**0.024*** **	-0.009	-0.013	**0.043*** **	-0.004	-0.011
	0.006	0.008	0.009	0.013	0.018	0.025
Lazio	**0.023*** **	-0.003	**-0.017*** **	**0.037*** **	0.002	-0.010
	0.003	0.004	0.004	0.005	0.007	0.009
Abruzzo	**0.021*** **	0.010	**-0.023*** **	**0.023*** **	0.009	0.007
	0.004	0.008	0.008	0.008	0.018	0.021
Molise	-0.004	-0.029	0.023	-0.024	-0.035	0.026
	0.020	0.023	0.022	0.037	0.029	0.031
Campania	**0.015*** **	-0.001	**-0.010** **	**0.024*** **	-0.001	-0.007
	0.004	0.005	0.005	0.007	0.012	0.013
Basilicata	**0.027** **	0.019	**-0.037** **	0.018	0.002	-0.025
	0.010	0.017	0.016	0.017	0.033	0.035
Puglia	**0.011*** **	-0.005	-0.006	**0.019*** **	0.002	-0.009
	0.004	0.005	0.005	0.006	0.014	0.015
Calabria	0.006	0.000	-0.008	0.021	-0.028	0.021
	0.008	0.011	0.011	0.016	0.035	0.036
Sicilia	**0.015*** **	-0.004	**-0.012** **	**0.019*** **	-0.005	-0.001
	0.003	0.005	0.005	0.007	0.010	0.012
Sardegna	0.005	-0.007	0.000	0.010	-0.023	0.023
	0.009	0.011	0.011	0.018	0.017	0.019

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

Figure 2 Share of variance captured by the principal components



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

Dependent variables of model in equation (2) will be $\hat{\beta}_r$ from both the full and the reduced-sample estimates in 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 a 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 and 4 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 emerges as a relevant source of heterogeneity.

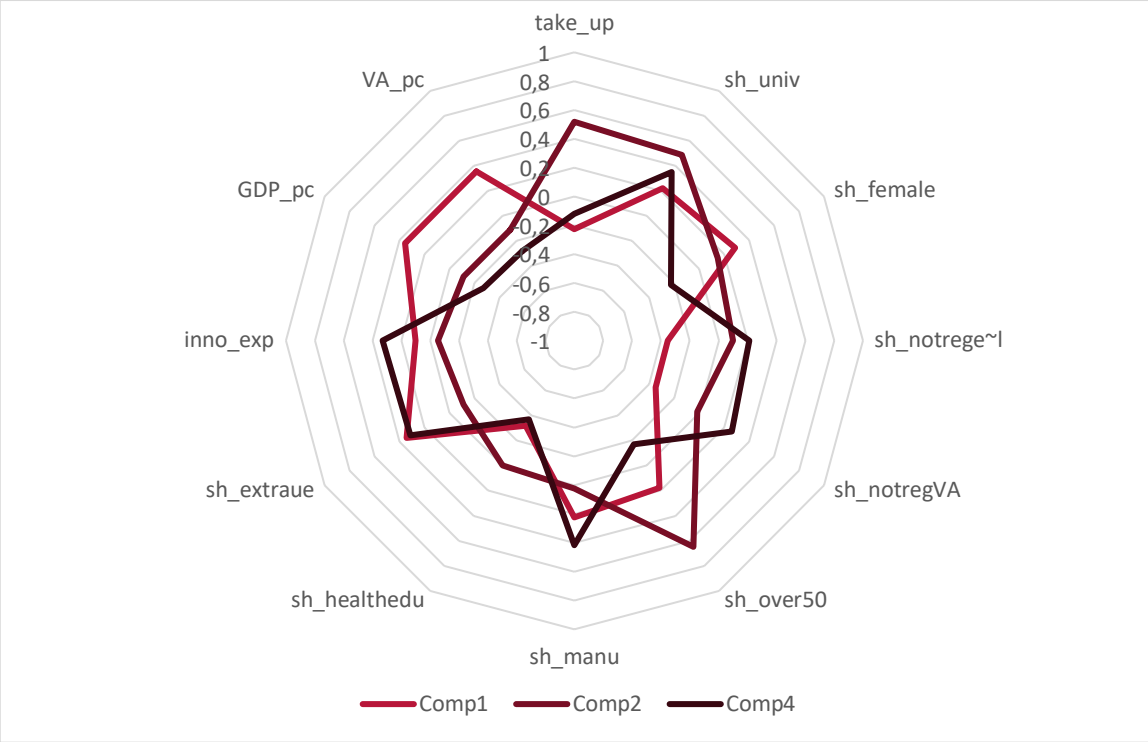
In order to give an economic meaning to the significant components, in Figure 3 we compare them through their factor loadings, as a way to understand which of the socio-economic drivers described above have a heavier bearing on them. Component 1, which positively affects the impact of the hiring incentives in the small sample, captures the regions with high GDP and value added per capita, and low non-regular economic activity. Component 2, that positively affects the same impact in both samples, captures instead regions with a high take-up rate and a high share of workers aged 50 or more, graduated and employed in the health private sector. The way component 4 qualifies is less clear-cut – and the share of covered variance smaller (around 6%); however, one may argue that some more innovation and non-regular economic activities are present.

Table 3 Estimates from model (2)

	$\hat{\beta}_r$ (incentive), full sample	$\hat{\eta}_r$ (interaction), full sample	$\hat{\beta}_r$ (incentive), firms 6-30
Component 1	0.0009359 0.266	0.0003291 0.732	**0.0031427***** 0.007
Component 2	**0.0028049***** 0.003	-0.0007969 0.274	**0.0036503**** 0.012
Component 3	-0.0009842 0.215	**-0.0022852*** 0.087	0.0005516 0.757
Component 4	**0.0050142***** 0.004	0.0025282 0.260	**0.0083401***** 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		

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

Figure 3 Factor loadings of components 1, 2 and 4



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

7. 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 in 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 impact on the components. In this way several patterns emerge. The impact of incentives on generating permanent contract relationships is higher in regions where GDP and VA per head are higher and where informal economy is limited (component 1); a larger share of older workers and of take up rate of the incentive (component 2) and of manufacturing and innovative activity (component 4). Reduced firing costs are never significant as a direct impact, and seldom

significant (negative) when interacted to wage incentives. Hence no detectable pattern across regions emerges.

All in all, we can conclude that regions where the economy is stronger are also those benefitting more of 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 this unintended side effects of interventions.

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Data annex

The construction of the dataset and its validation are an important part of this contribution. 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 impact of hiring incentives and reduced firing costs on young workers' probability of obtaining permanent contracts (Table 4). The two data sources, CICO and LoSaI, are disseminated by the Ministry of Labour and Social Policies[5] 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 Labour 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 to 2011. On the base of the available information, we can identify individuals eligible to 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 either be identified. On the contrary, the region where the job is performed is documented. Further information on the characteristics of the employment relationship is qualification, part-time and reason for termination and profession. 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 relation 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 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 in the job relation, 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 contribution reliefs introduced, 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).

[5] http://dati.lavoro.gov.it/microdati-la-ricerca

Table 4 Summary of 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 inferrable
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

The whole sample has information on wages, that 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, organised 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 to fully rely 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 actually incentivised and the firm size in term of employees. In addition, actual wages can be calculated. Nonetheless LoSaI misses two important dimensions, namely the region where the job is localised 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 region of work for the remaining subset.

Data construction

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

- 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) is matched to the same record in the master file (LoSaI) and vice versa. An example is given in Table 5, where individual X in LoSaI is matched with 8 individuals in CICO.

Table 5 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.

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:

$$PrecisionLoSai_{ij} = \frac{number\ of\ matches\ (idLoSai_j, idCico_{ij})}{number\ of\ work\ relations\ for\ idLoSai_j}$$

In the example presented above the id_cico with the highest number of matches is 5776467, 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.

Table 6 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	0.5714286	0	0.571429	0.174603

Source: LoSaI and CICO statistically integrated sample.

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 precision-1 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 7, 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.

Table 7 Sets of keys used for matching

	Key
1	rapporto_datainizio [Work_relation_start_date], regione_abitazione[6] [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 rational is that we let the constraint be gradually less stringent by widening the time window on which work relations are matched.

Validation

We use official INPS publications as a benchmark to assess the quality of our dataset in representing 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 tried and replicated the result reported. In particular we focussed 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 8. The table reports the number of permanent contracts activated in 2015, except from apprentices, separating new hires and conversions from temporary contracts. We further compute the number of incentivised work relations in the group identified above and its prevalence. The table clearly shows that our attempt correctly estimates the number of incentivised work relations among new hires while overestimates the number of new activations. On the

[6] CICO contains information on the place of living (variable codregionedomicilio) while LoSai registers the fiscal address of the worker (variable regione_residenza). Besides the information differs and we use them as a proxy for the place of residence.

contrary, conversions are correctly estimated both in the number of incentivised and total numbers.

Table 8 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 incentivised 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
% incetivised work relation on total		50%		57%			75%		76%			55%		61%

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

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