Science and Public Policy, 2023, **00**, 1–18
DOI: https://doi.org/10.1093/scipol/scad057
Article

Multilevel innovation policy mix: impact of regional, national, and European R&D grants

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Research and Development (R&D) grants are one of the most commonly employed programmes by regional, national, and European governments to promote innovation at the firm level. This study contributes to the existing literature on innovation policy mix by investigating whether combinations of the three funding sources can yield positive effects on various measurements of innovation outcomes. Using a panel of 10,045 Spanish firms from 2004 to 2016 and a flexible conditional difference-in-differences approach, our findings reveal that R&D grants funded by European sources exert the most substantial positive impact on firms' product and process innovations. Conversely, national funding demonstrates this impact on new-to-market innovations and patent applications. Notably, the positive effect on innovation outcomes is evident only when considering the combination of all three distinct funding schemes and the amalgamation of regional and national R&D grants. These results reject the possibility of substitutive effects among different funding schemes, particularly between regional and national institutions.

Keywords: innovation policy mix; output additionality; R&D grants; DID; treatment effects.

1. Introduction

Over the past 25 years, there has been widespread acknowledgement of the positive impact that public support can have on firm innovation (David, Hall, and Toole 2000; Zúñiga-Vicente et al. 2014; Dimos and Pugh 2016). As a result, governments at various levels, including regional, national, and supranational, have been motivated to design their innovation agendas and design policies aimed to foster innovation at the firm level (Vītola 2015; Ghazinoory and Hashemi 2021; Caloffi et al. 2022). This trend has been particularly strong in countries wherein governments of different institutional levels have the autonomy to allocate funds as they decide, multi-level governance designs (Borrás and Edquist 2013; Magro and Wilson 2013; Bai et al. 2021). In this contexts, different direct and indirect policy instruments within and across different levels offer foster firm-level innovation (Laranja, Uyarra, and Flanagan 2008; Flanagan, Uyarra, and Laranja 2011; Lenihan, Mulligan, and O'Driscoll 2020).

As Flanagan, Uyarra, and Laranja (2011: 709) analysed, the existence of different instruments from different sources creates multiple types of interactions, for example, between different instruments from the same source [e.g. tax credits and Research and development (R&D) grants (Dumont 2017)], between different instruments from different sources [e.g. soft loans and tax credits (Huergo and Moreno 2017)], and between the same instrument from different sources [e.g. R&D grants (Okamuro and Nishimura 2021)]. But it is the interaction between the same instruments from different sources which has attracted more attention from scholars and specifically the combination of R&D grants from different sources. Previous studies examine the interaction between 'national and supranational' R&D grants (Czarnitzki and Lopes-Bento 2014; Radicic and Pugh 2017; Bedu and Vanderstocken 2020), while others examine the interaction between those from 'regional and other funding sources' (Becker and Lucena 2022; Douglas and Radicic 2022; Shi et al. 2023). These analyses have revealed a positive impact on input additionality, but the results on output additionality remain inconclusive.

As Mulligan, Lenihan, and Doran (2019: 131) and Okamuro and Nishimura (2021: 6) point out, the existence of mixed results regarding output additionality could be caused by not considering all the possible funding sources in the region and due to the methodologies applied. To overcome these problems, a proper analysis of the innovation policy mix should consider the interaction between regional, national, and supranational funding sources (Mulligan, Lenihan, and Doran 2019; Okamuro and Nishimura 2021). Second, the evaluation of innovation policy mix requires the use of panel data to measure the impact on the medium and long term (Dumont 2017; Fiorentin, Pereira, and Suarez 2019; Lenihan 2023b). This last point is even more relevant when considering innovation outcomes that require maturation time, such as patents or innovation outcomes (Labeaga et al. 2021; Bastianin et al. 2022).

To address these previous literature limitations, this research aims to analyse the impact of the interaction among regional, national, and European R&D grants on output additionality at the firm level using a panel dataset with a Difference-in-Difference (DID) estimator and a sample of 10,045 Spanish firms from 2004 to 2016. Our findings reveal that only the combination of regional and national R&D grants, along with the combination of the R&D grants from the three types of funding sources, demonstrates a positive complementary effect on innovation outputs. These results suggest that only regional and national governments have complementary and aligned goals, indicating the existence of a possible virtuous 'Matthew effect' for those supported by all the funding sources (Fiorentin, Pereira, and Suarez 2019: 12). This study contributes to the innovation policy mix literature examining the effect of a multilevel innovation public policy of R&D grants with a novel approach that combines the three levels of funding sources and a DID panel data estimator.

This paper is organized as follows: Section 2 reviews the existing literature. Section 3 describes the research setting, the database used, and the methodological procedure. Section 4 presents the empirical findings, and Section 5 discusses them. Finally examines the main implications and suggests future research directions for innovation policy mix evaluation.

2. Literature review

2.1 Innovation policy mix evaluation at the firm level

Studies in innovation policy have primarily focused on assessing the impacts of individual mechanisms, such as R&D grants, tax credits, or innovation public procurement contracts at the firm level (Becker 2015). Nevertheless, over the last decade, there has been an increased interest in analysing the outcomes of the innovation policy mix (e.g. Magro and Wilson 2013; Schmidt and Sewerin 2019; Cocos and Lepori 2020). This interest has gained prominence in analyses due to the existence of what has been termed 'hidden treatment effects' (Guerzoni and Raiteri 2015). As elucidated by Guerzoni and Raiteri (2015: 726), these effects emerge when evaluating the impact of individual mechanisms in isolation, without accounting for the cumulative effects of other innovation policy mechanisms.

For the evaluation of innovation policy mix, Mohnen and Röller (2005) introduced the concepts of supermodularity and submodularity (The concept of supermodularity and submod-ularity, as introduced by Mohnen and Röller (2005), provides a mathematical framework for elucidating the interactions between policy instruments within the context of the inno-vation policy instrument mix. These terms stem from the broader field of economics and pertain to the relationships between the combined effects of multiple variables or policy instruments. In the realm of innovation policy mix, supermodularity denotes that the combined impact of two or more policy instruments surpasses the sum of their individual effects. This implies that the advantages of using these instruments in conjunction outweigh their isolated usage.

Conversely, submodularity suggests that the combined impact of two or more policy instruments is less than the sum of their individual effects. In such instances, employing these instruments together might yield diminishing returns or even counteract one another's effects). Recently, these mathematical terms have been simplified to refer to complementarity and substitutive effects. It should be noted that, while these two terminologies may appear analogous and have previously been used interchangeably (Milgrom and Roberts 1990: 516), they are distinct. Supermodularity implies that enhancing one input amplifies the influence of another input on an outcome, whereas complementarity indicates that the two inputs collaborate to produce a more substantial combined effect than when employed separately. Despite a few notable exceptions of articles utilizing the concepts developed by Mohnen and Röller (2005) (e.g. Ballot et al. 2015; Serrano-Bedia, López-Fernández, and García-Piqueres 2018), the latter terminology has gained more prominence in empirical studies examining innovation policy mixes (e.g. Flanagan, Uyarra, and Laranja 2011; Douglas and Radicic 2022). According to these studies, interactions within the policy mix could lead to (1) complementary or synergistic effects; (2) trade-offs, where one mechanism diminishes the efficacy of the other(s); and (3) no interactions between mechanisms.

Recent studies have endeavoured to untangle interactions within the innovation policy mix by crafting theoretical frameworks to enhance analysis (Rogge and Reichardt 2016; Mulligan, Lenihan, and Doran 2017; Schmidt and Sewerin 2019; Cocos and Lepori 2020). Rogge and Reichardt (2016) conducted a systematic literature review to gauge the efficacy of various combinations of innovation policy instruments and their impact on sustainable innovation. Mulligan, Lenihan, and Doran (2017) offer a conceptual framework for both *ex ante* and *ex post* evaluation of the impact of innovation policy instrument blends. Cocos and Lepori (2020) introduced a conceptual framework that categorizes dimensions of research policy mixes for innovation into four principal facets: policy rationales, implementation modalities, policy actors, and interactions of funding instruments. This framework presents a methodical approach to scrutinize and fathom the intricacies of innovation policy blends. Nevertheless, notwithstanding these theoretical advancements, further empirical investigations are required to comprehend the causes behind heterogeneous results (Zúñiga-Vicente et al. 2014; Becker 2019).

Aligning with this summons for empirical analyses, Dumont (2017, 2019) explored the effect of R&D support when firms concurrently benefit from multiple schemes. The findings unveiled that the effectiveness of R&D support tends to diminish in such scenarios, suggesting conceivable trade-offs or substitution effects. This signifies that combination of diverse R&D support mechanisms may not invariably yield cumulative benefits and policymakers ought to thoughtfully weigh potential conflicts when devising innovation subsidy programmes. Douglas and Radicic (2022) delved into the consequences of a multilevel policy mix for innovation on various types of cooperation networks. Their study indicated that an innovation policy mix involving support from different administrative tiers can generate heterogeneous effects on cooperative patterns among Spanish firms. The results hinted at possible complementary effects in specific cases, intimating that the combination of innovation policy instruments from different government levels can nourish more cooperative relationships among firms and costumers.

Recently, Caloffi et al. (2022) scrutinized the impact of technology and innovation advisory services coupled with innovation vouchers. Their analysis demonstrated that the combination of these policy instruments effectively heightens firms' proclivity to innovate. This suggests that endowing firms with both advisory services to address innovation requirements and vouchers to subsidize knowledge-intensive services can elevate firms' innovation endeavours and undertakings. In another study, Greco et al. (2022) assessed an innovation policy mix that fused general innovation policies with environmental policies. Their findings indicated stronger positive effects on eco-innovation compared to utilizing individual instruments in isolation. This infers that policy blends for innovation addressing both general innovation objectives and environmental sustainability can culminate in more marked enhancements in eco-innovation outcomes for firms.

These studies provide valuable insights into the conception and efficacy of innovation policy blends, underscoring the complexities of melding diverse instruments. Nonetheless, the understanding of interactions between the same instruments from different sources remains inadequately grasped, as Hünermund and Czarnitzki (2019: 6) contend. Comprehending these interactions is pivotal for formulating effective innovation support strategies, optimizing resource allocation, and fostering innovation for economic advancement.

2.2 Effect of multilevel policy of public R&D grants

In decentralized and federal countries, governments across different levels have the autonomy to allocate resources within their respective jurisdictions to promote innovation (Lenihan, Mulligan, and O'Driscoll 2020). Due to the structure of multilevel governance systems, decentralization has particularly influenced one innovation policy instrument: R&D grants (Bai et al. 2021). As elucidated by Fernández-Ribas (2009), R&D grants from upper-level governments gain from cross-border externalities, economies of scale, and indivisibilities of R&D input. Conversely, &D grants from lower-level governments possess greater capacity to address systemic issues and tailor programmes to local circumstances.

Theoretically, as expounded by Flanagan, Uyarra, and Laranja (2011), Schmidt and Sewerin (2019), and Okamuro and Nishimura (2021), companies that secure multilevel R&D grants could enhance their reputation, resources, and garner more attention within the region. This, in turn, might aid them in expanding their customer base, entering new markets, and collecting more private funds. Moreover, support from diverse institutions could cultivate a virtuous 'Matthew effect' in a multilevel innovation policy mix, enhancing a recipient's productivity beyond what single-level programmes would achieve (Fiorentin, Pereira, and Suarez 2019: 12). However, if misalignments occur and policymakers fail to coordinate their support programmes and instruments, the innovation policy mix could deteriorate into a 'policy mess' (Sorrell et al. 2003: 7; Greco et al. 2022: 2). In such a scenario, the presence of companies with rent-seeking attitudes might lead to substitutive effects because to obtain all the R&D grants, the project or project/s need to address different and various goals, which require the companies to move from their core R&D activities.

When delving into the study of the impacts of multilevel policies involving public R&D grants, empirical investigations have predominantly centred on input additionality analyses. A consensus has emerged, highlighting the presence of both additionality and complementary effects across diverse funding sources. For instance, Czarnitzki and Lopes-Bento (2014) examined the influence of national and European R&D grants on a sample of German manufacturing companies, revealing a modest yet positive impact on innovation endeavours. In a study encompassing European firms, Radicic and Pugh (2017) discerned encouraging and supplementary outcomes when integrating national and European Unio (EU) subsidy programmes, leading to augmented R&D expenditure. Heijs, Guerrero, and Huergo (2022) observed that Spanish firms benefiting from multiple R&D grants exhibited heightened input additionality, although this effect waned for companies with substantial backing. In a recent contribution, Okamuro and Nishimura (2021) showcased the sustained, beneficial impact of city and prefecture grants on total factor productivity among public R&D grants. Within this context, the complementary interplay between distinct sources could signify that the firm is perceived as an appealing investment in the market, thereby attracting a more substantial inflow of funds compared to being selected by a sole source.

With regard to other types of additionality effects, fewer empirical studies have explored them (Dimos and Pugh 2016; Becker 2019). Specifically, concerning output additionality, only a handful of studies have undertaken comprehensive analyses of the effect of an innovation policy mix of R&D grants at the firm level. The results here are less definitive. Although combining different funding sources may provide the firm with more resources to promote a 'new product in a new market', this form of investment is not linear and could yield varied effects. This is particularly true in the case of process innovation, where, for instance, training an employee in a new machine process might require an investment of time rather than money (Damanpour 1991).

Furthermore, comparing the outcomes of empirical studies is complex due to the diverse instruments employed to measure output innovation. For instance, Czarnitzki and Lopes-Bento (2014) found a nonsignificant additionality effect when combining R&D grants from national and European programmes on firms' sales of new-to-market products. Similarly, Mulligan, Lenihan, and Doran (2019) arrived at similar conclusions for most types of product and process innovation, using a sample of Spanish firms supported by regional, national, and European programmes. According to Mulligan, Lenihan, and Doran (2019), only the combination of national and European programmes reveals a positive impact on organizational innovations and the integration of regional and European programmes on incremental product innovation. Recently, by analysing a similar sample of Spanish firms, Becker and Lucena (2022) found that the combination of national and regional R&D grants positively affects firms' propensity to introduce new environmentally friendly products and processes.

Finally, previous studies indicate that dataset characteristics, especially the short time period considered, could limit their conclusions. Czarnitzki and Lopes-Bento (2014) and Mulligan, Lenihan, and Doran (2019) studied cross-sectional samples, but as argued by Okamuro and Nishimura (2021) and Fiorentin, Pereira, and Suarez (2019), a comprehensive evaluation of an innovation policy mix should employ panel data samples to account for the time effects resulting from receiving an innovation policy mix of R&D grants. As Bastianin et al. (2022) and Labeaga et al. (2021) note, the gestation period for new-to-market product innovation is approximately 5 to 8 years. However, Hameri and Vuola (1996) discovered that the incubation period for realizing revenues from new technological applications ranges from several years to a decade. A thorough analysis of a policy mix for innovation must factor in these time effects, especially when evaluating output additionality using different forms of innovation outputs, given the diverse nature of product innovation, processes, and patents.

3. Research setting, data, and methodology

3.1 Multilevel research setting: Spain

The context of the 'Europe of the Regions' provides an ideal research setting for assessing the outcomes of an innovation policy mix (Edler et al. 2012; Cunningham, Gök and Larédo 2016; Reillon 2016). Since the mid-1990s, both policymakers and scholars have advocated for the federalization of the European Union. This process entails nation states transferring competencies to supranational institutions and regional governments. The rationale for this dual movement lies in the broader perspective that European institutions hold regarding the Union's needs and the proximity of regional governments to the citizens. This transfer of competences has encountered resistance in some countries where the central government, such as France, Hungary, or Poland, has traditionally played a pivotal role. However, other countries like Belgium, Germany, or Spain have warmly embraced this multilevel design, granting significant competencies to regional governments for the promotion of education, taxation, and innovation.

Spain serves as an exemplar of transferring competencies both upwards and downwards from a previously highly centralized context. Since the conclusion of Franco's regime (1939–75), the degree of autonomy that Spanish Nomenclature of Territorial Units for Statistics (NUTS) 2 regions ('Autonomous Communities') possess is akin to that of regions in a federal country, if not more substantial (Federal states in Germany receive 29%, and the Canadian regions receive 34% (Moreno 2002)). Spanish Autonomous Communities receive over 30 per cent of the total personal income tax collected within their territory. This budgetary autonomy enables them to craft their innovation policies, tailoring programmes towards resolving regional issues and fostering local industries. However, despite the principle of subsidiarity guiding the formulation of these policies, alignment between innovation policies at regional, national, and/or European levels is not always guaranteed (Uyarra and Flanagan 2010).

For instance, a Spanish company could seek innovation support with distinct purposes from three levels. Regionally, governments like the Community of Madrid offer R&D grants to encourage collaborations with scientific partners for innovation development ('Traditional SME Innovation Check' public programme. Source: https://www.bocm.es/boletin/CM_Orden_BOCM/2022/04/18/BOCM-20220418-17.pdf). Nationally, the Spanish Ministry of Industry provides R&D grants to promote eco-innovations within traditional manufacturing sectors ('Innovation and Sustainability in Manufacturing' public programme. Source: https://www.boe.es/boe/dias/2021/08/16/pdfs/BOE-B-2021-35777.pdf). At the European level, 'Horizon Europe' offers R&D grants for radical innovation ('Horizon Europe' public programme. Source: https://ec.europa.eu/info/funding-tenders/opportunities/docs/2021-2027/horizon/guidance/programme-guide_horizon_en.pdf). If a Spanish manufacturing firm aims to secure maximum funds for fuelling its R&D endeavours, it would need to conceive a project that involves developing a radical eco-innovation through collaboration with a research institute. As Okamuro and Nishimura (2021) elucidate, this scenario could lead to the opportunity for acquiring more funds, resulting in higher returns than pursuing the activities individually. However, it could also result in a substitutive effect stemming from the combination of both R&D grants.

To our knowledge, only Mulligan, Lenihan, and Doran (2019) have analysed the impact of combining R&D grants from all three European levels using a cross-sectional analysis. They concluded that the combination of the three funding sources does not uniformly yield positive effects on all types of output innovation. As mentioned earlier, these authors found that only the combinations of 'national and European' and 'regional and European' R&D grants positively influence organizational and incremental innovation, respectively. However, concerning the impact of the interaction among the regional, national, and supranational R&D grants on innovation outcome, it is evident that a proper evaluation of an innovation policy mix should consider time effects and panel data (Becker 2019).

3.2 Dataset

To study whether a combination of R&D grants from regional, national, and European sources yields output additionality at the firm level, we draw upon data derived from the Panel of Technological Innovation (PITEC), the Spanish equivalent of the Community Innovation Survey (CIS). This database was initiated in 2003, but our study focuses on the years 2004–16 due to the unavailability of information concerning R&D grants for the entire period (Heijs, Guerrero, and Huergo 2022). The key rationale behind utilizing this database is its data structure, which enables us to lag most of the principal variables, thus mitigating endogeneity concerns (Becker and Lucena 2022). In constructing our dataset, we excluded firms from our sample that had experienced abrupt shifts in employment stemming from mergers or acquisitions, as well as those for which precise geographical location cannot be ascertained due to confidentiality considerations. This resulted in an unbalanced sample comprising 123,956 observations across 10,045 firms distributed throughout Spain's territory.

Figure 1 depicts the average amount of R&D grants per region over the studied period. As previous research has demonstrated (Herrera and Nieto 2008), the distribution of R&D grants within the Spanish innovation landscape follows a centre-periphery pattern. Leading in public funding reception are Madrid and the Basque Country. These regions are followed by Catalonia and the Valencian Community, where major cities such as Barcelona and Valencia coexist alongside significant agricultural districts. In the semi-peripheral regions, we can encompass those areas boasting prominent maritime ports and manufacturing sectors geared towards export activities, like Galicia, Andalusia, and Asturias. Lastly, peripheral regions are characterized by an orientation towards agricultural pursuits or tourism, as seen in Castile and Leon, Murcia, and the Balearic Islands.

While variations in the specifics of each survey might exist, the Spanish study brings distinct disparities when juxtaposed with particular European counterparts that could potentially reveal more uniform innovation trends across regions. Specifically, the Spanish centre-periphery distribution prompts

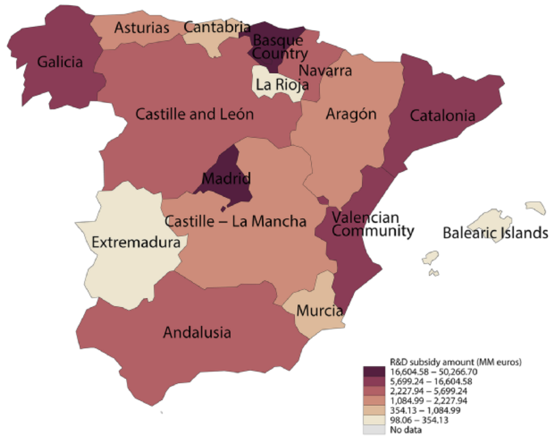

Figure 1. Average amount of R&D subsidies by NUTS 2 regions, 2014-2016. Note: For 2004 and 2006 there is missing data.

non-central firms to emphasize internal sources of innovation information. This accentuates the limited interaction between internal capacities and external market influences, a particularly pronounced dynamic due to the relatively diminished level of absorptive capacity among these enterprises (Guisado-González et al. 2018).

3.3 Variables

Following previous CIS studies, we classify our variables into three main categories: R&D grants by the funding source, innovation outcome measures, and firm technological and non-technological characteristics (Czarnitzki and Lopes-Bento 2014; Huergo and Moreno 2017; Heijs, Guerrero, and Huergo 2022). Our treatment variables are coded based on the funding source of the R&D grants. A positive value signifies that the firm has received support from regional (regional funding_{it}), national (national funding_{it}), and/or European institutions (European funding_{it}) and negative otherwise. Although to quantify the monetary value of additional or crowding-out effects, it would require knowing how much money is received. The PITEC dataset only offers information about the total innovation subsidy amount received.

After studying the goals of some R&D grants programmes from different Spanish government levels, we focus on patent applications and the introduction of new products and processes to measure innovation output additionality. In detail, we construct three dichotomous variables, coded as positive if the firm reports new products (Inno Prod_{it}), process innovation (Inno Proc_{it}), and new-to-market products ($\text{New-to-market}_{it}$), negative otherwise. In addition, following Czarnitzki and Lopes-Bento (2014) to account for other outcomes which required different incubation periods, we include the number of patent applications (Patent Applicat_{it}).

To control the covariates of our causal analysis, we focus on firms' technological and general characteristics. First, we include the following ones: the percentage of R&D employees over the total number of employees (R&D personnel_{it}). Previous studies found that this ratio directly impacts the firm's likelihood of receiving a subsidy and innovation performance (Herrera and Nieto 2008). In addition, we include a dichotomous variable related to the scientific stock to measure if the firm has a stock of patents (Patent Stock_{it}). As González-Blanco, Vila-Alonso, and Guisado-González (2019) point out, external collaboration is a crucial source of knowledge to innovate. We control it through a dichotomous variable which monitors whether the firms cooperate with external partners (Cooperation_{it}) or not. Finally, regarding the technological characteristics, we measure the type of R&D activities performed in the firm as dichotomous variables, coded as positive if firms report Basic Research (Basic Research_{it}) Applied Research (Applied Research_{it}), and/or Technological Development (Tech. Develop_{it}); negative otherwise. As Heijs, Guerrero, and Huergo (2022) show, the impact of each type of activity on the likelihood of receiving a subsidy varies across the different funding sources.

Regarding the firm's general attributes, we control for the main ones according to previous studies (Czarnitzki and Lopes-Bento 2014; Huergo and Moreno 2017; Heijs, Guerrero, and Huergo 2022). For example, we use a dichotomous variable to account for the firm's affiliation to a group (Group Affil_{it}). According to Becker and Lucena (2022), the cost to access external resources is higher for firms not part of any group. We also monitor the firm's exporting activities using a dichotomous variable coded as positive if the firm operates on foreign markets, and negative otherwise (Exporter_{it}). As Garcia and Mohnen (2010) have pointed out, there is a direct relationship between innovation and exports, directly impacting the firm's likelihood of receiving a subsidy.

In addition, we control for firm size, measured in terms of the number of employees (Size_{it}) and the firm's age in terms of years since its foundation (Age_{it}). Although these two variables are crucial in the impact assessment of innovation policy tools (Radicic and Pugh 2017), there is no strong agreement in the literature about whether the R&D supporting schemes tend to support small and young firms with innovative projects or if public institutions prefer to support well-established firms with a solid background of innovation activities. To clarify this point and avoid any potential non-linear relationships, we included its square value (Size^2_{it}). Additionally, a dichotomous variable to address whether the firm is a start-up (Start-up_{it}) is included.

Finally, we coded the firm's location and activity to control regional and industry effects. Following Herrera and Nieto (2008), we construct a proxy variable based on the firm's location of R&D internal expenses based on the Spanish NUTS 2 classification. To control for the firm's sector, we construct a categorical variable based on the two-digit Statistical Classification of Economic Activities in the European Community (NACE) Rev. 2 indicators following Pavitt's (1984) industrial taxonomy and Heijs, Guerrero, and Huergo (2022). Notice that one of the main advantages of this survey is that it covers a sample of innovative firms from the manufacturing and business-related services sectors. The industrial distribution of our sample is similar to that in previous pooled correctional studies for Belgium (Dumont 2017), Germany (Czarnitzki and Lopes-Bento 2014), and Spain (Heijs, Guerrero, and Huergo 2022).

Table 1 displays the mean values and the standard deviations for the main variables used in the analysis by total sample and funding source. Regarding the similarities and differences among the subsamples, we see a bottom-up distribution. Regional support is more related to the national ones and national to European ones. This trend can be explained if we focus on technological characteristics, such as the R&D

Table 1. Summary data.

Variables	Full sample		Regional subsidy		National subsidy		European subsidy	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Innovative Outcome								
Inno. Product (0/1)	0.451	0.498	0.730	0.444	0.748	0.434	0.717	0.451
Inno. Process (0/1)	0.097	0.297	0.671	0.470	0.675	0.468	0.667	0.471
Patents Applicat. (log.)	0.112	0.426	0.274	0.657	0.319	0.708	0.418	0.829
New-to-market (0/1)	0.451	0.498	0.483	0.500	0.518	0.500	0.542	0.498
Subsidies (0/1)								
Regional Funding	0.177	0.382	1.000	0.000	0.450	0.498	0.565	0.496
National Funding	0.184	0.388	0.468	0.499	1.000	0.000	0.681	0.466
European Funding	0.055	0.229	0.177	0.382	0.205	0.404	1.000	0.000
Technological Characteristics								
R&D Personnel (%)	21.675	28.116	29.936	31.962	32.496	31.683	40.437	35.359
Patent Stock (0/1)	0.264	0.441	0.227	0.419	0.251	0.433	0.296	0.457
Cooperation (0/1)	0.267	0.442	0.593	0.491	0.625	0.484	0.758	0.428
R&D Activity (0/1)								
Basic Research	0.063	0.244	0.127	0.333	0.137	0.344	0.189	0.391
Applied Research	0.304	0.460	0.579	0.494	0.618	0.486	0.701	0.458
Technological Development	0.359	0.480	0.696	0.460	0.744	0.437	0.749	0.434
Other Characteristics								
Group Affiliation (0/1)	0.388	0.487	0.391	0.488	0.491	0.500	0.431	0.495
Exporter (0/1)	0.342	0.474	0.383	0.486	0.469	0.499	0.461	0.499
Size (log.)	3.827	2.072	3.987	1.559	4.397	1.617	4.489	1.814
Size^2 (log.)	18.940	16.215	18.327	13.848	21.948	15.703	23.439	18.291
Age (years)	26.804	20.772	23.278	18.248	26.225	20.891	25.233	20.940
Start-up (0/1)	0.006	0.075	0.017	0.129	0.012	0.110	0.007	0.086
Foreign Firm (0/1)	0.034	0.180	0.029	0.169	0.033	0.179	0.025	0.158
Scientific. Park (0/1)	0.035	0.184	0.088	0.283	0.092	0.289	0.160	0.366
Pavitt's Taxonomy (0/1)								
Consumer Goods	0.189	0.391	0.172	0.377	0.168	0.374	0.108	0.311
Intermediate Goods	0.068	0.252	0.087	0.281	0.067	0.250	0.043	0.203
Specialized supplier	0.096	0.294	0.118	0.323	0.097	0.296	0.065	0.247
Scale-intensive	0.085	0.279	0.113	0.317	0.122	0.328	0.091	0.288
High-Tech Services	0.361	0.480	0.246	0.431	0.240	0.427	0.317	0.465
Construction	0.036	0.187	0.026	0.159	0.029	0.168	0.034	0.180
Observations	123,956		21,924		22,824		6,870	

Abbreviations: SE, standard errors.

activities reported by the firms supported. While few of them perform R&D activities on the regional subsample, most of the firms supported by national and European funds conduct research and/or development activities. Furthermore, the correlation coefficients between the different R&D grants shown in Appendix Table A.1 support this bottom-up relationship.

Table 2 shows the distribution of the sample by type of funding. As can be seen, 70.96 per cent of the firms do not receive any public funding during the period. In those supported firms, 8.86 per cent of the firms receive regional funding, 8.94 per cent national funding, and only 3.90 per cent European funding. Here, we can see the multilevel nature of the Spanish innovation funding system: 5.69 per cent of firms receive a regional and a national subsidy simultaneously. In comparison, the combination of national and European R&D grants reduces to 1.18 per cent, and the combination of regional and European ones to only 0.54 per cent. Appendix Table A.2 also expands the information about the sample distribution by type of public funding, source, and year. In addition, the number of firms receiving a subsidy during the euro crisis was dramatically reduced. The relationship between the European and national funds increased after 2010, and the relationship between regional and national funding decreased.

Table 2. Distribution of the sample by type of public funding.

	Yearly observations		Firms (in 2004–16)	
No R&D subsidy	87,960	(70.96%)	9,470	(94.28%)
Only regional funding	10,983	(8.86%)	3,840	(38.23%)
Only national funding	11,086	(8.94%)	3,813	(37.96%)
Only European funding	1,519	(1.23%)	795	(7.91%)
Regional and national funding	7,057	(5.69%)	2,513	(25.02%)
National and European funding	1,467	(1.18%)	662	(6.59%)
Regional and European funding	670	(0.54%)	424	(4.22%)
All types of public funding	3,214	(2.59%)	902	(8.98%)
Total	123,956		22,419	

3.4 Methodology

To estimate the effect of regional, national, and European R&D grants, we encounter the following challenges. First, none of the R&D grants are randomly assigned across firms but allocated depending on factors driving the agencies' choices on which firms to fund and the self-selection behaviour of firms (Czarnitzki and Lopes-Bento 2014; Heijs, Guerrero, and Huergo 2022). Second, an endogeneity problem arises when the factors determining self-selection and agencies' choices influence firms' innovative behaviour. Third, each funding source has its own roadmap and processing period, varying from 6 months to 3 years. Following previous literature research on innovation policy mix evaluation, we implement matching methods to generate the counterfactual outcome by identifying 'untreated' (unsupported) firms, which are equivalent in terms of their exogenous characteristics to the 'treated' (supported) firms (Hall and Lerner 2010). Using this information, we create comparison groups between treated and non-treated to measure the output additionally of the impact of each innovation policy mix combination.

First, we use a dynamic multinomial logit model to analyse the determinants influencing the firm's likelihood of receiving regional, national, and European R&D grants and match untreated and treated firms The benefit of using this model is that the estimators produce valid estimates in the presence of unobserved heterogeneity at the panel level. Following Börsch-Supan (1990), we apply an Multinomial Logistic Regression (MNL) method for modelling categorical outcome variables without a natural order. Unlike cross-sectional applications of the MNL model, in the context of panel data, each sequence can be thought of as a process that depends on individual characteristics. The introduction of unobserved heterogeneity by including an additional error term at the panel level accounts for heterogeneity at the observation (time) level. This equation is formalized in terms of a multivariate probit panel model given a random effect, which can be written as follows:

$$\Pr\left(y_{it} = m \mid X_{it-1}, \beta_j, u_{ij}\right) \tag{1}$$

where y_{it} denotes the probability of receipt of a fund from different funding sources m (regional, national, or European) conditioned on a vector of firm i control variables in the previous year named X_{it-1} and u_{ij} is the error term that collects the heterogeneity variance for random effects.

Second, after analysing the determinants for receiving a subsidy from each funding source, we create the treatment and non-treated groups to analyse the causal effects of each type of R&D grant and their combination. The research strategy used in this paper is embedded with previous literature on innovation policy mix analysis. However, to offer a panel data perspective, we apply the DID approach developed by Dettmann, Giebler, and Weyhb (2021), which modifies the conditional DID approach of Heckman et al. (1998) to include information on individual treatment timing from the panel into the matching process, to introduce a combined statistical distance function for matching, and to incorporate flexible observation durations into the estimation. This estimation approach considers individual treatment phases, and an exact definition of the time an individual is compared to its' statistical twin (Dettmann, Giebler, and Weyhb 2021).

In the last few years, new methodological papers on DID research design have created a dizzying array of causal treatment literature (Roth et al. 2022). This recent literature has proposed new estimators able to measure the average treatment effect on the treated (ATT), overcoming the traditional DID limitations. Although all of them offer valuable methods, two stand out: the one developed by Callaway and Sant'Anna (2021) and that of Imai, Kim, and Wang (2021). The first one proposes an estimator with multiple periods, variations in treatment timing, and when the 'parallel trends assumption' holds, potentially only after conditioning on observed covariates, while the second one proposes a matching-based DID estimator for time series cross-sectional data. Using standard matching procedures and weighting schemes, the estimator selects potential control observations for every treated unit in a specified time period.

The flexible panel DID estimator used in this study combines both approaches and introduces its own strategies for treating timing and duration (Xu and Guo 2023). On the one hand, like Callaway and Sant'Anna (2021), Dettmann, Giebler, and Weyhb's (2021) estimator uses the treatment starting point to apply a time dimension, adopting a quasi-staggered adoption perspective (In a quasi-staggered adoption, the treatment may be introduced to different subgroups of the population at different times due to natural circumstances, policy changes, or other factors. Quasi-staggered adoption can introduce complexities to the DID analysis, as it may lead to varying treatment effects based on the timing of the intervention across different subgroups). Also, they identified the treatment effect as the average effect of participation in the treatment. Like Imai, Kim, and Wang (2021), Dettmann, Giebler, and Weyhb (2021) select control observations individually for every treated unit and compare individual outcome developments for estimation. On the other hand, Dettmann, Giebler, and Weyhb's (2021) estimator differs from these two mentioned approaches, proposing a statistical matching procedure that gives equal weights to each included covariate. This statistical distance function gives a 'pure' description of the similarities and disparities regarding the individual covariates, and the overall indicator reflects the comparability of the observations without covariate weights in favour of 'significant' or remarkably similar/dissimilar covariates. This described approach can consider some of the problems associated with time-dependent heterogeneous treatment effects in a panel data context.

The flexible conditional DID estimates the effect as the mean of individual comparisons of ATTs. This approach compares differences in outcome development between a treated unit i and its control(s) j for individually defined outcome observation periods. Due to heterogeneous treatment durations, the observed periods may be heterogeneous among the treated individuals. The ATT is thus a weighted average of different observation periods:

$$\mathrm{ATT}(S) = \frac{1}{N_I}\sum_{i=1}^{I}\left[\left(Y_{1i,t_i+b_i+\alpha} - Y_{0i,t_i}\right) - \sum_{j=1}^{J} W_{N_I,N_J}(i,j)\left(Y_{0j,t_i+b_i+\alpha} - Y_{0j,t_i}\right)\right] \tag{2}$$

where ATT (S) denotes the ATT that fulfils the common support condition, Y_1 and Y_0 are the treatment and non-treatment outcomes, and the number of observations is denoted by N_I (treated) and N_J (controls). The indexes i with $i = 1, \ldots, I$ and j with $j = 1, \ldots, J$ mark treated and control units, respectively. Index t_i denotes the treatment start date of treated unit i as the beginning of outcome observation, b_i reflects the individual treatment duration, and α denotes the required observation time afterwards. Thus, $t_i + b_i + a$ denotes the end of the outcome observation of treated unit

i and its control(s) in relation to the treatment start time. $\sum_{j \in J} W_{N_I,N_J}(i,j) = 1$ weights the controls included in the individual comparison group of each treated unit i. In the case of nearest neighbour matching, $W_{N_I,N_J}(i,j) = 1$ applies. When more than one non-treated observation is selected, the control outcome for i is calculated as the mean over all individually selected controls, i.e. $W_{N_I,N_J}(i,j) = \frac{1}{N_I}$.

In conclusion, like Xu and Guo (2023) and Roth et al. (2022: 2231) explain, the flexible panel DID approach based on Heckman et al. (1998) is able to consider some of the problems associated with time-dependent heterogeneous treatment effects in a panel data context. The matching process removes potential calendar time effects. Defining different observation periods for the outcome comparisons (e.g. estimating more than one treatment effect) may also consider a dynamic treatment effect. Moreover, the flexible conditional DID helps to account for behavioural changes and it enables the researchers to consider knowledge or expectations on the anticipation timing when defining the outcome observation period (Dettmann, Giebler, and Weyhb 2021: 17).

3.5 Determinants of the receipt of an R&D subsidy

Table 3 shows the determinants of a firm's reception of R&D grants from each government level. Considering that we have information about three funding sources and panel data, we implement a dynamic multinomial logit panel model based on Equation (1). As expected, receiving a subsidy in the previous year significantly impacts the propensity to receive one in t, but regional R&D grants are less conditioned to previous support than national and European R&D grants. Regarding the influence of each type of subsidy on the other, Appendix Table A.3 shows the transition rates between R&D grants over the panel period. Most nonsupported firms remain in that status, while the number of supported firms does not vary significantly. Regarding the transition rates between the three funding sources, this table also shows that the most crucial transition is obtaining a European subsidy and complementing it with a national one.

An analysis of the other determinant variables shows crucial differences among the three funding schemes. For example, regarding technological characteristics, we can see how regional R&D grants do not consider having some R&D personnel crucial, while national and European ones do. The three types of support considered positive having obtained patents in the previous years, as well as external cooperation. However, the degree of importance varies. European R&D grants tend to value the stock of patents and external partners more than national and regional R&D grants. These differences in purposing knowledge can also be seen in R&D activities. European R&D grants consider performing basic R&D activities crucial for granting their support, while national and regional R&D grants are focus of applied research and technological development.

Finally, regarding the general characteristics of the companies, belonging to a group is considered negative for achieving a regional or European subsidy. The exporting activity is only evaluated positively for accessing European funding, and being established in a scientific park is a determinant for national and European supporting instruments. Regional funding sources preferred to fund young firms, while national and European preferred well-established firms.

Table 3. Dynamic multinomial logit model for probability of receiving support.

Variables	Regional subsidy Coefficients (SE)	National subsidy Coefficients (SE)	European subsidy Coefficients (SE)
Past inno. subsidies$_{t-1}$ (0/1)	2.230*** (0.034)	2.340*** (0.031)	2.745*** (0.063)
Technological characteristics			
R&D personnel$_{t-1}$ (%)	0.001 (0.001)	0.006*** (0.001)	0.008*** (0.001)
Patents$_{t-1}$ (0/1)	0.234*** (0.048)	0.464*** (0.040)	0.652*** (0.066)
Cooperation (0/1)	0.413*** (0.034)	0.649*** (0.030)	1.101*** (0.054)
R&D activities			
Basic research$_{t-1}$ (0/1)	0.022 (0.056)	0.013 (0.047)	0.410*** (0.073)
Applied research$_{t-1}$ (0/1)	0.369*** (0.034)	0.394*** (0.031)	0.547*** (0.055)
Technological development$_{t-1}$	0.581*** (0.035)	0.741*** (0.031)	0.700*** (0.057)
Other firm characteristics			
Group affiliation (0/1)	−0.282*** (0.043)	0.024 (0.038)	−0.295*** (0.072)
Exporter (0/1)	−0.459*** (0.036)	−0.154*** (0.030)	0.236*** (0.053)
Size$_{t-1}$ (log.)	0.655*** (0.040)	0.707*** (0.040)	0.597*** (0.778)
Size$_{t-1}^2$ (log.)	−0.070*** (0.005)	−0.049*** (0.004)	−0.027*** (0.008)
Age$_{t-1}$ (years)	−0.009*** (0.001)	−0.005*** (0.001)	0.002*** (0.008)
Start-up (0/1)	1.248*** (0.140)	1.394*** (0.135)	0.736*** (0.229)
Foreign firm (0/1)	−0.054 (0.891)	−0.036 (0.071)	−0.041 (0.138)
Scientific park (0/1)	0.060 (0.089)	0.197** (0.077)	0.533*** (0.110)
Constant	−3.560*** (0.114)	−5.379 (0.128)	−8.073 (0.259)
Var(u1)		1.158 (0.059)	
Var(u2)		1.313 (0.576)	
Var(u3)		5.710 (0.296)	
Log likelihood		−58,009.38	
Wald chi^2		24,594.15***	
Number of observations		112,384	
Number of firms		10,034	

***, **, and * indicate a significance level of 1 per cent, 5 per cent, and 10 per cent, respectively. t–1 denotes that the variable is included with one lag. All models include industry and regional fixed effects.
Abbreviation: SE, standard errors.

3.6 Innovation policy mix and output additionality

To evaluate the impact of innovation policy mix on firms' innovation output, as Equation (2) proposes, we need to have a sufficient sample of common supported firms and nonsupported firms. Following Dettmann, Giebler, and Weyhb's (2021) pre-treatment process, Appendix Table A.4 lists the treated group's size and their respective control group based on the kernel radius matching methodology. To account for the time effects that the combinations of R&D grants could suffer, we compute the average effect 1 year after receiving the support and 1 year after finishing it. This perspective shows the real impact of public support in the different stages of developing innovation outcomes.

In Table 4, odd columns show the average effect on innovation outcomes 1 year after receiving the support. Regarding individual support, only regional and national institutions show a positive result in all the innovation outcome variables considered: product innovation, process innovation patents applications, and new-to-market innovations. In detail, the bigger impact is produced by national innovation R&D grants on product and process innovation. Receiving support from the Spanish government increases by 4.6 per cent, 4.9 per cent, and 3.8 per cent the likelihood of introducing new products, processes, and patent applications 1 year after receiving the subsidy, respectively. Regarding European funding, the results have more nuances. For example, although 1 year after receiving supranational support is the one that produces the most significant impact on the likelihood of introducing product or process innovations (7.0 per cent and 6.6 per cent, respectively), it also shows a negative impact on patent application (−3.6 per cent). Only the combination of the three funding sources and the combination of regional and national effects show a positive effect. Receiving support from regional, national, and European institutions produces an increase product, process innovations, and patent innovation of 7.4 per cent, 5.3 per cent, and 14.8 per cent, respectively. Combining regional and national funding increases the likelihood of introducing a product, a process innovation, and applying for a patent by 5.4 per cent, 3.5 per cent, and 6.3 per cent, respectively.

Regarding the average effect on innovation outcomes 1 year after finishing the support, in Table 4, even-numbered columns let us measure the effects by counting the maturation periods of different innovation outcomes. The impact produced by regional and national innovation subsides almost doubles on product and process innovation compared with the previous studies. For example, receiving support from national intuitions increases the firms' likelihood of introducing product and process innovation by 12.4 per cent and 11.1 per cent, respectively. Regarding patent applications, although the impact of receiving support from these two funding sources shows a positive effect, these are lower than that in the analysis 1 year after receiving the R&D grants. Focusing on European support, the results are similar to the previous analysis.

Finally, as a robustness test, in Table 5, we rerun the principal analysis (Equation (2)) using a Nearest Neighbour Matching technique. In general, these results confirm our results in Table 4. Individually, European support positively impacts product innovation and process innovations. Its combination produces a complementary effect on firms' product innovation and on process innovation and patent application. Regarding the combination of different funding mechanisms, 'regional and national', 'national and European', and the combination of three

Table 4. Average effect of regional, national, and European R&D subsidies policy mix on firm innovation output.

	Product Innov. (0/1)		Process Innov. (0/1)		Patent Appl. (log.)		New-to-market (0/1)	
	Start DID (RSE)	End DID (RSE)	Start DID (RSE)	End DID (RSE)	Start DID (RSE)	End DID (RSE)	Start DID (RSE)	End DID (RSE)
Only regional funding	0.035*** (0.010)	0.079*** (0.014)	0.027** (0.011)	0.065*** (0.015)	0.018*** (0.007)	0.0142* (0.008)	0.024** (0.017)	0.046*** (0.013)
Only national funding	0.046*** (0.011)	0.124*** (0.015)	0.049*** (0.011)	0.111*** (0.015)	0.038*** (0.009)	0.0220** (0.009)	0.023** (0.011)	0.053*** (0.014)
Only European funding	0.070*** (0.025)	0.110*** (0.032)	0.066*** (0.022)	0.070** (0.029)	−0.036*** (0.013)	−0.042*** (0.015)	0.025 (0.024)	0.046 (0.031)
Regional and national funding	0.054*** (0.013)	0.065*** (0.023)	0.035** (0.015)	0.060** (0.025)	0.063*** (0.013)	0.017 (0.017)	0.023* (0.013)	−0.011 (0.024)
National and European funding	0.034 (0.027)	0.009 (0.052)	0.027 (0.027)	−0.002 (0.051)	0.035 (0.027)	−0.028 (0.046)	0.032 (0.029)	−0.001 (0.053)
Regional and European funding	−0.029 (0.041)	−0.051 (0.055)	−0.027 (0.044)	−0.133 (0.063)	0.014 (0.020)	0.002 (0.035)	−0.043 (0.041)	−0.042 (0.053)
All types of public funding	0.074*** (0.023)	−0.018 (0.057)	0.053** (0.025)	−0.040 (0.061)	0.148*** (0.030)	−0.031 (0.049)	0.035 (0.023)	−0.025 (0.057)

Notes: Column 'DID' shows the average effect from the DID estimators, column 'Start' shows the average effect 1-year after starting the support, column 'End' shows the average effect 1-year after finishing the support.
***, **, and * indicate a significance level of 1 per cent, 5 per cent, and 10 per cent, respectively. Consistent bias-corrected estimator as proposed in Abadie and Imbens (2006, 2011). Matching protocol: radius 0.5.
Abbreviation: RSE, robust standard errors.

instruments produce a positive effect on patent applications, and only 'regional and national' funding does in product and process innovation. Finally, the robustness check does not exhibit distinct effects based on whether it has been measured after the starting or ending period of the support.

4. Discussion

Our results show that European funding is the most effective mechanism in encouraging firms' innovative product and process innovation 1 year after starting to receive the support. As we mentioned in the literature review, Czarnitzki and Lopes-Bento (2014) and Mulligan, Lenihan, and Doran (2019) find similar results proving the importance of European funds in introducing new products and processes. However, regarding patent applications and new-to-market innovations, our results vary with respect to the previous ones. In detail, patent applications and new-to-market innovations are the national R&D grants that produce a bigger impact. Contrary to what is usually thought, our results show that receiving national R&D grants increases more radical innovation outcomes than European support. The most plausible explanation behind these results is that those firms which applied for European support (6th, 7th European Framework and Horizon 2020) have the innovation capacities they need to develop new-to-market innovations (R&D personnel, laboratories, and infrastructure) and could receive funds in the capital market. However, for those firms that receive national support, perhaps it is the first time they have applied, and they already have the innovation capacities needed to develop new-to-market innovations and could receive funds in the capital market. Public funding is crucial to hire the R&D personnel needed to develop new-to-market innovations.

Regarding innovation policy mix evaluation, our results show that apart from the three funding sources, the combination of national and regional support is the only one that produces a positive and statistically significant effect. These results are in line with what Bedu and Vanderstocken (2020) find in the French region of Aquitaine. As we discussed, when we described the Spanish innovation multilevel design, regional R&D grants are oriented to promote innovation through behavioural changes promoting collaboration with new types of partners, while the requirements to receive an innovation subsidy are focused on behavioural additionality and national ones are focused on promoting outcome additionality (Becker and Lucena 2022; Douglas and Radicic 2022). Thus, the complementary effect of pursuing innovation with an environmental approach or with external partners is what produces that combination of regional and national funding which increases the firms' product innovation, primarily if we focus on the effects produced if we measure the impact 1 year after receiving the subsidy. These conclusions align with what Mulligan, Lenihan, and Doran (2019) and Okamuro and Nishimura (2021) find in analysing this combination, namely, that it increases organizational process innovations and total factor productivity, respectively.

Contrary to what previous literature has found (Czarnitzki and Lopes-Bento 2014; Radicic and Pugh 2017; Mulligan, Lenihan, and Doran 2019), our results show that the combination of national and European R&D grants does not produce a significant effect. One reason behind this nonsignificant

Table 5. Robustness check—average effect of regional, national, and European R&D subsidies policy mix on firm innovation output.

	Product Innov. (0/1)		Process Innov. (0/1)		Patent Appl. (log.)		New-to-Market (0/1)	
	Start DID (RSE)	End DID (RSE)	Start DID (RSE)	End DID (RSE)	Start DID (RSE)	End DID (RSE)	Start DID (RSE)	End DID (RSE)
Only regional funding	0.047*** (0.013)	0.047*** (0.013)	0.022* (0.013)	0.022* (0.013)	0.014* (0.009)	0.014* (0.009)	0.012 (0.014)	0.012 (0.014)
Only national funding	0.034*** (0.012)	0.034*** (0.012)	0.037*** (0.013)	0.037*** (0.013)	0.020** (0.010)	0.020** (0.010)	−0.003 (0.013)	−0.003 (0.013)
Only European funding	0.094*** (0.029)	0.094*** (0.029)	0.116*** (0.031)	0.116*** (0.031)	−0.002 (0.018)	−0.002 (0.018)	0.001 (0.032)	0.001 (0.032)
Regional and national funding	0.037** (0.016)	0.037** (0.016)	0.049*** (0.016)	0.049*** (0.016)	0.051*** (0.016)	0.051*** (0.016)	0.022 (0.018)	0.022 (0.018)
National and European funding	−0.032 (0.037)	−0.032 (0.037)	0.006 (0.040)	0.006 (0.040)	0.067* (0.040)	0.067* (0.040)	0.001 (0.042)	0.001 (0.042)
Regional and European funding	−0.067 (0.045)	−0.067 (0.045)	−0.047 (0.048)	−0.047 (0.048)	0.015 (0.029)	0.015 (0.029)	−0.071 (0.053)	−0.071 (0.053)
All types of public funding	0.061 (0.026)	0.061 (0.026)	0.039 (0.030)	0.039 (0.030)	0.175*** (0.032)	0.175*** (0.032)	0.044 (0.033)	0.044 (0.033)

Notes: Column 'DID' shows the average effect from the DIDs estimators, column 'Start' shows the average effect 1 year after starting the support, and column 'End' shows the average effect 1-year after finishing the support.

***, **, and * indicate a significance level of 1 per cent, 5 per cent, and 10 per cent, respectively. Consistent bias-corrected estimator as proposed in Abadie and Imbens (2006, 2011). Matching protocol: Nearest Neighbour.

Abbreviation: RSE, robust standard errors.

effect could be that national and European R&D grants are highly related because both agencies see each other as a proxy for a 'winning project'. Then, rather to produce a 'virtuous' Matthew effect as Fiorentin, Pereira, and Suarez (2019: 12) discuss, firms are taking advantage of their reputation and training in applying to public funds and that is why there are substitutive effects. Then, the combination of the two funding schemes does not produce a bigger impact than receiving support from only one. Another explanation could be that national and European R&D grants do not have the same aligned goals; one could be focused on basic research projects, while the other could be focused on development, and the conflict between exploration–exploitation arises (Gao et al. 2021; Mulligan et al. 2022).

Finally, regarding the time dimension, our results show that European R&D grants significantly impact firms that have been working on previous innovations before applying for the subsidy (Lenihan et al. 2023b). That is why they could report introducing one innovation before finishing the project. However, national support is focused on those firms that cannot start to develop their innovation without public funding. National support plays a crucial role in increasing the firms' activities even after the subsidy ends. This implies that national R&D grants also have a behavioural additionality effect establishing innovation practices as a routine in those firms that have developed innovation previously and do it thanks to the national innovation support (Douglas and Radicic 2022).

5. Conclusions

Policymakers at different levels of governance use various subsidy programmes to boost innovation within companies (Becker 2015; Bai et al. 2021). This study aims to understand the impact of R&D grants from different levels of government on innovation outcome at the firm level. To do this, we focus on the Spanish context and examine data from 10,045 Spanish companies from 2004 to 2016.

From our analysis, we obtain three main findings. First, each individual funding source produces a favourable impact on both product and process innovation. Second, it is only through the combination of the three funding mechanisms and the synergy between regional and national R&D grants that a noteworthy influence on product, process innovations, and patent applications emerges, engendering a virtuous Matthew effect (Fiorentin, Pereira, and Suarez 2019: 12). Third, the impact of the innovation policy mix, evident 1 year after the inception of support from the three funding sources, tends to reveal statistically positive outcomes (Okamuro and Nishimura 2021). Notably, only the combination of national and regional funding guides firms to sustain innovation activities after the conclusion of R&D grants. Collectively, these outcomes constitute a significant contribution to the academic literature and an advance methodologically.

In the realm of innovation policy mix literature, our study extends prior analyses by delving into the effects of complementary interactions on firms' innovation outcomes with a new panel data methodology. First, in contrast to previous studies that exclusively examined 'regional and national' or 'national and European' combinations, our work breaks new ground by incorporating all three funding sources and their implications for output additionality. Furthermore, employing a DID methodology enables us to rigorously analyse causal effects (Dettmann, Giebler, and Weyhb 2021; Xu and Guo 2023), accommodating for observable and unobservable firm characteristics, thus transcending the limitations of cross-sectional perspectives found in prior research (Czarnitzki and Lopes-Bento 2014; Mulligan, Lenihan, and Doran 2019; Becker and Lucena 2022; Douglas and Radicic 2022; Heijs, Guerrero, and Huergo 2022).

Turning to the discourse on innovation policy mix, our study offers evidence that distinct institutions adopt varying approaches to policies, fostering either complementary or substitutive effects between them. Furthermore, our results suggest that, despite firms' observed or unobserved attributes and the treatment year, Spanish companies benefit from the combination of regional and national funding schemes in advancing innovation outcomes. However, we also uncover that European R&D grants fail to display a complementary relationship with other funding sources. These findings contribute to the ongoing debates surrounding the effectiveness of multilevel government designs, notably within the context of the European Research and Innovation Strategy and the existence of virtuous and negative Matthew effects (Fiorentin, Pereira, and Suarez 2019; Lenihan, Mulligan, and O'Driscoll 2020).

However, this study is not without limitations that merit consideration in future research endeavours. First, while our quantitative analysis yields valuable insights, a more profound comprehension necessitates qualitative and theoretical exploration to cogently elucidate the dynamics underlying the complementarity or substitutability of innovation subsidies from diverse sources. This exploration can build upon the foundational work established by Mulligan, Lenihan, and Doran (2017), Schmidt and Sewerin (2019), Cocos and Lepori (2020). Second, although our study delves into 'complementary and substitutive' effects, forthcoming investigations should undertake meticulous assessments of super- and submodularity, deploying innovative methodologies suitable for panel data analysis. Third, our analysis omits the consideration of R&D tax credits or fiscal benefits for R&D, thus warranting their incorporation in future studies, as highlighted by Dumont (2017). In tandem, an in-depth exploration into the ramifications of the innovation policy mix on diverse types of innovation, including basic research, applied research, and development, remains a pertinent avenue of inquiry (Heijs, Guerrero, and Huergo 2022; Mulligan et al. 2022). Fourth, as pointed by Lenihan et al. (2023a), future studies ought to analyse the influence of the policy mix of innovation subsidies from disparate sources on firm-level innovation, encompassing both foreign-owned subsidiaries and domestically owned firms. Furthermore, future studies should delve into the sequencing of policy instruments within the context of innovation subsidies from varied sources (Coburn et al. 2021; Cunningham and Link 2021; Lenihan et al. 2023b).

Lastly, concerning regional innovation studies, future research should delve into the provision of public support for firm-level innovation in European countries classified as 'moderate innovators' and 'weak innovators' based on the European Innovation Scoreboard. Countries in this category encounter challenges such as firms with limited absorptive capacities, underdeveloped institutional frameworks, and restricted government capabilities in navigating the intricate landscape of innovation policies (Cirera and Maloney 2017; Fitjar, Benneworth, and Asheim 2019).

A well-considered innovation policy mix could address these challenges, particularly for 'moderate innovator' countries in Europe striving to catch up with leaders such as Greece, Italy, Portugal, the Czech Republic, and the Baltics. Moreover, less-developed nations should initiate robust data collection and evaluations to facilitate policy enhancement and knowledge dissemination. This paper underscores the importance of policymakers and national statistical agencies heeding this call for proactive action.

Finally, our study provides valuable insights for policy and managerial considerations. Policymakers are advised to rekindle the trend of aligning regional and national R&D grants, especially given their demonstrated complementary effects that were momentarily forsaken during economic crises. European institutions are encouraged to exercise caution in combining their programmes with pre-existing R&D grants, instead of striving for better alignment of objectives. Furthermore, we advocate for sustained funding in basic research by European institutions, as it appears that European R&D grants predominantly support this aspect rather than applied research. For managers, our study underscores the pitfalls of a rent-seeking strategy for R&D grants, suggesting that it may not optimally enhance innovation outcomes and can lead firms away from their core innovation capacities, potentially diminishing their innovation results.

Acknowledgements

We thank the comments on early versions of this work received from participants at the EU-SPRI Seminar and DRUID 2022 conference. Furthermore, we are immensely thankful to the editor and reviewers for their valuable feedback, which has been instrumental in refining our work. We remain fully responsible for the paper's contents and any mistakes herein.

Conflict of interest statement. None declared.

Funding

Spanish Ministry of Science, Innovation and Universities, Grant/Award Numbers: PID2019-105140RB-I00, PID2022-137379NB-I00, FPU18/00343.

Data availability

Data available on request from the authors.

Appendix

TABLE A.1. Correlation matrix.

	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	
Regional funding	1.000																				
National funding	0.340	1.000																			
European funding	0.247	0.311	1.000																		
Inno. Product	0.260	0.284	0.129	1.000																	
Inno. Process	0.206	0.214	0.105	0.418	1.000																
Patents Applic.	0.177	0.231	0.174	0.210	0.142	1.000															
New-to-market	0.230	0.274	0.153	0.661	0.307	0.229	1.000														
R&D Person	0.136	0.183	0.162	0.155	0.063	0.104	0.149	1.000													
Cooperation	0.342	0.384	0.269	0.367	0.340	0.197	0.320	0.183	1.000												
Basic Research	0.122	0.145	0.125	0.165	0.134	0.113	0.152	0.046	0.144	1.000											
Appl. Research	0.277	0.324	0.209	0.382	0.292	0.206	0.321	0.147	0.336	0.304	1.000										
Tech. Develop.	0.326	0.381	0.197	0.452	0.329	0.221	0.380	0.170	0.363	0.226	0.373	1.000									
Patent Stock	0.203	0.245	0.162	0.252	0.165	0.798	0.265	0.077	0.217	0.140	0.233	0.257	1.000								
Group Affilat.	0.003	0.101	0.022	0.095	0.144	0.087	0.070	0.046	0.162	0.017	0.062	0.079	0.067	1.000							
Exporter	0.040	0.127	0.061	0.177	0.131	0.116	0.125	0.168	0.124	0.025	0.134	0.141	0.086	0.148	1.000						
Size	0.036	0.131	0.077	0.154	0.255	0.114	0.105	−0.064	0.166	0.054	0.115	0.130	0.094	0.495	0.154	1.000					
Size^2	−0.018	0.088	0.067	0.063	0.177	0.103	0.050	−0.121	0.126	0.029	0.046	0.052	0.067	0.481	0.067	0.941	1.000				
Age	−0.079	−0.013	−0.018	−0.003	0.043	0.020	−0.018	−0.103	0.015	−0.008	0.002	−0.027	−0.003	0.118	0.132	0.222	0.246	1.000			
Start-up	0.071	0.042	0.006	0.065	0.024	0.006	0.035	−0.019	0.038	0.041	0.047	0.061	0.037	−0.014	−0.049	−0.048	−0.047	−0.085	1.000		
Foreign Affilat.	−0.011	−0.001	−0.011	0.034	0.045	0.008	0.029	−0.068	0.023	0.019	0.029	0.023	0.022	0.203	−0.134	0.154	0.156	0.012	−0.000	1.000	
Scientific Park	0.133	0.148	0.164	0.072	0.043	0.108	0.078	0.233	0.123	0.052	0.092	0.093	0.086	0.016	0.066	−0.002	−0.022	−0.076	−0.011	−0.029	1.000

TABLE A.2. Distribution of the sample by type of public funding and year.

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	At least one obs.	Total observations
No funding	4,446 (59.65%)	5,580 (58.15%)	6,248 (63.76%)	6,431 (65.66%)	6,504 (66.43%)	6,708 (68.27%)	6,881 (71.11%)	7,141 (73.46%)	7,405 (76.75%)	7,671 (79.09%)	7,634 (78.52%)	7,601 (79.14%)	7,710 (80.10%)	9,470 (94.28%)	87,960 (70.96%)
Only regional funding	1,005 (59.65%)	1,506 (15.69%)	1,405 (14.34%)	1,208 (12.33%)	1,122 (11.46%)	1,002 (10.20%)	803 (8.30%)	681 (7.01%)	561 (5.81%)	477 (4.92%)	451 (4.64%)	398 (4.14%)	364 (3.78%)	3,840 (38.23%)	10,983 (8.86%)
Only national funding	709 (9.51%)	1,018 (10.61%)	898 (9.16%)	934 (9.54%)	947 (9.67)	950 (9.67%)	916 (9.47%)	952 (9.79%)	866 (8.98%)	796 (8.21%)	726 (7.47%)	680 (7.08%)	694 (7.21%)	3,813 (37.96%)	11,086 (8.94%)
Only Euro-pean funding	233 (3.13%)	135 (1.41%)	107 (1.09%)	94 (0.96%)	86 (0.88%)	73 (0.74%)	77 (0.80%)	75 (0.77%)	108 (1.12%)	120 (1.24%)	130 (1.34%)	145 (1.51%)	136 (1.41%)	795 (7.91%)	1,519 (1.23%)
Regional and national funding	619 (8.31%)	855 (8.91%)	762 (7.78%)	768 (7.84%)	763 (7.79%)	719 (7.32%)	610 (6.30%)	495 (5.09%)	361 (3.74%)	276 (2.85%)	318 (3.27%)	280 (2.92%)	231 (2.40%)	2,513 (25.02%)	7,057 (5.69%)
National and Euro-pean funding	99 (1.33%)	101 (1.05%)	85 (0.87%)	85 (0.87%)	81 (0.83%)	82 (0.83%)	92 (0.95%)	119 (1.22%)	113 (1.17%)	121 (1.25%)	153 (1.57%)	173 (1.80%)	163 (1.69%)	662 (6.59%)	1,467 (1.18%)
Regional & Euro-pean funding	68 (0.91%)	75 (0.78%)	49 (0.50%)	42 (0.43%)	41 (0.42%)	45 (0.46%)	54 (0.56%)	40 (0.41%)	35 (0.36%)	45 (0.46%)	54 (0.56%)	55 (0.57%)	67 (0.70%)	424 (4.22%)	670 (0.54%)
All types of funding	274 (3.68)	326 (3.40%)	246 (2.51%)	232 (2.37%)	247 (2.52%)	247 (2.51%)	243 (2.51%)	218 (2.24%)	199 (2.06%)	193 (1.99%)	256 (2.63%)	273 (2.84%)	260 (2.70%)	902 (8.98%)	3,214 (2.59%)
Total	7,453	9,596	9,800	9,794	9,791	9,826	9,676	9,721	9,648	9,699	9,722	9,605	9,625	10,045	123,956

Table A.3. Transition rates across participation status.

	No subsidy (%)	Only regional subsidy (%)	Only national subsidy (%)	Only European subsidy (%)	Regional and national subsidies (%)	National and European subsidies (%)	Regional and European subsidies (%)	All types of subsidies (%)
No subsidy	92.43	2.87	3.22	0.38	0.75	0.16	0.08	0.11
Only Regional subsidy	32.56	51.15	4.86	0.55	8.92	0.15	1.07	0.74
Only national subsidy	29.72	4.63	53.19	0.97	8.14	2.13	0.19	1.01
Only European subsidy	34.86	3.26	6.67	42.46	1.16	5.43	3.84	2.32
Regional and national subsidy	13.82	14.11	14.10	0.29	50.94	1.00	0.51	5.24
National and European subsidy	10.52	1.46	15.13	7.22	3.38	48.54	1.38	12.37
Regional and European subsidy	18.80	16.47	3.16	7.15	4.16	2.66	32.61	14.98
All types of subsidies	5.56	2.44	3.70	1.25	10.65	6.34	2.68	67.38
Total	72.17	8.25	8.76	1.09	5.50	1.18	0.51	2.55

Table A.4. Number of observations during the preprocessing stage and during the average treatment effect.

			Matching method radius (0.5)				Matching method NN1			
			Start (1)		End (1)		Start (1)		End (1)	
Treatment	Variable	Total number of treated firms	Number of treated observations	Number of unique controls	Number of treated observations	Number of unique controls	Number of treated observations	Number of unique controls	Number of treated observations	Number of unique controls
Only regional subsidy	Product Inno.	3,840	3,096	4,761	2,358	4,766	3,096	1,625	3,096	1,625
	Process Inno.	3,840	3,096	4,761	2,358	4,766	3,096	1,631	3,096	1,631
	Patent Appl.	3,840	3,096	5,124	2,358	5,131	3,096	1,619	3,096	1,619
	New-to-market	3,840	3,096	4,826	2,358	4,766	3,096	1,118	3,096	1,118
Only national subsidy	Product Inno.	3,813	2,818	4,724	2,029	4,728	2,818	1,496	2,818	1,496
	Process Inno.	3,813	2,818	5,003	2,029	5,011	2,818	1,442	2,818	1,442
	Patent Appl.	3,813	2,818	4,830	2,029	4,836	2,818	1,507	2,818	1,507
	New-to-market	3,813	2,818	4,207	2,029	4,728	2,818	1,499	2,818	1,499
Only European subsidy	Product Inno.	795	521	5,852	387	5,855	521	381	521	381
	Process Inno.	795	521	7,120	387	7,125	521	365	521	365
	Patent Appl.	795	521	5,247	387	5,250	521	365	521	365
	New-to-market	795	521	6,100	387	5,855	521	342	521	342
Regional and national subsidies	Product Inno.	2,513	1,550	3,951	739	3,960	1,550	942	1,550	942
	Process Inno.	2,513	1,550	5,593	739	5,597	1,550	947	1,550	947
	Patent Appl.	2,513	1,550	6,283	739	6,291	1,550	955	1,550	955
	New-to-market	2,513	1,550	6,352	739	3,960	1,550	946	1,550	946
National and European subsidies	Product Inno.	662	312	7,368	116	7,351	312	221	312	221
	Process Inno.	662	312	7,368	116	7,351	312	238	312	238
	Patent Appl.	662	312	7,142	116	7,106	312	238	312	238
	New-to-market	662	312	7,142	116	7,351	312	215	312	215
Regional and European subsidies	Product Inno.	424	185	6,336	103	6,292	185	158	185	158
	Process Inno.	424	185	6,691	103	6,652	185	158	185	158
	Patent Appl.	424	185	7,147	103	7,061	185	144	185	144
	New-to-market	424	185	4,308	103	6,292	185	143	185	143
All types of subsidies	Product Inno.	902	538	5,424	128	5,392	538	342	538	342
	Process Inno.	902	538	6,318	128	6,260	538	327	538	327
	Patent Appl.	902	538	7,323	128	7,253	538	360	538	360
	New-to-market	902	538	7,114	128	5,392	538	330	538	330

Abbreviation: NN1, Nearest Neighbour 1:1.

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