Technological Forecasting & Social Change 197 (2023) 122915

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Fostering rural entrepreneurship: An ex-post analysis for Spanish municipalities

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ARTICLE INFO

JEL classifications:
L26
L29
R58

Keywords:
Entrepreneurship
Technological adoption
Innovation
Entrepreneurial ecosystems
Rural entrepreneurship

ABSTRACT

Entrepreneurs in rural areas contribute enormously to these territories, but they also face challenges not encountered by their urban counterparts. These problems include lack of basic infrastructure and fewer opportunities to exploit new technologies and engage in innovation projects. Research into the limitations experienced by rural entrepreneurs is scarce. The present study seeks to provide a better understanding of these problems through an ex-post analysis of an innovative policy designed to foster rural entrepreneurship. This policy adopts a "bottom-up" approach to promoting relationships among different parts of the entrepreneurial ecosystem. Among the recipients of this policy, some also benefited from other programs aimed at promoting technological innovation, technology adoption and basic infrastructure improvements. To assess the influence of the policy we conducted a municipality (LAU-2) level analysis using unique data on some 12.6 million beneficiary projects. We employed a recently developed difference-in-difference method to estimate the causal effect of this bottom-up policy on local workers. We did not identify any spillover effects from the implementation of this policy. We found a positive impact which was effective for reducing unemployment in the treated areas. Unemployment levels also reduced significantly in municipalities that received funds for innovation and enhanced infrastructure; however, among the group that received help for technology adoption unemployment levels did not change. This points to the importance of basic infrastructure to enable innovation and increase technology adoption in rural areas. Also, the lower effects found for female workers - one of the most vulnerable groups within the ecosystem – suggest that the policy should be refined to avoid these unintended effects on rural inequality.

1. Introduction

The effects of the entrepreneurial ecosystem (EE) on the development of communities are attracting the attention of the policy-making and academic communities (Aguilar, 2021). Entrepreneurship and the EE have the potential to foster job creation (Fairlie et al., 2019), boost economic growth (Urbano et al., 2019) and solve social and environmental problems (Makhloufi et al., 2022; Sutter et al., 2019). Technology entrepreneurs contribute also by bridging the digital divide (Agwu, 2021) and promoting innovation and knowledge spillovers (Ahn et al., 2022). The EE literature proposes a systemic framework which contextualizes entrepreneurial activity and integrates the regional dimension, which had been neglected and relegated to other disciplines (Aguilar, 2021).

Currently, most ecosystem studies examine industrial districts in urban areas (Wurth et al., 2022). Although this research provides some useful findings, it does not recognize other entrepreneurial endeavors, and in particular, generally fails to consider the different regional contexts in which entrepreneurs operate depending on their urban or rural location (Aguilar, 2021). However, the opportunities and problems experienced by entrepreneurs working in rural and urban environments are not really comparable (Dong et al., 2021; Xie et al., 2021). The broadband infrastructure quality and innovation capabilities have an effect on the quantity and quality of rural entrepreneurial endeavors (del Olmo-García et al., 2023; Xie et al., 2021). The scant literature on innovation and entrepreneurialism in rural contexts means that policymakers and prospective entrepreneurs have less information on best practices for rural projects (Aguilar, 2021). There is a need for programs designed specifically to exploit the potential of entrepreneurs in rural areas and reduce the barriers to innovation and technology entrepreneurship. In urban settings, public support initiatives may be less important but in rural areas they can be critical which calls for more

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https://doi.org/10.1016/j.techfore.2023.122915
Received 9 March 2023; Received in revised form 8 August 2023; Accepted 2 October 2023
Available online 11 October 2023

evidence on their potential contribution to the rural ecosystem (Fotopoulos and Storey, 2019).

In this paper we analyze the Community-Led Local Development (CLLD) program, an EU policy designed to foster entrepreneurship in rural areas. Rather than being a top-down initiative, it empowers local communities and allows them to choose how to cultivate regional entrepreneurial dynamics. The CLLD program promotes entrepreneurship within a functioning EE by strengthening relationships among different stakeholders and providing funding for entrepreneurial ventures. To address the challenges specific to rural areas, this policy was implemented in combination with other initiatives in order to establish or improve basic broadband infrastructure, promote product and process innovation and enable technology adoption. We analyze the effects of the CLLD on those groups who benefitted from these initiatives. The program and related initiatives were implemented between 2014 and 2020 in various countries as part of the European Union Common Agricultural Policy. To our knowledge, in the case of Spain where close to 20 % of its population live in a rural area (World Bank, 2022), there has been no ex-post analysis of the most recent waves of funding under the program and no ex-post examination at the municipal level of the effects of the entire program. The lack of research on the effects of the program in combination with other technological and innovation initiatives could be due to data availability. For the present study, we built a dataset which includes information on over 12.6 million beneficiary projects in rural areas between 2012 and 2021.

We estimate the effect of the policy on unemployment and, given the well-known vulnerability of women (Aguilar, 2021), we analyze its impact on female workers through a separate estimation. The analysis takes account of several factors. First, the importance of technology and innovation for rural entrepreneurs which we consider by analyzing municipalities that also benefited from technology adoption, innovation and basic infrastructure programs. Second, we need to ensure appropriate attribution of causal effects to public aid and estimate resultant spillover effects. Goodman-Bacon (2021) shows that estimation of average treatment effects can be biased in settings that include multiple periods and covariates, both conditions that affect our analysis. To address this issue, we employ the difference-in-difference (DiD) estimator developed by Callaway and Sant'Anna (2021). It should be noted that although several studies report considerable spillover effects within EEs which result in large policy impacts (Briglauer et al., 2019; Ganotakis et al., 2021), few examine the effect of these spillovers on rural ecosystems. This is an important oversight since there is evidence showing that although social networks may be narrower in rural settings, they are often more robust (Miles and Morrison, 2020). Analysis of the spillover effects will allow a more accurate mapping of rural EEs and their dynamics (Fischer et al., 2022).

2. Background and theory

The concept of EE is based on the understanding that entrepreneurship is not an isolated phenomenon but is part of a comprehensive system (Xie et al., 2021). Some consider this idea as originating in the regional clusters literature (Basole et al., 2019; Haak et al., 2014) and particularly Porter's (1998) market-based model and the entrepreneurial perspective model proposed by Birch's (1979) and Kirchhoff's (1994). Both models include some characteristics of EEs. The former sees firms as system integrators while the latter employs a bottom-up approach to the analysis of firm creation and economic growth (Haak et al., 2014). Autio et al. (2018) state that the difference between EE and other similar concepts such as knowledge clusters, industrial districts and innovation systems is the focus in EE on the pursuit of entrepreneurial opportunities as the defining aspect of EE dynamics. Although Roundy et al. (2018) argues that the field needs to develop more comprehensive accounts of the interactions among its elements, there is evidence suggesting that correct identification and promotion of the EE can foster entrepreneurship and innovation and generate value for society (Acs et al., 2018; Muñoz et al., 2022; Wurth et al., 2022). This explains the interest of practitioners in EE and its positive effects (Feldman et al., 2019). At the same time, it has been highlighted that the concept of EE is short of theoretical underpinnings (Cao and Shi, 2021; Stam and van de Ven, 2021). The popularity of EE among practitioners and policymakers has resulted in the provision of instruments not always supported by solid research (Audretsch et al., 2019; Roundy and Burke-Smalley, 2021). Further, most EE research examines high-growth firms in urban environments which does not produce generalizable results (Acs et al., 2022).

Awareness of these theoretical limitations have led to some comprehensive literature reviews which provide syntheses of the concept. For example, Stam and van de Ven (2021) highlight the idea of "entrepreneurship" and the process of discovering, evaluating and exploring opportunities related to new goods and services (Schumpeter, 1934) and the implication in the word "ecosystems" that it involves a set of mutually interdependent actors. Wurth et al. (2022) emphasize that most ontological definitions of EE include sets of interdependent actors and the factors such as available infrastructure and innovation which enable productive entrepreneurship. Therefore, most authors acknowledge the importance of the contextual elements and the interdependence of the different stakeholders (Cao and Shi, 2021; Leendertse et al., 2021) while also considering the output of EE in terms of value creation (Cobben et al., 2022).

2.1. Rural entrepreneurial ecosystems

There is growing evidence showing that rural and urban settings are markedly different and their study requires tailored approaches (Miles and Morrison, 2020; Roundy, 2017).[1] In addition, there are differences related to developing and developed economies which further emphasize the need for a framework that is able to capture the idiosyncrasies related to rural ecosystems in advanced economies (Cao and Shi, 2021). These many differences include elements distinctive to rural EEs such as their network operations, rural cultural values, resource endowments and role of formal institutions (Aguilar, 2021). Given the importance of formal institutions we discuss them in a separate section (Section 2.2).

First, in the case of social networks in rural environments, the literature discusses the role of agglomeration effects (Autio et al., 2018; Yang et al., 2021). While new firms in urban areas may benefit from the clustering of similar businesses, this is less likely in rural settings (Luo et al., 2020). Entrepreneurs in rural areas generally are unable to access as wide a system of producers and buyers or to benefit from local market "size" and "thickness" (Abreu et al., 2019). They are likely to suffer from less competitive pricing and less reliable distribution networks (Habersetzer et al., 2019). Rural entrepreneurs may also be deprived of the positive externalities (e.g. innovations, knowledge spillovers) from research centers and other businesses which reduces their ability to identify growth opportunities (Fischer et al., 2022; Yang et al., 2021).

Second, rural cultural values can shape social capital dynamics and the propensity to own a business. In both urban and rural areas, trust between businesses varies depending on social unity, member heterogeneity and community size but there is some evidence that although the networks of entrepreneurs in rural areas may be narrower (Merrell et al., 2022), network ties are stronger than in urban areas (de Guzman et al., 2020). Research on the territorial embeddedness of business founders shows that the benefits of belonging to local communities are higher in rural compared to urban areas (Baù et al., 2019). This might be because small firms in rural settings experience scarcer opportunities and thus are more dependent on the resources and knowledge of family and friends (Davidsson and Honig, 2003). It has been shown that territorial

[1] In this study, a rural environment is understood in terms of the Eurostat classification of Degree of Urbanization which is based on population density (European Commission et al., 2021).

embeddedness can foster innovation among rural businesses (De Massis et al., 2018). Further, while rural areas have overall lower numbers of firms, recent research shows that in some rural settings entrepreneurial activity levels are significantly high, resulting in higher business density per capita in these areas (Novejarque et al., 2021). Individuals in these regions are more likely to manage their own firms and to engage in early-stage entrepreneurship (Ozusaglam et al., 2022). This is likely due to the prevalence of smaller businesses, reduced employment opportunities and the demographic structure of these territories (del Olmo-García et al., 2023; Fotopoulos and Storey, 2019). The fact that larger proportions of rural populations are engaging in entrepreneurial endeavors points to the importance of studying the EE in rural settings.

Finally, work on the resource endowments provided by EEs also shows considerable regional disparities within developed countries (Content et al., 2020). Entrepreneurs in rural areas are faced with problems such as in reliable internet access (Briglauer et al., 2019), insufficient transport structures (Székely and Novotný, 2022), and limited access to basic services (Rechel et al., 2016) and financial institutions (Kärnä and Stephan, 2022), which are less frequent in urban contexts. Affordable financing is more difficult for rural firms which tend to be small and medium enterprises with bigger credit constraints (Ughetto et al., 2019). This makes engagement in innovation and technological projects more difficult (del Olmo-García et al., 2023). Other problems include depopulation and an aging population structure (del Olmo-García et al., 2023; Serra et al., 2014) which reduce local demand (Nicotra et al., 2017) and make recruiting more difficult (Fischer et al., 2022; Roundy, 2017). All of these factors contribute to making rural regions less attractive and reduce the number of businesses that decide to locate there which increases unemployment and outward migration (ESPON, 2020). These consequences are exacerbated in the case of female workers in rural settings where unemployment levels are significantly higher than for both their male and urban counterparts (Kovačiček and Franić, 2019). Females are less likely to become entrepreneurs and manage small and medium-sized companies despite policy efforts to ease these conditions (Carter et al., 2015; Orser et al., 2019). Acknowledgment of these problems has led to the introduction of a range of public programs to promote – particularly female - entrepreneurship in rural areas and to foster innovation (Aguilar, 2021; Berger and Kuckertz, 2016; del Olmo-García et al., 2023).

2.2. Public policies to foster rural EEs

While in urban environments the role of public institutions may be less important, it is crucial for rural EEs (Muñoz and Kimmitt, 2019). In industrialized countries, this role includes supra-national, national, regional and local institutions (Habersetzer et al., 2019). For instance, in the case of basic information and communication technology (ICT) and broadband infrastructure, in the absence of public intervention investment is unlikely to come from private actors (Ashmore et al., 2017; Breschi et al., 2009).

There is a stream of work on the impact of institutions on EEs and their effect on productive entrepreneurship (Stam, 2015). Some studies show that public programs can increase entrepreneurial intention (Barnett et al., 2019), address infrastructure limitations (Galvão et al., 2020), foster innovation (Autio et al., 2008) and influence a variety of productive dimensions of entrepreneurship (Barber et al., 2021; Miles and Morrison, 2020). Some authors study the wider impact of entrepreneurs on local employment and show that programs to foster entrepreneurial activity contribute in two ways (Szerb et al., 2019). On the one hand, they may increase self-employment and provide opportunities for local workers by providing new job openings (Dong et al., 2021). On the other hand, they result in spillover effects from connections between companies in the focal area, promoting innovation and knowledge exchanges and enhancing business activity (Fotopoulos, 2022). Spillovers can also arise from entrepreneurs' consumption of other local businesses (Briglauer et al., 2019).

Despite these positive effects, ex-post program evaluations show that policies designed to foster entrepreneurship and innovation do not always produce the intended benefits (Fotopoulos and Storey, 2019). Some policies aimed at rural areas have had negative effects on local unemployment (Nicotra et al., 2018). These negative effects result from failure to foster entrepreneurial activity (Fotopoulos and Storey, 2019), increased productivity and mechanization which requires fewer labor force units (Alexiadis et al., 2013), crowding out of some sectors (McGowan and Vasilakis, 2019), regional characteristics (Wurth et al., 2022) and indirect effects (Guriev and Vakulenko, 2015). Several studies find a mixed direct effect on employment due to heterogeneous effects across sectors, measures and geographical scope (Schuh et al., 2019). These differences highlight the need for customized analyses at the finest grained geographical level possible to avoid overlaps with other effects (Karlsson and Dahlberg, 2003).

2.3. A policy for rural entrepreneurs: Community-Led Local Development

Among the variety of public policies aimed at fostering EE, CLLD is distinguished by its novel approach. It is a relatively new policy which initially was funded by the European Agricultural Fund for Rural Development. Given its promise, the last wave of CLLD funding was extended to include three other European funds (European Commission, 2014). The main novelty of the program is its decentralized bottom-up framework which empowers local communities to decide which entrepreneurial initiatives to support. These initiatives are based on the principle of subsidiarity and the tailoring to each context to address local needs with greater flexibility (European Commission, 2014; Servillo, 2019). Rather than central decision-making, the responsibility is given to local action groups of local representatives (European Network for Rural Development, 2018a).

These local action groups include several stakeholders in the EE such as public institutions, private businesses and civil-society organizations. Besides fostering development, the second objective of the policy is to contribute to building stronger networks and opportunities for collaboration and innovation among these stakeholders (European Commission, 2014). These local action groups were established in the first stage of the funding period. Their decisions about which entrepreneurial projects to fund followed European, national and regional guidelines and gave priority to projects that addressed social, economic and environmental needs within the ecosystem. All funded projects had to create at least one new job -which could be self-employment- which remained in place for at least three years. To avoid opportunistic behaviors, funding under the program was only awarded to projects which began after the program was implemented (European Parliament, 2013).

Inevitably, CLLD has some shortcomings including the administrative burden imposed on local action groups, which might reduce the ability to implement local and flexible initiatives (European Network for Rural Development, 2018a). Also, more ex-post evaluation is needed to provide guidance for future waves of CLLD aid (European Commission, 2022; European Court of Auditors, 2022).

2.4. Management of technology and innovation for rural entrepreneurship

The challenges faced by rural entrepreneurs go beyond funding and include lack of investment in innovation and technology, a prominent problem in rural areas (Aparicio et al., 2016; Novejarque Civera et al., 2021). Innovation can enhance rural entrepreneurial activity in several ways, including the promotion of new businesses (Buratti et al., 2022; Wu et al., 2017), creation of stakeholder value (Chebo and Wubatie, 2021), increased propensity to undertake new entrepreneurial projects (Barnett et al., 2019) and provision of incentives for opportunity entrepreneurship (del Olmo-García et al., 2023). Thus, good management of innovation can result in higher levels of productivity (McGowan and Vasilakis, 2019), differentiation from competitors (Rosenbusch et al., 2011), environmental improvements (Zhu et al., 2023), improved ability to develop further innovations (Annosi et al., 2022) and promotion of economic growth (Aparicio et al., 2016). However, it has been shown that the relationship between innovation and performance is context dependent; not all types of innovation are equally beneficial (Mikołajczak and Pawlak, 2017). In the particular case of small and medium size enterprises -which tend to be prevalent in rural areas- a strategic innovation orientation seems to be more effective than a focus on developing innovative products (Rosenbusch et al., 2011). Similarly, Müller et al. (2018) found that business model innovations can help small businesses to create more value than if they were to focus solely on marketable innovation (Rosenbusch et al., 2011). Finally, innovation can produce knowledge spillovers which benefit different members of the ecosystem (Autio et al., 2018; Ganotakis et al., 2021). For instance, universities contribute to technology developments which provide non-monetary benefits for society (McGowan and Vasilakis, 2019). These results are particularly relevant for rural areas of Spain were the resources devoted to innovation are often significantly lower than those available in urban territories (del Olmo-García et al., 2023).

At the same time, firms in rural environments benefit from more affordable rents and stronger networks which enable specialized innovation (Álvarez-Coque et al., 2012). Access to public and private resources and human capital could result in their potential competitiveness being comparable to that of their urban counterparts (Calvo et al., 2022). Thus, several public policies seek to invest in rural innovation and technology. Some offer financing for innovation, others are aimed at promoting collaboration among different EE members in different stages of the production process. The European Rural Development Program included three measures to foster rural innovation: promoting investments in forestry innovation, seeking stronger collaboration among different entities and encouraging partnerships among farmers and other stakeholders. Although none of these initiatives is aimed solely at entrepreneurs, some were granted in combination with CLLD funding. It should be noted that in some cases, innovation was one among several objectives of the program. These technological partnerships and collaborations can increase the propensity for both product and process innovation substantially (Calvo et al., 2022). However, outcomes can be affected by the strength of the relations among participants (Autio et al., 2018), the context and a range of firm-specific factors (Rosenbusch et al., 2011).

In addition to enhancing innovation, technology management and adoption increase the opportunities for entrepreneurs in rural areas. They encourage relocation of entrepreneurial ventures to rural areas which offer better quality of life (Lafuente et al., 2010; Price et al., 2021), cheaper rents and the possibility of shared working spaces (Mariotti et al., 2023). As working from home has become more established, rural territories provide alternatives to residence in densely populated cities. Relocation of businesses to rural areas favors job creation and can help to reduce the rural digital divide (Esteban-Navarro et al., 2020). A good digital infrastructure would also allow entrepreneurs in diverse geographical settings to access knowledge from distant entities (Cuvero et al., 2022). However, some rural areas lack even the most basic infrastructure required for technology entrepreneurs to relocate there (Bowen and Morris, 2019; Mariotti et al., 2023). An understanding of the importance of good broadband access and technology infrastructure led to several policies to improve rural infrastructures. The European Rural Development Program provides aid to guarantee a minimum level of basic infrastructure and services, including ICTs and broadband which are crucial for digital inclusion of rural territories (Romero-Castro et al., 2023).

At the same time, rural areas include several industries such as agriculture and farming which are heavily reliant on technology (Bowen and Morris, 2019). This highlights the key role of good technology management for rural entrepreneurs and the adoption of new technologies (Annosi et al., 2022). Ganotakis et al. (2021) found that emergent entrepreneurs were more likely to adopt advanced technology while latent entrepreneurs were satisfied by the more basic versions of these technologies. The adoption of new technologies can also be very important for both digital and financial inclusion; older inhabitants in rural areas may be less willing to adopt new banking technologies which increases the risk of their exclusion from various services (Romero-Castro et al., 2023). Thus, the European Rural Development Program includes a program that provides training in new information technologies and promotes technology adoption. There are several factors that can shape the effectiveness of technology adoption programs in agriculture. Among them are farmers' attitudes to risk, local cooperation between public and private entities and resource constraints (Annosi et al., 2022). Technology adoption is influenced also by levels of human capital and experiential knowledge, which tend to be higher among emergent entrepreneurs (Ganotakis et al., 2021).

3. Data and methodology

3.1. Empirical strategy

The objective is to quantify the causal effect of the policy on the workers in different EEs, taking account of whether the entrepreneur or business which benefited from funding is located in a rural area. The analysis involves three main steps. First, calculation of the policy's average treatment effect on the treated (ATT) using the estimator proposed by Callaway and Sant'Anna (2021). This captures the causal effect of CLLD on unemployment levels in treated municipalities. It should be noted that EEs are not limited to particular municipalities. Unfortunately, we do not have data on individual EEs and therefore our measure is based on municipalities that could include more than one EE. Our test for spillover effects examines the effects beyond municipality borders. Goodman-Bacon (2021), Sun and Abraham (2021) and others show that the classical two-way fixed effects estimation can produce biased results in settings with multiple time periods, variations in treatment timing (different groups starting treatment at different points in time) and conditional parallel trend assumptions. All three conditions apply to our context. The period of time when aid was received ranges between 2014 and 2020, different municipalities received the treatment at different points in time and the rural municipalities are so different that the parallel trend assumption only holds after conditioning on degree of rurality. These three conditions mean that the traditional DiD estimator would produce biased results for ATTs (Rios-Avila et al., 2020).We performed the same estimation for the sample of women, who are the more vulnerable group of workers in the EE. Our interest is in whether the funding to promote entrepreneurship helped to reduce local unemployment.

Second, we analyzed the impact of the CLLD for the groups that received technology and innovation programs. In this case, we divided the sample into sub-sets and ran the same estimations excluding the policies analyzed as control variables. The parallel trend assumption was not met in the case of several of the estimations; we therefore ran a test for the significance of the differences in mean unemployment across policy recipients and non-recipients.

Third, we estimated spillover effects through proximity analysis. This provides a more accurate picture of the EE that is not restricted by the geographical limits of the municipality and captures the full effect of the policy including knowledge and labor spillovers. To understand how spillovers affect rural EEs that received the treatment we ran regressions using two different estimators for exposure. One reflects whether the municipality is neighbor to a treated municipality and the other computes the percentage of treated neighboring municipalities in order to estimate exposure. In line with the recommendations in Goodman-Bacon (2021), to avoid possible bias when analyzing a multi-year period, we analyzed spillover effects related to the first year of the policy which avoids any risk of a contaminated sample.

3.2. Sampling procedure

One of the main problems related to investigation of rural contexts is availability of data at the municipal (LAU-2) level (European Commission, 2022). This matters because rural municipalities are often the targets of other aid programs which if not controlled for could bias our results. Analyses at higher levels of aggregation would not allow identification of overlapping effects (Faraz et al., 2022). We therefore constructed a dataset which includes all programs in Spanish municipalities financed by the European common agricultural policy (CAP) from 2014 to 2020 – a total of 12,673,012 beneficiary programs over the six-year period. These are incorporated in the estimations as controls. CLLD was provided to 9721 entrepreneurs and companies aggregated at the municipality (LAU-2) level. This is our main explanatory variable. The dataset incudes panel data for each municipality and its yearly funding via the policies. The data for these projects are published by the Spanish Agrarian Guarantee Fund yearly and are removed after two years. We accumulated these releases to analyze the latest wave of CLLD funds (2014–2020) and combined them with unemployment data, different definitions of “rural” environment and other demographics. The data were collected from the OECD, Eurostat, the Spanish Ministry of the Environment, Rural and Marine Affairs, the Spanish National Statistics Institute and the degree of rurality classification in Goerlich et al. (2017). Our yearly frequency data refer to the period October 2012 to October 2021.[2] With the exception of municipalities which either separated or merged during the study period, all of Spain’s 8131 municipalities are included in the analysis. In the case of separated municipalities, it was not possible to allocate projects or unemployment levels in a consistent way. They account for a total of 35 municipalities, constituting 0.43 % of the initial sample.

3.3. Variables

3.3.1. Local unemployment

CLLD was aimed at promoting entrepreneurship and rural EEs to contribute to rural development. We explore its impact on unemployment. We are limited by data availability, but future studies could include other measures, such as employee well-being or relationships among members of the EE. We measure unemployment using data from the Spanish National Statistics Institute. To avoid effects driven by territory size, we measure local unemployment as a percentage of the local population. In our robustness check, we exclude members of the population aged over 65 years, since they might influence the percentages.

3.3.2. Rurality

Rural areas have been defined in various ways. The main estimation is based on Eurostat’s degree of urbanization classification, which uses a rural-urban continuum that includes three categories: rural, towns and semi-dense areas and urban areas (European Commission et al., 2021). Local administrative units are separated according to 1 sq km population grid cells, based on the share of local population and contiguity with an urban center. Although population density is the most commonly used measure, some specifications combine population density with urban center size within a region (OECD, 2011), or accessibility and ground use (Goerlich et al., 2017), or employ different thresholds (BOE, 2007). We employ these different measures in our robustness check specifications.

3.3.3. Technology and innovation programs

Given the importance of technology and innovation for rural ventures, several other programs were implemented alongside the CLLD. They focus on technology adoption, innovation and technology infrastructure. Annex I describes these programs and their conditions in detail. Here we offer an overview of their objectives. First, the technology adoption initiatives were aimed at providing training in use of new information technologies, access to recent research and advances in product quality. They tried to bridge between the worlds of research and practice in the agriculture, food and forestry sectors. Second, the innovation initiatives included three programs. The first provided funds for forestry innovations and technology; the second fostered collaboration among firms to promote product, process and technology innovations; and the third was designed to promote partnerships among firms operating at different stages in the production process to produce innovations. The focus was on agriculture and food firms, and collaboration between farmers, food processing firms and other stakeholders. Finally, the technology infrastructure program was designed to increase access to basic services in rural areas through provision of better infrastructure and ICTs. In some cases, these technology and innovation programs were part of a more comprehensive policy to improve business and living conditions in rural areas.

3.3.4. Control variables

Our control variables are all other policies implemented as part of the Rural Development Program 2014–2020 and those implemented in the two years before 2014 – a total of over 12.6 million funded initiatives. Some of these programs, similar to CLLD, were aimed at promoting entrepreneurship or at influencing other dimensions of the EE by fostering collaboration, promoting exports, improving infrastructures and providing training to local actors. Not including these policies would have serious consequences for our estimations.

4. Results

4.1. Descriptive statistics

Table 1 presents the descriptive statistics for rural and urban areas. In line with prior findings for rural ecosystems, rural settings show marked differences with urban municipalities. Population levels are lower in rural regions and have been aggravated further by population losses due to natural deaths and migration due to the lack of opportunities (The World Bank, 2022). As a result, these areas are characterized by aging populations with significantly higher shares of people aged over 65 years (Goerlich et al., 2017). An older population can influence technology adoption dynamics, since older people are often reluctant to

Table 1
Descriptive statistics.

	Full sample	Cities	Semi-urban areas	Rural areas
Average population	5764.51	1.2e+05	13,745.24	927.75
	(47,104.1)	(262,198.4)	(11,760.3)	(1440.0)
Percentage of population over 65	0.29	0.17	0.17	0.32
	(0.116)	(0.0430)	(0.0467)	(0.111)
Percentage of women	0.47	0.51	0.50	0.47
	(0.0454)	(0.0114)	(0.0109)	(0.0471)
Percentage of CLLD recipients	0.33	0.03	0.12	0.85
	(0.472)	(0.465)	(0.462)	(0.474)
That received any technological program	0.22	0.02	0.11	0.55
	(0.415)	(0.503)	(0.480)	(0.386)
That received funds for technological adoption	0.02	0.01	0.02	0.02
	(0.390)	(0.257)	(0.422)	(0.400)
That received funds for innovation	0.21	0.02	0.11	0.53
	(0.412)	(0.503)	(0.478)	(0.382)
That received funds for technological infrastructure	0.04	0.00	0.03	0.10
	(0.391)	(0.000)	(0.362)	(0.405)
N	8095	217	1100	6778

Standard deviations in parentheses.

[2] Therefore, there is a two-month mismatch between aid and unemployment data, which has yearly frequency ranging from January to December.

adopt new technologies (Romero-Castro et al., 2023). Rural area populations also tend to include fewer women which is one of the reasons why the CLLD prioritizes female entrepreneurship. Table 1 row 4 presents the percentage of treated municipalities in each area. Consistent with the policy objectives, most are rural areas. The last row in Table 1 presents the proportions that received other funding to foster technological adoption, innovation and technological infrastructure improvements. These figures show the differences between rural areas and cities -where this investment was not needed- and the importance of the policy for digital inclusion (Romero-Castro et al., 2023). It should be noted that those territories with poorer infrastructure are likely to experience higher barriers to innovation and lower rates of technology adoption which explains the overlap of some of the policies across rural territories.

Fig. 1 left side shows the distribution of the program to promote rural entrepreneurship and the municipalities that received this aid between 2014 and 2020. A total of 9721 projects in 2706 municipalities received funding which accounts for 33.43 % of Spanish municipalities. Fig. 1 right side depicts the evolution of the population between 2003 and 2014 – the 10 years prior to implementation of the policy. Note that those areas which lost larger shares of their population correspond roughly to those areas that received the program. This is an important point, since the results might have been affected had there been a systematic bias in the distribution of CLLD unrelated to municipality characteristics.

We are interested also in the year that projects were funded. Table 2 shows that most (88.24 %) were funded in the period October 2017 to October 2020, a distribution that is consistent with the functioning of the program. Local action groups had to be constituted prior to receipt of financing (European Network for Rural Development, 2018a). In Spain, most (95 %) were formally selected between 2014 and first half 2017 – a delay that led to the calls for projects being published mainly in second half 2017 which in turn resulted in most projects being funded subsequent to that date (European Network for Rural Development, 2018b).

4.2. Estimation of the parallel trend assumption

The parallel trend assumption is key to the DiD estimation of causal effects (Rios-Avila et al., 2020). We condition the parallel trend assumption on whether the territory belongs to a rural area (following Eurostat criteria) and on all other aid implemented as part of the Rural Development Program 2014–2020. Both elements if not included could bias the parallel trend assumption. On the one hand, the pattern of development in rural areas differs considerably from the patterns in urban and semi-urban areas. On the other hand, the trends in territories might change with receipt of additional aid in the same period. Thus, to make territories comparable, we need to account for this factor. We employ a doubly robust inverse probability weighting estimator. The parallel trend assumption holds only when conditioning on degree of rurality and other programs received. We verified this assumption, rejecting the null hypothesis that all pre-treatment is equal to zero.

Another issue related to estimation of the parallel trend assumption is the possibility that the policy was anticipated. If recipients increased their entrepreneurial activities in expectation of receiving the funding before the policy started, this would bias our analysis (Callaway and Sant'Anna, 2021). However, we consider only projects launched after 2014. The model developed by Callaway and Sant'Anna (2021) allows use of not-yet-treated municipalities to be used as controls; in our estimations, we consider the most rigorous setting in which the comparison group is never-treated municipalities.

In the case of recipients of CLLD and technological and innovation funds, the parallel trend assumption was not fulfilled across several estimations. This implies that some parameters could not be provided using Callaway and Sant'Anna's (2021) DiD. This would seem reasonable given the huge differences among several rural territories in terms of infrastructure and development. For example, for the group that received infrastructure funding, the parallel trend assumption was fulfilled only with an alpha of 0.1. For these estimations, the analysis was complemented using another indicator. We performed several *t*-tests to examine whether the mean decrease in unemployment was significantly stronger for recipients of CLLD that also received technology and innovation funding. Though less rigorous than Callaway and Sant'Anna's (2021) estimate, it complements the analysis by highlighting the importance of these policies. However, it should be noted that causality cannot be inferred from this second set of indicators; they serve only as complements for informative purposes.

4.3. Impact of Community-Led Local Development on local unemployment

Table 3 reports the results for the ATT. It shows the causal effect of CLLD on unemployment for treated municipalities. All estimators use bootstrapped standard errors at the municipality level. Following Callaway and Sant'Anna (2021), the columns "Partially Aggregated" and "Single Parameters" respectively present the estimations of these effects for different groups and periods and the aggregate effect of the policy. Municipalities that received this program have 5.38 % lower unemployment levels than non-aided municipalities, and the estimations are highly significant.

The row "Calendar Time Effects" shows ATTs by year (October to October each year). The reduction in unemployment was highly significant for all the years the policy was implemented, with larger effects found for 2016 to 2018. Year 2021 is omitted since it was probably influenced by the Covid-19 pandemic.[3] Analysis of whether the effect in the treated municipalities was different during the Covid crisis is beyond the scope of this paper. The row "Group-Specific Effects" captures the total average treatment effects for the cohort that received the program in each year. Effects are much bigger for those cohorts that were treated at an earlier point in time, probably because the effects of the policy had more time to develop. For the groups treated between October 2018 (group 2018) to October 2020 (group 2019) there seems to be no significant reduction in unemployment. It might be that the effects of the policy take time to emerge, but it would be useful to repeat the analysis at a later date to compare the results. On the other hand, it might be that the final months of 2020 were affected by the Covid pandemic. The last row presents ATTs by length of exposure and shows that despite a slight trend towards reduced unemployment, the effect changed markedly after implementation of the policy. As already discussed, the effects seem to accumulate over time. It should be noted that the slightly positive sign on the group treated in 2019 does not reverse the overall unemployment reduction effect in that year.

Fig. 2 depicts the magnitude of the ATT and the confidence intervals and provides a better picture of the sizeable decrease after implementation of the policy.

We next consider how the effects of the policy change with the length of time since implementation of the policy. Fig. 3 presents the yearly effects for the cohorts treated across time. As before, with the exception of the group treated in 2019 most estimates show a cumulative effect of the policy due possibly to the fact that the full effect of the policy needs time to emerge.

This interpretation is consistent with Fig. 4 which depicts ATTs aggregated by cohort on the left side of the figure and ATTs aggregated by period on the right side. For all except the 2019 cohort we see a sizeable decrease in unemployment. The group treated in 2016 shows both a large effect and a considerably wider confidence interval compared to those treated in other years. This might be because fewer projects were funded in 2016 which would increase the probability of a more dispersed confidence interval. Finally, as before, the effects seem

[3] When we included 2021, the effect remained negative and significant at the same level of confidence and with a very similar coefficient of 5.05 %.

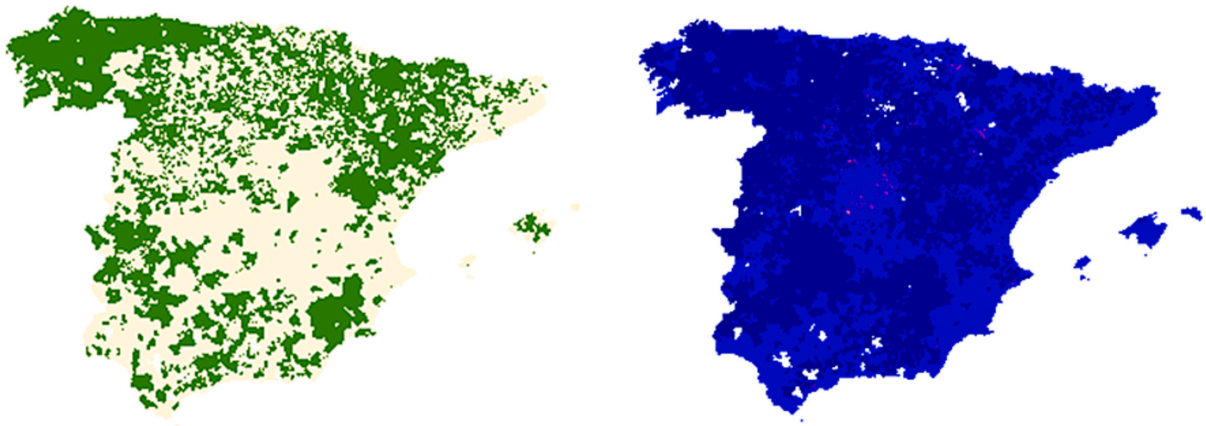

Fig. 1. Distribution of the program (left-hand side) and evolution of population (right hand side).
Source: authors based on Spanish National Institute of Statistics (2022) data.

Table 2
Yearly distribution of Community-Led Local Development.

Year	Treated municipalities	Percentage	Cumulative percentage
October 2014–October 2015	0		
October 2015–October 2016	121	2.37	2.37
October 2016–October 2017	479	9.39	11.76
October 2017–October 2018	1176	23.05	34.80
October 2018–October 2019	1567	30.71	65.51
October 2019–October 2020	1760	34.49	100
N	5103		

mostly to be cumulative, with the exception of those projects treated between October 2019 and October 2020 where the full effect of the policy may not yet be observable. Access to more data would allow estimations for a longer time span which would yield a more complete picture.

4.4. Effects for recipients of technology and innovation programs

Since the lack of infrastructure and poor innovation capacity might be significant obstacles to entrepreneurial activity, this section examines the effect for groups that received technology and innovation funding in addition to CLLD funds. The three technology and innovation programs were set up to foster technological adoption, promote innovation and provide basic infrastructure. Since this analysis is based on a sub-sample of the population, it cannot be compared to the general effect of the policy. However, it allows us to examine the effect of CLLD in municipalities that also received this extra funding.

Table 4 displays the effects of CLLD for different groups using Callaway and Sant'Anna's (2021) DiD estimator. It can be seen that those that were granted CLLD along with any of the technology and innovation measures experienced a reduction in unemployment of 2.18 %. The largest reduction in unemployment (4.05 %) was observed for municipalities which received aid for broadband and ICT infrastructure, possibly due to their importance for business activity (Ashmore et al., 2017; Briglauer et al., 2019). The group that received aid to promote collaboration and innovation also saw a significant decrease in unemployment (2.41 %). This is consistent with prior studies emphasizing the importance of innovation for rural businesses and entrepreneurs (del Olmo-García et al., 2023). However, the group that received aid for

Table 3
Average Treatment Effects on the Treated (ATTs), by group and period groups.

Simple weighted average	Partially aggregated							Single parameters	
								−0.0538***	
Calendar time effects	*t* = 2015 −0.018**	*t* = 2016 −0.120**	*t* = 2017 −0.069***	*t* = 2018 −0.066**	*t* = 2019 −0.024**				
Group-specific effects	g = 2015 −0.042**	g = 2016 −0.197**	g = 2017 −0.007*	g = 2018 −0.005	g = 2019 0.025***				
Event study	t-3(2012) −0.008	t-2(2013) −0.004*	t-1(2014) −0.013**	t + 0(2015) −0.019**	t + 1(2016) −0.045***	t + 2(2017) −0.106***	t + 3(2018) −0.125**	t + 4(2019) −0.062***	
With 2020									−0.0505***
Simple weighted average									
Calendar time effects	t = 2015 −0.018**	t = 2016 −0.120**	t = 2017 −0.069***	t = 2018 −0.066**	t = 2019 −0.024**	*t* = 2020 −0.042**			
Group-specific effects	g = 2015 −0.046**	g = 2016 −0.203**	g = 2017 −0.009**	g = 2018 −0.008*	g = 2019 0.020***				
Event study	t-3(2012) −0.008	t-2(2013) −0.004*	t-1(2014) −0.013**	t + 0(2015) −0.019**	t + 1(2016) −0.031**	t + 2(2017) −0.072***	t + 3(2018) −0.061***	t + 4(2019) −0.187**	t + 5(2020) −0.068***

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

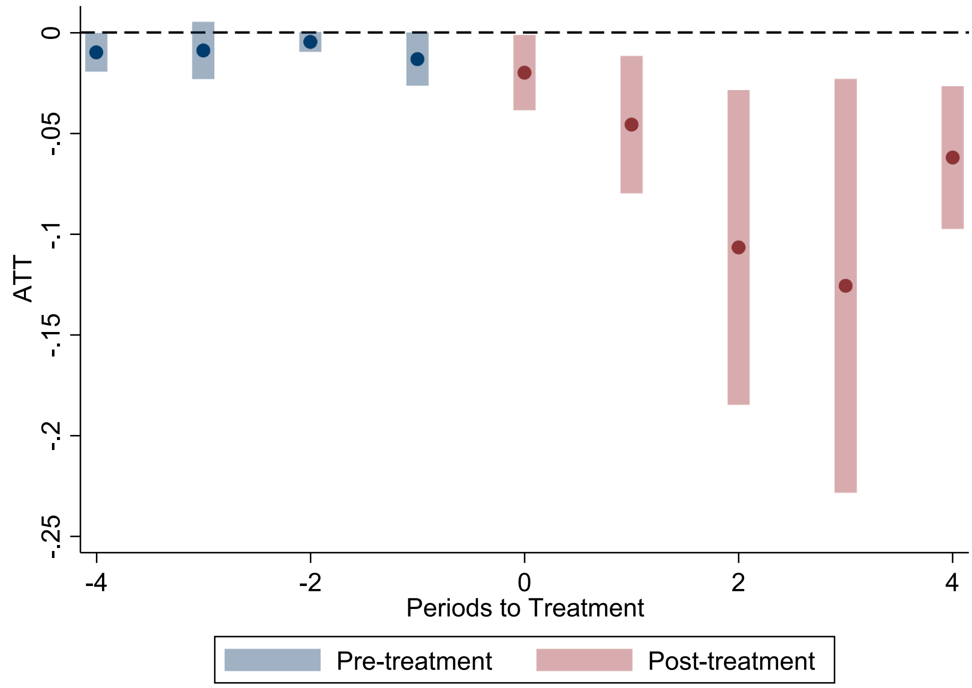

Fig. 2. Average Treatment Effects on the Treated (ATT) by event study.

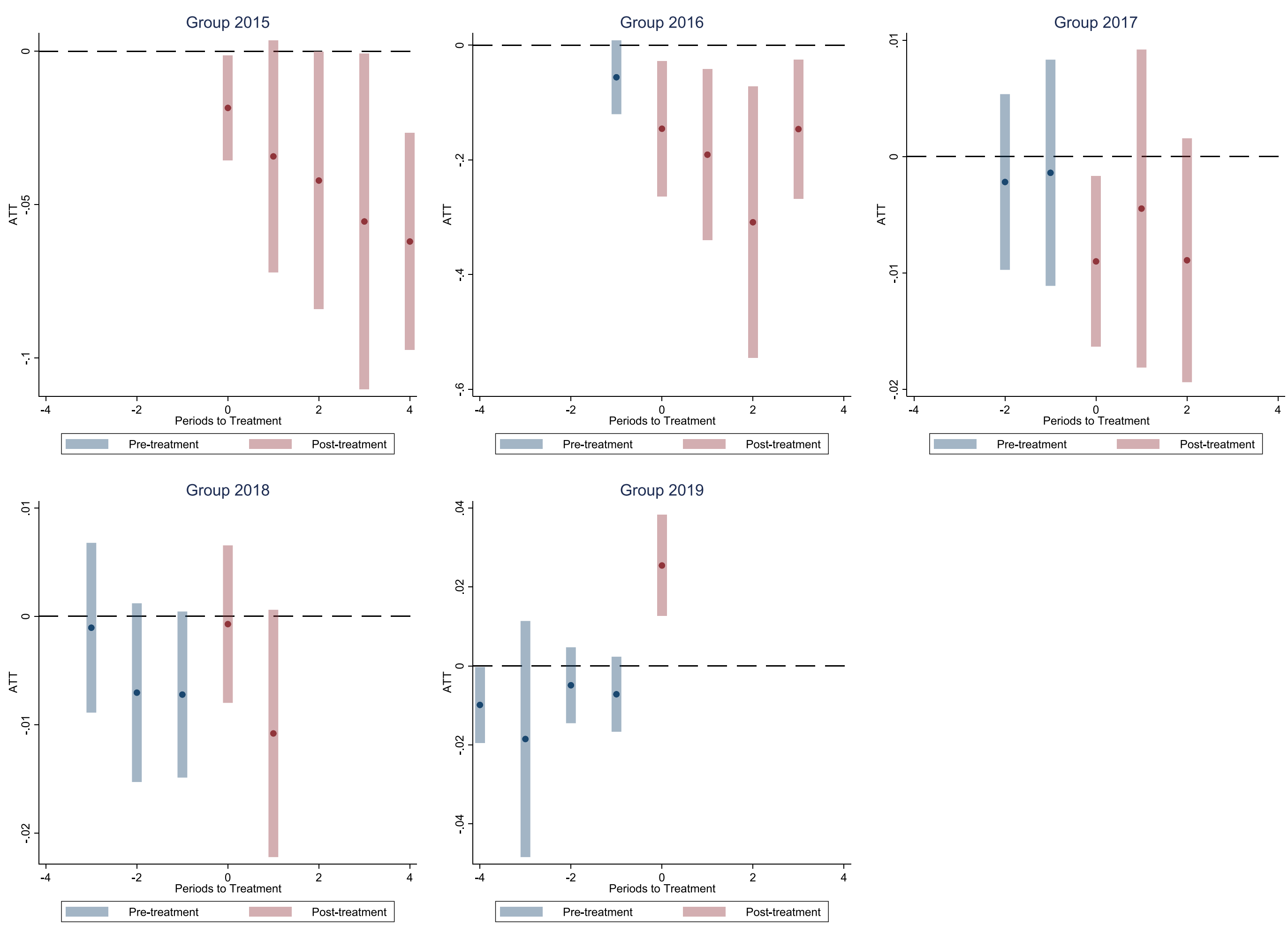

Fig. 3. CLLD group-time Average Treatment Effects on the Treated (ATTs).

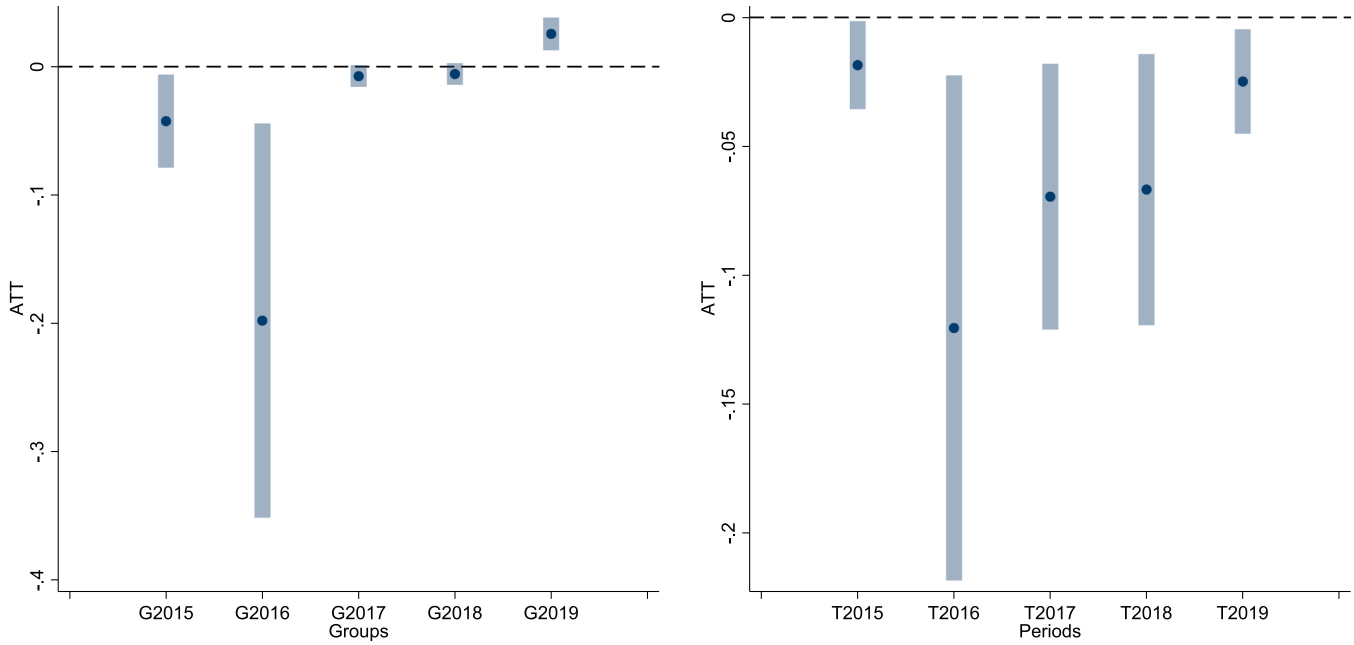

Fig. 4. ATTs by cohort and time period.

Table 4
ATTs for recipients of CLLD and technological or innovation programs.

	Received technological and innovation aid	Did not receive technological and innovation aid
	(1)	(2)
	ATT	ATT
Technological aid (any program)	−0.0218**	0.0147
Innovation	−0.0241***	PTA not fulfilled
Technological infrastructure	−0.0405***	−0.0202
Technological adoption	−0.0032	PTA not fulfilled

** $p < 0.01$.
*** $p < 0.001$.

technology adoption showed no significant decrease in unemployment. It should be noted that the estimate does not measure the general effect of the technology adoption program. Rather, it shows only the effect of CLLD for the group that was also granted funds towards technology adoption. Further research is needed to ascertain whether the technology adoption program had a positive effect on businesses which did not receive CLLD. There are several factors that might influence the effectiveness of CLLD for this group including the relatively low number of projects funded, the lack of basic infrastructure, the age and characteristics of recipients and the interplay among local institutions (Annosi et al., 2022; Romero-Castro et al., 2023). As explained in Section 4.2, the parallel trend assumption is not fulfilled in the case of the group that did not receive technological and innovation programs, meaning that they cannot be compared using Callaway and Sant'Anna's (2021) DiD.

Therefore, for indicative purposes, Table 5 presents an additional estimation for the difference in mean unemployment (as a percentage of the local population) before and after the programs. Across the different estimations, the groups that received technology and innovation programs (column 3) enjoyed a larger reduction in unemployment than those that received only CLLD funds (column 6). Consistent with the results using Callaway and Sant'Anna's (2021) DiD, the reduction in unemployment is particularly large for municipalities that received funding for infrastructure in terms of ICTs and broadband access. This group also shows the largest difference compared to those that did not receive any technology or innovation programs, for whom the reduction in unemployment is considerably smaller. Though a more detailed analysis would be required to establish a causal relationship, the difference in means is consistent with the importance many authors attribute to these variables for rural entrepreneurship (Annosi et al., 2022; Ganotakis et al., 2021; Romero-Castro et al., 2023).

Fig. 5 depicts the effect of CLLD for the groups that received any technological and innovation program and the individual effects of each program. For the groups that received any technology and innovation measures, unemployment is reduced and the effect increases over time (panel I). For the group receiving innovation policies (panel II) the reduction in unemployment is larger for the most recent two periods. The effect could have been boosted by spillover effects from earlier interventions (Ganotakis et al., 2021). The effects for the group that

Table 5
Mean differences in unemployment for recipients of CLLD and technological or innovation programs.

	Received technological and innovation aid			Did not receive technological and innovation aid		
	(1)	(2)	(3)	(4)	(5)	(6)
	Before	After	Difference in unemployment	Before	After	Difference in unemployment
Technological aid (any program)	0.9107	0.6471	−0.2636***	0.8054	0.6084	−0.1969***
Innovation	0.9142	0.6496	−0.2645***	0.8054	0.6060	−0.1993***
Technological infrastructure	0.9620	0.6270	−0.3350***	0.8639	0.6361	−0.2277***
Technological adoption	1.1218	0.8143	−0.3075***	0.8614	0.6231	−0.2382***

*** $p < 0.001$.

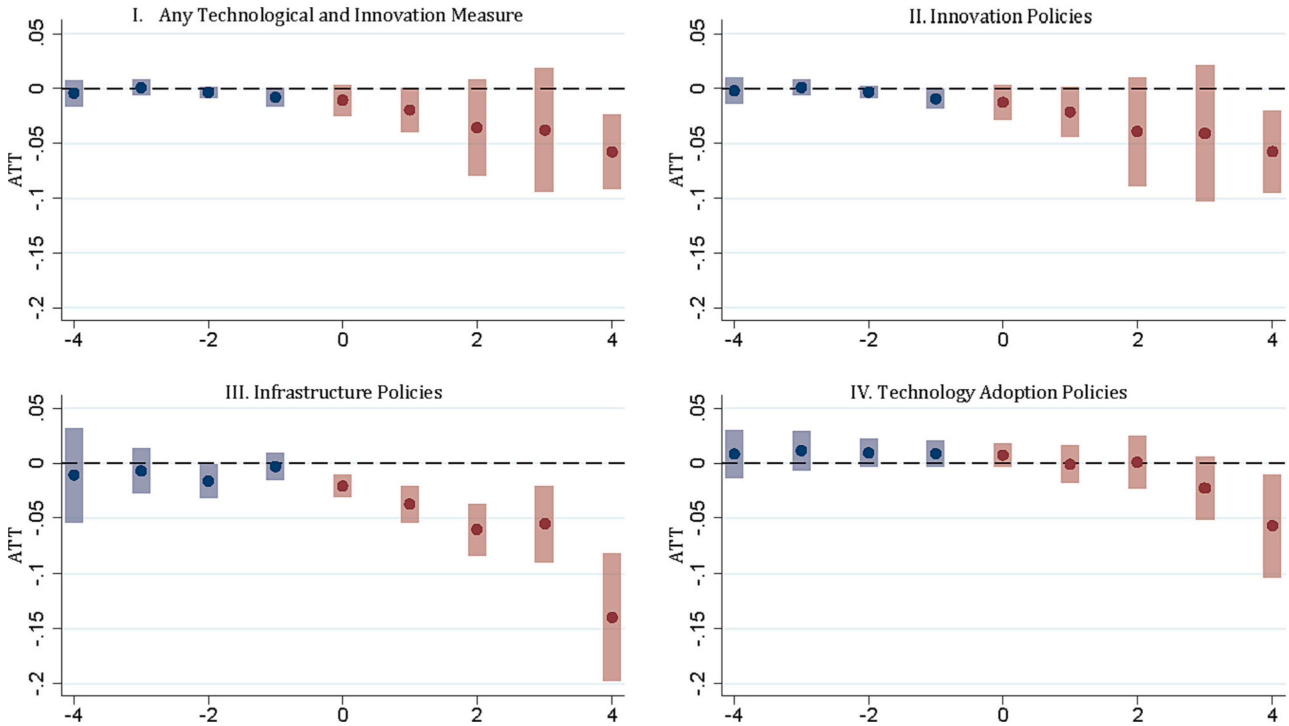

Fig. 5. ATTs for the recipients of each technological and innovation measure.

received infrastructure policies (panel III) are considerably larger compared to the effects due to the other programs and particularly in the most recent period. Finally, we see that the effects for those that received technology adoption programs are markedly lower than for other groups (panel IV). These effects are non-significant although they appear to increase over time which might imply that it takes time for the effects to emerge.

4.5. Effects for female workers

Since women in rural EE suffer from both higher rates of unemployment and lower probability of engaging in entrepreneurial activity (Carter et al., 2015; Kovačićek and Franić, 2019) they are one of the main actors targeted by the CLLD (European Commission, 2014). We analyze the effect on female workers in the ecosystem; similar to the general specification, the parallel trend assumption requires

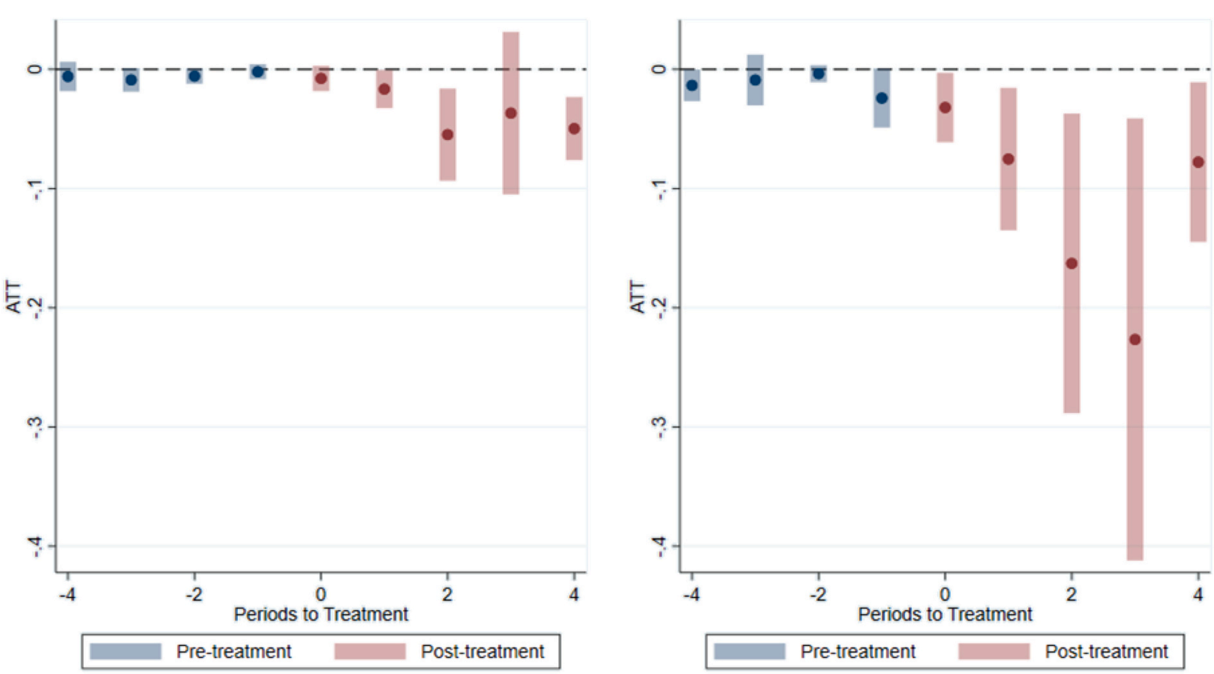

Fig. 6. ATTs event study for women (left) and for men (right).

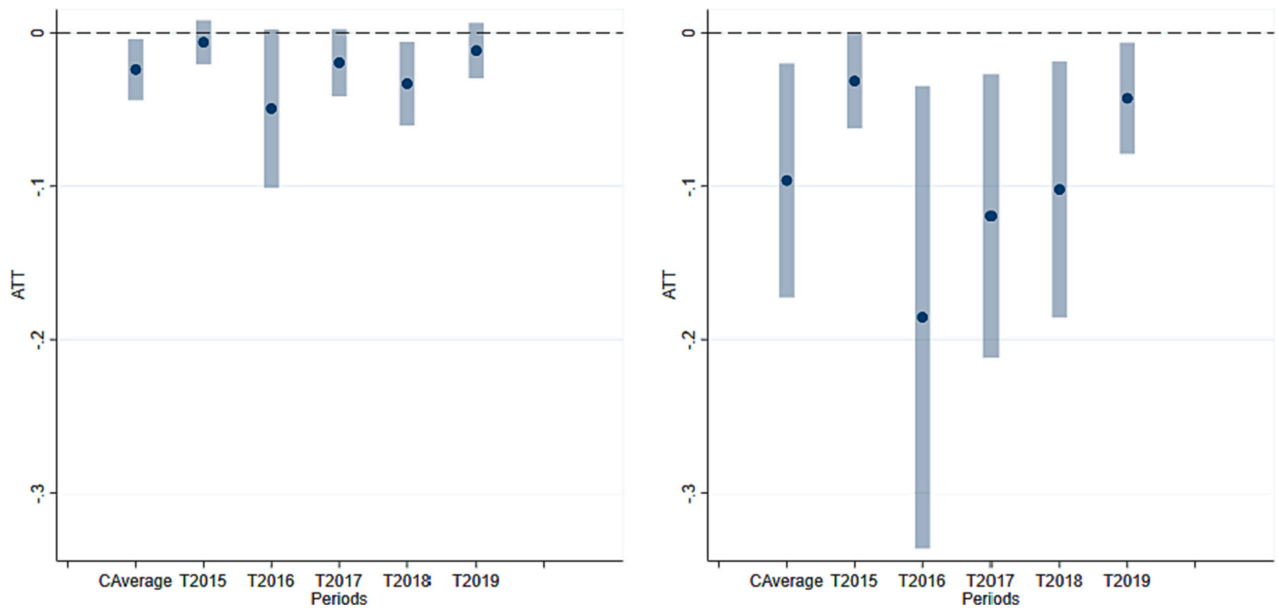

Fig. 7. ATTs by period for women (left) and for men (right).

conditioning on degree of rurality and other aid implemented in the same period.

Table 5 shows that the effects of the CLLD plan were positive for women; municipalities that received funding show levels of female unemployment 2.26 % lower on average compared to municipalities that did not receive the funding. However, the unemployment reduction effect is lower for women than for men for whom unemployment decreased by 8.69 %. Table 4 provides a breakdown by date/time effects, group-specific effects and event study estimations for women (upper part of the table) and men (lower part of the table).

Fig. 6 depicts the ATTs for women (left side) and men (right side). Again, the effects of the policy are positive for both groups but with sizeable differences in impact. This is a crucial result; it is possible that the policy is widening the gap between women and men in the ecosystem and this is a result which should be taken into account in future policy design.

Although CLLD targeted women entrepreneurs in particular, fewer women benefited from funding which is consistent with the demographic structure of rural ecosystems. Analysis of the distribution of the policy at the individual level would shed more light on this. However, there are other contextual factors which might influence the effectiveness of CLLD for women (Arshed et al., 2019; Orser et al., 2019), including structural difficulties (Carter et al., 2015; Orser et al., 2019) and program configuration (Ahl and Nelson, 2015; Berger and Kuckertz, 2016). Also, women seem less keen to pursue entrepreneurial endeavors which might make other policies more effective for reducing female unemployment (Arshed et al., 2019).

Both groups exhibit the general trend observed in the main estimation although the effect for female unemployment is much smaller across most estimations. Fig. 7 depicts the accumulation of the effects over time, and shows they are greater for those groups that received the treatment earlier. Similar to the results of the general estimation, it seems the policy has been particularly helpful for those that received the funding between October 2016 and October 2017. Fig. 7 shows also that male unemployment accounts for most of the average reduction in unemployment observed in the prior estimations.

Table 6
ATTs by gender.

	Partially aggregated								Single parameters
For women workers									
Simple weighted average									−0.0226**
Calendar time effects	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019				
	−0.006	−0.049*	−0.019*	−0.033**	−0.011				
Group-specific effects	g = 2015	g = 2016	g = 2017	g = 2018	g = 2019				
	−0.028***	−0.064*	−0.012***	−0.009	0.023***				
Event study	t-3(2012)	t-2(2013)	t-1(2014)	t + 0(2015)	t + 1(2016)	t + 2(2017)	t + 3(2018)	t + 4(2019)	
	−0.008*	−0.005*	−0.002	−0.007	−0.016**	−0.054***	−0.036	−0.049***	
For male workers									
Simple weighted average									−0.0869**
Calendar time effects	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019				
	−0.031**	−0.185**	−0.119**	−0.102**	−0.042**				
Group-specific effects	g = 2015	g = 2016	g = 2017	g = 2018	g = 2019				
	−0.058***	−0.332**	−0.005	−0.003	0.025***				
Event study	t-3(2012)	t-2(2013)	t-1(2014)	t + 0(2015)	t + 1(2016)	t + 2(2017)	t + 3(2018)	t + 4(2019)	
	−0.008	−0.003	−0.024*	−0.032**	−0.075**	−0.162**	−0.226**	−0.077**	

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 7
Spillover effects of CLLD.

	(1)	(2)	(3)
	Traditional DID estimation	DID with spillover exposure	DID with continuous spillover exposure
Treatment	−0.0311**	−0.0296*	−0.0309*
	(0.0120)	(0.0128)	(0.0127)
Treatment with exposure		−0.0120	−0.00873
		(0.0361)	(0.271)
N	32,380	32,380	32,380
Adj. R^2	0.937	0.937	0.937

Standard errors in parentheses.
* $p < 0.05$.
** $p < 0.01$.

Table 8
Alternative specifications.

Parameter	Simple weighted average
Main estimation. Using Eurostat's definition of rurality.	−0.053***
Changing the dependent variable	
Using only population between 16 and 64 years old	−0.068**
Changing the definition of rurality	
Using the OECD's (2011) definition of rurality	−0.071***
Using the LDSMR definition of rurality	−0.068***
Using Goerlich et al. (2017) definition of rurality	−0.046**

** $p < 0.01$.
*** $p < 0.001$.

4.6. Policy spillover effects

Table 6 presents the CLLD spillover effects. Following Goodman-Bacon (2021), we provide the effect only for the first period of the policy to avoid risk of a biased estimator due to a setting with multiple time periods. The most recent advances in the econometric literature on DiD estimators still do not integrate the discontinuous treatment which would enable our spillover analysis (Butts, 2021). Table 6 column 1 estimates Eq. (1) and shows the effect of the program using the traditional DiD approximation. We observe a slightly lower effect than reported in Callaway and Sant'Anna (2021) but also observe a significant decrease in unemployment for the treated municipalities.

$$y_{it} = \alpha + \delta_t + \delta_i + \beta PostTreatment_{it} + \varepsilon_{it} \quad (1)$$

Columns 2 and 3 present the effect with spillovers for two different specifications for exposure. The first includes exposure using treated municipality as the dummy variable. The second estimates the percentage of treated neighbors in the number of neighboring municipalities to quantify the degree of that exposure. Both estimations are based on Eq. (2) but employ different definitions of exposure.

$$y_{it} = \alpha + \delta_t + \delta_i + \beta PostTreatment_{it} + \tau_1 Exposure + \varepsilon_{it} \quad (2)$$

The results show that spillover effects are non-significant in both cases (Table 7). This could be due to the idiosyncrasies of rural networks (Aguilar, 2021; Xie et al., 2021) which mean that it takes longer for a positive effect to emerge. Also, were we to consider the whole policy period the results might differ. While the extent of the positive effects appear slightly disappointing, it is encouraging to observe that neighboring municipalities do not suffer from any adverse effects such as if entrepreneurs in a proximate municipality to the one receiving treatment were to abandon their own territory to take advantage of the policy. In that case, the coefficient of treatment with exposure would be positive and significant.

Therefore, for the first year of treatment, there is no evidence of spillovers of knowledge or innovation to other municipalities and no adverse effect of attraction of entrepreneurs from neighboring rural municipalities. This could change over the succeeding years of the program.

4.7. Robustness tests

To further check the reliability of our results we performed several additional estimations. In the first, given the large share of older individuals residing in rural areas, our dependent variable is percentage of total unemployment in the population aged between 16 and 64 years to ensure that demographic changes are not affecting the outcome. This avoids deaths of those aged older than 64 years being computed as increased unemployment. The effect is similar to although slightly higher than the main estimation.

Finally, as a robustness check, we used different variables for rural to check whether this changed the results.[4] For instance, we included the OECD classification, the Eurostat degree of rurality (European Commission et al., 2021), the criteria included in the Spanish Law on Sustainable Development of Rural Environments and a rurality classification developed by Goerlich et al. (2017) for Spanish municipalities. We repeated our analysis using these different definitions of rurality. The results in Table 8 were similar to our main estimation although using the OECD definition produced slightly higher results compared to the Eurostat definition. This might be because the estimations consider only rural or urban areas whereas the Eurostat definition includes semi-rural territories (European Commission et al., 2021). The final estimation which included the six rural and urban typologies proposed by Goerlich et al. (2017) shows a similar although slightly lower effect. Again, although the definition of rurality used might be affecting the outcome slightly, the results are robust across all the alternative estimations analyzed and provide very similar estimates.

5. Conclusion

Rural EEs face several problems which are unique to their context. However, most studies do not take account of these particularities. This paper tries to fill this gap by conducting an ex-post analysis of a novel policy –CLLD- designed to foster entrepreneurship in rural areas. We found a positive effect of the policy on unemployment; municipalities with funded projects have 5.38 % lower unemployment on average than non-treated municipalities. The effect seems to accumulate over time, with groups receiving funding earlier showing the largest effects. We found no spillover effects of the CLLD. A positive finding is that the

[4] Another way to test robustness would be use of a regression discontinuity design (RDD) but in our case this is not feasible. The principle of subsidiarity means that local authorities are allowed to set their own requirements to suit their particular context which makes a comparable threshold across all municipalities impossible even for a fuzzy RDD.

treated municipalities do not seem to be attracting entrepreneurs away from neighboring rural municipalities which would result in a substitution effect and no new job creation. We also found that the policy reduced female unemployment although less than the reduction enjoyed by males (2.26 % for women versus 8.69 for men). This result requires careful consideration in relation to whether the policy might be increasing inequality in rural areas. Account should be taken of this possibility when designing future waves of aid.

Given the importance of technology and innovation management for rural entrepreneurs, we examined how the CLLD affected recipients also receiving funding to improve basic infrastructure, foster innovation and increase technology adoption. The results show that the CLLD was highly significant for the groups that received infrastructure and innovation funding but we found no significant decrease in unemployment for the beneficiaries of technology adoption funds. Further analysis is needed to assess the effectiveness of this measure for other groups. The results highlight the value for rural entrepreneurial activity of investing in the broadband and ICT infrastructures. Digital infrastructure investments are an important pre-requisite for technology adoption and promotion of entrepreneurial activities (Bowen and Morris, 2019). Our results also stress the importance of innovation for rural entrepreneurs and point to the need for more research on the effectiveness of technology adoption programs.

Our work has some limitations. Although it includes the whole Spanish territory, the results may not be generalizable to other countries as shown by related studies in other European regions (Olar and Jitea, 2021; Ashmore et al., 2017). It should be noted that the effect of this funding extends beyond reducing local unemployment. It would be interesting to analyze the effect of this funding across different EE dimensions including the impact on local innovation (Autio et al., 2018). It would also be interesting to replicate the analysis using EE as the unit of analysis, since EEs vary in their size and configuration (Basole et al., 2019). Also, since the analysis focuses on the most recent wave of aid, it was not possible to assess the long-term effects of the program; some effects might increase over time. The long-term effects of the policy should be investigated to check whether they persist over time. Another shortcoming is that our estimation of spillover effects was limited by the econometric developments in this area and would benefit greatly from the most recent advances in the DiD literature. Finally, future work could focus on the dynamics shaping distribution of the policy which might help explain the different results for male and female workers.

Declaration of competing interest

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors declare no competing interests relevant to the content of this research and no relevant financial or non-financial interests.

Data availability

Data will be made available on request.

Acknowledgements

We thank Iván de las Heras, Miguel Ángel Borrella Mas and two anonymous reviewers whose insightful contributions substantially improved this paper.

Annex I. Regulation for technology and innovation policies

Dimension	Brief description	Objective	Article regulating this policy
Technology adoption	Training in new information technologies	To provide vocational training in several areas for individuals in the Agricultural, Food and Forestry sectors. Among them, in new information technologies, research and product quality.	V/B.1.1. Article 21. Title IV, Chapter I of Regulation (EC) No. 1698/2005.
Innovation	Forestry innovation and technology	To promote investment in the development and protection of forests, in forestry innovation and in forest technology.	IV/A.8. DR Article 21 (22–26). Title III, Chapter I of Regulation (EU) No 1305/2013 of the European Parliament.
	Promote technology and process innovation	To foster collaboration among two or more firms with the objective of developing new products, processes and technology.	IV/A.21. DR Article 35. Title III, Chapter I of Regulation (EU) No 1305/2013 of the European Parliament.
	New products, processes and technologies in the agricultural, food and forestry sectors	To foster partnerships among farmers, food processing firms and other stakeholders to comprehensive and innovative approaches. In particular, through the creation of new products, processes and technologies.	V/B.1.9. Article 29. Council Regulation (EC) No 1698/2005
Technology infrastructure	Provision of basic infrastructure	To provide funding for basic services, including local access to information and communication technologies (ICTs).	V/B.3.4. DR Article 56. Council Regulation (EC) No 1698/2005
	Provision of basic services and broadband access	Development of infrastructure, broadband access and renewable energy sources.	IV/A.7. DR Article 20. Title III, Chapter I of Regulation (EU) No 1305/2013 of the European Parliament.

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