Working Papers

5/2022 | Maggio

IRPET Istituto Regionale Programmazione Economica della Toscana

Assessing the effects of a deliberate policy mix: the case of technology and innovation advisory services and innovation vouchers[1]

Annalisa Caloffi[2], Marzia Freo[3], Stefano Ghinoi[4], Marco Mariani[5], Federica Rossi[6]

Abstract

While innovation policy mixes combining several policy instruments have been advocated as a response to complex problems, there is very little evidence of their effectiveness compared to that of individual instruments. By considering a set of Italian regional policy programmes implemented in 2011-2014, we analysed a policy mix composed of: (i) technology and innovation advisory services, the aim of which is to help small and medium enterprises (SMEs) to gain a better awareness of their innovation needs and of how to address them; and (ii) innovation vouchers, which are used to subsidise SME purchases of knowledge-intensive services. To draw causal inferences on their differential effectiveness, we adopted a propensity-score-matching approach extended to multiple treatment levels.

We found that advisory services are more effective than innovation vouchers and as effective as policy mixes in increasing SME propensity to innovate and engage in R&D collaborations. Conversely, policy mixes are more effective than each individual instrument in increasing productivity. Hence, merely providing SMEs with technology and innovation advice is not sufficient to elicit productivity improvements; SMEs also need to act on such advice by working with external providers of knowledge-intensive services in order to implement efficiency-producing changes.

1. INTRODUCTION

Among the many types of policy interventions that governments implement to support innovation in small and medium-sized enterprises (SMEs), one of the most widespread is the provision of public subsidies for the purchase of specialist services, particularly knowledge-intensive ones (OECD, 2000; Storey, 2003; DG ENTR-Unit D2, 2009; IEG, 2013).[7]

These interventions, which usually come in the form of subsidies or innovation vouchers, partially cover the costs that SMEs need to sustain in order to access knowledge (e.g., technological, organisational,

---

[1] Acknowledgements: The draft of the paper was written while Marzia Freo was working for the University of Bologna and it was finalized while she joined the JRC. The scientific output expressed does not imply a policy position of the European Commission. Neither the European Commission nor any person acting on behalf of the Commission is responsible for the use which might be made of this publication. We are very grateful to Margherita Russo for her valuable comments and discussions of an earlier version of the manuscript. We also thanks the anonymous reviewers for their very thoughtful and valuable comments. Any errors are our own.

[2] *Corresponding author*. Department of Economics and Management, University of Florence. annalisa.caloffi@unifi.it, via delle Pandette 9, 50127 Firenze, Italy.

[3] European Commission, Joint Research Center (JRC) & Department of Statistics, University of Bologna, marzia.freo@unibo.it

[4] Department of International Business and Economics, University of Greenwich & Department of Economics and Management, University of Helsinki, S.Ghinoi@greenwich.ac.uk

[5] IRPET - Tuscany's Regional Institute for Economic Planning, marco.mariani@irpet.it

[6] Birkbeck College, University of London, f.rossi@bbk.ac.uk

[7] For example, according to the OECD-STIP database, (https://stip.oecd.org/stip/policy-instruments/Innovation_vouchers, accessed on 27 February 2021), such policies were implemented in 30 countries.

marketing, logistic, legal, or other competencies) provided by external organisations (Vossen, 1998; Storey, 2003). Once SMEs have received an innovation voucher, they are expected to identify the specialist knowledge-intensive services they need, as well as the suppliers best suited to provide them. However, financial constraints, while obviously being an issue for many SMEs, are not likely to be the only obstacles to their innovation, and are not necessarily the most consequential (Galia and Legros, 2004, D'Este et al., 2012, Iammarino et al., 2021). Indeed, SMEs often lack not only the resources to invest in innovation, but also the ability to identify the knowledge they need in order to innovate, or the suppliers most appropriate to provide it (Ortega-Argilés et al., 2009; D'Este et al., 2012). Although subsidies for the purchase of knowledge-intensive services may alleviate the financial constraints that hamper SME investment in innovation, they do not improve such firms' limited awareness of their own knowledge needs and of how to address them.

It has been argued that those policymakers who are willing to support innovation in SMEs should experiment with appropriate mixes of policy instruments (Nauwelaers et al., 2009; OECD, 2010; Flanagan et al., 2011; Borrás and Edquist, 2013; Cunningham et al., 2016) combining financial and non-financial incentives. In this study, we focussed on a particularly interesting mix that bundles innovation vouchers (which provide financial support) with technology and innovation advisory services (aimed at helping SMEs to become aware of their knowledge needs, and to find ways to address them; Galia and Legros, 2004; Cowling, 2010; Cunningham et al., 2016).

Technology and innovation advisory services are usually provided by technology centres or similar types of innovation intermediary organisations (Howells, 2006), and delivered by expert staff. Such services often involve a thorough assessment of a firm's current knowledge and technology, an exploration of its potential avenues of development (Shapira and Youtie, 1998, 2016), and networking and matchmaking opportunities (Bessant and Rush, 1995; Den Hertog, 2000; Howells, 2006). Publicly-funded innovation intermediaries usually offer technology and innovation advisory services for free or at low cost.

The combination of technology and innovation advisory services and innovation vouchers may generate positive effects for the beneficiary firms. By receiving technology and innovation advice, a firm gains a better awareness of its competitive strengths and weaknesses, and becomes exposed to a variety of potential partners; this should enable it to make better use both of the voucher –in sourcing the 'right' type of service from the 'right' supplier– and of the service, once it has been provided. Our aim was to assess the differential effects of: i) innovation vouchers for the purchase of knowledge-intensive services; ii) technology and innovation advisory services provided by innovation intermediaries, and iii) a policy mix that comprises both instruments –i.e., innovation vouchers and guidance from innovation intermediaries.

We performed our empirical analysis on data drawn from two innovation policy programmes implemented in the Italian region of Tuscany. The first involved the provision to SMEs of innovation vouchers to buy knowledge-intensive services from accredited providers. The second consisted in the establishment of public innovation intermediaries tasked with providing SMEs with technology and innovation advisory services. Although neither of these policy instruments was new in the Italian context (e.g., Taddeo et al., 2017; Caloffi and Mariani, 2018; Russo et al., 2019), these two programmes had been specifically designed so that firms could apply to both at the same time. To draw causal inferences, we adopted a propensity-score-matching approach extended to the case of multiple treatments (Imbens, 2000; Lechner, 2002; Yang et al., 2016).

This paper adds to the existing literature in two main respects. First, while several studies had advocated innovation policy mixes to address complex problems (Flanagan et al., 2011; Borrás and Edquist, 2013; Cunningham et al., 2016), very little evidence had hitherto been provided in regard to deliberately planned policy mixes (Rogge and Reichardt, 2016), and no study had yet referred to the type of policies we consider here. The empirical literature on firm innovation had so far considered unplanned policy mixes –i.e., situations whereby firms could simultaneously benefit from different policy instruments that were totally unconnected (see e.g., Guerzoni and Raiteri, 2015; Neicu et al., 2016; Dumont, 2017; Montmartin et al., 2018; Douglas and Radcic, 2020). Instead, we analysed the effect of a planned policy mix that had been designed as such by the policymaker. The mix had been devised upon the assumption that the combination of the two instruments would be more effective than each taken individually. We explored whether such assumption had found general support in the data, or whether such support was to be found only for some types of SMEs. For example, we could have expected R&D SMEs to be more likely to develop innovation strategies on their own, and to identify their related knowledge needs, while we could have anticipated non-R&D SMEs to experience greater difficulties in doing so, therefore potentially benefiting more from the policy mix.

Second, we provide causal evidence of the effects on SME performance of a policy mix that combined a non-financial instrument (advisory services) with a financial one (innovation vouchers). So far, scholars had only analysed the two policy instruments individually (for innovation and knowledge advisory services, see Mole et al., 2011; Shapira and Youtie, 2016; for innovation vouchers, see Good and Tiefenthaler, 2011; Sala et al., 2016; as well as the causal studies by Cornet et al., 2006, and Bakhshi et al. 2015).

The paper is organised as follows. In Section 2, we outline the logical framework for our analysis, reviewing the literature on innovation policy mixes and their evaluation, and on innovation vouchers and advisory services, which are included in the policy mix we examined. We also conceptualise the effects that could emerge from the combination of such instruments in a policy mix. In Section 3, we describe our case study. In Section 4, we illustrate our methodology and, in Section 5, we describe our data sources and the variables we used in the empirical analysis. In Section 6, we present our results, which we then discuss in Section 7. Section 8 concludes.

2. THE LOGICAL FRAMEWORK

2.1 Innovation policy mixes and their evaluaton

Innovation policy mixes combine different policy instruments either across the same policy space (i.e., different instruments aimed at the same recipients), or across the same governance space (i.e., instruments that target different recipients involved in the same social or economic process). Policy mixes can also develop over time (e.g., when the policy instruments overlap over time) or space (e.g., when policymakers operating at different levels target the same recipients or processes) (Flanagan et al., 2011; Borrás and Edquist, 2013; Magro and Wilson, 2013; Cunningham et al., 2016). Innovation policy mixes can have different degrees of complexity in terms of the policy instruments they include and of goals they pursue. Some mixes are the result of deliberate, single or multilevel, design (i.e., strategic single or multilevel policy mixes), while others simply come about as the outcome of multi-actor, multi-level decisions that are not strictly coordinated (Laranja et al., 2008; Flanagan et al., 2011; Magro and Wilson, 2013; Lanahan and Feldman, 2015; Howlett and del Rio, 2015; Matti et al., 2017). In innovation policy practice, the deliberate combination of different tools is difficult to achieve because it often requires coordination between different policymakers, who work with different objectives, time frames, policy processes, and stakeholders (Borrás and Edquist, 2013; Magro and Wilson, 2018).

Policy mixes provide firms with wider ranges of opportunities than the individual policy instruments they combine. For this reason, they can be expected to be more effective than each of their individual constituent instruments. In the best case scenarios, policy mixes may lead to synergies and opportunities that are greater than the sum of those provided by the individual instruments they comprise. From a less favourable perspective, any conflicts among their constituent instruments may reduce the range of such opportunities (Flanagan et al., 2011; Howlett and Rayner, 2013; Cunningham et al., 2016).

The empirical evidence pertaining to the effects of policy mixes is still scarce and mostly refers to unplanned ones (Magro and Wilson, 2013, 2018; Rogge and Reichardt, 2016). Scholars have looked at the combined effects of the unplanned policy mixes that come into being when firms that receive R&D subsidies also receive tax credits (Bérubé and Mohen, 2009; Neicu et al., 2016) or R&D loans (Huergo and Moreno, 2017), generally finding positive effects. While Cunningham et al. (2016) reported some evidence in relation to deliberate innovation policy mixes, they did not find any example of evaluation of such mixes.

We believed it to be appropriate and interesting to bridge this twofold gap in the literature –the lack of studies on planned policy mixes on the one hand, and the lack of studies on policy mixes that combine financial and non-financial support on the other. In fact, these policy mixes are explicitly designed to produce combined effects that strengthen the capabilities of companies, rather than just increase their resources. Therefore, our causal analysis was aimed at assessing the existence of any positive benefits stemming from a policy mix of innovation vouchers and technology and innovation advisory services, compared to those that firms would enjoy by participating in its individual constituent programmes. As we lacked information about those firms that had not participated in any of the constituent policy programmes under consideration (i.e., a non-treated control group), we were unable to interpret whether any effects of the policy mix had reflected the simple sum of the opportunities offered by each policy instrument individually, or from any synergistic effects emerging from the interaction of such instruments. However, we believed that the presence of any positive differential effects in favour of the policy mix could in itself provide an important indication for innovation policies.

2.2 An innovation policy mix for SMEs: innovation vouchers and technology and innovation advisory services

The specific innovation policy mix that we examined involved two policy instruments. The first consisted of innovation vouchers aimed at subsidising the purchase of knowledge-intensive services by SMEs. The second consisted of the provision to SMEs, by publicly-funded innovation intermediaries, of free advice on technology and innovation.

The policy rationale for subsidising firms' acquisition of knowledge-intensive services is that, in order to remain competitive in environments characterised by increasingly complex innovation processes and high levels of turbulence, firms need to mobilise a wide range of knowledge and skills, some of which might not be available in-house (Muller and Zenker, 2001; Storey, 2003). However, the cost of acquiring such specialist services may appear prohibitive for SMEs, which may discourage them from doing so. Innovation vouchers can alleviate this financial burden, thus making the purchase of external services more attractive. Such vouchers are akin to credit notes issued by the public administration in favour of purchasing firms; these involve delegation of payment and translate into the direct disbursement of the amount due to the service provider (or of part of it) by the public administration (Schade and Grigore, 2009; Sala et al., 2016; Coletti and Landoni, 2018). The amount covered by a voucher is usually small, thus being suitable for the purchase of relatively inexpensive services (OECD, 2000).

Those firms that receive innovation vouchers are typically working on innovative projects (concerning, for example, the improvement of existing processes, products or services, or the production of brand-new products, services, processes, or strategies) the implementation of which requires knowledge that is unavailable in-house. Upon receiving a voucher, a firm first identifies an appropriate service and a service provider. Then, the firm and the selected service provider engage in a mutual learning process intended to tailor the chosen service to the former's specific features and needs (Caniëls and Romijn, 2005). The objective of this policy is achieved when, thanks to the service purchased, the firm is able to carry out its innovation project (Bakhshi et al., 2015).

At least in principle, the acquisition of knowledge-intensive services may also have some secondary outcomes. In particular, the acquisition of a service could trigger learning processes in the firm, and this, in turn, might have positive effects on its innovation inputs (increased R&D investment) and on other innovation-related activities (increased external collaborations or greater commitment to future innovation). However, previous empirical studies on the effectiveness of innovation vouchers warn against too much optimism (Cornet et al., 2006; Good and Tiefenthaler, 2011; Bakhshi et al., 2015). Some authors identified improvements in products or services and innovative capabilities, but did not detect any relevant effects with respect to the propensity to collaborate with external partners in innovative projects, or to undertake future innovation projects (Cornet et al., 2006; Bakhshi et al., 2015). Moreover, probably also due to the small amounts covered by the vouchers, the effects found were not very strong.

The second policy instrument consists in the provision of technology and innovation advisory services, usually on the part of innovation intermediaries such as technology and innovation centres, technology transfer centres, or similar organisations (Howells, 2006; Shapira and Youtie, 2016; Russo et al., 2019). The main mission of these organisations, which are often the recipients of public funding, is to enhance the quality of firm-level innovation and encourage collaborations (Howells, 2006; Knockaert et al., 2014; Russo et al., 2019). Some such organisations are also specifically expected to provide SMEs with expert advice (Shapira and Youtie, 2016) aimed at addressing any potential lack of capabilities (Bessant and Rush, 1995; Knockaert et al., 2014). By their very nature, innovation intermediaries are also expected to address any so-called network failures by facilitating the networking of firms with any relevant contacts (Klerkx and Leeuwis, 2009).

Those SMEs that draw upon this kind of policy instrument are likely to be in need of support in relation to devising innovative projects or strategies. Once a firm has been matched with an advisor, the latter assesses the former's knowledge and technology, identifies its strengths and weaknesses, and advises it on the implementation of an appropriate innovation strategy (Shapira and Youtie, 2016; Russo et al., 2019). Moreover, the advisor can help the firm to access a network of contacts that it can then exploit for various purposes (searching for information, finding collaborators for projects, etc.). The objective of this policy instrument is achieved when a SME increases its awareness and becomes able to articulate the knowledge it needs, if any. For example, a SME may become more aware of the internal or external competencies it needs in order to organise an R&D project, or achieve a better understanding of a particular technology and of how it could apply it (Rosenkopf and Nerkar, 2001). A SME may also increase its propensity to network with external organisations and, by learning how to better use its resources and capabilities to innovate, improve its innovation performance (by improving its existing production processes, products or services, or even by producing brand new products and implementing new processes or strategies) (Klerkx and Leuuwis, 2009; Shapira and Youtie, 2016). At a later stage, such improvements may lead to increases in sales or productivity.

2.3 The expected effects of a policy mix

The policy instruments described above can be usefully implemented together. The customised guidance and networking opportunities offered by technology and innovation advisory service providers can play an important role in guiding SMEs towards the best possible use of an innovation voucher and, therefore, in ensuring a better performance at a later stage. Conversely, the mere reception of free technology and innovation advice may not be conducive to improved performance if a SME does not have the financial resources needed to purchase the suggested specialist services; accordingly, an innovation voucher, on its own, may not result in improved performance if the receiving SME is incapable of determining the most appropriate knowledge-intensive service to demand (Nauwelaers et al., 2009).

However, if we consider the whole range of possible outcomes generated by these policy instruments, we could expect a policy mix to be more effective than individual instruments with respect to some outcomes, but not necessarily with respect to others. In particular, we could expect the achievement of any outcomes common to both policy instruments to be facilitated by a policy mix, while the achievement of any outcomes that are only typical of one of the instruments may not be.

According to the literature, there are outcomes that are common to both policy instruments. Innovation vouchers and technology and innovation advisory services are both expected to facilitate innovation outputs, such as improvements in existing processes or products, the development of brand-new products, and the implementation of new-to-the-firm production processes or market strategies (Shapira and Youtie, 2016). The two instruments may also engender learning processes that lead the company to enhance its innovative capabilities and to increase its participation in collaborative innovation projects (Bakshi et al, 2015). In relation to these outcomes, the policy mix may be more effective than each of the instruments taken individually: combining advisory services and vouchers may help SMEs to identify those products or processes that it needs to renew and the knowledge and competencies it requires to bring about such renewal, as well as to actually source the necessary external specialist services by removing any financial constraints. It must be noted that the effectiveness of a policy mix may differ for different types of firms, particularly it might be higher for those that have more limited internal innovation capabilities, such as those SMEs that do not carry out internal R&D. Indeed, R&D-performing SMEs may not need external advice to identify innovative strategies and to define their demand for innovative services.

Other types of outcomes are more likely to be attributable to a single specific instrument in the mix. For example, technology and innovation advisory services are designed to increase a firm's awareness of its needs and to help it design an innovative strategy; as such, we would expect them to be more effective than innovation vouchers. Consequently, the effect of a policy mix on a firm's awareness may not be radically different from that of advisory services alone. At the same time, innovation vouchers could be expected to be more effective than advisory services with respect to their ability to increase revenues in the short term. For this reason, the short-term effect of a policy mix on revenues may not be too different from that of innovation vouchers.

3. REGIONAL POLICIES IN SUPPORT OF SME INNOVATION: THE CASE OF TUSCANY

The use of innovation vouchers is common practice in several countries and regions (OECD, 2008). Since the 2001 devolution of enterprise policy to regions, Italian regional policymakers have implemented several policy programmes aimed at providing SMEs with financial support (in the form of either subsidies or vouchers) for the acquisition of knowledge-intensive services (Caloffi and Mariani, 2018). However, the devolution to the regions of such responsibilities did not go hand in hand with the assignment of a corresponding and sufficiently broad financial autonomy; for this reason, these programmes have often been co-financed by the European Union (e.g., through the European Regional Development Fund).

In Tuscany, innovation voucher policies have been issued for many years, albeit with periodic interruptions due to the need to organise funding for subsequent policy waves. A change of course occurred in 2011, when the regional government established publicly-funded innovation intermediaries, called 'innovation poles', in order to streamline and strengthen the whole regional innovation and technology transfer support system (Regione Toscana, 2010). The publicly-funded provision of innovation services had grown extensively in the previous decades. In particular, in the 1990s, several small-scale publicly-funded innovation centres had emerged with the remit to provide knowledge and innovation advisory services, as well as a wider array of innovation services to support SMEs in the main industrial districts of the region, specialised in traditional manufacturing (especially textiles, clothing, footwear, and jewellery) (Brusco, 1990; Cariola and Rolfo, 1999). However, in the 2000s, most of these organisations no longer seemed adequate to support businesses in the new digital environment (Pietrobelli and Rabellotti, 2007; Bortolotti et al., 2009). To streamline and upgrade this system, the regional government closed some innovation centres and encouraged the aggregation of the remaining ones into 12 innovation poles. These pole, which were specialised in different technologies and/or sectors, corresponding to the main specialisations of the regional economy, were expected to promote the emergence of new activities by connecting with universities and technology transfer offices (Russo et al., 2019).

Similar innovation poles had been set up by several other Italian regions, such as Piedmont and Lombardy. However, while in these regions the innovation poles were conceived as networks of excellence combining highly innovative enterprises, universities and research centres, those established in Tuscany had been tasked from the start to also serve the less innovative SMEs (Taddeo et al., 2017; Dell'Atti, 2019), by providing them with a range of innovation services. These included technology and innovation advisory services whereby experts from the innovation pole would visit the member SMEs with the aim of understanding their production and innovation processes, the markets in which they already operated, and their potential for expansion in other markets. Drawing on their assessments of the firms' technology and knowledge bases, these experts would identify their strengths and weaknesses and suggest the appropriate innovation strategies.

In order to further facilitate the nascent poles in their mission, the policymakers had chosen to link these poles to the pre-existing innovation voucher policy; however, such link lasted only a few years (2011-2014).

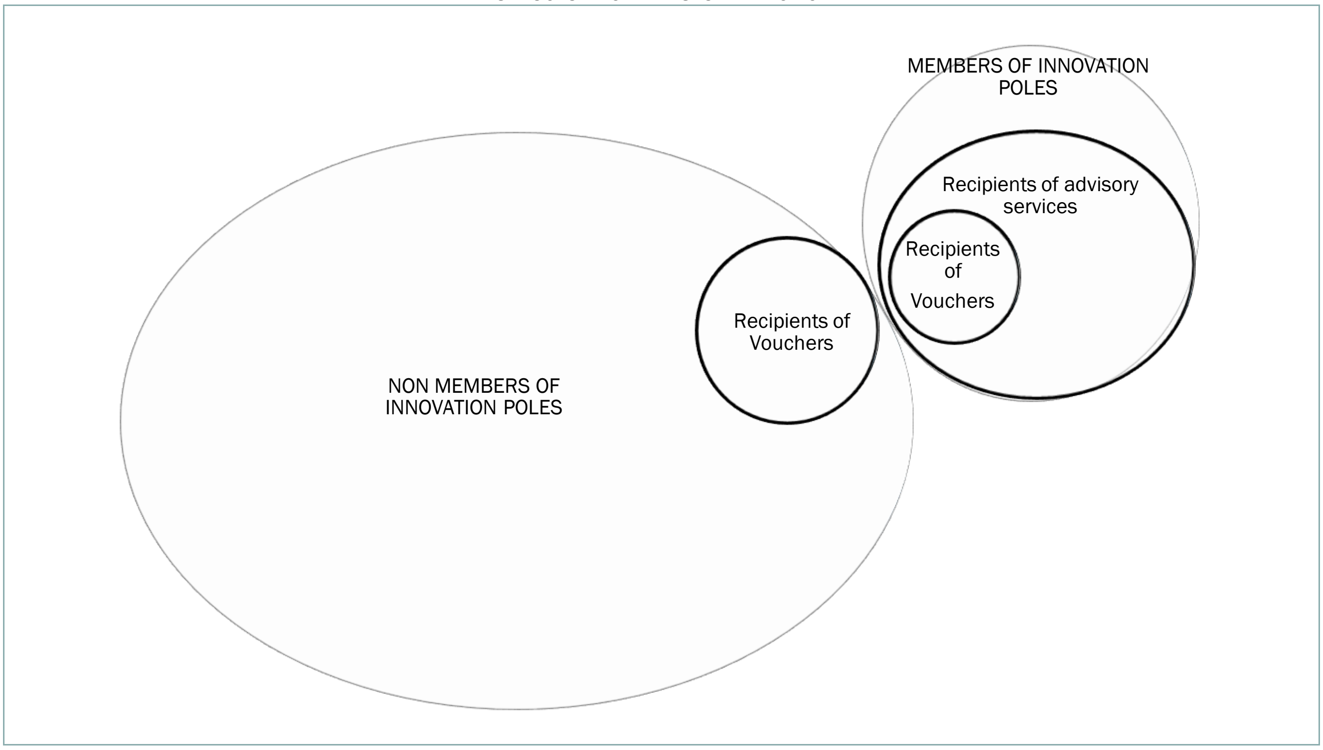
During this period, the experts that had visited the SMEs had not only helped them to formulate feasible innovation strategies, but had also provided them with information about possible financing opportunities, including any innovation vouchers they could obtain from the regional government. Additionally, the experts had helped the SMEs choose the types of services that suited their needs, and had supported them in their funding applications.

The voucher policy provided SMEs with vouchers that they could use to purchase one or more services from an official list of eligible ones (the "regional portfolio of knowledge-intensive services") supplied by both private and public providers. Such services ranged from design or other technical expertise to the quality testing and marketing of innovative products. A voucher would cover up to 80% of a service's cost.

The two policy instruments could be used either jointly or separately. SMEs could enlist in the poles and receive technology and innovation advisory services regardless of whether they also chose to benefiting from vouchers. Alternatively, they could choose to benefit from vouchers with or without becoming members of the poles.

Figure 1 shows the structure of the policy mix we analysed. We looked at cases in which firms had benefited from at least one of the two policy instruments depicted (the circles with the bold outlines in the figure) and we excluded all the rest (see also Section 5). The firms outside the bold circles in Figure 1 either were not members of any pole or they were but had not received any technology and innovation advice. The latter were mainly large firms.

Figure 1.
THE STRUCTURE OF THE STUDIED POLICY MIX



To the best of our knowledge, the regional government of Tuscany was the only one in Italy to have tried to build such a policy mix; this was linked to the fact that, at least initially, the innovation poles had been conceived as tools to support even the most fragile enterprises. The two-sided nature of these poles would cause some problems in the following years, as they would not always prove to be able to support both stronger and weaker firms (Russo et al., 2019). For this reason, among others, after 2014, the Tuscan regional policymakers had decided to take an approach akin to those of the other Italian regions. Some innovation poles had been reorganised and merged with others, and their activities had gradually shifted from the provision of support to the weakest enterprises and towards the promotion of excellence. Since then, the poles have essentially stopped providing technology and innovation advisory services to SMEs. Consequently, after 2014, the policy mix has no longer been available.

4. METHODOLOGY

We conducted comparisons between the average outcomes of firms that could be expected to fall in three distinct levels of incentivisation (henceforth also referred to as treatment levels): i) the innovation vouchers alone (henceforth also denoted as V), ii) the advisory services provided by the poles alone (A), and iii) a combination of advisory services and innovation vouchers (M, i.e., the policy mix).
To estimate the differential average treatment effect (ATE) in the case of multivalued treatments, we made the following methodological choices. First, in order to estimate the differential causal effects, we resorted to the Generalised Propensity Score (GPS) matching method, which is an adaptation of the standard Propensity Score method for settings with more than two treatments (Yang et al., 2016). As pointed out, among others, by Lechner (2002) and Sianesi (2008), if one wishes to estimate ATEs, the procedure can be viewed, conditional on covariates, as a multiple-treatment experiment wherein the GPSs are estimated using multinomial probability models (Imai and Ratkovic, 2016; Yang et al., 2016). Indeed, just like the traditional Propensity Score (Rosenbaum and Rubin, 1983), the GPS is aimed at improving the matching by removing any bias associated with the observed pre-treatment variables and adjusting the matching for a number of scalar functions of pre-treatment variables equal to the number of treatments minus one. Yang et al. (2016) showed that, under the assumptions of weak unconfoundedness of the assignment mechanism (Imbens, 2000) and overlap, the GPS may reduce the matching dimensions to one, irrespective of the number of covariates and treatments.

In our triple treatment case, the treatment was denoted as $W_i \in \mathbb{W} = \{V, A, M\}$ and, for each unit *i*, there were three potential outcomes, $Y_i(w)$, $w \in \mathbb{W}$. We observed that the outcome corresponding to a treatment actually received, $Y_i^{obs} = Y_i(W_i)$, and a vector of values of pre-treatment variables X_i.
We were interested in the causal estimand ATE, which is defined as

$$ATE(w, w') = E[Y_i(w) - Y_i(w')]$$

The caution with the ATE in a multiple treatment setting is that the expectation has to be taken with respect to those units that, given their observed characteristics, are likely to receive all (three) treatments. Indeed, as Yang et al. (2016) underlined, the goal of comparing the effects of alternative treatments by matching one treatment with another at a time does not lead to an ATE, as the population receiving two out of the three treatments may systematically differ from the overall population. Thus, we decided to estimate the average values of the potential outcomes for each treatment by means of a matching method that used the GPS, which estimates the conditional probabilities of receiving each treatment level:

$$p(w|x) = pr(W_i = w|X_i = x) \quad \forall\, w \in \mathbb{W}$$

and, under the assumptions of weak unconfoundedness of the assignment mechanism and overlap, the *ATE* became:

$$\begin{aligned} E[Y_i(w) - Y_i(w')] &= E[Y_i(w)] - E[Y_i(w')] \\ &= E\left[E[Y_i^{obs}|W_i = w, p(w|X_i = x)]\right] - E\left[E[Y_i^{obs}|W_i = w', p(w'|X_i = x)]\right] \end{aligned}$$

where the dimension of the conditioning variables was reduced to a scalar. For each unit *i*, the GPS estimated the values of $p(w|X_i)$ for $w \in \mathbb{W}$. To impute the three potential outcomes, the procedure adopted the approach of a 1-nearest neighbour matching with replacement. In doing so, it searched the triplet of units nearest to every unit *i* for any level of the treatment *j*=V, A, M as follows:

$$m_{GPS}(w|X_i) = \arg\min_{j:W_j = w} \|p(w|X_j) - p(w|X_i)\|$$

where ||.|| denotes the GPS metric. The potential outcome estimate under each treatment was:

$$\hat{Y}_i(w) = Y_{m_{GPS}(w|X_i)}^{obs}$$

Note that, in each triplet, $m_{GPS}(w = W_i|X_i) = i$ because the minimisation ran over all units. For instance, if the unit *i* was treated with A, the triplet of treated-controls would be

$$\{Y_{m_{GPS}(V|X_i)}^{obs}, Y_i^{obs}, Y_{m_{GPS}(M|X_i)}^{obs}\}$$

Once the potential outcomes were estimated, the ATE was computed as:

$$\widehat{ATE}(w, w') = N^{-1} \sum_{i=1}^{N} \left(Y_{m_{GPS}(w|X_i)}^{obs} - Y_{m_{GPS}(w'|X_i)}^{obs}\right)$$

A second methodological choice concerned the estimation of the GPS. Following the standard approach, the GPS is usually estimated by imposing a Multinomial Logit specification. This approach requires an assessment of whether the covariate distributions in the different treatment groups are balanced conditional on the GPS and, if needed, to focus on a region of common support. To achieve the statistical balance of covariates, a stepwise procedure is suggested for including the relevant covariates and their higher-order terms in the propensity score (Imbens and Rubin, 2015). To improve the overlap of propensity scores in different treatment groups, many authors, including Lechner (2002), Cerulli (2015) and Crump et al. (2009) have discussed or suggested methods that involve trimming the sample. However, as pointed out in Imbens and Rubin (2015) and Yang et al. (2016), dropping units with extremely high or low propensity scores entails refocussing the estimand of interest on a partially different reference population.

To facilitate the achievement of overlap and covariate balance, the GPS may be estimated using the Covariate Balancing Propensity Score method (Imai and Ratkovic, 2014) (CBPS, hereinafter). We chose this approach because it mitigates the consequences of the possible misspecification of propensity score models, which may ultimately produce biased estimates of treatment effects. The CBPS models the treatment assignment while optimising the covariate balance. Indeed, it estimates the propensity score under a set of moment conditions that are implied by the covariate-balancing property. It imposes mean independence between the treatment and covariates after inverse propensity score weighting. Imai and Ratkovic (2014) provided empirical evidence that the CBPS can improve the performance of propensity score weighting and matching methods.
Furthermore, we carried out an exact match within the subgroups of R&D performers and non-performers, and we derived the overall results as weighted averages over subgroups.[8]

5. DATA

We focussed on firms from the manufacturing and construction sectors that had participated once in either of the two programmes (and in no other public programme) during the 2011-2014 period. The dataset for our study combined data drawn from different sources. As a first step, the regional administration provided us with data on the participants in the two programmes. Then, these databases, which included basic information on the two programmes and their participants, were integrated with information taken from public (Statistical Archive of Active Enterprises –ASIA– maintained by the Italian Institute of Statistics) and private (Aida Bureau van Djik) archives (see Table 1). The integration with Aida referred only to limited-liability firms that were obliged by law to publish their balance sheets. Fortunately, it was possible to retrieve some basic balance-sheet information regarding the rest of the firms (about 20%) using data provided by the Fiscal Authority (FA in Table 1). The time-varying data collected from these databases referred to two different time points: information about the firms' background characteristics, which referred to the year before the launch of the policy, and information on the outcomes of interest, which referred to first and second years following the end of the policy.
The collection of information on the innovative strategies of the participant firms was based on an *ad hoc* telephone survey conducted in 2016. Due to budgetary constraints, we had to select a random sample of 515 units to be surveyed, within the strata defined by treatment levels, from an initial population of about 3,000 manufacturing firms that, between 2011 and 2014, had participated in either of the two programmes. The distribution of the sample firms' background characteristics (sector, legal form, employees, sales, labour productivity, export) was extremely similar to that of the initial population (available upon request to the authors). However, it is worth describing the finite population of firms participating in the programmes, from which we drew our sample (Table A1, in Appendix). Compared to the population of all those that were active in Tuscany's manufacture and constructions, our sample firms were found to involve a higher percentage of firms operating within sectors characterised by intermediate or high technological intensity. Also, our participating firms were found to be tendentially larger than average, both in terms of employees and revenues. Hence, the typology of firms taking part in the programmes –which, in the following analysis, were represented by our sample– was partly different from those found in most of Tuscany's regional manufacturing and construction sectors. This point helps to improve the understanding of the type of firms for which our inference can be expected to be valid.
Out of the 515 responding firms in the sample, 194 had only availed themselves of innovation vouchers, 193 had only received technology advisory services, and 128 had received both.
The survey questionnaire included questions pertaining to two time periods: 2010 (the year before the launch of the policy), and 2015 (the year following the end of the policy). We asked questions pertaining to different aspects of the sample firms' innovative behaviours, such as innovation in products/services, processes and strategies, R&D investment, and external collaborations; the full list is provided in Table 1.

[8] The R package used for the CBPS estimation was "CBPS", developed by Fong et al. (2019). The R package used for matching was "multilevelMatching", developed by Yang and Barkley (2019).

5.1 Outcome variables

To capture the variety of possible effects that the two different policy instruments (and their combination) had generated, we considered a broad range of outcome variables. The outcomes collected through the survey pertained to the year following the end of the policy (i.e., 2015). The other outcomes refer to the first and second years (2015 and 2016) (Table 1). The first group of variables was related to the behaviours of the firms with respect to R&D. As for R&D inputs, we considered a binary variable indicating whether a firm had invested in internal R&D (set to 1 if so and to 0 if not) (*internal R&D*), and a binary variable for whether a firm had been involved in unsubsidised collaborative R&D projects with other organisations (*R&D collaborations*). As for the R&D outputs, we considered a binary variable for whether the firm had innovated its products, processes, or strategies (*innovations*). To include behavioural aspects, we asked the interviewees to self-assess their capabilities and awareness with respect to the following topics. First, we asked them to assess whether, between 2010 and 2015, their respective firms had improved their ability to: i) design their own R&D projects (binary); and ii) identify external organisations as potential candidates for future innovation partnerships (binary). Secondly, we asked them whether, between 2010 and 2015, their respective firms had improved their awareness of: i) their own technological needs (binary); and ii) their own human capital needs (binary). The third group of variables referred to more general performance aspects that could have been affected by the policies, and which were available in the aforementioned public and private databases. It included the following continuous variables: number of employees (*employees*); *labour productivity*, measured as added value per employee; and *total revenues*.

Table 1.
LIST OF OUTCOME AND MATCHING VARIABLES

	Name	Time	Type	Source
***Part A:* Outcome Variables**				
Firm …				
… invests in internal R&D	Internal R&D	+1	1/0	Interview
… collaborates with external organizations	R&D collaborations	+1	1/0	Interview
… innovates products, processes or strategies	Innovation output	+1	1/0	Interview
From 2010 to 2015, the firm …	Improved ability …			
… has improved its ability to write own R&D projects	… to design R&D projects	+1	1/0	Interview
… has improved ability to identify organisations that might be candidates for future innovation partnerships	… to identify potential partners	+1	1/0	Interview
	Improved awareness of …			
… has improved awareness of its own technological needs	… technological needs	+1	1/0	Interview
… has improved awareness of its own human capital needs	… human capital needs	+1	1/0	Interview
Number of Employees	Employees	+1; +2	Cont.	ASIA
Value Added per employee (thousands of euro)	Value Added per employee	+1; +2	Cont.	ASIA+AIDA+FA
Total revenues (thousands of euro)	Total revenues	+1; +2	Cont.	ASIA+AIDA+FA
***Part B:* Matching Variables**				
Firm				
… invests in internal R&D - 2010	Internal R&D	-1	1/0	Interview
…collaborates with external organization - 2010	R&D collaborations	-1	1/0	Interview
…uses innovative services provided by external organization - 2010	Innovaton services	-1	1/0	Interview
…innovates products, processes or strategies - 2010	Innovation Output	-1	1/0	Interview
…has got patents - 2010	Patents	-1	1/0	Interview
Number of Employees - 2010	Employees	-1	Cont.	ASIA
Number of R&D Employees - 2010	R&D Employees	-1	Cont.	Interview
Value Added per Employee - 2010	Labour Productivity	-1	Cont.	ASIA+AIDA+FA
Total Revenues (thousand Euros) - 2010	Total revenues	-1	Cont.	ASIA+AIDA+FA
Firm exports the most of its production - 2010	Mainly Export	-1	1/0	Interview
Industry: Low Technology	Low Tech.	-1	1/0	ASIA
Industry: Medium-Low Technology	Medium-Low Tech	-1	1/0	ASIA
Industry: Medium-High Technology	Medium-High Tech	-1	1/0	ASIA
Industry: Constructions	Constructions	-1	1/0	ASIA
Legal form: Stock Companies, Cooperative, Consortia	Stock, Coop, Consort.	-1	1/0	ASIA

Table 2 reports the observed means, the standard deviations of the previous outcomes, and the mean differences between alternative treatment groups. Obviously, these differences are not adjusted through statistical matching. Therefore, they do not represent estimates of the causal quantities of interest in this study.

Table 2.
MEAN AND STANDARD DEVIATIONS OF OUTCOME VARIABLES WITHIN GROUPS AND DIFFERENCE OF MEANS

Outcome variables	Time	Mix		Advisory Service		Voucher		Difference of Means		
		mean	sd	mean	sd	mean	sd	M:A	M:V	A:V
Internal R&D	+1	0.438	0.498	0.316	0.466	0.376	0.486	0.121	0.061	-0.060
R&D collaborations	+1	0.688	0.465	0.715	0.453	0.186	0.390	-0.028	0.502	0.529
Innovations	+1	0.695	0.462	0.585	0.494	0.340	0.475	0.110	0.355	0.245
Improved capabilities:										
- to design R&D projects	+1	0.781	0.415	0.648	0.479	0.582	0.494	0.134	0.199	0.065
- to identify potential partners	+1	0.867	0.341	0.813	0.391	0.567	0.497	0.054	0.300	0.246
Improved awareness:										
- of technological needs	+1	0.875	0.332	0.845	0.363	0.902	0.298	0.030	-0.027	-0.058
- of human capital needs	+1	0.906	0.293	0.855	0.353	0.923	0.268	0.051	-0.016	-0.068
Employees	+1	30.9	35.3	35.2	137.4	23.9	30.6	-4.3	7.0	11.3
	+2	30.7	43.7	41.2	199.5	30.4	106.8	-10.5	0.3	10.8
Total revenues	+1	8631	30630	4473	11827	5009	11047	4158	3622	-536
(thousand Euros)	+2	10276	31047	4852	9739	9426	48770	5424	850	-4575
Value added per employee	+1	83.1	165.2	112.9	244.9	58.1	75.5	-29.7	25.0	54.8
(thousand Euros)	+2	120.4	254.5	47.5	68.4	47.1	35.5	72.9	73.4	0.5

5.2 Matching variables

As for the choice of matching variables, the guidance provided by the methodological literature underlines the importance to prioritise, especially with small samples, any covariates that are highly related to the outcome of interest (Stuart, 2010). In economic applications, this principle usually translates into using the pre-treatment value of outcomes, which are likely to be rather good predictors of the outcomes themselves (Imbens, 2004; Imbens and Rubin, 2015). Also, adjusting for such pre-treatment outcomes enabled us to neutralise the influence of any time-invariant factors affecting the outcomes, which were unobservable in the data at hand.

In line with such guidance, the CBPS was estimated by controlling for the lagged values of the outcome variables, the choice of which was motivated by the field literature discussed in Section 2. In addition, we also considered each firm's sector, its number of patents, its legal form, and its propensity to export. All these variables were measured for the year before the firms' participation in the innovation programmes (i.e., 2010).

Before using the CBPS for matching, it is important to carefully check for the presence of overlap (also termed common support) between the distributions of propensity scores in different treatment groups. In our study, the CBPS guaranteed a satisfactory overlap of these distributions, which enabled us to avoid having to trim out-of-support observations in any of the treatment groups (See Table A2 in Appendix), and to refocus the target in regard to any statistical inference on smaller subsets of such groups. Exploiting the estimated CBPS, we ran a one-to-one matching procedure, with replacement. The absolute distances –in terms of the propensity scores computed over each pair of matched units– provided matches of good quality, which never exceeded the acceptability threshold of 0.1 suggested by the relevant literature (See Figure A1 in Appendix) (Imbens and Rubin, 2015).

Table 3 summarises the means and standard deviations of covariates in the three groups. In line with the methodological literature (e.g., Imbens and Wooldridge, 2009; Imbens and Rubin, 2015) we also show the absolute differences of standardised means between the covariates observed under alternative treatment levels. Before matching, the three groups were found to slightly differ in terms of the pre-treatment variables (Table 2, panel 1). On average, the SMEs that had received the policy mix were found to have engaged in more internal and external R&D, and to be more likely to be exporters than the other treated firms. The sample SMEs that had only availed themselves of the advisory services provided by the pole were found to be relatively larger (in terms of employees) and to have a higher level of labour productivity than the other treated firms. The sample SMEs that had only received the innovation voucher were found to be relatively smaller and less productive than the other treated firms.

In the methodological literature, standardised mean differences under 0.25 are deemed acceptable, and those under 0.10 are deemed very good (Imbens and Rubin, 2015). Prior to matching, the absolute differences in standardised means appeared to be somehow unbalanced in our case, as the threshold of 0.25 was sometimes exceeded. In accordance with Sianesi (2004), we computed the median and the mean of the pre-treatment standardised mean differences, which we found to be equal to 0.098 and 0.133, respectively. Conditional on the CBPS, the previous imbalances were reduced (Figure A2 in Appendix). Finally, after the CBPS was used for matching, the residual covariate imbalances were found to be fully satisfactory. Indeed, the overwhelming majority of the standardised mean differences drops were found to be well below the 0.10 threshold, with just a few of them barely crossing it (Table 2, panel 2). The median and the mean of the post-treatment standardised mean differences were found to be 0.045 and 0.055, respectively.

Table 3.
MEAN AND STANDARD DEVIATIONS OF THE CONTROL VARIABLES WITHIN GROUPS AND ABSOLUTE DIFFERENCES OF STANDARDISED MEANS, BEFORE AND AFTER MATCHING

	Mix		Advisory Service		Voucher		Absolute Differences of Standardised Means		
	mean	sd	mean	sd	mean	sd	M:A	M:V	A:V
Variables Before Matching									
R&D internal investment	0.695	0.462	0.575	0.496	0.680	0.468	0.253	0.031	0.222
R&D collaborations	0.383	0.488	0.347	0.477	0.289	0.454	0.075	0.199	0.124
Innovation services	0.641	0.482	0.389	0.489	0.588	0.494	0.516	0.109	0.408
Patents	0.242	0.430	0.155	0.363	0.186	0.390	0.219	0.143	0.076
Innovation Output	0.445	0.499	0.440	0.498	0.397	0.491	0.010	0.098	0.088
Employees	27.7	33.2	34.5	142.2	22.3	27.5	0.079	0.063	0.142
R&D employees	2.3	2.7	1.9	4.7	1.7	2.7	0.118	0.164	0.045
Labour productivity	62.8	107.9	106.7	236.4	52.0	69.8	0.282	0.070	0.352
Ln(Total revenues)	7.6	1.7	7.2	1.6	7.5	1.4	0.265	0.053	0.212
Stock, Coop, Consort.	0.797	0.404	0.808	0.395	0.804	0.398	0.029	0.018	0.010
Mainly Export	0.328	0.471	0.223	0.417	0.237	0.426	0.240	0.207	0.033
Low Technology Industry	0.320	0.468	0.358	0.481	0.387	0.488	0.078	0.138	0.061
Medium-Low Tech.	0.266	0.443	0.249	0.433	0.232	0.423	0.039	0.078	0.039
Medium-High Tech.	0.258	0.439	0.202	0.403	0.186	0.390	0.136	0.176	0.040
Buildings	0.102	0.303	0.109	0.312	0.139	0.347	0.023	0.117	0.094
Variables After Matching									
R&D internal investment	0.682	0.466	0.629	0.484	0.693	0.462	0.111	0.025	0.136
R&D collaborations	0.346	0.476	0.322	0.468	0.334	0.472	0.049	0.025	0.025
Innovation services	0.499	0.500	0.520	0.500	0.530	0.500	0.043	0.062	0.019
Patents	0.202	0.402	0.186	0.390	0.231	0.422	0.038	0.072	0.110
Innovation Output	0.412	0.493	0.427	0.495	0.433	0.496	0.031	0.043	0.012
Employees	25.0	32.4	28.9	92.6	24.2	30.6	0.065	0.013	0.079
R&D employees	2.1	2.4	1.8	3.5	1.8	2.5	0.105	0.111	0.006
Labour productivity	63.1	99.1	74.8	157.3	75.6	141.4	0.086	0.092	0.006
Ln(Total revenues)	7.3	1.7	7.4	1.4	7.5	1.5	0.083	0.143	0.060
Stock, Coop, Consort.	0.825	0.380	0.810	0.393	0.802	0.399	0.040	0.060	0.020
Mainly Export	0.237	0.426	0.274	0.446	0.287	0.453	0.084	0.114	0.031
Low Technology Industry	0.309	0.462	0.330	0.471	0.353	0.478	0.045	0.095	0.050
Medium-Low Tech.	0.258	0.438	0.241	0.428	0.239	0.427	0.041	0.045	0.005
Medium-High Tech.	0.214	0.410	0.239	0.427	0.212	0.409	0.061	0.005	0.065
Buildings	0.115	0.319	0.122	0.328	0.120	0.326	0.024	0.018	0.006

6. RESULTS

Table 4 shows the estimated ATEs for each possible combination of treatment levels. A positive $ATE(w, w')$ indicates that, had the firms under investigation received treatment w, their average potential outcome would have been higher than it would have been had such firms received the alternative treatment w'.

Table 4.
ESTIMATED AVERAGE TREATMENTS EFFECTS

Outcome variable	Time	Mix vs. Advice[1]			Mix vs. Voucher[2]			Advice vs. Voucher[3]		
		ATE(M,A)		***S.E.***	***ATE(M,V)***		***S.E.***	***ATE(A,V)***		***S.E.***
Internal R&D	+1	0.126		0.09	0.035		0.093	-0.091		0.082
R&D collaborations	+1	-0.027		0.09	0.470	***	0.086	0.497	***	0.077
Innovations	+1	0.132		0.11	0.317	***	0.104	0.184	**	0.085
Improved capabilities:										
- to design R&D projects	+1	0.097		0.09	0.140		0.097	0.043		0.087
- to identify potential partners	+1	0.002		0.07	0.266	***	0.089	0.264	***	0.077
Improved awareness:										
- of technological needs	+1	0.000		0.08	-0.043		0.072	-0.043		0.064
- of human capital needs	+1	0.023		0.06	-0.014		0.069	-0.037		0.057
Employees	+1	3.1		8.7	2.8		7.4	-0.3		6.9
	+2	-28.9		36.0	-0.5		15.9	28.5		38.1
Total revenues (thousand Euros)	+1	2456		3986	2406		4020	-50		1222
	+2	4116		4212	-979		6392	-5096		5111
Value added per employee (thousand Euros)	+1	15.1		35.7	41.3		36.0	26.2		18.7
	+2	94.1	**	42.5	94.5	**	42.2	0.5		7.2

[1] Test of H_0: M=A vs H_1: M>A. [2] Test of H_0: M=V vs H_1: M>V. [3] Test of H_0: A=V vs H_1: A≠V.
* Result significant at 95%, ** Result significant at 99%; ***Result significant at 99.9%
Note: To account for the issues related to performing multiple tests on the same data, we adopt the approach by Benjamini and Hochberg (1995) based on False Discovery Rates (FDR). The statistical significance (at 5%) of our estimated treatment effects is preserved by setting the maximum proportion of false positives that one is willing to accept at 10%. Notice that a FDR of 10% entails that, if we had ten tests that are statistically significant, one is likely to be a false positive. In the Table, the number of tests that are significant at 5% is: one for ATE(M,A); four for ATE(M,V); and three for ATE(A,V). In worst of the previous cases, ATE(M,V) the probability of a false positive is less than half of a single test. In the other cases, such probability it is even lower.

Overall, our results did not provide strong support for the concept underpinning the creation of the policy mix –i.e., that a combination of advisory services and innovation vouchers would perform better across the board than the two policy instruments taken individually. Indeed, the policy mix was found to perform better than vouchers alone when considering certain outcome variables, but its superiority over advisory services was found to be questionable.

The policy mix was found to be superior to both advisory services and vouchers only in relation to value added per employee at time +2 (i.e., in the second year following the end of the policy). Indeed, by that time, labour productivity was found to be significantly higher under the policy mix than under the other two treatment levels. Moreover, as the estimated *ATE(A,V)* for labour productivity at time +2 was found to be not statistically different from zero, advice and vouchers may be equally important in raising productivity when combined in the mix. However, it may take some time before such combination translates into internal improvements that positively affect labour productivity. Interestingly, the improvement in productivity does not seem to come from higher revenues, as both the related *ATE(M,A)* and *ATE(M,V)* at time +2 were found to be positive but statistically not significant. At the same time, the improvement in productivity was found to not depend on any reduction in number of employees. More likely, as value added is obtained by subtracting from the revenues the expenditures for the external sourcing of materials and services, such improvement could be led by a decrease of such expenses. If so, this result could have stemmed from some innovative reorganisation –induced by the policy mix– of a firm's internal processes: a firm could have made its sourcing process more efficient and/or it could have widened the range of activities it performed internally, thus reducing those it outsourced.

When considering other outcomes, the policy mix was found to be superior to vouchers –but not necessarily to advisory services– in the case of R&D collaborations, innovation, and the capability to identify potential partners. For instance, our sample SMEs were found to have a significantly higher probability to engage in R&D collaborations under the policy mix than under vouchers (+47%). Instead, no such effect was found in regard to the policy mix versus advisory services (-2.7%, statistically not significant). If one looks at the *ATE(A,V)*, firms appeared to have received advisory services rather than vouchers, this had been sufficient to raise their probability to perform collaborative R&D by almost 50%. This result is in line with the policymaker's expectations, as stimulating collaboration had been one of the objectives of this type of intervention (see section 2.2). The results related to the introduction of innovations (in products/services/processes/markets), and the improvement in the capability to identify potential partners can be interpreted in the same fashion. In all these cases, both the policy mix and advisory services were found to have outperformed vouchers, but the main reason for the success of the policy mix was found to lie in the presence of advisory services. This result probably also depended on the fact that, in the case we analysed, the advice was being provided by innovation intermediaries –i.e., the innovation poles. This could have had two implications for the increased probability to engage in collaborations. First, innovation poles may have provided advice that underlined the potential benefits of external collaborations, which, in the case of SMEs, could act as innovation drivers. Second, the innovation poles may have directly increased the firms' opportunities for collaborations to occur by giving them access to a network of contacts that they would not have otherwise had. Advisory services were still found to play a more important role than that of vouchers (*ATE(A,V)*=18.7%) with respect to the introduction of innovations. However, in this latter case, the results on labour productivity showed us that the addition of vouchers may have been important in ensuring that, at a later stage, innovations would translate into actual economic gains. Summarising, one must conclude that, in order to increase collaborations, there had been no need for the policy mix, as the advisory services provided by innovation poles would have been able to achieve this outcome on their own.

Table 5 reports the ATEs estimated in the two SME subsamples: those that had been R&D performers prior to policy participation, and those that had not. The needs for guidance and support for R&D performers may have differed from those of non-performers. While the former had possessed some skills and in-house knowledge in relation to how to innovate processes, products, and/or services in markets, the latter may have not. Non-performers may also have lacked proper innovation strategies. A policy mix might thus have been more beneficial for the R&D non-performer subsample.

Table 5.
AVERAGE TREATMENTS EFFECTS BY THE PRESENCE/ABSENCE OF PRE-TREATMENT R&D EMPLOYMENT (CBPS)

	Time	Mix vs. Advice[1]		Mix vs. Voucher[2]		Advice vs. Voucher[3]	
R&D NON-PERFORMERS							
(*n* = 238)		*ATE(M,A)*	*S.E.*	*ATE(M,V)*	*S.E.*	*ATE(A,V)*	*S.E.*
Internal R&D	+1	0.197 *	0.11	0.130	0.102	-0.067	0.083
R&D collaborations	+1	0.042	0.08	0.605 ***	0.086	0.563 ***	0.069
Innovations	+1	0.118	0.13	0.206 *	0.124	0.088	0.087
Improved capabilities:							
- to design R&D projects	+1	0.168 *	0.10	0.189 *	0.113	0.021	0.093
- to identify potential partners	+1	-0.013	0.08	0.197 **	0.101	0.210 ***	0.080
Improved awareness:							
- of technological needs	+1	-0.034	0.09	-0.118	0.089	-0.084	0.065
- of human capital needs	+1	0.000	0.08	-0.076	0.088	-0.076	0.061
Employees	+1	4.1	10.7	-2.0	9.6	-6.2	8.4
	+2	13.2	10.4	14.2	10.4	1.0	4.7
Total revenues	+1	4926	5750	5029	5759	104	988
	+2	7461	5979	-838	8329	-8299	6150
Value added per employee	+1	42.7	44.1	85.8 *	45.9	43.1 **	20.1
	+2	151.2 **	59.6	153.3 ***	59.3	2.0	8.9
R&D PERFORMERS							
(*n* = 277)		*ATE(M,A)*	*S.E.*	*ATE(M,V)*	*S.E.*	*ATE(A,V)*	*S.E.*
Internal R&D	+1	0.065	0.08	-0.047	0.085	-0.112	0.081
R&D collaborations	+1	-0.087	0.10	0.354 ***	0.087	0.440 ***	0.083
Innovations	+1	0.144	0.09	0.412 ***	0.085	0.267 ***	0.084
Improved capabilities:							
- to design R&D projects	+1	0.036	0.08	0.097	0.081	0.061	0.081
- to identify potential partners	+1	0.014	0.06	0.325 ***	0.079	0.310 ***	0.074
Improved awareness:							
- of technological needs	+1	0.029	0.06	0.022	0.053	-0.007	0.063
- of human capital needs	+1	0.043	0.04	0.040	0.047	-0.004	0.054
Employees	+1	2.2	6.4	6.9	5.0	4.8	5.3
	+2	-65.1	48.2	-13.0	19.5	52.1	51.8
Total revenues	+1	334	1097	153	1271	-181	1394
	+2	1243	1530	-1100	4065	-2343	4022
Value added per employee	+1	-8.7	26.5	3.0	24.7	11.7	17.4
	+2	44.9 **	17.7	44.1 **	17.5	-0.8	5.3

[1] Test of H0: M=A vs H1: M>A. 2 Test of H0: M=V vs H1: M>V. 3 Test of H0: A=V vs H1: A≠V.

* Result significant at 95%, ** Result significant at 99%; ***Result significant at 99.9%.

Note: To account for the issues related to performing multiple tests on the same data, we adopt the approach by Benjamini and Hochberg (1995) based on False Discovery Rates (FDR). FDR of 10% is always sufficient to preserve the statistical significance (at 5%) of our estimated effects between each pair of treatments. In fact, a FDR of 5% would very often be sufficient to this end.

The results yielded by the R&D-performer subsample were found to be fully in line with the general results discussed earlier. As for R&D non-performers, not only were the general results confirmed, but the analysis offered additional insights.

The first such insight was that the policy mix had been superior to both advisory services and vouchers in relation to the improved capability to design R&D projects. This suggested that, to upgrade this capability, our sample SMEs may have required an adequate combination of expert advice and targeted external services.

The second additional insight was related to the probability of non-performers beginning to invest in internal R&D activities. The policy mix was found to have been more effective than advisory services –but not necessarily than vouchers– in increasing this probability. Indeed, it was found to be likely that, in the case of those of our sample SMEs that were not R&D performers, beginning to engage in internal R&D activities would have required the purchase of external skills through vouchers.

The third and final additional insight was related to labour productivity. While advisory services were found to have outperformed vouchers in the short term, when considering labour productivity at time +2, we found that these two treatments had become equally important, also when bundled in the policy mix. This result could be explained as follows. Although, during the first year, productivity improvements had begun to emerge thanks to the internal reorganisation of the processes induced by the technology and innovation advisory services provided by the innovation poles, the attainment of further productivity gains over time had required the purchase of external skills through vouchers.

7. DISCUSSION

Our results show that, although advisory services may be more effective than innovation vouchers in raising SME propensity to innovate and engage in R&D collaborations, the bundling of both may be essential in ensuring actual productivity gains later on. The results also show that the benefits of policy mixes are stronger for those SMEs that are not initially R&D performers.

The superiority of advisory services to vouchers in raising SME propensity to innovate and to engage in R&D collaborations suggests that the main problem for such firms is not their lack of funds to acquire specialised services in the market (Galia and Legros, 2004; D'Este et al., 2012). Rather, SMEs struggle to understand what kind of services they need, how best to use them, and where to best source them (Brusco, 1990; Shapira and Youtie, 2016). In particular, the emergence of new digital technologies that require interoperability (Schwab, 2016) –a context in which innovation necessarily has a collaborative dimension– may make it useful for advisors to be also able to act as intermediaries supporting R&D collaborations. On the other hand, in line with previous studies, vouchers do not seem able to stimulate networking (Cornet et al., 2006; Bakhshi et al., 2015).

The implication of these findings is that those policymakers who intend to support innovation in SMEs should prioritise the provision of technology and innovation advisory services through appropriate intermediaries. This point is relevant because advisory services, unlike the specialised innovation services that can be bought through vouchers, do not have a clear market demand. Indeed, SMEs might not be willing to pay for technology and innovation advisory services. Moreover, even where they perceive the usefulness of such services, establishing the fair price to be paid may not be easy, as these services are expensive (as they involve specialists spending time at the purchasing company) and their content is fairly broad and undefined (Delannoy et al., 2017). Hence, the free or cheap provision of such services to SMEs (for example, by bundling their offer within general membership packages that give access to a range of services provided by intermediaries) may enable them to gain valuable insights that they would not otherwise be able to access (because they would not actually consider requesting them).

It should be noted that advisory services are not easy to implement. Service providers need to organise teams of experts to visit SMEs, ensuring that such experts' skills and knowledge are adequate to understand and address the firms' problems and to communicate with them. This is probably one of the reasons for the relative underrepresentation of these instruments in the innovation policy portfolios of many countries and regions, where direct subsidies take the lion's share (Youtie and Shapira, 2016).[9]

Although advisory services should be prioritised, vouchers facilitating access to external services could be profitably bundled with advisory services in order to help SMEs translate new innovation strategies into practice and to draw productivity gains from them. We have seen that a policy mix increases productivity in the long run more than each of the policy instruments taken individually, and that this

[9] See also the overview of innovation policies implemented by the OECD - STIP compass (https://stip.oecd.org/stip.html, last accessed on 15 April 2021)

holds for both R&D performers and non-performers. The combination of increased awareness of technology and innovation needs, and of knowledge-intensive services acquired from external providers enables firms to become more efficient (by reducing the cost of the external sourcing of materials and services) and increase their long-term productivity. Advisory services may enable firms to become aware of any inefficiencies (linked to their internal organisation, the structuring of their value chains, and/or their use of materials), and the acquisition of external knowledge-intensive services enables organisational improvements (e.g., through: the better use of internal resources and competencies; a review of internal competencies, suppliers, and supply contracts; the prototyping of more efficient processes; and so on). Hence, in order to achieve productivity improvements, firms need to engage in processes that are more complex than the mere reception of advice; they also need to act on such advice by working with external specialists that enable them to put any appropriate changes in place.

8. CONCLUSION

From a policy design perspective, our study contributes to the identification of innovation policy instrument combinations that have the potential to be relatively more effective in increasing revenues, employment, and productivity. We found that a policy mix is not always preferable because, in some cases, its differential effects are not unambiguously positive with respect to each of its constituent policies. In fact, we found that, although a mix of technology and innovation advisory services and vouchers for acquiring knowledge-intensive services provides better results in increasing long term SME performance, the provision of technology and innovation advice alone is sufficient if the objective is to increase SME R&D collaboration activities, their innovations, and their ability to identify potential R&D collaboration partners. For these objectives, innovation vouchers are less valuable.

Our statistical inferences can be expected to be valid for firms having the characteristics of those under investigation. Although these firms are mostly small, they are quite unlikely to be the micro, innovation-reluctant firms that still represent wide strata of the manufacturing and construction enterprises in Tuscany and other Italian regions.

Including information on completely untreated units could enable the assessment of the ‘absolute’ effects of providing SMEs with vouchers, advisory services, or both, rather than with nothing. Although this kind of reasoning was not the focus of our study, it would indeed provide some interesting additional insights. Unfortunately, we could not perform this further type of analysis with the data at hand, if not at the cost of sharply reducing covariates and outcomes to the extremely small subset that is available for all. This, on the one hand, would have made our identification assumptions hardly plausible and, on the other hand, would have shifted our focus towards outcomes that would have been questionable, given the policy schemes analysed here.

Our findings have implications for policy design and implementation. Technology and innovation advice –which has been proven to be important to help SMEs to innovate and to engage in R&D collaborations– could become part of the portfolio of interventions available to those policymakers who seek to raise the innovativeness of SMEs in their region. In our case, technology and innovation advisory services were provided to the members of innovation poles. As we noted in the previous section, the choice to provide these services for free as part of a membership package had probably been instrumental in increasing their takeup on the part of SMEs, as many such firms would not normally wish to spend on such broad and undefined services, and may not even consider requesting such services in the first place. Hence, policymakers wishing to provide SMEs with technology and innovation advisory services might want to consider their inclusion within packages of services offered to members of innovation poles or similar innovation intermediaries. Should this option be unavailable and to ensure that these services are taken up by SMEs, they might want to bundle them with other services more likely to be requested by such firms.

The finding that the policy mix outperforms individual policy instruments in relation to raising long term productivity –and that the policy mix is particularly effective in improving the capability of R&D non-performers to design R&D projects– suggests that the policy mix does have some value and that policymakers should consider implementing it, particularly when targeting regional contexts characterised by the presence of many SMEs who do not perform R&D.

A more general problem that policymakers encounter when trying to support SMEs, particularly those that do not perform R&D –which would benefit the most from these policy instruments– is that these

firms are unlikely to engage with innovation poles or with other kinds of policy programmes. Hence, in designing policy mixes that include technology and innovation advisory services, policymakers would need to develop strategies aimed at ensuring that weaker SMEs take advantage of them. For example, they could design outreach activities aimed at providing firms with information about these services by contacting them directly or by engaging them through any associations of which they are members or through any services they already use.
Further research developments could aim to expand the empirical evidence, both by considering large nationwide programmes and –from a comparative analysis perspective– any interventions implemented in other regions. Finally, a more-in-depth analysis of the absorptive capacity of the target firms and of the quality of the services they receive could provide further valuable insights, which might prove useful for the future design of this kind of policies.

REFERENCES

Bakhshi, H., Edwards, J. S., Roper, S., Scully, J., Shaw, D., Morley, L., Rathbone, N. (2015). Assessing an experimental approach to industrial policy evaluation: Applying RCT+ to the case of Creative Credits. Research Policy, 44(8), 1462-1472.

Bérubé, C., Mohen, P. (2009). Are firms that receive R&D subsidies more innovative? Canadian Journal of Economics, 42: 206-225.

Bessant, J., Rush, H. (1995). Building bridges for innovation: The role of consultants in technology transfer. Research Policy, 24(1), 97-114.

Borrás, S., Edquist, C. (2013). The choice of innovation policy instruments. Technological Forecasting and Social Change, 80(8), 1513-1522.

Bortolotti F., Boscherini F., Califfi A., Cinti T. (Eds.) (2009). Confronto, metodologie ed analisi sul sistema toscano del trasferimento tecnologico alle imprese. Regione Toscana, Giunta Regionale, Firenze.

Brusco, S. (1990). The idea of the industrial district: Its genesis, in Pyke, F., Becattini, G., Sengenberger, W. (Eds.). Industrial districts and inter-firm co-operation in Italy. International Institute for Labour Studies. 1991, 25-34.

Caloffi, A., Mariani, M. (2018). Regional policy mixes for enterprise and innovation: A fuzzy-set clustering approach. Environment and Planning C: Politics and Space 36 (1), 28-46.

Caniëls, M. C., Romijn, H. A. (2005). What works, and why, in business services provision for SME: insights from evolutionary theory. Managing Service Quality: An International Journal, 15(6), 591-608.

Cariola, M., Rolfo, S. (1999). La valutazione delle politiche locali per l'innovazione: il caso dei centri servizi in Italia. Torino: CERIS-CNR Working Paper n.1/1999. Available at: http://www.ceris.cnr.it/ceris/workingpaper/1999/wp01_99_Cariola_Rolfo.pdf. Last accessed on 30 January 2021.

Cerulli, G. (2015). Econometric Evaluation of Socio-Economic Programs. Heidelberg: Springer.

Coletti, M., Landoni, P. (2018). Collaborations for innovation: a meta-study of relevant typologies, governance and policies. Economics of Innovation and New Technology, 27(5-6), 493-509.

Cornet, M. B., Roomen, V., Van der Steeg, M. (2006). Do innovation vouchers help SMEs to cross the bridge towards science? CBP Discussion Paper n. 58: CBP.

Cowling, M. (2010). Economic Evaluation of the Small Firms Loan Guarantee (SFLG) Scheme, Brighton: Institute for Employment Studies.

Crump, R. K., Hotz, V. J., Imbens, G. W., Mitnik, O. A. (2009). Dealing with limited overlap in estimation of average treatment effects. Biometrika, 96(1), 187-199.

Cunningham, P., Edler, J., Flanagan, K., Larédo, P. (2016). The Innovation Policy Mix. In: Edler, J., Cunningham, P., Gök, A., Shapira, P. (Eds.), Handbook of Innovation Policy Impact. Edward Elgar Publishing, Cheltenham, UK.

Dell'Atti, M. (2019). Politica industriale: i poli di innovazione nuovo strumento di policy. Rivista Italiana di Public Management, 2(1): 169-190.

Delannoy, T., Kessler, B., Lavaste, M., Martin, M., Araújo, N. L., Smid, S. (2017). Market Gap Analysis for Advisory Services under the European Investment Advisory Hub (EIAH) – Phase II. https://eiah.eib.org/publications/attachments/market-gap-analysis-advisory-smes-phase-ii-en.pdf, last accessed on 15 April 2021.

Den Hertog, P. (2000). Knowledge-intensive business services as co-producers of innovation, International Journal of Innovation Management, 4(4), 491-528.

D'Este, P., Iammarino, S., Savona, M., von Tunzelmann, N. (2012). What hampers innovation? Revealed barriers versus deterring barriers. Research Policy, 41(2), 482-488.

DG ENTR-Unit D2 (2009). Availability and Focus on Innovation Voucher Schemes in European Regions, ed. EU Brussels.

Douglas, D., Radicic, D. (2020). Network additionality and policy mix of regional and national public support for innovation. Economics of Innovation and New Technology, 1-25.

Dumont, M. (2017). Assessing the policy mix of public support to business R&D. Research Policy, 46(10), 1851-1862.

Flanagan, K., Uyarra, E., Laranja, M. (2011). Reconceptualising the 'policy mix' for innovation. Research Policy 40(5), 702-713.

Fong, C., Ratkovic, M., Imai K. (2019). CBPS: Covariate Balancing Propensity Score. R package version 0.21. https://CRAN.R-project.org/package=CBPS

Galia, F., Legros, D. (2004). Complementarities between obstacles to innovation: evidence from France. Research Policy, 33(8), 1185-1199.

Good, B., Tiefenthaler, B. (2011). Innovation voucher - small is beautiful. Plattform Forschungs- und Technologie evaluierung, Vienna, December 2011.

Guerzoni, M., Raiteri, E. (2015). Demand-side vs. supply-side technology policies: Hidden treatment and new empirical evidence on the policy mix. Research Policy 44(3), 726-747.

Howells, J. (2006). Intermediation and the role of intermediaries in innovation. Research Policy 35(5), 715-728.

Howlett, M., Del Rio, P. (2015). The parameters of policy portfolios: Verticality and horizontality in design spaces and their consequences for policy mix formulation. Environment and Planning C: Government and Policy, 33(5), 1233-1245.

Howlett, M., Rayner, J. (2013). Patching vs packaging in policy formulation: Complementary effects, goodness of fit, degrees of freedom, and feasibility in policy portfolio design. Annual Review of Policy Design, 1(1), 1-19.

Huergo, E., Moreno, L. (2017). Subsidies or loans? Evaluating the impact of R&D support programmes. Research Policy 46(7), 1198-1214.

Iammarino, S., Sodano, T., Vittorino, G. (2021). Firms' Perceptions of Barriers to Innovation and Resilience: The Italian Region of Friuli Venezia Giulia during the Crisis. Scienze Regionali – Italian Journal of Regional Science, 1, 25-54.

IEG - Independent Evaluation Group (2013). Evaluation of the World Bank Group's targeted support for small and medium enterprises (English). IEG approach paper. Washington DC: World Bank.

Imai, K., Ratkovic, M. (2014). Covariate balancing propensity score. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 76(1), 243-263.

Imbens, G. W. (2000). The role of the propensity score in estimating dose-response functions. Biometrika, 87(3), 706-710.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics*, *86*(1), 4-29.

Imbens, G. W., Rubin, D. B. (2015). Causal inference in statistics, social, and biomedical sciences. Cambridge University Press.

Imbens, G. W., Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1), 5-86.

Klerkx, L., Leeuwis, C. (2009). Establishment and embedding of innovation brokers at different innovation system levels: Insights from the Dutch agricultural sector. Technological Forecasting and Social Change, 76, 849-860.

Knockaert, M., Spithoven, A., Clarysse, B. (2014). The impact of technology intermediaries on firm cognitive capacity additionality. Technological Forecasting and Social Change, 81, 376-387.

Lanahan, L., Feldman, M. P. (2015). Multilevel innovation policy mix: A closer look at state policies that augment the federal SBIR program. Research Policy, 44(7), 1387-1402.

Laranja, M., Uyarra, E., Flanagan, K. (2008). Policies for science, technology and innovation: Translating rationales into regional policies in a multi-level setting. Research Policy, 37(5), 823-835.
Lechner, M. (2002). Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. Review of Economics and Statistics 84(2), 205-220.
Magro, E., Wilson, J. R. (2013). Complex innovation policy systems: Towards an evaluation mix. Research Policy 42(9), 1647-1656.
Magro, E., Wilson, J. R. (2018). Policy-mix evaluation: Governance challenges from new place-based innovation policies. Research policy, 103612.
Matti, C., Consoli, D., Uyarra, E. (2017). Multi level policy mixes and industry emergence: The case of wind energy in Spain. Environment and Planning C: Politics and Space, 35(4), 661-683.
Mole, K. F., Hart, M., Roper, S., Saal, D. S. (2011). Broader or deeper? Exploring the most effective intervention profile for public small business support. Environment and Planning A, 43(1), 87-105.
Montmartin, B., Herrera, M., Massard, N. (2018). The impact of the French policy mix on business R&D: How geography matters. Research Policy, 47(10), 2010-2027.
Muller, E., Zenker, A. (2001). Business services as actors of knowledge transformation: The role of KIBS in regional and national innovation systems. Research Policy 30(9), 1501-1516.
Nauwelaers, C., Boekholk, P., Mostert, B., Cunningham, P., Guy, K., Hofer, R., Rammer, C. (2009). Policy Mixes for R&D in Europe. European Commission – Directorate – General for Research, Maastricht.
Neicu, D., Teirlinck, P., Kelchtermans, S. (2016). Dipping in the policy mix: do R&D subsidies foster behavioral additionality effects of R&D tax credits?. Economics of Innovation and New Technology, 25(3), 218-239.
OECD (2000). The Bologna Charter on SME Policies. Proceedings of the Bologna Conference. Available at http://www.oecd.org/cfe/smes/englishfrenchitalianversionsofbolognaconferenceproceedingsand workshoppapers.htm. Accessed on: 3 July 2018.
OECD (2008). A Review of Local Economic and Employment Development Policy Approaches in OECD Countries, OECD, Paris.
OECD (2010). The Innovation Policy Mix, in OECD (Ed.), OECD Science, Technology and Industry Outlook 2010, OECD: Paris, 251-279.
Ortega-Argilés, R., Vivarelli, M., Voigt, P. (2009). R&D in SMEs: a paradox? Small Business Economics, 33(1): 3-11.
Pietrobelli, C., Rabellotti, R. (2007). Business Development Service centres in Italy: close to firms, far from innovation. World Review of Science, Technology and Sustainable Development, 4(1), 38-55.
Rogge, K. S., Reichardt, K. (2016). Policy mixes for sustainability transitions: An extended concept and framework for analysis. Research Policy 45(8), 1620-1635.
Rosenbaum, P. R., Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55.
Rosenkopf, L., Nerkar, A. (2001). Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. Strategic Management Journal, 22(4), pp. 287-306.
Regione Toscana (2010). Avviso pubblico per la presentazione di domande di contributo per il cofinanziamento dell'attività di funzionamento e animazione dei Poli di Innovazione 2011-2014. Available at: https://www.sviluppo.toscana.it/sites/default/files/decreto%206377.pdf, last accessed on 30 January 2021.
Russo, M., Caloffi, A., Rossi, F., Righi, R. (2019). Innovation intermediaries and performance-based incentives: a case study of regional innovation poles. Science and Public Policy, 46(1), 1-12.
Sala, A., Landoni, P., Verganti, R. (2016). Small and Medium Enterprises collaborations with knowledge intensive services: An explorative analysis of the impact of innovation vouchers. R & D Management 46, 291-302.
Schade, S., Grigore, C. (2009). Availability and Focus on Innovation Voucher Schemes in European Regions, Survey Report prepared by DG ENTR-Unit D2 "Support for innovation", November.
Schwab, K. (2016). The fourth industrial revolution. Cologny (Switzerland): World Economic Forum.
Shapira, P., Youtie, J. (1998). Evaluating Industrial Modernization: Methods, Results and Insights from the Georgia Manufacturing Extension Alliance, Journal of Technology Transfer, 23, 1, 17-27.
Shapira, P., Youtie, J. (2016). Impact of technology and innovation advisory services. In Edler, J., Cunningham, P., Gök, A. (Eds.). Handbook of innovation policy impact. Edward Elgar Publishing.

Sianesi, B. (2004). An evaluation of the Swedish system of active labor market programs in the 1990s. *Review of Economics and Statistics*, *86*(1), 133-155.
Sianesi, B. (2008). Differential effects of active labour market programs for the unemployed. *Labour Economics*, *15*(3), 370-399.
Storey, D. J. (2003). Entrepreneurship, small and medium sized enterprises and public policies. In Acs, Z. J., & Audretsch, D. B. (Eds) Handbook of entrepreneurship research (pp. 473-511). Springer, Boston, MA.
Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, 25(1), 1-21.
Taddeo, R., Simbioli, A., Ioppolo, G., Morgante, A. (2017). Industrial Symbiosis, Networking and Innovation: The Potential Role of Innovation Poles. Sustainability 9(2), 169.
Vossen, R. W. (1998). Relative Strengths and Weaknesses of Small Firms in Innovation. International Small Business Journal, 16, 88-94.
Yang, S., Barkley, B. G. (2019). multilevelMatching: Propensity Score Matching and Subclassification in Observational Studies with Multi-Level Treatments. R package version 1.0.0. https://shuyang1987.github.io/multilevelMatching/
Yang, S., Imbens, G. W., Cui, Z., Faries, D. E., Kadziola, Z. (2016). Propensity score matching and subclassification in observational studies with multi-level treatments. *Biometrics*, 72(4), 1055-1065.

APPENDIX

Table A1.
Distribution (%) of firms by industry, class of employees, and class of revenues. Comparison between the full population of construction and manufacturing firms in the Tuscany region and the subset of firms participating in the programmes under analysis. Year 2010.

	Full population	Participating firms
Industry		
Construction	54.5	13.2
Low Technology Manufacture	31.2	35.9
Medium-Low Technology Manufacture	10.9	24.7
Medium-High Technology Manufacture	2.9	21.0
High Technology Manufacture	0.5	5.2
Class of Employees		
Fewer than 5 employees	81.4	20.4
5 to 9	10.3	22.1
10 to 49	7.7	47.0
50 to 99	0.4	7.0
More than 250 employees	0.2	3.5
Class of Revenues		
Less than 200 Thousand Euro	71.2	16.1
200 to 999	19.7	25.7
1,000 to 3,999	6.6	33.2
5,000 to 9,999	1.6	15.7
10,000 to 49,999	0.8	8.4
More than 50,000 Thousand Euro	0.1	0.8

Table A2.
Centiles of Propensity Scores distributions, and absolute distances between centiles of distributions by treatment.

	Centiles										
	0	**1**	**2**	**5**	**25**	**50**	**75**	**95**	**98**	**99**	**100**
P(M|W=M)	0.101	0.102	0.119	0.158	0.215	0.274	0.326	0.433	0.463	0.474	0.477
P(M|W=A)	0.072	0.089	0.100	0.138	0.186	0.210	0.286	0.378	0.443	0.451	0.458
P(M|W=V)	0.125	0.131	0.142	0.158	0.200	0.243	0.307	0.411	0.474	0.485	0.504
abs[P(M|W=M)- P(M|W=A)]	0.029	0.013	0.019	0.021	0.029	0.064	0.041	0.055	0.020	0.023	0.019
abs[P(M|W=M)- P(M|W=V)]	0.024	0.028	0.023	0.000	0.015	0.032	0.019	0.022	0.012	0.010	0.028
P(A|W=M)	0.131	0.138	0.155	0.186	0.239	0.311	0.412	0.591	0.770	0.823	0.841
P(A|W=A)	0.108	0.149	0.183	0.213	0.322	0.423	0.506	0.717	0.834	0.866	0.879
P(A|W=V)	0.106	0.132	0.139	0.162	0.238	0.306	0.428	0.550	0.644	0.754	0.757
abs[P(A|W=A)- P(A|W=M)]	0.023	0.011	0.028	0.027	0.082	0.112	0.095	0.126	0.064	0.042	0.038
abs[P(A|W=A)- P(A|W=V)]	0.025	0.006	0.016	0.024	0.002	0.005	0.016	0.041	0.127	0.069	0.084
P(V|W=M)	0.054	0.056	0.105	0.199	0.319	0.388	0.450	0.542	0.583	0.619	0.631
P(V|W=A)	0.034	0.036	0.048	0.131	0.286	0.344	0.408	0.517	0.538	0.584	0.597
P(V|W=V)	0.101	0.114	0.160	0.245	0.351	0.406	0.485	0.589	0.629	0.633	0.652
abs[P(V|W=V)- P(V|W=M)]	0.020	0.020	0.057	0.067	0.033	0.044	0.042	0.024	0.045	0.035	0.034
abs[P(V|W=V)- P(V|W=A)]	0.047	0.058	0.055	0.047	0.032	0.019	0.035	0.047	0.046	0.015	0.021

Note: Table A1 displays centiles of estimated propensity scores for receiving the respectively Mix, Advisory services and Vouchers treatments (M, A, V) conditional on each level of actual treatment. Then, the absolute distances between estimated propensity scores at specific centiles of distributions are reported.

Figure A1.
Absolute distances of propensity scores between treated units and their closest control matches, by level of treatment

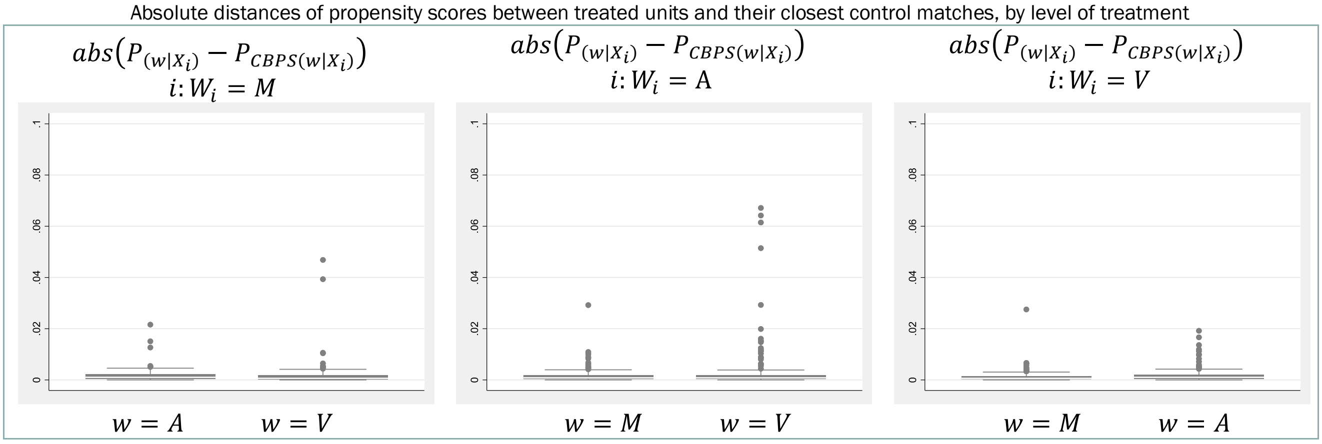
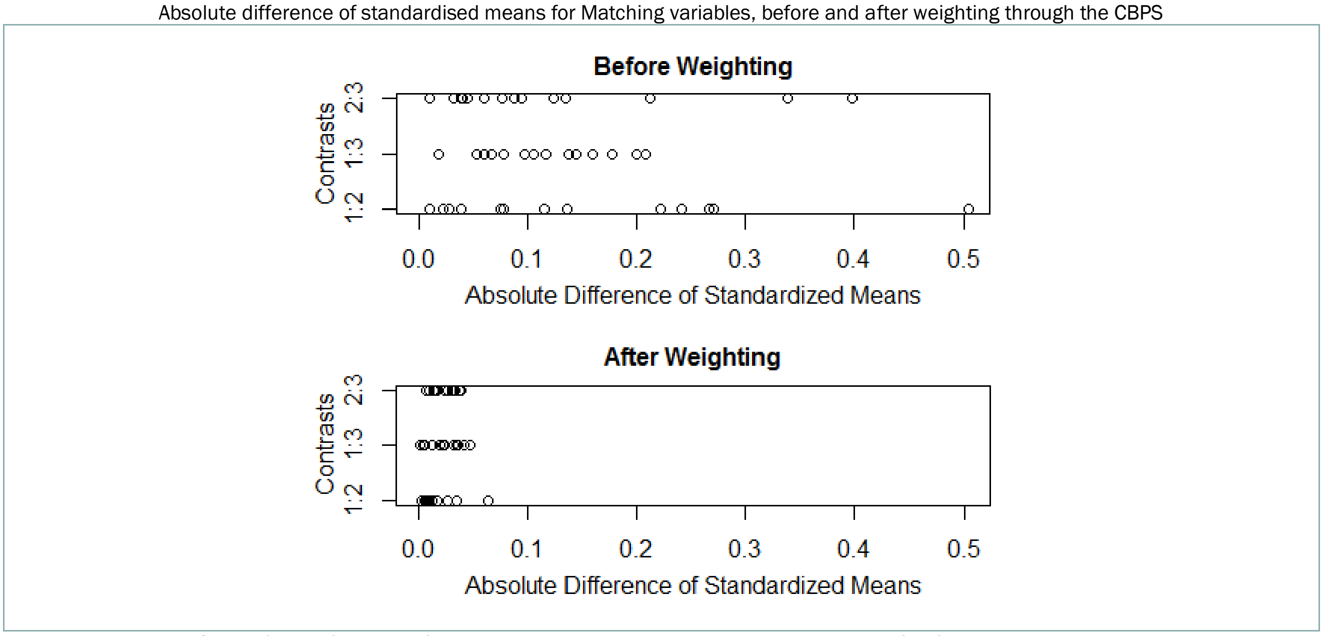


Figure A2.
Absolute difference of standardised means for Matching variables, before and after weighting through the CBPS



Note to figure: 1=Mix; 2=Advice; 3=Voucher. The weighting procedure used to assess CBPS-adjusted covariate balance is based on Imai and Ratkovic (2014).