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The Effect of EU Funds on Labor Demand: the case of Italian Provinces

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The Effect of EU Funds on Labor Demand: the case of Italian Provinces

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Abstract

This article examines how EU structural funds affect local labor demand. Using Lightcast granular data on online-job postings in Italy, we match quarterly information on EU project disbursements with variations in labor demand at NUTS-3 provincial level. By relying on a shift-share type of instrument, we find that EU structural funds have a positive effect on the number of job postings. The resulting impact is mostly driven by the European Social Fund (ESF) and is particularly strong on jobs that require green and digital skills. Moreover, the results suggest that the effect on labor demand manifests itself only in areas with middle-high socio-economic conditions, while it is not significant in poorest areas. From a policy perspective, our findings point to a negative role played by EU structural funds in reducing geographical disparities in terms of employment opportunities across Italian provinces.

JEL Codes: C21, F35, H23, H77, R11

Keywords: EU Structural Funds; Labor Demand; Green and Digital Skills

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1. Introduction

As a relevant fraction of the EU budget has long been devoted to transfers aimed at reducing inequality among European regions (around one third in the period 2014-2020), the effectiveness of the EU cohesion policy has been under scrutiny since the 1990s. Several outcomes have been evaluated over time in the literature, although with a predominant focus on regional's aggregate economic growth (see Römisch, 2020; von Erlich, 2024). While an average positive growth effect is generally found (see for instance Becker *et al.*, 2012, 2010; and Lang *et al.*, 2023), questions persist regarding (i) the countercyclical role and the actual capacity of EU structural funds to reduce disparities across EU regions, (ii) the heterogeneity of the effect across type of funds and (iii) the channels through which it manifests itself.

Although the allocation of EU funds is predominantly targeted to poorer, peripheral, and less-developed European subnational areas, recent evidence suggests that EU structural funds hardly play any role in reducing polarization and regional disparities. Canova and Pappa (2025) found that lower income and peripheral EU regions do not take full advantage of the funds and generally do not help areas that are lagging behind – mostly because of government inefficiencies, lack of medium-term planning, shortage of entrepreneurship, or low average level of human capital. They also found considerable heterogeneity in the effect across type of structural funds: while European Regional Development Fund (ERDF) disbursements seem useful for short run stabilization purposes, the European Social Fund (ESF) is better suited to foster medium-term objectives. Becker *et al.* (2013) led to similar conclusions about the lack of inter-regional “catching-up” and relate the marginal impact of EU funds on low-income regions to their limited “*absorptive capacity*”, which in turn depends on the availability of human capital and high-quality institutions. In other words, according to Becker *et al.* (2013) funds are most effective where income per capita is already relatively high – i.e. in areas where private sector, human capital, governance and administrative capacity are sufficiently strong to turn allocated funds into a rise in economic growth. On the contrary, more deprived, poorer and peripheral areas – where most of EU's structural funds are allocated - tend to benefit very little or not at all from EU fund disbursements. Along similar lines, Becker *et al.* (2012) relate the limited role of EU funds in favoring convergence to the (i) non-linear returns of transferred funds and (ii) the big-push or poverty trap theory of development. More specifically, there might be a certain minimum threshold of allocated funds that must be exceeded in order for these transfers to become effective. By the same token, we might expect that the effectiveness of structural funds drops after a maximum desirable level of transfers – which follows the diminishing returns to investment and the standard neoclassical production theory (see Becker *et al.*, 2012 and Cerqua and Pellegrini, 2018).

While most of the literature looked at the aggregate economic growth effects, little is known about the effectiveness of EU structural funds in creating employment opportunities. On theoretical grounds, however, a positive growth effect doesn't necessarily lead to a stimulus in labor demand. Indeed, for instance, funds may stimulate the volume and change the structure of investment which foster automation and the adoption of labor substituting technology (Acemoglu and Restrepo, 2019). This channel is likely to be particularly relevant in the European context given the strong focus/effort of the EU in fostering a greener and digital economy. In support of this argument, Becker *et al.* (2010) show a positive and significant causal impact on economic growth of EU cohesion funds, but do not find any employment effects during the period in which transfers are allocated. In contrast, Mohl and Hagen (2011) find heterogeneous effects on employment depending on local human capital: specifically, EU structural funds are positively related to employment in areas with a low share of low-skilled population, and negatively associated with employment in regions with a high share of low-skilled population. Along similar lines, Arbolino *et al.* (2020) show that EU funds contributed to the resilience of Italian regional labor markets, although the impact on regional economies were conditional on the heterogeneous quality of local institutions. Finally, Coelho (2019) finds both

positive local output and employment multipliers. It must be noted, however, that all these studies which focus on labor market outcomes rely on standard aggregate employment indicators that do not provide accurate information on the capacity of EU funds to generate employment opportunities – as they describe a situation where the matching between supply and demand in local labor markets have already taken place. In the present study we address this issue by looking at the specific direct effects on labor demand.

EU structural funds are not alike, as they vary both in terms of aims, purposes and priorities. This heterogeneity in the type of funds is likely to lead to differentiated impacts on local labor market dynamics. For instance, while ERDF specifically included *employment* and *labor mobility* among its “priorities” in the 2021-2027 budget cycle, the same priorities were absent in the cycle 2014-2021.¹ On the contrary, ESF explicitly aims at improving employment, human capital, and education opportunities, by paying special attention to youth employment and the most vulnerable citizens at risk of poverty. Given the purpose and design of these programs, we can broadly and loosely classify ERDF as investments in manufacturing and research, while ESF should be regarded as investments for employment, human capital and education development (see Canova and Pappa, 2025). In this regard, Canova and Pappa (2025) rely on data for 281 NUTS2 EU regions and investigate the dynamic average multiplier effects for six regional macroeconomic variables of interest, separately for ERDF and ESF programs. According to their findings, only ESF funds have positive medium term average consequences – boosting the average growth rate of private output, investments as well as labor market outcomes such as employment, workers’ compensation and labor force participation. While our analysis is similar in spirit to Canova and Pappa (2025) - as we also distinguish structural funds across type of transfers - it differs in a number of dimensions. *First*, our focus is only on labor market dynamics, specifically on labor demand. *Second*, the empirical analysis is at a more disaggregated NUTS-3 provincial level for the Italian case. *Third*, by relying on a unique dataset on online job postings, not only we are able to disaggregate across types of transfers, but we also separately look at the effects of structural funds on different types of jobs, especially those requiring *digital* and *green* skills.

In this paper we focus on the effects of the main EU *structural funds* – namely ERDF and ESF - on the Italian labor market at geo-localized provincial level (NUTS-3) for the period 2014-2022. Contrary to most of the existing studies (see for instance Arbolino *et al.*, 2020; Cerqua and Pellegrini, 2018; Porro and Salis, 2017; Ciani and De Blasio, 2015 for the Italian case), we do not focus our attention to standard employment indicators; rather, we specifically concentrate on how *structural funds* affect local labor demand. Labor demand variations are more indicative of the capacity of local firms and institutions to turn funds into job opportunities: in principle, for instance, a demand stimulus for high-skilled labor may translate into poor employment performances in locations mostly characterized by low-skilled workforce. Indeed, slow hiring processes and (especially) skill mismatches are only two of several reasons why job vacancies might remain unfilled. We proxy for labor demand by relying on a unique dataset on online job postings provided by Lightcast.² The available information includes not only the location and the date of the job vacancy, but also the sector as well as the skills requested for the specific position. Although the dataset includes only job vacancies advertised online, several contributions demonstrate how Lightcast data on online job offerings are closely connected with the information collected in public employment centers - where available (see for example OECD, 2024). Similarly to the literature on foreign aid (see for instance Dreher *et al.* 2021), we address endogeneity concerns by relying on a

¹ In the 2014–2021 budget cycle the ERDF programme included the following thematic concentrations: (i) innovation and research; (ii) digital agenda; (iii) support for small and medium-sized enterprises; and (iv) low-carbon economy. The added themes for the 2021–2027 cycle are: (a) green transition, (b) labor mobility, (c) employment, (d) culture, (e) tourism, (f) health care support, and (g) urban development.

² See Woessman (2024) for a survey concerning the evidence on the link between multidimensional skills and earnings, and the matching between skill supply and demand, with a particular focus on Large Online Data Sources as Lightcast.

shift-share instrument where the probability of receiving structural funds is interacted with a plausibly exogenous component – namely the EU’s BoP balance value of financial intermediation services.

We find that *Structural Funds* have a positive effect on the number of job postings, particularly on those requiring green and digital skills. Interestingly, we find that the number of projects (extensive margin) has a stronger effect than the amount of the project disbursement (intensive margin) which seems compatible with the diminishing returns hypothesis. When the socio-economic conditions of provinces are considered, our results suggest that the impact on labor demand is particularly strong in the middle-high income provinces, while it is not significant in poorest areas. This finding is in line with results obtained by Becker *et al.* (2013) on the role of human capital and good-quality institutions for the effectiveness of cohesion policies. As expected, the effect of interest progressively decreases in magnitude over time: while the largest impact on labor demand comes from transfers disbursed a quarter before time t , funds disbursed more than a year before do not play any role in influencing labor market dynamics. In line with Canova and Pappa (2025), our results point to a heterogeneous impact across type of EU structural funds. We find that the aggregate impact of structural funds on labor demand is solely driven by ESF transfers, while ERDF doesn’t play any role in influencing labor market dynamics. This result is not fully surprising as *improving employment* appears among the key priorities of ESF funds, while it’s not part of the thematic concentrations of the ERDF – at least for the 2014-2021 budget cycle, which covers most of the period of our analysis. Finally, we also exploit the information on sectoral classification of online job postings and found that structural funds influence job offerings particularly in the production sector.

The structure of the paper is as follows. Section 2 discusses the data, the econometric specification and addresses endogeneity concerns. Section 3 presents the main results. Section 4 concludes.

2. Data, Econometric Specification and Endogeneity Concerns

Data on job postings are from Lightcast, which provides detailed information on online job openings including the date when the job opening appears online, the location of the firm/institution advertising the position, the sector as well as the skills required for any given job. For the purpose of our analysis we have aggregated the number of job postings at provincial level in Italy for each quarter-year and across skill levels over the period 2014-2022. More specifically, our focus is on the total number of job offerings across provinces, particularly those specifically requiring green and digital skills, which are the core sectors of the EU Green New Deal initiatives and are also important determinants of EU funds’ allocation decisions (see Canova and Pappa, 2025). Although fully aware that online job postings do not represent the entire national labor demand, the analysis of online job postings can provide interesting insights and can be considered a reliable benchmark/proxy of aggregate trends in labour demand, especially in recent years characterized by the growing and widespread use of digital platforms as a means of recruiting personnel. Although this is a very recent type of data, several contributions demonstrate how Lightcast data on online job postings are in line with the information collected in public employment centers - where available (see for example OECD, 2024). This indicates a close connection between the variations in online advertisements utilized in this paper and those of overall labor demand, both at national level as well as across regions and provinces.

As mentioned above, we aggregate at provincial NUTS-3 level the number and volume of EU’s *Structural Funds* - i.e. public fund disbursements from both the ERDF and the ESF. Data are from *OpenCoesione.gov.it* which also includes information on funded ERDF or ESF projects with private co-financing and public-private partnerships (PPPs). ERDF and ESF funds represent the majority of the aggregate volume of the European Structural and Investment Funds (ESIF) and practically all Italian regions receive funds from these programs. In addition, they are subject to the same rules as

far as programming, management, and monitoring are concerned (Canova and Pappa, 2025).³ The focus of our analysis is predominantly on public funded projects, which represent the lion share ($\approx 80\%$) of total financing in our period of interest (2014-2022). However, while we assume that both purely public funding and public-private partnerships positively influence and stimulate labor demand at local level, there might be heterogeneity in the aggregate effect across type of funds. We address this issue in one of our numerous robustness tests below and find that adding separately funds from public-private partnerships hardly influence the impact of funds' disbursements on labor demand.

The descriptive statistics reported in Figure 1 illustrates the pattern of EU funds' allocation and volume of job postings across Italian provinces. The evidence suggests an allocation pattern which significantly varies across provinces in terms of intensive (center panel) and extensive margins (right panel) of EU funded projects. Indeed, most funded projects are allocated in the north part of Italy, which is characterized by a relatively higher level of income and where labor markets are typically more dynamic. On the contrary, the value of disbursements per project is significantly higher in the South part of the country. In other words, bigger EU projects – those which have presumably a stronger positive effect on labor demand at local level – have been allocated in Southern provinces. By the same token, also the geographical distribution of job postings is heterogenous across Italian provinces, with most of online job offerings that are concentrated in the Center-North part of the country, particularly in urban areas (left panel). It must be noted that roughly the same geographical distribution of job postings across provinces applies when we separately analyze job offers that require green and digital skills, as shown in Figure 2.

Our baseline specification relies on the following model where the per-capita number of job postings in province i , sector k at time t is a function of the per-capita volume of EU investments:

$$\ln Y_{i,j,t}^{(k)} = S_{j,t} + S_{k,t} + S_i + \beta_1 \ln(EUinv_{i,t-1}^{(k)}) + \beta_2 X_{i,t-1} + \epsilon_{i,j,t}^{(k)} \quad (1)$$

$S_{j,t}$, $S_{k,t}$ are fixed effects that capture all time-varying (quarter-year) characteristics at sectoral and regional level, respectively, while S_i absorbs the effect of all time-invariant characteristics at provincial level. The term $X_{i,t-1}$ is a vector of origin-specific control variables at provincial level which include the per capita number of private firms (source: ISTAT and Unioncamere) as well as several indicators that proxy for the quality of local institutions (source: ISTAT) - such as the share of young mayors (<40 years old), population residing in municipalities with separate waste collection, as well as measures of irregularities in the electrical service and overcrowding of penal institutions. The main variable of interest $EUinv$ enters the model with a quarter-lag to partially mitigate potential reverse causality, i.e. the possibility that variations in labor demand affects EU investment inflows at the origin. The use of lagged values is also justified by the process of advertising job postings after the actual disbursements/acquisition of EU funds by private firms as well as public institutions, which is expected to take time. We also investigate whether the effect manifests itself through the intensive or extensive margins of EU disbursements, by exploiting the information available on the number (N) as well as the volume (€) of EU funded projects. $\epsilon_{i,j,t}^{(k)}$ is the error term.

The relationship between EU disbursements and labor demand in Equation (1) is potentially subject to endogeneity concerns - particularly reverse causality and omitted variables - which we address in several ways. Indeed, there might be factors that simultaneously affect both labour demand as well as project disbursements at provincial level that are not accounted for in the model. For instance,

³ The cohesion fund (CF) is not considered as it targets countries rather than regions, whose per-capita GNI is less than a fixed percent of the EU average.

provinces characterized by efficient institutions and a dynamic private sector might be more capable to attract EU projects and be more efficient in turning allocated funds into actual job offerings. By the same token, some of the decentralized regulations in force at provincial level in Italy (e.g. health care, education services, environmental regulations etc.) which might play a role in the capacity to turn allocated funds into job opportunities depends on the region the province belongs to. As for reverse causality, while it is true that EU funds could stimulate labor demand and lead to a higher number of offered online job positions in a given province, it might also be true that funds are allocated to areas characterized by a more active and dynamic local labor market (see Bouvet and Dall’Erba, 2010). It must be noted, however, that the evidence showed in Figure 1 and described above suggests that this concern potentially applies only to the extensive margin of EU funds’ allocation pattern.

To partially address all these issues, we include the per capita number of private firms at province-time level as a control variable in the baseline specification, along with several indicators that proxy for the quality of local institutions. Furthermore, Lightcast data on job postings available at sector level allows to deal with a relatively high number of observations in our sample and therefore include a set of fixed effects which absorb all time varying sectoral (j) and regional characteristics (k) - that might act as confounding factors in our model. Lastly, to test how long the EU funds’ effect on labor demand lasts over time and further attenuate reverse causality issues, we include up to six quarter lagged values of EU funds with respect to job posting variations.

More importantly, to address endogeneity concerns we rely on an instrumental variable strategy using a shift-share type of instrument along the lines of Dreher *et al.* (2021, 2019) and Lanati *et al.* (2023). More specifically, we construct the IV by interacting the lagged probability of receiving EU funds in a given province i with EU’s BoP values of *Financial Intermediation Services* (indirectly measured) / FISIM. More specifically, the first stage is specified as follows:

$$\ln(EUinv_{i,t-1}^{(k)}) = S_{k,t} + S_i + \partial_1 \ln \left[\sum_{i=1}^{(k \neq i)} EUfis_{i,t-1}^{(k)} * \overline{p_{i(k)}} \right] + \tau_{i,t-1} \quad (2)$$

We define the probability of receiving EU funds as $\overline{p_{i(k)}} = \frac{1}{36} \sum_{t=1}^{36} p_{i(k),t}$ where $p_{i(k),t}$ is a binary indicator assuming value one if province i hosts at least one EU project at time t . This term is interacted with the EU BoP value (exports minus imports) of financial intermediation services between residents and non-residents that are not directly charged but are implicit in interest rate spreads. Such constructed IV is plausibly related to the volume of funded EU projects in a given province under the commonly adopted assumption that an exogenous shock in the total supply of EU funds should affect the allocation of volume of EU investments proportionally. The coefficient ∂_1 indicates the correlation of the proposed instrument with the endogenous variable. We expect a positive correlation - as a positive *FISIM* balance indirectly strengthens domestic EU’s spending capacity by adding to the current account surplus. The first stage statistics reported in Table 3 confirm our conjectures, pointing to a strong positive and significant relationship between the proposed IV and the endogenous variable. In addition, the reduced form test suggests that the instrument affects the number of postings only through its correlation with the endogenous variable, while the Kleibergen-Paap (KP) F-statistic is above the conventional levels for most of the specifications, a fact that corroborates the validity of the instrument. At conceptual level, the exclusion restriction is expected to hold, as the BoP balance value of Financial Intermediation Services hardly plays any specific role in determining local labor market variations. However, given the model is exactly

identified we cannot perform a standard test for overidentifying restrictions, and therefore we cannot formally test for the exogeneity of the instrument.⁴

To substantiate our claim on the exogeneity of the proposed IV, we follow Dreher *et al.* (2021, 2019) and plot the trends displayed by per capita job postings and EU disbursed funds over time. One of the potential issues in the proposed IV strategy is the endogeneity of the time-invariant component of our instrument (Borusyak *et al.*, 2021). However, controlling for province fixed effects in model (2) reduces the identification strategy to a difference-in-differences framework. Hence – as pointed out by Dreher *et al.* (2021) - to prove that the exogenous variation in the provision of EU funds does not differentially affect local job postings, it is sufficient to show that the parallel trend assumption holds for provinces with a higher or lower probability to receive EU funds. Figure 3 shows that trends in EU funds and job postings do not overlap with the trend in the *FISIM balance* (bottom panel) and are parallel across the two groups (top panels), supporting our assumption on the excludability of the instrument.

Considering the grouped structure of the data in the model specification, within-cluster observations are likely to be correlated. It must be noted that since disregarding within-group correlations leads to downward-biased standard errors (see Shore-Sheppard, 1996), the estimates are reported with clustered standard errors at the instrument level (province-year-quarter).⁵

3. Results

Table 1 reports the baseline results estimated with OLS. Without accounting for endogeneity, only the number of EU projects are positively and significantly correlated with the number of job postings in per capita terms. In other words, the effect of interest manifests itself only through the extensive margins, while the average size of EU projects as well as the total volume of disbursements are not significantly related to labor demand variations. Conversely, the 2SLS estimates reported in Table 2 show that the number of per-capita postings in a given Italian province is sensitive not only to the number of allocated projects, but also to the volume of EU disbursements and the average size of EU projects. In other words, once endogeneity is accounted for, the EU disbursement effect manifests itself both through the extensive as well as the intensive margins, although the former dominates given the impact of the number of projects is greater in magnitude. Among the control variables, the provincial number of private firms has the expected sign but is always not statistically significant; also, the remaining controls that proxy for the quality of local institutions do not play any role in influencing labor demand at local level – and their inclusion leave our coefficients of interest substantially unaffected.

Table 4 reports the estimates of Equation (1) with the variable of interest *EUinv* lagged up to t-6, namely up to 6 quarters pre-determined with respect to the dependent variable. The statistics suggest -as expected - that the *t-x* coefficients of interest progressively decrease in magnitude with higher values of *x*. Furthermore, funds disbursed more than a year before do not play any role in influencing labor market dynamics at time *t*. Taking these results together, it appears that the impact of disbursed EU project funds on labor demand at local level lasts around 12 months, which is approximately the average maximum time needed by private and public institutions to advertise job postings in response to the actual acquisition of EU resources.

⁴ In one of our robustness tests we utilize an alternative shift-share type of instrument where the probability of receiving funds is interacted with the volume of EU (ERDF and EFS) investments received by all provinces in region *k* but province *i* (Table A3 in the Appendix). This component can be considered exogenous with respect to labour demand only when assuming that local labour market dynamics are hardly affected by funds allocated in other provinces.

⁵ We also performed the same IV estimates of model (1) with robust standard errors and found no substantial differences, so that the significance levels of the coefficients are not affected.

Table 5 explores potential heterogeneous effects across different types of jobs advertised at provincial level. More precisely, in light of the EU's Green New Deal and the commitment to both green and digital transitions, we are interested in whether EU funds stimulated the creation of new job offerings that specifically demand/request *digital* and *green* skills. To do so, we exploit the information included in the *Lightcast* dataset and aggregate all job postings at provincial level in a given year-quarter that involve *digital* and *green* skills. As expected, we find that the coefficients of interest are all larger in magnitude with respect to the baseline IV-2SLS statistics. This suggests that EU funds lead to larger positive variations in the creation of jobs that specifically request *digital* and *green* skills. In particular, the elasticity of postings requesting *green skills* is approximately five to six times larger in magnitude compared to the baseline parameters estimated in Table 2.

Table 6 reports the estimates of Equation (1) when disaggregating across different types of EU funds (ESF vs ERDF). The results clearly indicate that the labor demand stimulus at local level that comes from the aggregate volume of structural funds is driven by the ESF. This result is very much in line with the recent evidence showed by Canova and Pappa (2025), who find that – contrary to ERDF disbursements - European Social Funds are way more effective in boosting the labor market side with respect to the production side. More generally, the effectiveness of EFS in stimulating labor demand at local level could be considered a transmission mechanism/driver of the significant medium term growth effect of EFS funds detected by Canova and Pappa (2025).

In Table 7 we investigate whether the effect of EU funds varies with the pre-existing socio-economic conditions of provinces. To test whether there are non-linearities in the effect of EU_{inv} , we leverage on the information provided by National Accounts and Structural Business Statistics on the manufacturing value added (MVA) and divide Italian provinces according to the quartiles of the MVA distribution. The 2SLS estimates suggest that the impact of EU funds on labor demand – both at the intensive and extensive margins – manifests itself only in middle-high income provinces, while it is not significant in Italian poorer areas i.e. below the 34th percentile. We find this non-linearity in the effect plausible, as the capacity of provinces to turn funds into job opportunities require local absorptive capacity, governance quality, adequate levels of human capital in the public and private sectors as well as a sufficient level of efficiency in the public administration (see Lang *et al.*, 2023). By the same token, in low-income provinces – notably in the south part of the country – governance and administrative capacity are not sufficiently strong to turn allocated EU structural funds into a labor demand stimulus.

Table 8 shows the estimates of Equation (1) with job postings disaggregated according to the macro sectors of the private (or public) firms advertising the position. It turns out that the larger effects of EU funds are on postings from the Production sector, while the coefficients substantially decrease in magnitude when focusing on Services. We find these results plausible in light of the higher (semi)elasticities reported for digital and especially green job postings, as the Agriculture, Energy and Manufacturing are the sectoral areas where these skills are requested the most.

4. Concluding Remarks

Given the importance of EU funds to reduce disparities across different regions by boosting economic growth and improving labor market performance, this paper studies how the local labor markets in Italian provinces are affected by two specific EU *structural funds*: ERDF which mostly supports innovation and the competitiveness of regions, and ESF which focuses more on employment, education, training and social inclusion. However, instead of concentrating on their effects on employment indicators as in much of the existing literature, our focus is on how such funds affect the

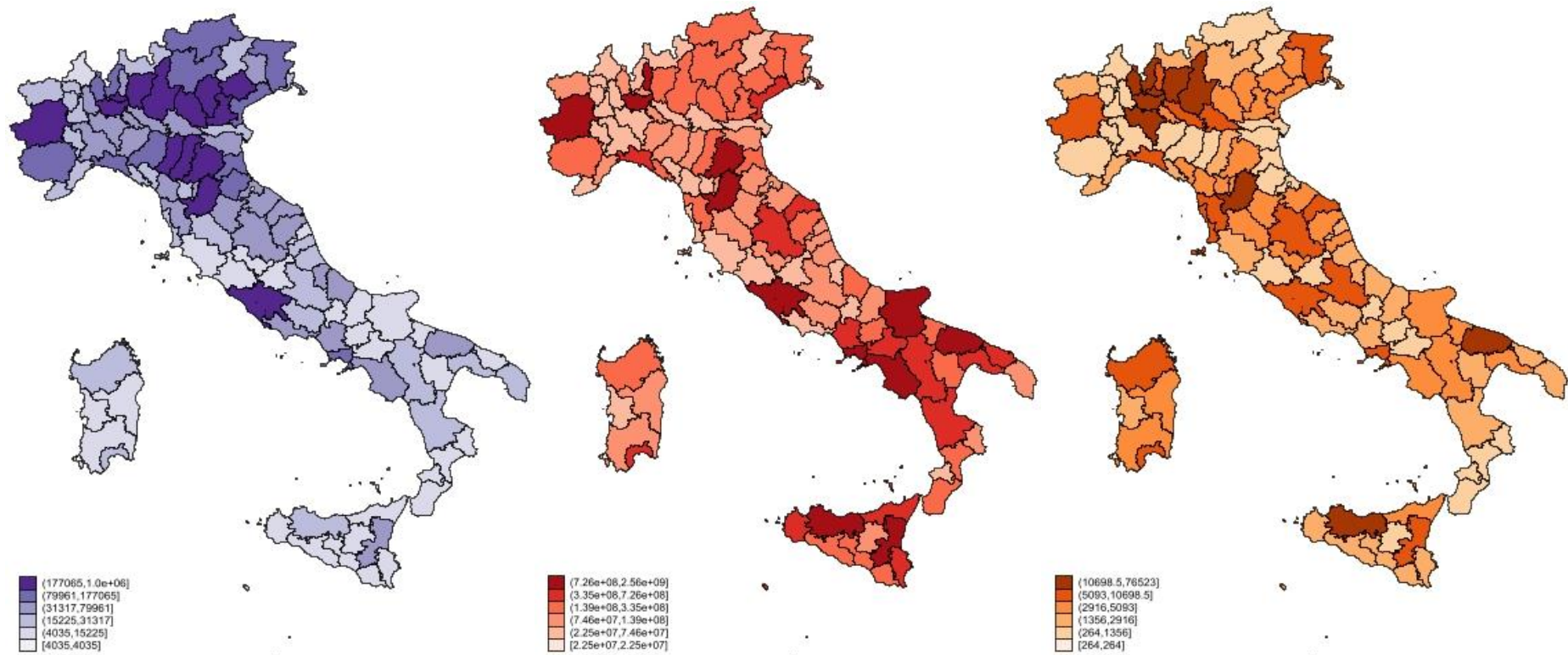
local demand for labor – which we deem as a more appropriate/adequate indicator of the capacity of local firms and institutions to turn funds into job opportunities.

To this aim, we use Lightcast data on online job postings to proxy for labor demand, given the close alignment between the variations in online vacancies collected by Lightcast and the information available in public employment centers - where accessible (see for example OECD, 2024). Compared to other studies on the geo-localized effects of EU structural funds in the literature (e.g. Canova and Pappa, 2025), our analysis is performed at the NUT3 level and allows to provide a more granular overview of labor markets' differences across Italian provinces.

Our main results show that *Structural Funds* have a positive effect on the number of job postings, particularly those specifically requiring green and digital skills, which are the core sectors of the EU Green New Deal initiatives and the Digital Single Market Strategy. Specifically, our results suggest that the number of projects (extensive margin) has a stronger effect than the amount of the project disbursement (intensive margin) which seems compatible with the diminishing returns hypothesis. We also find that the aggregate effect of structural funds on jobs creation is only driven by ESF disbursements: this interesting finding is very much in line with the recent results showed by Canova and Pappa (2025), who show that ESF funds lead to higher growth rates of employment, production, and investments compared to ERDF - and are better suited to foster medium-term objectives. Finally, by dividing provinces in terms of socio-economic characteristics proxied by manufacturing value added, we find that – despite the bulk of the funding is allocated to less-developed regions to help them catching up and reduce economic disparities across areas - the impact on labor demand is particularly strong in the middle-and-high income provinces, while it is not significant in poorest areas. This finding is in line with results obtained by Becker *et al.* (2013), on the role of local administrative and entrepreneurial capacities to turn allocated funds into job opportunities.

The present paper can thus be considered as an additional step to understand the complex and heterogenous effects of EU structural funds on the Italian labor market performances. In particular, by taking the results together, it seems that EU structural funds are more effective in stimulating jobs' creation in richer provinces. From a policy perspective, therefore, our findings point to a negative role of EU structural funds in reducing regional disparities in the Italian context in terms of employment opportunities. In order to halt this vicious circle, policy makers should focus on creating the conditions to raise the returns of funds also in peripheral and poorer areas – by improving human capital and the efficiency of institutions – so that local workforce will not be forced to emigrate to look for better job opportunities.

Figure 1⁶



⁶ Left hand side: N Postings. Center: Volume of funds (€). Right hand side: N of EU funded Projects.

Table 1: Baseline Model / OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Depvar	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Type of Funds	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>
Log Funds pc, t-1	0.00107 (0.79)				0.000883 (0.65)			
Log N Proj pc, t-1		0.0181*** (3.74)				0.0165*** (3.45)		
Log Funds Ppj, t-1			-0.000547 (-0.39)				-0.000571 (-0.40)	
Dummy, t-1				-0.0144 (-1.10)				-0.00371 (-0.21)
Log N Firms pc, t-1					0.380 (0.82)	0.381 (0.83)	0.376 (0.82)	0.376 (0.82)
Irrlight, t-1					0.00195 (0.17)	0.00108 (0.10)	0.00195 (0.17)	0.00196 (0.17)
Wastesort, t-1					-0.00177 (-0.80)	-0.00151 (-0.68)	-0.00182 (-0.83)	-0.00182 (-0.83)
Payoung, t-1					0.00263 (0.80)	0.00226 (0.69)	0.00265 (0.80)	0.00265 (0.80)
Prison, t-1					0.000218 (0.67)	0.000233 (0.71)	0.000220 (0.68)	0.000220 (0.68)
Servwastesort, t-1					0.000833 (1.38)	0.000678 (1.11)	0.000849 (1.41)	0.000850 (1.41)
<i>N</i>	78645	78645	78645	78645	78645	78645	78645	78645
Province FEs	X	X	X	X	X	X	X	X
Region*Year*Quart FEs	X	X	X	X	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X	X	X	X	X
Controls	No	No	No	No	Yes	Yes	Yes	Yes

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; the table reports the estimates of model 1 using as the variable of interest the volume of funds in Euro, the Number of Projects, the volume of funds per project and a dummy which equals 1 if a project is financed at time *t*, respectively. Standard Errors are clustered at province-year-quarter level.

Table 2: Baseline Model / IV-2SLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Depvar	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Type of Funds	Total	Total	Total	Total	Total	Total	Total	Total
Log Funds pc, t-1	0.0410** (2.16)				0.0391** (2.18)			
Log N Proj pc, t-1		0.132** (2.08)				0.132** (2.09)		
Log Funds Ppj, t-1			0.0593** (1.98)				0.0556** (2.02)	
Dummy, t-1				0.407** (2.31)				0.393** (2.32)
Log N Firms pc, t-1					0.505 (1.49)	0.414* (1.82)	0.544 (1.37)	0.457 (1.48)
Irrlight, t-1					0.00126 (0.15)	-0.00379 (-0.46)	0.00338 (0.36)	0.00281 (0.36)
Wastesort, t-1					-0.0000465 (-0.03)	0.000685 (0.44)	-0.000354 (-0.24)	-0.000764 (-0.67)
Payoung, t-1					0.00177 (0.96)	-0.000712 (-0.29)	0.00282 (1.43)	0.00276* (1.66)
Prison, t-1					0.000175 (0.90)	0.000361* (1.91)	0.0000972 (0.43)	0.000133 (0.73)
Servwastesort, t-1					0.000240 (0.57)	-0.000619 (-0.82)	0.000602 (1.59)	0.000465 (1.35)
N	78645	78645	78645	78645	78645	78645	78645	78645
Province FEs	X	X	X	X	X	X	X	X
Region*Year*Quart FEs	X	X	X	X	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X	X	X	X	X
Controls	No	No	No	No	Yes	Yes	Yes	Yes
KP F-Stat	14.851	10.803	9.529	28.417	16.053	11.068	10.606	29.697

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$:

The table reports the estimates of model 1 using as the variable of interest the volume of funds in Euro, the Number of Projects, the volume of funds per project and a dummy which equals 1 if a project is financed at time *t*, respectively. Standard Errors are clustered at province-year-quarter level.

Table 3: First Stage Statistics

Estimator	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
	First Stage	First Stage	First Stage	First Stage	Reduced Form Test
Depvar	Log Funds pc, t-1	Log N Proj pc, t-1	Log Funds Ppj, t-1	Dummy, t-1	Log N Posts
IV, t-1	0.0079048*** (3.85)	0.0024479*** (3.29)	0.005457*** (3.09)	0.0007962*** (5.33)	0.0003238** (2.55)
<i>N</i>	78645	78645	78645	78645	78645
Controls	No	No	No	No	No
Fixed Effects	yes	yes	yes	yes	yes
KP F-Stat	14.851	10.803	9.529	28.417	
Kleibergen-Paap rk LM statistic	17.248	11.761	10.659	34.101	
Cragg-Donald Wald F statistic	381.356	409.919	212.920	732.660	

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

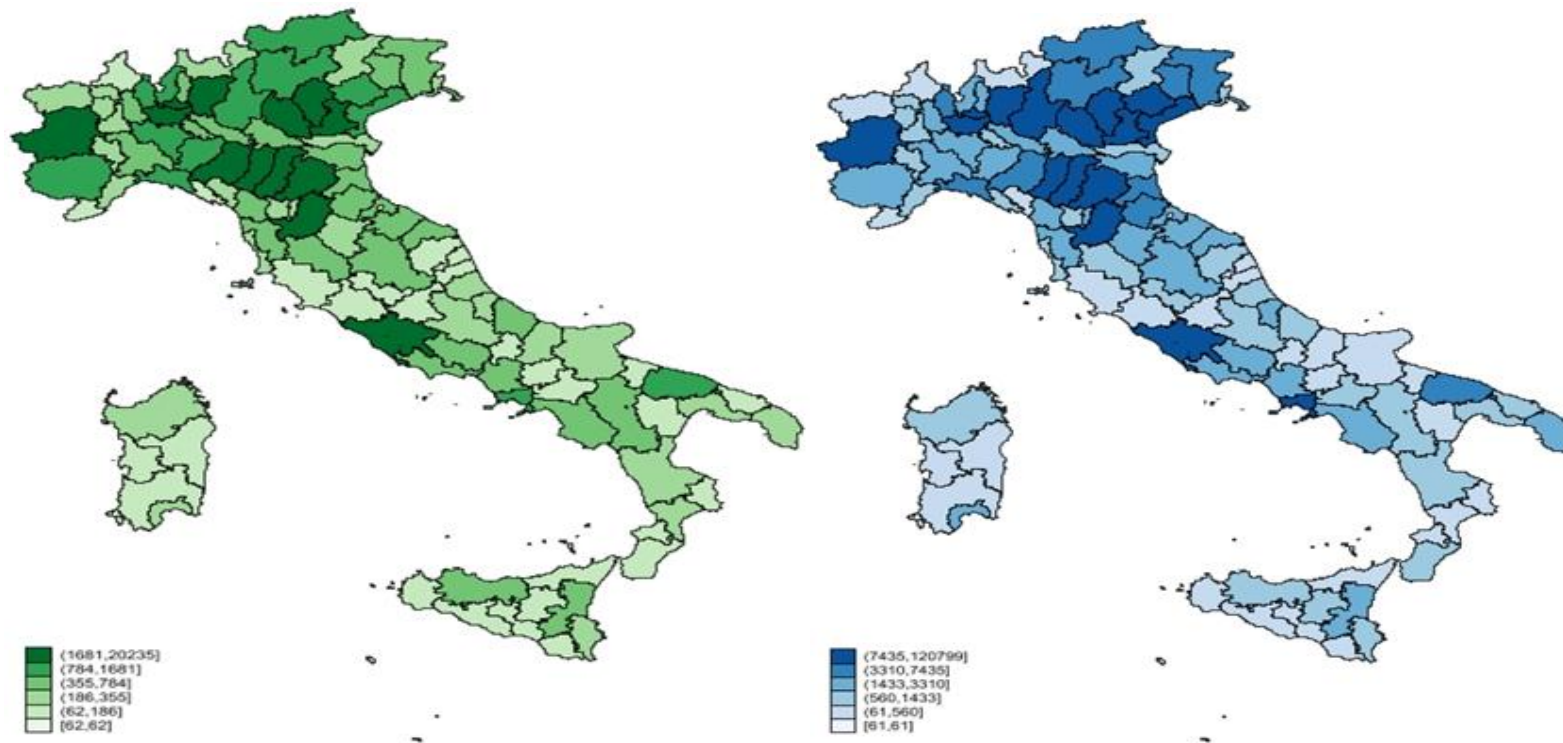
Notes: the statistics refer to the first stage statistics of the 2SLS estimates reported in Table 2 (column 1-4)

Table 4: Lagged Funds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Depvar	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Type of Funds	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>
Lag Funds	Lag 1	Lag 1	Lag 1	Lag 1	Lag 2	Lag 2	Lag 2	Lag 2	Lag 3	Lag 3	Lag 3	Lag 3
Log Funds pc, t-x	0.0410** (2.16)				0.0238** (2.29)				0.0194** (2.16)			
Log N Proj pc, t-x		0.132** (2.08)				0.106** (2.16)				0.0908** (2.01)		
Log Funds Ppj, t-x			0.0593** (1.98)				0.0307** (2.21)				0.0247** (2.12)	
Dummy, t-x				0.407** (2.31)				0.267** (2.32)				0.220** (2.19)
<i>N</i>	78645	78645	78645	78645	76398	76398	76398	76398	74151	74151	74151	74151
KP F-Stat	16.053	11.068	10.606	29.697	31.680	13.644	25.338	46.004	38.154	15.530	31.404	53.676
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Depvar	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts	Log N Posts
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Type of Funds	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>
Lag Funds	Lag 4	Lag 4	Lag 4	Lag 4	Lag 5	Lag 5	Lag 5	Lag 5	Lag 6	Lag 6	Lag 6	Lag 6
Log Funds pc, t-x	0.0154** (2.00)				0.00716 (1.29)				0.00640 (1.26)			
Log N Proj pc, t-x		0.0712* (1.91)				0.0325 (1.27)				0.0280 (1.23)		
Log Funds Ppj, t-x			0.0196** (1.98)				0.00919 (1.29)				0.00830 (1.26)	
Dummy, t-x				0.179** (2.02)				0.0874 (1.29)				0.0802 (1.26)
<i>N</i>	71904	71904	71904	71904	69657	69657	69657	69657	67410	67410	67410	67410
KP F-Stat	44.732	19.708	36.807	58.508	75.334	34.012	57.219	87.457	85.803	39.906	62.982	94.685

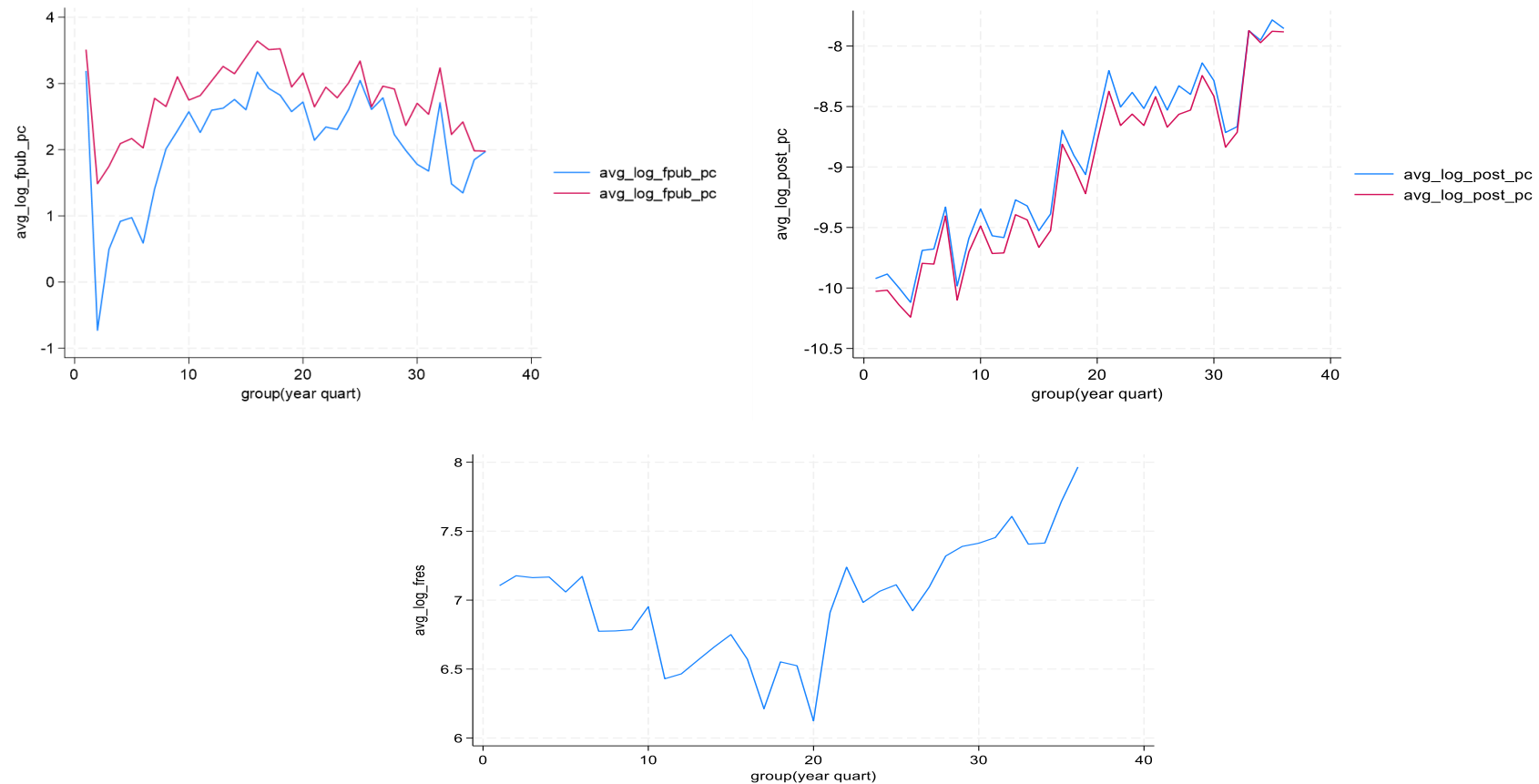
Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports the estimates of model 1 using as the variable of interest the volume of funds in Euro, the Number of Projects, the volume of funds per project and a dummy which equals 1 if a project is financed at time *t*, respectively. Standard Errors are clustered at province-year-quarter level. The model includes control variables whose coefficients are not reported.

Figure 2: Green Posts vs Digital Posts⁷



⁷ Left: Number of Green Job Postings; Right: Number of Digital Job Postings

Figure 3: IV - Parallel Trends



Blue: Provinces with values below the median of the probability of receiving EU funds

Red: Provinces with values above the median of the probability of receiving EU funds

Notes: Upper LEFT: logarithm of the average per capita financing over the years (province vs quarter) based on the probability of accessing EU funds. Upper RIGHT: logarithm of the average per capita job postings over the years (province vs quarter) based on the probability of accessing EU funds. Bottom: logarithm of the average value of the FISIM EU Balance “*Services Indirectly Measured Services: financial intermediation services indirectly measured*”. Source: European Union and euro area balance of payments - quarterly data (BPM6) (bop_eu6_q)

Table 5: EFS vs ERDF

Depvar	(1) Log Posts	(2) Log Posts	(3) Log Posts	(4) Log Posts	(5) Log Posts	(6) Log Posts	(7) Log Posts	(8) Log Posts
Estimator	<i>OLS</i>	<i>OLS</i>	<i>OLS</i>	<i>OLS</i>	<i>OLS</i>	<i>OLS</i>	<i>OLS</i>	<i>OLS</i>
Type of Funds	<i>EFS</i>	<i>EFS</i>	<i>EFS</i>	<i>EFS</i>	<i>ERDF</i>	<i>ERDF</i>	<i>ERDF</i>	<i>ERDF</i>
Log Funds pc, t-1	0.00317*** (3.45)				-0.000227 (-0.29)			
Log N Proj pc, t-1		0.0106*** (3.16)				0.0113*** (2.64)		
Log Funds Ppj, t-1			0.00309*** (3.04)				-0.000662 (-0.81)	
Dummy, t-1				0.0321*** (2.87)				-0.0136 (-1.33)
Estimator	<i>IV-2SLS</i>	<i>IV-2SLS</i>	<i>IV-2SLS</i>	<i>IV-2SLS</i>	<i>IV-2SLS</i>	<i>IV-2SLS</i>	<i>IV-2SLS</i>	<i>IV-2SLS</i>
Type of Funds	<i>EFS</i>	<i>EFS</i>	<i>EFS</i>	<i>EFS</i>	<i>ERDF</i>	<i>ERDF</i>	<i>ERDF</i>	<i>ERDF</i>
Log Funds pc, t-1	0.0547*** (3.22)				0.219 (0.50)			
Log N Proj pc, t-1		-0.648 (-1.50)				1.876 (0.30)		
Log Funds Ppj, t-1			0.0504*** (3.65)				0.248 (0.47)	
Dummy, t-1				0.415*** (4.25)				0.764 (1.42)
<i>N</i>	78645	78645	78645	78645	78645	78645	78645	78645
Province FEs	X	X	X	X	X	X	X	X
Region*Year*Quart FEs	X	X	X	X	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X	X	X	X	X
Controls	yes	yes	yes	yes	yes	yes	yes	yes
KP rk LM Stat	18.773	2.180	26.506	47.037	0.288	0.090	0.245	4.410
Cragg-Donald Wald F Stat	795.328	81.971	1186.143	1998.358	6.078	2.520	5.263	90.037
KP F-Stat	17.280	2.297	25.506	45.418	0.280	0.088	0.238	4.188

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table reports the estimates of model 1 using as the variable of interest the volume of funds in Euro, the Number of Projects, the volume of funds per project and a dummy which equals 1 if a project is financed at time *t*, respectively. Column 1-4 focus on FES type of funds, while column 5-8 focus on FESR funds. Standard Errors are clustered at province-year-quarter level. The models include control variables whose coefficients are not reported. The estimates are obtained using 2SLS with a shift-share instrument, which is the product of the probability of receiving EFS or ERDF funds in a given province multiplied by the quarter-year EU's BoP FISIM value.

Table 6: Green Posts vs Digital Posts

Depvar Estimator	(1) Log D Posts IV-2SLS	(2) Log D Posts IV-2SLS	(3) Log D Posts IV-2SLS	(4) Log D Posts IV-2SLS	(5) Log G Posts IV-2SLS	(6) Log G Posts IV-2SLS	(7) Log G Posts IV-2SLS	(8) Log G Posts IV-2SLS
Type of Funds	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>
Log Funds pc, t-1	0.133*** (3.35)				0.218*** (3.55)			
Log N Proj pc, t-1		0.451*** (3.00)				0.738*** (3.15)		
Log Funds Ppj, t-1			0.190*** (2.84)				0.310*** (2.96)	
Dummy, t-1				1.341*** (4.04)				2.194*** (4.46)
<i>N</i>	78645	78645	78645	78645	78645	78645	78645	78645
Province FEs	X	X	X	X	X	X	X	X
Region*Year*Quart FEs	X	X	X	X	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X	X	X	X	X
Controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
KP F-Stat	16.053	11.068	10.606	29.697	16.053	11.068	10.606	29.697

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard Errors are clustered at province-year-quarter level. The model includes control variables whose coefficients are not reported.

Table 7 – Disaggregating According to Local Socio-Economic Conditions

Depvar	(1) Log Posts	(2) Log Posts	(3) Log Posts	(4) Log Posts	(5) Log Posts	(6) Log Posts	(7) Log Posts	(8) Log Posts	(9) Log Posts	(10) Log Posts	(11) Log Posts	(12) Log Posts
Tertile	0-33 rd	0-33 rd	0-33 rd	0-33 rd	34 th -66 th	34 th -66 th	34 th -66 th	34 th -66 th	67 th -100 th	67 th -100 th	67 th -100 th	67 th -100 th
<i>IV-2SLS</i>												
Log Funds pc, t-1	-0.223 (-0.58)				0.0525* (1.84)				0.0275* (1.72)			
Log N Proj pc, t-1		11.89 (0.03)				0.131** (2.08)				0.199 (1.41)		
Log Funds Ppj, t-1			-0.219 (-0.59)				0.0876 (1.48)				0.0320* (1.71)	
Dummy, t-1				-2.060 (-0.92)				0.472** (2.18)				0.389* (1.74)
<i>N</i>	26460	26460	26460	26460	26460	26460	26460	26460	25725	25725	25725	25725
Province FEs	X	X	X	X	X	X	X	X	X	X	X	X
Region*Year*Q FEs	X	X	X	X	X	X	X	X	X	X	X	X
Sector*Year*Q FEs	X	X	X	X	X	X	X	X	X	X	X	X
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Cragg-Donald F Stat	7.903	0.056	9.094	20.135	178.229	284.781	84.726	360.345	555.032	116.249	461.065	576.740
KP F-Stat	0.366	0.001	0.380	1.021	4.518	5.257	2.776	9.939	16.413	4.799	14.426	16.340

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$;

The table reports the estimates of model 1 using as the variable of interest the volume of funds in Euro, the Number of Projects, the volume of funds per project and a dummy which equals 1 if a project is financed at time *t*, respectively. The sample is divided according to the quartiles of the provinces' distribution of the average of manufacturing value added. Standard Errors are clustered at province-year-quarter level. The model includes control variables whose coefficients are not reported.

Table 8 – Macro-Sectoral Disaggregation of Job Postings

Sector	(1) <i>Production</i>	(2) <i>Production</i>	(3) <i>Production</i>	(4) <i>Production</i>	(5) <i>Services</i>	(6) <i>Services</i>	(7) <i>Services</i>	(8) <i>Services</i>
IV-2SLS								
Log Funds pc, t-1	0.0618** (2.24)				0.0301* (1.75)			
Log N Proj pc, t-1		0.209** (2.15)				0.102* (1.69)		
Log Funds Ppj, t-1			0.0877** (2.06)				0.0427* (1.66)	
Dummy, t-1				0.621** (2.42)				0.302* (1.81)
<i>N</i>	22470	22470	22470	22470	56175	56175	56175	56175
Province FEs	X	X	X	X	X	X	X	X
Region*Year*Quart FEs	X	X	X	X	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X	X	X	X	X
Controls	yes	yes	yes	yes	yes	yes	yes	yes
KP F-Stat	15.640	10.784	10.334	28.934	15.987	11.022	10.562	29.575

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; The model includes control variables whose coefficients are not reported.

The table reports the estimates of model 1 using as the variable of interest the volume of funds in Euro, the Number of Projects, the volume of funds per project and a dummy which equals 1 if a project is financed at time *t*, respectively. Standard Errors are clustered at province-year-quarter level. The sample is divided according to a macro-sector disaggregation, namely: Production (column 1-4) and Services (column 5-8)

Production: Manufacturing; Electricity, gas, steam and air conditioning supply; Water supply; sewerage, waste management and remediation activities; Mining and quarrying; Agriculture, forestry and fishing; Accommodation and food service activities; **Services:** Activities of extraterritorial organisations and bodies; Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; Administrative and support service activities; Arts, entertainment and recreation; Construction; Education; Financial and insurance activities; Human health and social work activities; Information and communication; Other service activities; Professional, scientific and technical activities; Public administration and defence; compulsory social security; Real estate activities; Transportation and storage; Wholesale and retail trade; repair of motor vehicles and motorcycles

Appendix

This section presents a series of robustness tests to corroborate the results of the main analysis. In particular, in this section we report:

Table A1: Adding Private Funds. This table reports the results of the baseline model where we add co-financed private flows on top of the EU public transfers

Table A2: Excluding COVID Period. The table shows the estimates of the baseline model where we exclude 2020, the year in which most of COVID restrictions occurred in Italy.

Table A3 – Robustness /Alternative Instrument. The Table reports the estimates of the baseline IV model with an alternative instrument – in which the exogenous component is the volume of EU transfers to the region k of province i in year-quarter t , with the exception of the ones allocated to province i .

Table A4 – Robust Standard Errors. The Table reports the OLS and IV-2SLS baseline statistics obtained with robust standard errors.

Table A5 – Poisson PML. The Table shows the Poisson Pseudo Maximum Likelihood estimates of the baseline model using different types of funds

Appendix Table A1 – Robustness /Adding Private Funds

	(1)	(2)	(3)	(4)
Depvar	Log N Posts	Log N Posts	Log N Posts	Log N Posts
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Type of Funds	<i>Public +Private</i>	<i>Public +Private</i>	<i>Public +Private</i>	<i>Public +Private</i>
Log Funds pc, t-1	0.0429** (2.11)			
Log N Proj pc, t-1		0.159** (1.98)		
Log Funds Ppj, t-1			0.0587** (1.98)	
Dummy, t-1				0.407** (2.31)
<i>N</i>	78645	78645	78645	78645
Province FEs	X	X	X	X
Region*Year*Quart FEs	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X
Controls	No	No	No	No
KP F-Stat	12.799	7.895	9.758	28.417
Kleibergen-Paap rk LM statistic	14.796	8.632	10.963	34.101
Cragg-Donald Wald F statistic	340.896	316.474	220.642	732.660

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Standard Errors are clustered at province-year-quarter level.

Appendix Table A2 – Robustness /Excluding COVID Period

	(1)	(2)	(3)	(4)
Depvar	Log N Posts	Log N Posts	Log N Posts	Log N Posts
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Type of Funds	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>
Log Funds pc, t-1	0.0400** (2.11)			
Log N Proj pc, t-1		0.134** (2.02)		
Log Funds Ppj, t-1			0.0569* (1.94)	
Dummy, t-1				0.398** (2.26)
<i>N</i>	69657	69657	69657	69657
Province FEs	X	X	X	X
Region*Year*Quart FEs	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X
Controls	No	No	No	No
KP F-Stat	111.147	26.626	111.147	70.103
Kleibergen-Paap rk LM statistic	63.240	32.159	63.240	33.447
Cragg-Donald Wald F statistic	9636.784	676.312	9636.784	5412.704

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Standard Errors are clustered at province-year-quarter level.

Appendix Table A3 – Robustness /Alternative Instrument

	(1)	(2)	(3)	(4)
Depvar	Log N Posts	Log N Posts	Log N Posts	Log N Posts
Estimator	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
Type of Funds	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>
Log Funds pc, t-1	0.0112*** (3.11)			
Log N Proj pc, t-1		0.0486*** (3.23)		
Log Funds Ppj, t-1			0.0145*** (2.99)	
Dummy, t-1				0.455** (2.31)
<i>N</i>	78645	78645	78645	78645
Province FEs	X	X	X	X
Region*Year*Quart FEs	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X
Controls	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>
KP F-Stat	63.240	33.447	72.526	10.436
Kleibergen-Paap rk LM statistic	111.147	70.103	56.016	9.249
Cragg-Donald Wald F statistic	9636.784	5412.704	6471.372	983.149

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Standard Errors are clustered at province-year-quarter level.

Appendix Table A4 – Robust Standard Errors

Depvar Estimator	(1) Log N Posts OLS	(2) Log N Posts OLS	(3) Log N Posts OLS	(4) Log N Posts OLS	(5) Log N Posts IV-2SLS	(6) Log N Posts IV-2SLS	(7) Log N Posts IV-2SLS	(8) Log N Posts IV-2SLS
Type of Funds	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>	<i>Total</i>
Log Funds pc, t-1	0.000883 (0.72)				0.0391*** (2.71)			
Log N Proj pc, t-1		0.0116*** (3.23)				0.132*** (2.70)		
Log Funds Ppj, t-1			-0.00015 (-0.11)				0.0556*** (2.70)	
Dummy, t-1				-0.00371 (-0.22)				0.393*** (2.72)
<i>N</i>	78645	78645	78645	78645	78645	78645	78645	78645
Province FEs	X	X	X	X	X	X	X	X
Region*Year*Quart FEs	X	X	X	X	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X	X	X	X	X
Controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
KP F-Stat					337.192	232.486	222.783	623.793

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimates are obtained with robust standard errors. The model includes control variables whose coefficients are not reported.

Appendix Table A5 – Poisson PML

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Depvar	N Posts	N Posts	N Posts	N Posts	N Posts	N Posts	N Posts	N Posts	N Posts	N Posts	N Posts	N Posts
Estimator	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML	PPML
Type of Funds	Total	Total	Total	Total	ESF	ESF	ESF	ESF	ERDF	ERDF	ERDF	ERDF
Log Funds pc, t-1	0.00232 (1.61)				0.00268** (2.52)				0.00105 (1.08)			
Log N Proj pc, t-1		0.00342 (0.78)				0.0111*** (3.13)				-0.00842 (-1.57)		
Log Funds Ppj, t-1			0.00220 (1.43)				0.00242** (2.03)				0.00150 (1.46)	
Dummy, t-1				0.0362* (1.91)				0.0254** (2.01)				0.0267* (1.93)
<i>N</i>	76291	76291	76291	76291	76291	76291	76291	76291	76291	76291	76291	76291
Province FEs	X	X	X	X	X	X	X	X	X	X	X	X
Region*Year*Quart FEs	X	X	X	X	X	X	X	X	X	X	X	X
Sector*Year*Quart FEs	X	X	X	X	X	X	X	X	X	X	X	X
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimates are obtained with robust standard errors. The model includes control variables whose coefficients are not reported.

References

- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3-30.
- Albanese G, G de Blasio, & Locatelli A. (2021). Does EU regional policy promote local TFP growth? Evidence from the Italian Mezzogiorno. *Papers in Regional Science*, 100, 327–348.
- Arbolino, R., Di Caro, P., & Marani, U. (2020). Did the Governance of EU Funds Help Italian Regional Labour Markets during the Great Recession? *Journal of Common Market Studies*, 58 (2), 235-255.
- Becker, S. O., Egger, P. H., & V. Ehrlich, M. (2010). Going NUTS: The effect of EU structural funds on regional performance. *Journal of Public Economics* 94(9), 578–590.
- Becker, S. O., P. H. Egger, & V. Ehrlich, M. (2012). Too much of a good thing? on the growth effects of the EU's regional policy. *European Economic Review*, 56, 648-668.
- Becker, S. O., P. H. Egger, & V. Ehrlich, M. (2013). Absorptive capacity and the growth and investment effects of regional transfers: A regression discontinuity design with heterogeneous treatment effects. *American Economic Journal: Economic Policy*, 5.
- Canova, F., & Pappa, E. (2025). The macroeconomic effects of EU regional Structural Funds. *Journal of the European Economic Association*, 23(1), 327-360.
- Coelho, Maria (2019). Fiscal Stimulus in a Monetary Union: Evidence from Eurozone Regions. *IMF Economic Review*, 67, 573–617.
- ISTAT 2024 Anitori, P., De Gregorio, C., & Giordano–ISTAT, A. Low wages, employees and employers in Italy: a longitudinal analysis.
- OECD 2024, OECD Employment Outlook 2024.
- Bouvet, F., & Dall'Erba, S. (2010). European regional structural funds: How large is the influence of politics on the allocation process?. *Journal of Common Market Studies*, 48(3), 501-528.
- Borusyak, K., Hull, P., & Jaravel, X. (2021). Quasi-experimental shift-share research designs. *The Review of Economic Studies*. <https://doi.org/10.1093/restud/rdab030>.
- Cerqua, A., & Pellegrini, G. (2018). Are we spending too much to grow? The case of Structural Funds. *Journal of Regional Science* 58, 535–563.
- Ciani, E. & de Blasio, G. (2015). Getting Stable: An Evaluation of the Incentives for Permanent Contracts in Italy. *IZA Journal of European Labor Studies*, 4 (1), 1–29.
- Dreher, A., Fuchs, A., & Langlotz, S. (2019). The effects of foreign aid on refugee flows. *European Economic Review*, 112, 127–147.
- Dreher, A., Fuchs, A., Parks, B., Strange, A. M., & Tierney, M. J. (2021). Aid, China, and growth: Evidence from a new global development finance dataset. *American Economic Journal: Economic Policy*, 13(2), 135–174.
- Ehrlich, M. V. (2024). The Importance of EU Cohesion Policy for Economic Growth and Convergence. CRED Research Paper No. 46.
- Lang, V., Redeker, N. & Bischof, D. (2023). Place-Based Policies and Inequality Within Regions. Working Paper, University of Mannheim.

- Mohl, P., & Hagen, T. (2011). Do EU structural funds promote regional employment? Evidence from dynamic panel data models (No. 1403). ECB Working paper.
- Porro, G. & Salis, V. (2017). Do Local Subsidies to Firms Create Jobs? Counterfactual Evaluation of an Italian Regional Experience. *Papers in Regional Science*, 97 (4), 1039–1056.
- Römisch, R. (2020). Can we Justify EU Cohesion Policy?. WIIW Policy Notes and Reports, 42, 2020.
- Shore-Sheppard, L. D. (1996). The precision of instrumental variables estimates with grouped data (No. 753).
- Woessmann, L. (2024). Skills and Earnings: A Multidimensional Perspective on Human Capital. CESifo WP No. 11428.