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Abstract. We study the causal effect of workplace unions on the adoption of advanced digital technologies in Italy. Using an IV approach that eliminates simultaneity bias and builds upon a lagged internal instrument combined with a measure of lagged political participation, we find that union presence encourages the probability of advanced digitalization by around 15 percentage points per year, and the number of different technologies adopted by 0.4, casting doubts on policies aiming at a weaker role for unions. Results survive when we drop cybersecurity and prove robust when the internal instrument is combined with propensity score matching or paired with an alternative measure of political capital.

Keywords: advanced digital technologies; unions; instrumental variables; political participation

JEL: J51; O14; O31

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1. Introduction

The advent of advanced digital technologies (hereafter ADT) such as robots, internet of things, and big data analytics is dramatically changing the world of work (Acemoglu and Restrepo, 2019). While the implications on job polarization are well understood (Autor and Salomons, 2018), economists devote increasing attention to the drivers behind their adoption (Cheng et al., 2019). Among them, little has been said about the role of employee organizations (hereafter EO; see Belloc et al., 2022).

The present article contributes to fill this gap by assessing the impact of workplace unionism on the adoption of ADT in Italy. In doing so, it expands on the debate on the effects of EO on technological expenditures (Berton et al., 2021). Negative views suggest that EO hold-up investments through wage-bargaining (Cardillo et al., 2015) and oppose labor-displacing technologies unless they automate dangerous or physically demanding tasks (Genz et al., 2019). Others advocate that the voice ability of EOs favors the introduction of organizational innovations complementary to technological restructuring (Antonioli et al., 2011) and reduce workers' flows, spurring investments through reduced turnover costs (Heavey et al., 2013) and higher human capital investments (Bellmann et al. 2018).

Few studies have explored the relationship between industrial relations and ADT. Some use aggregate data (Presidente, 2021). Others focus on Germany (Dauth et al., 2021; Genz et al., 2019). The study we feel closest to ours is Belloc et al. (2022), as we also use company-level data on Italy. Instead of relying on an RDD approach, however, we use an IV method. We deem our strategy preferable as the discontinuity in workplace representation exploited in Belloc et al. overlaps with another discontinuity in Italy's employment protection, which may affect autonomously the adoption of ADT.

Using a large and nationally representative survey of firms, we find that workplace EOs enhance the probability of introducing at least one ADT by around 15 percentage points per year, and the number of technologies adopted by 0.4. Results survive when we disregard cybersecurity and when we combine the internal instrument with propensity score matching or with an alternative measure of political participation.

2. Identification and data

Our instrument is built in two steps. First, we expand on Devicienti et al. (2018) and use the average incidence of unionized firms at 2-digit sector and NUTS1 regions in 2010 as a unique instrument. By doing so we preserve variability across sectors – a pivotal source of heterogeneity for both ADT and EOs – but we fail with respect to geographical variability, relevant as well. We therefore pair the internal instrument with a NUTS3-specific measure of political participation dating back in the past, namely the turnout at the 1974 abrogative referendum on divorce at the NUTS3-level. That political participation and union membership are tightly correlated is both intuitive and documented (e.g., Turner et al. 2020; Trentini, 2022). By using this lagged measure of political participation, in turn, we also contribute to the literature on historical explanations of current industrial relations outcomes (Bryson and Davies, 2019).

Our firm-level data source is RIL, a partially panel survey conducted by the National Institute for Public Policy Analysis on a nationally representative sample of firms in the Italian non-agricultural private sector. Observables include information on management and corporate governance, firms' productive characteristics, internal labor market and workforce composition in terms of gender, age, education, and contractual type. Crucial to us, RIL asks whether a workplace union currently exists and, in the 2018 wave, whether the firm adopted an ADT in the current or previous two years, to choose among i) Internet of things; ii) robotics; iii) big data analytics; iv) augmented reality, and v) cybersecurity.

Through province identifiers, we merge RIL to our measure of political participation, which is drawn from Nannicini et al. (2013). To allow for lagged regressors, prevent simultaneity bias and ensure a minimum of innovative activity, we focus on firms observed both in 2018 and 2015 and with at least ten employees: 6,974 firms survive in the sample. On average, 46.5% (20.6%) of them adopted at least an ADT in 2018, including (excluding) cybersecurity, with an average of 0.69 (0.29) per-firm innovations. The 2,641 unionized firms did it more frequently: 56.1% (27.4%) in terms of share and 0.86 (0.39) in absolute terms, while figures for non-unionized firms (4,333) are 43.8% (18.7%) and 0.64 (0.26) respectively.[1]

3. Specification and results

In the first stage of our 2SLS strategy we estimate linearly the following specification:

$$U_{i2015} = \alpha \overline{U}_{r,s\ 2010} + \delta X_{i\ 2015} + \sigma \mathrm{s} + \lambda \mathrm{p} + \varepsilon_{i\ 2015}$$

where $i =$ firm, $r =$ NUTS1 region and s the two-digit sector, U_{i2015} is a dummy for EOs, $\overline{U}$ is the lagged average presence of EOs, s (p) are sector- (province-) fixed effects, and X_{i2015} are controls on management, firm and workforce characteristics (Appendix A). This first-stage equation is then augmented with $\beta Div_{p,1974}$ – i.e. referendum turnout in 1974 – to improve on geographical variability of the instruments.

The predicted values of U_{i2015} ($\widehat{U}_{i2015}$) are then plugged into the second-stage equation:

$$Digit_{i2018} = \mu \widehat{U}_{i2015} + \tilde{\delta} X_{i2015} + \tilde{\sigma} \mathrm{s} + \tilde{\lambda} \mathrm{r} + \varepsilon_{i2018}$$

where $Digit_{i2018}$ is a dummy capturing firms that adopted at least one ADT or the number of such innovations, with and without cybersecurity; it is estimated linearly, with error terms

[1] See Devicienti et al. (2018) for the institutional background; Appendix A for descriptive statistics and https://inapp.org/it/dati/ril for RIL data.

clustered at the firm-level. Lagging U_i and X_i is necessary to ensure predeterminess. Estimates of μ must be divided by three to get per-year impacts.

Table 1 shows the estimation results: OLS appears in the first column for comparability, while IV in the last two.

Table 1. Estimation results

	OLS	*Internal instrument only (Devicienti et al., 2018)*	*Augmented with referendum turnout*
		Panel a - First stage	
$\hat{\alpha}$	-	0.706*** (0.033)	0.715*** (0.036)
β	-	-	-16.346*** (6.465)
F-statistic	-	451.43	202.02
# Obs.	6,974	6,969	6,508
		Panel b - Second or unique stage (for OLS): ADT (Y/N)	
$\hat{\mu}$	0.051*** (0.014)	0.461*** (0.043)	0.442*** (0.044)
Hansen J	-	-	1.867 (0.1719)
		Panel c - Second or unique stage (for OLS): ADT (Y/N) excluding cybersecurity	
$\hat{\mu}$	0.048*** (0.012)	0.474*** (0.047)	0.443*** (0.048)
Hansen J	-	-	0.104 (0.7474)
		Panel d - Second or unique stage (for OLS): number of ADTs	
$\hat{\mu}$	0.121*** (0.027)	1.280*** (0.111)	1.210*** (0.114)
Hansen J	-	-	1.170 (0.2795)
		Panel e - Second or unique stage (for OLS): number of ADTs excluding cybersecurity	
$\hat{\mu}$	0.075*** (0.020)	0.860*** (0.093)	0.804*** (0.093)
Hansen J	-	-	0.120 (0.7291)

Source: computations on RIL and Nannicini et al. (2013) data. **Notes:** Standard errors clustered by firm in parenthesis; the Hansen J test reports the p-value. For OLS we regress $Digit_{i2018}$ on U_{i2015} directly.

Both our exactly and over-identified IV estimates display first-stage F-values largely above the thresholds suggested in the literature (Baum et al., 2007), as well as significant first-stage coefficients, supporting the relevance of our instruments (panel a). Also, the overidentified models yield reassuring values of the Hansen test of overidentification (last column). The second-stage impact estimates are aligned across IV methods and prove the sizeable downward bias of OLS. They suggest that the presence of workplace EOs enhances the probability to adopt ADTs by around 15 p.p. per year (panel *b*), a magnitude in line with what Bryson and Dale-Olsen (2022) find in Norway for innovation in general. While ADTs affect the organization of production (with a-priori ambiguous effects on capital/labor substitution), cybersecurity should have no such organizational implications. This is why we re-estimate our models dropping cybersecurity. All our results are substantially confirmed (panel *c*). Panels *d* and *e* show the impact on the number of ADTs adopted, with and without cybersecurity: per-year estimates are no less than 0.4 and 0.26 respectively.

We test the robustness of our results in two directions. First, we reduce the room for unobserved heterogeneity in the exactly-identified specification by propensity-score matching firms with and without EOs before running the IV model. Then, we substitute referendum turnout with an alternative measure of political participation in the overidentified model, namely, the share of newspaper readers.[2] Results appear in Appendix B. PSM diagnostics show that the residual mean bias and Rubin's B-test are fine, while the Sianesi-LR and Rubin's R-test are not; estimates – displaying a higher magnitude of the effects: 0.26 (0.26) p.p. and 0.58 (0.39) in terms of probability of adopting an ADT and number of ADTs adopted respectively, including (excluding) cybersecurity – should be taken cautiously. Instead, results using the share of newspaper readers – which proves to be a valid instrument – in place of referendum turnout are perfectly aligned with those in Table 1.

4. Concluding remarks

The present article shows that workplace unions have a positive and sizeable effect on the adoption of advanced digital technologies in Italy. This may seem counterintuitive, as some of them such as robots may have labor-saving effects. The explanation may lie in the Italian two-

[2] Gentzkow et al. (2011) show that reading a newspaper increases the probability of voting by 4 percentage points.

tier collective bargaining system: since the most sensitive issues such as wages and safety are negotiated at the sectoral level, room is left for workplace representatives to engage in a productive social dialogue with managers (Kriechel et al., 2014). While the first-hand implication is that policies aimed at reducing union power should be implemented cautiously, it also suggests that unionism should be neither fully decentralized nor fully centralized, as each layer of industrial relations systems may have unique effects on economic performance.

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Appendix A: Descriptive Statistics

Table A1. Descriptive statistics, RIL components

Variable	*Mean*	*Standard Deviation*
Key variables		
At least one advanced digital technology (0/1)	0.465	0.499
At least one advanced digital technology - no cybersecurity (0/1)	0.206	0.405
Number of advanced digital technologies	0.691	0.920
Number of advanced digital technologies – no cybersecurity	0.291	0.651
Workplace union (0/1)	0.225	0.417
Management characteristics		
Tertiary education (0/1)	0.274	0.446
Upper-secondary education (0/1)	0.537	0.499
Lower-secondary or elementary education (0/1)	0.189	0.391
Female (0/1)	0.117	0.321
Family ownership (0/1)	0.840	0.366
External management (0/1)	0.049	0.215
Workforce composition		
Share with tertiary education	0.107	0.186
Share with upper-secondary education	0.466	0.284
Share with lower-secondary or elementary education	0.427	0.316
Share of executives	0.037	0.084
Share of white collars	0.369	0.295
Share of blue collars	0.593	0.316
Share of females	0.339	0.260
Share of workers with a fixed-term contract	0.109	0.183
Firm characteristics		
Involved in foreign trade (0/1)	0.376	0.484
Log of value added per employee	11.854	1.289
Age (years)	27.716	27.203
R&D (0/1)	0.127	0.333
No. of observations: 6,974		

Source: computations on the longitudinal component (2015-8) of RIL data. Notes: management characteristics are formalized as dichotomous variables, hence – e.g. – education refers to the highest attainment within management and gender to its head; workforce shares are computed with respect to total employment; explanatory variables are computed on 2015 wave (hence refer to 2014-5), dependent variables (i.e. measures of advanced digital technologies) on 2018 wave (and refer to 2015-7).

Table A2. Descriptive statistics, political participation components

Variable	*Mean*	*Standard Deviation*	*Observations*
Referendum turnout	0.878	0.074	91
Newspaper readers[a]	77.874	37.967	103

Source: computations on Nannicini et al. (2013) data; CONI is the Italian Olympic Committee. Figures here are not weighted by province population; (a) = every 1000 inhabitants.

Appendix B: PSM and share of newspaper readers

Table B1. Estimation results

	Internal instrument combined with PSM	*Internal instrument augmented with share of newspaper readers*
	Panel a - First stage	
$\hat{\alpha}$	0.510*** (0.106)	0.709*** (0.034)
β	-	-0.004* (0.002) [(a)]
F-statistic	22.97	214.41
# Obs.	5,219	6,808
	Panel b - Second stage: ADT (Y/N)	
μ	0.793*** (0.206)	0.445*** (0.044)
Hansen J	-	0.191 (0.6623)
	Panel c - Second stage: ADT (Y/N) excluding cybersecurity	
μ	0.792*** (0.226)	0.457*** (0.048)
Hansen J	-	0.934 (0.3340)
	Panel d - Second stage: number of ADTs	
$\hat{\mu}$	1,746*** (0.487)	1.242*** (0.113)
Hansen J	-	0.149 (0.6991)
	Panel e - Second stage: number of ADTs excluding cybersecurity	
$\hat{\mu}$	1.175*** (0.352)	0.834*** (0.094)
Hansen J	-	0.866 (0.3520)

Source: computations on RIL and Nannicini's data. **Notes:** Standard errors clustered by firm in parenthesis; the Hansen J-test reports the p-value; (a) p-value is 0.052.

Table B2. PSM diagnostics

Sample	*Ps-R2*	*LR chi2*	*P > chi2*	*Mean bias*	*Median bias*	*B*	*R*	*% Var*
Unmatched	0.123	1100.01	0.000	20.9	19.6	86.2	1.58	88
Matched	0.007	48.10	0.000	5.7	2.9	18.4	0.22	38

Source: computations on the longitudinal component (2015-8) of RIL data.