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Targeting Constellations of Diverse R&I Actors?

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Title page

Innovation Policy Instruments for Grand Challenges: Targeting Constellations of Diverse R&I Actors?

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Abstract

Many countries have created research and innovation (R&I) policy instruments with the mission of addressing grand challenges. The new policy rationale suggests that these instruments must target civil society actors in new and more diverse constellations, combining them with 'traditional' R&I actors (universities and firms). Investigating the extent to which policy instruments are designed according to this requirement, this paper analyses co-occurrences of targeted R&I actors in science, technology and innovation policy instruments and identifies five typical constellations of targeted R&I actors. We focus on two constellations that are likely to include civil society actors. Wide constellations (dominated by universities and firms) are positively associated with grand challenge policy instruments. Civil-society-led constellations are less heterogeneous and possibly associated with grand challenge instruments. This original contribution shows partial consistency between the grand challenge policy rationale and its instruments, and evidence of civil-society-led actor constellations not yet considered in the literature.

Keywords: Grand challenges, Transformative innovation policy, Innovation policy instruments, Policy mix, Mission innovation.

JEL: O31; O38; O33

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1. Introduction

A new rationale for research and innovation (R&I) policy has gradually gained ground over the last decade, proposing that R&I policy develop policy instruments focused on solving grand challenges (GC) that affect current societies (Foray, Mowery, and Nelson 2012; Mazzucato 2016; Weber and Rohracher 2012), complementing other existing policy instruments. In so doing, this rationale supports the idea that governments' R&I policies should not only focus on generating value for the scientific community (advancing the human knowledge frontier) and for the economy (fostering economic growth, competitiveness and job creation), but also generate value for society by tackling a series of complex challenges, such as climate change, environmental sustainability, ageing societies, or neglected diseases (Schot and Steinmueller 2018).

A core feature of this policy rationale is the suggestion that the policy instruments addressing grand challenges require the involvement of 'new constellations of innovation actors to emerge and become active' (Kuhlmann and Rip 2018, 449). In so doing, this rationale closely follows previous suggestions from the 'mode 2' (Nowotny, Scott, and Gibbons 2003), 'citizen science' (Irwin 2002), and 'quintuple helix' approaches (Carayannis, Barth, and Campbell 2012) as 'having a focus on collaborations among diverse disciplines and heterogeneous actors, these approaches are relevant in the context of the grand challenges idea' (Ulnicane 2016, 8).

Recent studies have empirically analysed new actors at the project level, either as 'organizational knowledge integrators' (Knudsen, Tranekjer, and Bulathsinhala 2019), or as the influence of 'advocacy groups' in applicant project funding success (Olsen, Sofka, and Grimpe 2016). Together, these studies provide insights into the project-level role of new R&I actors, but say little

about how policy instruments have been designed. Studying the design of policy instruments helps us understand the extent to which the abstract suggestions of policy rationales are actually being 'translated' into the design of specific policy instruments, in a way that fits the purpose of the rationale.

This matter is relevant for at least two reasons. Firstly, some theoretical accounts assume a co-evolutionary process between the suggestions of policy rationales and the actual policy design of policy instruments (Mytelka and Smith 2002). However, evidence shows that this process is not even because important elements from previous rationales might prevail in the design of new instruments (Dodgson et al. 2011). Therefore, assumptions of co-evolution should not be over-emphasised (Kuhlmann, Shapira, and Smits 2010) because the suggestions of the new policy rationale might not always translate automatically in the design of policy instruments, which is complex and subject to fundamental uncertainties (Flanagan and Uyarra 2016). Secondly, following from the fundamental uncertainties of policy instrument design, it is essential to understand how countries deal in practice with the calls for widening the scope of targeted R&I actors. The newly targeted R&I actors are not part of the traditional constituencies of R&I policy-making, and are typically small organisations with limited management capacity. The design of policy instruments might reflect this, particularly in the composition of the constellations of R&I actors that those instruments target.

The extent to which grand challenge policy instruments target civil society actors in new, more diverse, constellations of R&I actors, the specific composition of these constellations, and therefore whether the design of those policy instruments complies with core tenets of the new policy rationale, remains empirically unexplored. This paper studies the patterns of targeted R&I actors across all policy instruments, asking: How far are grand challenge-oriented R&I policy

instruments designed to target civil society and more diverse constellations of R&I actors? To answer this research question we extract a large sample of more than 3,800 policy instruments from 52 countries from the STIP Compass of 2017; a dataset collected, curated, and quality-checked by the OECD and the EU in collaboration (EC/OECD 2018). Overall, the dataset defines that 449 of these policy instruments are oriented towards grand challenges.

The next section shows how the literature has approached issues related to the wider involvement of stakeholders in grand challenges-oriented R&I policy instruments, and issues of consistency between policy rationales and the design of policy instruments. This serves to further contextualise the research question in the theoretical approaches regarding the policy rationale of grand challenge instruments. Section 3 describes the data, the variables, and the estimation strategy that combines latent class analysis and logistic regression to answer the research question. Section 4 presents the analysis. We analyse the unseen patterns of constellations of targeted actors emerging from all the policy instruments in the dataset, and then study how far the constellations of R&I actors with more diverse targeted R&I actors and where civil society figures prominently are positively associated with grand-challenge-oriented policy instruments. Two robustness checks accounting for potential measurement errors in our dataset underscore the analysis. Section 5 discusses the findings of the paper in view of the current literature and delves into its original contribution. We find five different constellations of targeted R&I actors in innovation policy instruments, a variation not discussed previously in the literature. The findings add a nuanced perspective to the literature, empirically showing the relatively limited way in which civil society actors are actually targeted by grand challenge policy instruments, and providing empirical evidence on the partial consistency between the grand challenges policy rationales and its policy instruments. The obvious practical implications of these findings are that policy-makers concerned

with grand challenges must target civil society actors more actively when designing policy instruments. Section 6 answers the main research question, addresses the limitations of the current study, and identifies four possible lines for future research.

2. On grand challenges in R&I policy rationales

The notion of grand challenges (GC) in R&I policy-making has changed over time (Flink and Kaldewey 2018). The term appears in the USA for the first time in the early 1990s in relation to solving scientific and engineering problems (Hicks 2016; Modic and Feldman 2017). Now, grand challenges refer to complex social problems such as those identified in the UNs Sustainable Development Goals (SDGs). In the European Union, the notion of GC first appeared in the Lund Declaration, with the understanding that 'European research must focus on the grand challenges of our time moving beyond current rigid thematic approaches' (Swedish Presidency of the Council of the EU 2009). This approach has gradually translated in EU and national R&I policies (European Commission, Directorate General for Research and Innovation 2018; Lundin and Schwaag Serger 2018).

Public policies have always been related to the solution of problems (Peters, 2018). What is new in the GC-oriented R&I policy rationale is that the scope of the problems have expanded substantially. This relates to the widening and deepening of innovation policy during the past decades (Borrás 2009), which aims to secure multiple goals related to sustainable economic, social and environmental development (Chaminade, Lundvall, and Haneef 2018) as 'transformative failures' (Weber and Rohracher 2012). The scale of the solutions has also expanded (Wanzenböck,

et al., 2020). The new focus on GCs in innovation policy rationales responds to system-level change, understanding that the solutions to those challenges are embedded in complex institutional and organisational systems (Fagerberg 2018) that span geographical areas (Coenen, Hansen, and Rekers 2015) and sectoral contexts (Rogge and Schleich 2018).

A core tenet of the grand challenges R&I policy rationale is the suggestion to involve civil society (such as non-governmental organisations (NGOs), patient organisations, grass-roots associations, etc.) as new types of actors performing research and innovation; and the need to bring them closer to traditional R&I-performing actors (such as universities, industry, and public research organisations) in wider and more diverse, constellations (Cagnin, Amanatidou, and Keenan 2012; Kallerud et al. 2013).

> *The scope of innovation policy needs to be reconsidered, and the coherence between innovation policy and other thematic policy improved. This implies incorporating actors that go well beyond the range of 'usual suspects' and puts much more emphasis on actors on the demand side of innovation. It also coincides with growing claims and possibilities for participation of society in research and innovation activities; citizens can play a much more active role in R&I, and not only as data providers but also in shaping agendas and conducting research themselves.* (Weber and Truffer 2017, 109)

The new policy rationale suggests that besides traditional university–industry-led R&I activities, another type of constellation involves scientists and members of the public promoting the co-creation of R&I (Keenan et al. 2012; Weber et al. 2016). Hence, it is about 'empowering new players to address global and social challenges through innovation' (OECD 2010, 182). It is also about creating more heterogeneous and diverse constellations of R&I actors: 'While the notion of 'partnerships' are becoming common as a venue for addressing grand and global challenges, these

partnerships are conceived as having to be particularly extensive, inclusive and heterogeneous' (Kallerud et al. 2013, 19). It is important to underline that the grand challenges policy rationale does not downplay the relevance of traditional R&I-performing actors (such as public research organisations, firms, or universities). On the contrary, it suggests the importance of constellations of R&I actors, combining 'old' and 'new' actors (Mazzucato 2018; Olsen, Sofka, and Grimpe 2016).

The scarce empirical literature about this matter has tended to focus on the research project level. Recent studies have examined the role of 'organisational knowledge integrators' in R&D-funded projects towards GCs and found that they have positive effects on projects' outcomes (Knudsen, Tranekjer, and Bulathsinhala 2019). These knowledge integrators are firms or organisations with specific interest in pulling knowledge together and may or may not include new types of R&I actors as defined above. Other studies at the project level have studied the effect of 'advocacy groups' in applicant project consortia. They show that projects including advocacy groups (as new types of R&I actors) are more likely to receive EU-level research funding (Olsen, Sofka, and Grimpe 2016).

These perspectives provide relevant insights into the roles and effects of new non-traditional types of R&I actors at the project level, but say little about the design of policy instruments. In particular, we still do not know the extent to which GC policy instruments actually target civil society as part of more diverse constellations of R&I actors, and are therefore consistent with the statements of the new policy rationale.

By studying the design of R&I policy instruments, this paper fills a gap in the literature by focusing on the level of policy instruments' design. The design of individual policy instruments are typically

studied using qualitative methods in small-n comparisons or single case studies. The STIP dataset used in the current study offers a unique opportunity to examine empirical questions under a new light. It allows for a large-n testing and identifying unseen patterns of the current topic of interest.

The next section provides a definition of GC policy instruments, with examples from the database used. It also explains the data, the variables and the steps in the analysis.

3. Methods

3.1 Data

This paper uses data from the 'International Survey on Science, Technology and Innovation Policies', jointly conducted by the OECD and the European Commission (EC/OECD 2018). The countries included in the survey are the Member States of the EU and the OECD and additional emerging economies including China, India and Russia. The survey data has been used previously for studies of technology transfer and research commercialisation and technology upgrading through global value chains (Kergroach 2019; Kergroach, Meissner, and Vonortas 2018). Five survey waves have been completed since 2012. We use data from the fourth wave (the survey conducted between 2017 and 2018), for two reasons. First, the data collection methods have improved in this wave compared to previous ones because survey administrators created an online tool that allowed storing and updating responses in the database instantly. This makes it easier for respondents (the corresponding national representatives) to complete the survey and for OECD survey administrators to process the data, and has helped to improve the quality of the data. Second, the questionnaire varies across the survey waves. The data from the fourth wave contain

more questions about GC instruments than the fifth one, since survey administrators reduced the overall number of questions for the fifth wave to improve convenience for respondents. Therefore, data from the 2017–18 survey contain suitable responses about the design of GC-oriented instruments. Changes in the survey design can also be a reaction to limited quality of the responses given to specific questions. Our analysis below includes robustness checks accounting for that risk.

The complete dataset contains 6,856 observations, unevenly distributed across countries. According to the survey terminology, the observations are 'policy initiatives', the main unit of data collection in the STIP database. The definition of policy initiatives provided by the OECD reads: 'A public action that i) aims to achieve one or several public policy goals in the policy area of science, technology and innovation; ii) is expected to modify the behaviours of actors and stakeholders, being national, domestic or foreign, who are part of or influential on, the national innovation systems; and iii) is implemented with a minimum time horizon or on a continuous basis (i.e. not as a one-off 'event')' (Meissner and Kergroach 2019; OECD 2016, 189). The survey terminology distinguishes between 'initiatives' and 'instruments' and considers that 'initiatives' comprehend one or more 'instruments' as means of implementing 'initiatives'. The survey distinguishes between 28 functional types of 'instruments' belonging to five groups (direct financial support; indirect financial support; networks and collaborations; guidance, Regulation and incentives; and governance).

Our analysis uses the survey 'initiatives' as observations. We refer to these 'initiatives' as 'policy instruments' because we follow the widespread terminology in the academic literature according to which a policy instrument is 'a set of techniques by which governmental authorities wield their power in attempting to ensure support and effect (or prevent) social change' (Vedung, 1998) (p.

15).[1] Likewise, we use the term 'measures' to refer to their specific sub-elements and include these measures in our analysis. The reason for this choice is that our terminology allows this paper to follow the debates in the academic literature, to use the richness of the data in the survey in a systematic and consistent manner, and to consider the specific variation of measures in our analytical models.

Some of the observations in the OECD dataset are not assigned to any survey questions since the survey administrators deemed that they do not belong to the policy areas of science, technology and innovation. We remove these observations as well as those from the EU-level. Further, the survey identifies some observations as 'policy strategies', which are large and broad planning and strategic texts that set a general perspective. We have not included them in our sample because they are not policy instruments. We also remove observations with missing information about R&I actors. Our final sample comprises 3,823 observations from 52 countries. The median number of observations per country is 69, with the highest number of observations from Belgium (177).

Removing observations with missing information about the targeted R&I actors might introduce a bias in our sample. India and Malaysia provided no actor information and were removed from our final sample. Among the remaining countries, there is variation in information about R&I-targeted actors (see Table i in the appendix). The amount of information on targeted R&I actors the respondents from different countries supply could relate to the relevance that the respondents attribute to the survey and/or with the country's resources for STI policymaking. In sum, the instruments included in our sample might be more representative of countries that are able to

[1] OECD's term ´initiative' is not used in the academic literature of policy analysis; likewise, OECD's term 'instrument' is usually referred to as 'measure' in the academic literature. In this paper we follow the terminology in the academic literature of policy analysis.

devote considerable resources to STI policy. To mitigate reporting differences, our analyses account for country fixed effects.

3.2 Variables

The first part of the analysis uses information about policy instruments' targeted R&I actors to identify their patterns of co-occurrence. For each instrument, the survey respondents could select one or several options from a drop-down menu of eight types of R&I actors, divided into 31 sub-types. We reduced the original eight types into six types of R&I actors and constructed corresponding binary categorical variables (see Table ii in the appendix). Our first type of R&I actors, '**Researchers'**, encompasses the two OECD types 'Researchers, students and teachers' and 'Research and education institutions' (2,500 observations). We consider that these two types of actors belong to the same type as they are traditional research-performing institutions and their employees (universities, public research laboratories, etc). The second type of actors are '**Firms and Entrepreneurs**'. For the same reason, we grouped 'Firms by age' and 'Firms by size' (1,589 observations) together, as both entries correspond to the same type of R&I actor. We included 'Entrepreneurs' within this type of actor, although the drop-down menu of the OECD survey includes them in 'Capital and labour', because entrepreneurship manifests itself as a micro or small firm. The third type of actor is '**Government'**, which includes 'National government' and 'Subnational government' from the OECD type 'Governmental entities' (691 observations). The fourth type of R&I actors are '**Intermediaries**', from the OECD survey type 'Intermediaries', which includes incubators and technology transfer offices as R&I actors (456 observations). The fifth type of actors, '**Capital and Labour**', includes 'Workers with tertiary education and above

specifically', 'Labour force in general', 'Private investors' and 'Entrepreneurs'. We moved 'Entrepreneurs' to another actor type, so our 'Capital and labour' group is formed by the other three sub-groups (308 observations). Our sixth type of actor is '**Civil Society**', which corresponds to the OECD type 'Social groups especially emphasised', and is formed by 'Civil society', 'Disadvantaged and excluded groups', and 'Women' (514 observations).

Following the analysis of R&I actor co-occurrences, this paper seeks to relate patterns of targeted R&I actors' co-occurrences to grand challenges policy instruments. To this end, we derive a binary dependent variable from the dataset, indicating whether each observation (the policy instruments) explicitly aims to address grand challenges. Four of the six survey questions collecting information on policy instruments in the survey section 'Research and Innovation in Society' focus on policy instruments aiming to address GCs: 'What policy initiatives exist, if any, specifically dedicated to supporting innovation for tackling health and aging issues?' (134 observations); 'What policy initiatives exist, if any, to specifically address sustainable development challenges through research and innovation?' (216 observations); 'What policy initiatives exist, if any, specifically dedicated to supporting research and innovation in developing and less advanced countries?' (54 observations); and 'What policy initiatives exist to promote a broad and diversified public engagement in research and innovation policy making with a view to improving the integration of social values in research and innovation processes and results?' (84 observations). In total, 449 instruments are linked to one or more of these questions. While the list of grand challenges covered by these four questions might not be exhaustive, it makes it possible to identify the policy instruments addressing grand challenges that are included in this dataset.

Table 1 describes the frequency of different actor types in grand challenges instruments and other instruments. In both subsets of instruments, 'researchers' are by far the most frequently mentioned

actor types, followed by ‘firms and entrepreneurs.’ In GC instruments, ‘civil society’ actor types are the third-most frequently mentioned group, followed by ‘government’ actors, whereas in other instruments, ‘government’ actors appear more frequently than civil society actors. In both subsets of instruments, ‘intermediaries’ and ‘capital and labour’ are the least frequent actor types.

[Insert Table 1 about here: Frequency Table of Grand Challenges Instruments and R&I Actor Types]

An example of the type of R&I actors targeted by a GC policy instrument is the ‘Global Development Lab’, a policy instrument run by the US Agency for International Development that seeks ‘to increase the application of science, technology, innovation, and partnerships’. According to our dataset, this instrument targets five of the 31 sub-types of actors in the OECD survey: ‘Research and education institutions|Public research institutes’; ‘Researchers, students and teachers|Established researchers’; ‘Social groups especially emphasised|Civil society’; ‘Social groups especially emphasised|Disadvantaged and excluded groups’; ‘Social groups especially emphasised|Women’ (spelling quoted from the survey). With our coding scheme (see Table ii in the appendix), we consider that this policy instrument targets two types of R&I actors: ‘Researchers’ and ‘Civil society’. Table 2 offers examples of policy instruments.

[Insert Table 2 about here: Examples of Grand Challenges Policy Instruments in the Sample]

Using additional information from the dataset, this paper controls for instrument budgets, for the functional classification of the measures, and for country fixed effects. Controlling for instrument budgets is essential since the scale of instruments varies considerably; budgets range from less than 1 million Euro to more than 500 million Euro (see Table iii in the Appendix). For instruments with missing budget information, we impute the budget mean and add a dummy variable controlling for the imputation. Similarly, we include control variables for the functional type of measures used by policy instruments (see section above on terminology) because R&I actor constellations might be associated with specific functional types of measures. These control variables refer to whether instruments use the measures of Direct financial support; Indirect financial support; Collaborative platforms and infrastructure; Guidance, Regulation and other incentives; and/or Governance (see Table iv in the Appendix). Thirdly, we control for the reporting behaviour of survey respondents with dummy variables for the eight thematic sections of the survey, such as 'Public Research System', 'Innovation in firms' and 'Knowledge Transfer' (see table v in the appendix). Each instrument belongs to one or more of these sections. These control variables remediate possible cases of unbalanced reporting, where respondents from a given country report many instruments in some sections of the survey, and few instruments in others. Finally, we control for country fixed effects to reduce the effects of country-level differences in the style of reporting.

3.3 Estimation strategy

This paper proceeds in two steps to estimate the associations between constellations of targeted R&I actors and GC instruments. First, we study the constellations of R&I actors that all policy

instruments target, paying particular attention to the constellations where civil society actors appear more prominently, and to the constellations with more diverse types of R&I actors.[2] To do so, we examine the patterns of co-occurrence of different types of R&I actors. Second, we relate these actor constellations to policy instruments addressing grand challenges.

To identify the constellations of targeted R&I actors, we use latent class analysis, a method for identifying latent structures in qualitative data (Formann 2014; Schreiber 2017; Vermunt and Magidson 2014). This method is comparable to factor analysis but it accepts categorical variables as input and identifies categorical latent variables in the data, as our analysis requires (Brusco, Shireman, and Steinley 2017; Magidson and Vermunt 2002).

In the equations below, *y* denotes the observed categorical indicators used to estimate the latent classes and *x* denotes the latent classes. *K* denotes the number of the observed categorical indicators, and *C* denotes the number of latent classes. Equation 1 formulates the assumption that the probabilities of the observed categorical indicators *P(y)* are equal to the joint mixture of *C* class-specific distributions of probabilities *x* for these indicators (Magidson and Vermunt 2002; Vermunt and Magidson 2014). Equation 2 formulates the assumption that within each latent class, the *K* class indicators are independent of each other (ibid.). Plugging Equation 1 into Equation 2 results in a general formulation of the latent class model in Equation 3.

$$P(y) = \sum_{x=1}^{C} P(X = x)P(y \mid X = x) \qquad (1)$$

[2] Hence, we are not studying the performance of these policy instruments in terms of the actual funded/supported project consortia. See the last section of this paper about the limitations of this study, and possible future research.

$$P(y \mid X = x) = \prod_{k=1}^{K} P(y_k \mid X = x) \quad (2)$$

$$P(y) = \sum_{x=1}^{C} P(X = x) \prod_{k=1}^{K} P(y_k \mid X = x) \quad (3)$$

To estimate the latent classes, we used the six variables for the different types of actors as indicators (y). Since this method requires the researcher to supply the value of K for the number of latent classes, we compared the fit of models with two to six classes with the data to choose our final latent class model. We include country fixed effects as covariates in the estimation process. The use of covariates introduces the additional assumption that the class indicators are independent of the covariates given the latent classes (Vermunt and Magidson 2016). Put differently, we assume that country differences regarding the prevalence of any type of actors are due to country differences in the prevalence of classes.

Having identified and described the different constellations of targeted R&I actors with latent class analysis, we relate the constellations in which civil society actors figure prominently to GC instruments using logistic regression models. In these models, a binary dependent variable indicates whether an instrument addresses a GC and the predictors are predicted probabilities of latent class memberships. Thus, the regression models incorporate the uncertainty of assigning observations to specific latent classes/constellations of actors. The models control for instrument budgets, the types of measures used, reporting behaviour and country fixed effects.

3.4 Robustness checks on potential misclassifications

A potential problem with the dataset is the possible misclassification of some GC instruments (the dependent variable in our regressions). The survey respondents are national officials with a profound knowledge of the instruments they report, and the survey data has been curated by the OECD. Nevertheless, we cannot rule out possible measurement errors. We conducted two robustness checks to examine how potential measurement errors in the dependent variable affect the results (see Section 4.3).

The first check involved re-estimating our main models as linear probability models. Compared to non-linear models, linear probability models are less susceptible to measurement error in the dependent variable resulting from misclassification of GC instruments. In non-linear models, it is difficult to assess how measurement errors affect the results, since they have non-linear effects on the estimates. In linear models, measurement errors generally count towards the error term and therefore inflate the model variance rather than affecting the coefficients. While measurement errors that are unevenly distributed across countries could still lead to biased estimates, this robustness check provides an indication of the stability of the estimates.

As a second robustness check, we re-estimated our main models using a dependent variable that we recoded after manually reviewing the 449 GC instruments in our sample. For the review, both authors separately identified supposed cases of misclassification (two coders review), then re-examined them one by one, and discussed the individual cases where their views dissented.

Specifically, we identified three possible problems of misclassification of policy instruments. Firstly, some broad R&I programmes seek to generate societal benefits in general terms, but do

not refer to specific grand challenges; secondly, some instruments for international R&I cooperation that are generic and do not explicitly refer to grand challenges. Thirdly, some policy strategies refer to grand challenges but are not policy instruments.[3]

We identified 116 instruments that could have been misclassified as grand challenges instruments. Suggesting a misclassification rate of up to 26 per cent, this underlines the relevance of conducting robustness checks. Section 4.3 presents logistic regression models using a new dependent variable that is based on our revised classification.

4. Analysis

4.1 Patterns of co-occurrence of R&I actors

As mentioned, we investigated patterns of co-occurrence of the targeted R&I actors of all policy instruments to identify typical constellations of R&I actors emerging from the data. First, latent class analysis requires us to choose the number of classes. A lower number of classes is easier to interpret but prone to bias, while a higher number should fit the data better so that fewer cases with ambiguous latent class membership remain. For a parsimonious choice, we estimated and compared models with one to six classes. Table vi in the appendix provides summary data comparing the six models. The L^2 values indicate that the amount of association among the variables remaining unexplained after estimating the model decreases when the number of classes increases, so models with higher numbers of classes fit the data better. P-values below 0.05 indicate

[3] As described, we removed policy strategies from the dataset prior to conducting our analyses. However, some strategies remained in the dataset since they were classified as policy instruments.

that models do not hold true for the population, so we rejected the models with 1–3 classes. The Bayesian Information Criterion (BIC) value is lowest for the four-class model, suggesting that this is the best choice. However, relying on the BIC might lead to conservative choices (McLachlan and Peel 2004). We opted for the five-class model since the variance explained of the indicator variable for civil society increases to 34 per cent compared to 18 per cent in the four-class model, making this model more suitable for our analysis, which focuses on civil society actors.

[Insert Table 3 about here: Assessing the fit of a five-class model with multinomial logistic regressions]

Table 3 describes the relationship of the different types of actors to the five classes as multinomial logistic regression fits with Class1 as the reference category for the coefficients. Each of the variables for actor types contributes significantly to the model's ability to discriminate between the classes as all p-values are below 0.05. The variance explained is lower for the smaller type of actor – 'Capital and Labour' (13 per cent) – and highest for the three largest types: 'Researchers' (56 per cent), 'Firms and Entrepreneurs' (73 per cent) and 'Government' (74 per cent). To examine model fit in more detail, we consider bivariate residuals, which indicate how much of the pairwise associations of actor types the chosen five-class model retains, compared to a model with only one class (Table vii in the appendix)(Schreiber 2017; Vermunt and Magidson 2016). The model has a good fit regarding all pairwise associations of actor types except for the associations of 'Capital and Labour' with 'Firms and Entrepreneurs' and with 'Civil Society', and of the association of 'Civil Society' with 'Government'.

Table 4 uses the five-class model to study the different patterns in which the six types of R&I actors tend to cluster into five distinct constellations. We assigned specific labels for each of these constellations. The first class comprises approximately 41 per cent of all instruments. We label it '**Traditional research constellations**' because those instruments have a close to 100 per cent probability for targeting the type of actors 'Researchers', and probabilities of between less than 1 per cent and 6 per cent of targeting other type of actors. Class 2 comprises 25 per cent of all instruments. We label it '**Traditional firm-led constellations**' because those instruments have a probability of close to 100 per cent of including 'Firms and Entrepreneurs', 27 per cent of including 'Researchers', and below 2 per cent of targeting other type of actors.

Class 3 comprises around 15 per cent of all instruments and is rather heterogeneous. We label it '**Wide constellations**'. Those instruments have 87 per cent probability of including 'Researchers', 79 per cent of including 'Firms and Entrepreneurs', 56 per cent of including 'Intermediaries', 44 per cent of including 'Government' actors, 26 per cent of including 'Capital and Labour', and 29 per cent of including 'Civil society'. This is a widespread range of probabilities, so it is the type of constellation that has a more balanced composition of actor types than the other constellations.

Class 4 comprises around 11 per cent of all instruments. Since it has close to 100 per cent probability of including 'Government' actors, 28 per cent for 'Researchers' and 13 per cent for 'Firms and Entrepreneurs', we labelled it '**Government-led constellations**'. This class also has a 12 per cent probability of including 'Civil society' actors, although bivariate residuals indicate that the model does not capture the pairwise association of 'Civil society' with 'Government' well. Finally, Class 5 comprises around 8 percent of all instruments. We label it '**Civil-society-led constellations**' because instruments belonging to this class have a 75 per cent probability of

including ‘Civil society’ actors, compared to 18 per cent of including ‘Researchers’, and only 7 per cent of including ‘Firms and Entrepreneurs’ and 6 per cent probability of including ‘Intermediaries’. This class also has a 20 per cent probability of including ‘Capital and Labour’ actors.

Hence, we can observe from Table 4 that ‘Civil society’ actors figure prominently in ‘Wide constellations’ (29 per cent) and in ‘Civil-society-led’ constellations (75 per cent). ‘Wide constellations’ are formed by a high diversity of actors. ‘Civil-society-led constellations’ are less heterogeneous, with the highest probabilities for R&I actors apart from civil society being those for ‘Researchers’ (18 per cent) and Capital and Labour’ (20 per cent).

[Insert Table 4 about here: The five constellations of R&I actors according to the mean predicted probabilities per class]

4.2 ‘Wide constellations’ and ‘civil-society-led constellations’ in grand challenge instruments

Having identified and labelled the five typical constellations of R&I actors that all policy instruments tend to target, we examined the relationship of grand challenge-oriented policy instruments and those constellations in which civil society actors figure prominently, namely ‘wide constellations’ and ‘civil-society-led constellations’. To do this, we use the predicted probabilities that instruments belong to these constellations as predictors. As we use the predicted probabilities rather than the latent class assignments of observations, we include the uncertainty of the assignment of observations to different latent classes in the analysis.

The estimates in Table 5 describe the association of grand challenges instruments with 'wide constellations' and with 'civil-society-led constellations' of R&I actors given the control variables for instrument budgets, type of measure and reporting behaviour. The table presents a model including only the control variables, and a model for each of the two selected constellations. Throughout the models, the sign of coefficients does not change and there are only minor changes in the significance of coefficients. Moreover, the Akaike Information Criterion indicates that the models including predictors fit the data better. Therefore, our comments focus on the models including the predictors. They show that both 'wide constellations' (Model 2) and 'civil-society-led constellations' (Model 3) are positively and significantly associated with grand challenges. The significances of the estimates suggest that 'wide constellations' are characteristic for grand challenges instruments with a much higher confidence level (99 per cent) than 'civil-society-led constellations (90 per cent).

Turning to the control variables, in both Models 2 and 3 the functional classifications of measures as 'Direct financial support' and as 'Governance' significantly increase the probability that an instrument is a GC instrument. In both these models, the functional classifications of measures as 'Indirect Financial Support' and as 'Guidance, regulation and other incentives' significantly decrease this probability. Only in Model 2 ('wide constellations' of stakeholders) does the functional classification of measures as 'Collaborative platforms and infrastructure' significantly decrease this probability as well. In both models, instrument budgets and the imputation dummy for the instrument budget are not significant, indicating that neither instrument budgets nor their imputation affect the results.

[Insert Table 5 about here: Logistic Regression Coefficients (with Country Fixed Effects)]

To grasp effect sizes, we consider average partial effects that describe how changes in the predictors affect the probability that an observation is a GC instrument, taking all observations from the dataset into account (Table 6). The probability that an observation will be a GC instrument increases by 8.4 percentage points when it addresses 'wide constellations' of R&I actors. The involvement of 'civil-society-led constellations' of R&I actors increases this probability by 3.1 percentage points. The average partial effects might be skewed. Given that the non-GC subset is much larger than the GC subset, for each observation there is initially a higher likelihood that an observation is not a GC instrument. If the two subsets were of the same size, the average partial effects might appear higher than the values reported here.

[Insert Table 6 about here: Average Partial Effects of Logistic Regression]

Turning to the performance of both regression models, we consider the probabilities they assign to each instrument for being a GC instrument. The model's rates of true positive and false positive predictions depend on the cut-off value that defines the probability threshold above which an instrument is considered a GC instrument. Receiver operating characteristic (ROC) curves for Models 2 and 3 are provided in the appendix (Hanley 2014). The ROC curves summarise the predictive ability of the models by comparing their rates for true positive and false positive predictions for all possible cut-off values. If the size of the area under the ROC curve (AUC) is 0.5, the model's predictions are as good as pure chance; an AUC equal to 1 suggests that the model's predictions are perfect. The AUC of Model 2 is 0.813 and the AUC of Model 3 is 0.811, which indicates that our models are useful for identifying GC instruments correctly, even though

our analysis focuses only on actor constellations as one specific aspect characterising these instruments.

4.3 Robustness checks

Table 7 presents linear probability models using the same variables as the models presented above. The coefficients from these linear models indicate the change in the probability that an instrument will be a GC instruments associated with one-unit changes in the predictors. This makes them better comparable to the average partial effects from the main regression model in the previous section than to its logistic regression coefficients that indicate changes in the log-odds ratio. Providing confirmatory evidence, these models show that, under the assumptions of a linear relationship between the predicted probabilities of latent classes and the classification of GC instruments, GC instruments are significantly more likely to target 'Wide constellations' and 'civil-society-led constellations' of actors. We conclude that the estimates in the logistic regression models in Table 5 represent the lower threshold of the association between GC instruments and R&I actor constellations.

[Insert Table 7 about here: Linear Regression Coefficients (with Country Fixed Effects and Robust Standard Errors]

Table 8 presents logistic regression estimates using the same variables as the models above, but also including our corrections to the classification of GC instruments. The models in this table do not include country fixed effects, since including control variables for these effects led to a problem of perfect separation.[4] The coefficient of 'Wide constellations' of R&I actors in Model 2 remains positive and significant, while the coefficient of 'Civil-society-led constellations' of R&I actors in Model 3 is not significant. Moreover, the control variables still indicate that 'Direct financial support' types of measures are significantly more likely in GC instruments, and that 'Indirect financial support' types of measures are significantly less likely in GC instruments. The other types of measures display no significant associations with GC instruments.

[Insert Table 8 about here: Logistic Regression Coefficients with re-classified grand challenges policy instruments]

In sum, both robustness checks confirm the significant positive association of GC instruments with 'Wide constellations' of R&I actors. They also show a significant positive association of GC instruments with 'Direct financial support' types of measures, and a negative association with 'Indirect financial support' types of measures. The picture is mixed regarding the evidence on the association between GC instruments and civil-society-led constellations of R&I actors and with other types of measures. This aligns with the results from the main models, where GC instruments

[4] As Table I in the appendix shows, our sample contains only one observation from each of South Africa and Slovakia. The fixed effects for these countries were not the cause of the problem of complete separation.

are associated with 'Wide constellations' with a higher level of confidence than with civil-society-led constellations of R&I actors.

5. Discussions of the findings

The extent to which grand challenge policy instruments target civil society actors in new, more diverse, constellations of R&I actors is an empirical question that remains unexplored. With this in mind, this paper has analysed patterns of co-occurrence of different types of R&I actors, identifying five constellations of R&I actors across all policy instruments, and has examined how the constellations in which civil society actors figure prominently ('wide constellation' and 'civil-society-led constellation') relate to policy instruments for grand challenges. Thereby, we have specified how policy instruments target civil society actors and in which constellations; and have put the idea of co-evolving grand challenge policy rationales and policy instruments to an empirical test. We examined the main findings from our analysis, discussing their implications in relation to the literature.

Firstly, we found two different constellations of targeted R&I actors in innovation policy instruments that involve civil society actors to a relevant degree: the 'Wide constellations' and the 'Civil-society-led constellations'. Both constellations describe ways in which policy instruments target civil society actors. This variation has not been discussed previously in the literature and indicates the need to consider theoretically and empirically how civil society actors are actually being explicitly targeted in the design of any type of policy instruments.

Secondly, our findings add nuance to discussions about GC policy instruments and 'new' civil society as R&I actors (Cagnin, Amanatidou, and Keenan 2012; Kuhlmann and Rip 2018; Weber et al. 2016, 201), because we show empirically the relatively limited way in which civil society actors are actually targeted by GC policy instruments. The mode described by 'Wide constellations' is a case in point. In those 'Wide constellations' researchers, firms and entrepreneurs, and intermediaries are the dominant actors, with 87 per cent, 78 per cent and 56 per cent probability, respectively, of appearing in these constellations; whereas civil society actors have a 29 per cent probability (see Table 4). Hence, 'Wide constellations' are heterogeneous constellations, combining traditional R&I actors (researchers, firms, etc.) with civil society actors. However, civil society actors represent an optional party here, included only in a minority of the instruments assigned to this latent class. This resonates well with the literature, which expects that grand-challenge-oriented instruments target more heterogeneous constellations in extensive and inclusive partnerships, which do not downplay the relevance of traditional R&I actors (Kallerud et al. 2013; Mazzucato 2018; Olsen, Sofka, and Grimpe 2016). Nevertheless, the difference in probabilities between 'traditional' and 'new' R&I actors is remarkable. We interpret this empirical finding as an expression of the fact that while constellations are more heterogeneous, civil society actors are still additional parties and are perhaps not entirely 'empowered' in grand challenge instruments as initially suggested (OECD 2010).

For their part, in 'civil-society-led constellations' civil society are the leading R&I actors. Our findings show that these constellations are less heterogeneous. While 75 per cent of the instruments assigned to this class target civil society actors, they hardly target any other actors, with researchers and capital and labour achieving the highest probabilities of being targeted, at 18 per cent and 20 per cent, respectively). Hence, it seems that in 'Civil-society-led constellations', civil society

actors are frequently the only targeted actors. This is an important finding. These civil-society-led constellations can be seen as another way of engaging civil society, which deserves attention in the literature in at least in two ways. Firstly, the literature does not consider the possible existence of such type of civil-society-led constellations. These types of constellations are relevant for different instruments (grand challenges, or not), and deserve closer examination in their own terms. Secondly, regarding grand challenge innovation policy, the literature has only considered the presence of civil society actors in wide constellations, disregarding any other possible forms of involving them. Despite unequivocal evidence for 'wide constellations' figuring more prominently in GC policy instruments, the evidence on two constellations of targeted actors in which civil society plays a larger role indicates that there might be different types of GC instruments. Policymakers concerned with grand challenges could experiment with involving civil society actors in ways not anticipated by the literature. Consequently, the literature could discuss civil-society-led constellations, and theoretically explore the various possible ways in which GC policy instruments could be designed for involving civil society actors.

Our results also add nuance to understanding civil society involvement in innovation policy instruments by showing that both constellations of actors in which civil society actors play a larger role are associated with the direct funding of R&I activities (different sorts of funding programs), rather than other types of indirect funding instruments (like tax incentives, or similar, more typically targeted at firms).

All this brings to the fore a relevant discussion vis-à-vis the literature about innovation policy; namely, the link between rationales and instrument design on one hand, and the processes of learning and policy experimentation on the other. Experimentation in innovation policy-making has been associated with the needs of finding new solutions to grand challenges like social

inclusion (Chaminade et al. 2009), and is therefore a key feature in the full deployment and implementation of the transformative thrust of the challenge-oriented policy rationale approach (Lundin and Schwaag Serger 2018; Schot and Steinmueller 2018). The literature suggests that this process takes time, as it is about configuring interactive learning spaces among theory, practice and political strategies (Kuhlmann, Shapira, and Smits 2010). While our analysis does not include a time-dimension, our findings about the partial consistency between the grand challenge policy rationale and policy instrument design might indicate, indirectly, that this process has been initiated. Variation about how these 'interactive learning spaces' take form might explain the variation in these two modes (the two constellations). While 'Wide constellations' are a clear effort to add civil society actors into an expansion of traditional R&I actors in GC instruments, the more experimental 'Civil-society-led constellations' are currently very marginal and not clearly associated to grand challenge instruments.

These remarks highlight more practical aspects. It is important to keep in mind the relative size of our findings. Even without specific yardsticks, we can see that GC policy instruments represent only a small share the overall bulk of R&I policy instruments (12 per cent of all R&I instruments). Likewise, our findings show that R&I policy instruments assigned to the 'Wide constellations' and 'Civil-society-led constellations' represent only a small share of all instruments (15 per cent and 8 per cent, respectively; see Table 4). Hence, if policymakers want to 'empower' civil society and target more diverse actors in their instruments (GC-oriented or not), they should consider at least two aspects. Firstly, when designing instruments targeting 'wide constellations', they should pay more attention to civil society actors that have remained relatively marginal in those constellations (with only 29 per cent probability of being targeted by those instruments). Secondly, when designing instruments targeting civil-society-led constellations, policy-makers would need bring

more diverse actors into those constellations. This is because our evidence shows that civil-society-led constellations are less heterogeneous.

6. Conclusions and future lines of research

It has been argued that the grand challenge discourse has the 'structural potency' to induce important policy change because it has rapidly expanded in the formulation of R&I policies around the world (Ulnicane, 2016), has become part of transdisciplinary curricula in leading universities, and is increasingly referred to in prestigious scientific journals (Flink and Kaldewey 2018). However, there is also an understanding that this potential might not be inevitably realised, as the consistency of rationales, instruments and practices is a process that cannot be taken for granted, but is rather in a constant development (Kuhlmann, Shapira, and Smits 2010). We take the starting point from the understanding that there are important organisational challenges in addressing grand challenges (Boon and Edler 2018; Grillitsch et al. 2019). For that reason, advancing the new rationale depends largely on the extent to which its core suggestions have been translated in the design of grand-challenge-oriented policy instruments and, most importantly, the core suggestion to target more decidedly new and more diverse R&I actors.

This paper makes three specific contributions to the literature. Firstly, by examining the various actor constellations that all policy instruments target, we have specified the way in which GC instruments relate to them. This detailed specification provides important empirical evidence to the discussions in the literature regarding the nature of policy instruments design. Our findings move beyond general statements about how complex and varied policy instrument design is, and

bring forward a nuanced and realistic picture about the gradual, yet still limited, way in which policy instruments target these new and more diverse R&I actors. The characterisation of these five R&I actor constellations, and the identification of two constellations in which civil society figures most prominently in comparative terms, is an important empirical novelty to understand the role of these new R&I actors throughout all policy instrument design, particularly in relation to grand challenge policy instruments.

Secondly, we found that despite the advancement of the GC policy rationale, there is only partial consistency with the design of its policy instruments. We have identified a positive association between GC instruments with the probability of targeting 'wide constellations' of R&I actors, where civil society forms part (albeit marginally, with only 29 per cent probability). Regarding 'civil-society-led constellations' (where civil society actors are very prominent, with 75 per cent probability of forming part of this constellation), we do not find sufficient statistical evidence about their association with GC instruments. Therefore, our evidence shows that there is only partial consistency between policy rationales and policy instrument design.

Lastly, the third contribution of this paper lies in the identification of constellations of actors that instruments target. This analytical perspective and the method of latent class analysis might be useful for answering other research questions about research and innovation policy instruments.

This study has four limitations that can help guide future research. Firstly, our empirical findings focus on the design of policy instruments, not on their implementation. Therefore, a future line of research could study similar questions and hypotheses focusing on the implementation of these instruments. It would be particularly relevant to study the types of R&I actors in project consortia that have received R&D funding (or have applied to it), and whether there are significant

differences between GC and non-GC policy instruments in that regard. Such analysis would require another dataset, as well as a modified analytical focus.[5]

Secondly, the current study does not tell us how other relevant dimensions of GC instruments' design (such as their directionality, their coordination in policy mixes, etc.) are nested together into coherent policy design (Howlett 2018), or how they are organisationally anchored in their respective administrative structures. These are important unexplored aspects about the design of grand-challenge-oriented R&I policy instruments, which could be analysed with a qualitative research approach.

Thirdly, the STIP dataset is a truly path-breaking dataset available for researchers. It offers unique opportunities for comparing the design of policy instruments using a large-n approach, like this one. While we have made use of this data, it is naturally limited by the theoretically informed questions that guided this research. Hence, future research could formulate other relevant questions about the design of policy instruments, as the STIP dataset offers a wealth of different variables to explore.

Finally, the current study does not tell us about policy mixes. We examined the features of policy instruments from the perspective of their individual design. This is an important perspective, given the current empirical research gap about these questions and the methodological research gap about large-n studies about policy instruments' design. However, the rapidly growing literature about policy mixes points to the relevance of examining the combined effects of different policy instruments. Therefore, a future line of research could address this matter. We need to understand how the new GC policy instruments interact with each other, and with other policy instruments, in

[5] For example, the data is actually available for the European Union framework programs and for many national in Europe, the data is actually available, such as through the data infrastructure RISIS (risis2.eu).

order to bring transformative change to socio-technical systems. This relates to a holistic and problem-oriented approach (Borrás and Edquist 2019) and to the need for more consistent linkages among various policy instruments.

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Tables and Figures

Table 1: Frequency Table of Grand Challenges Instruments and R&I Actor Types

	Researchers	Firms and Entrepreneurs	Civil Society	Government	Intermediaries	Capital and Labour
Grand Challenges Instruments	289	181	133	132	60	42
Other Instruments	2211	1408	381	559	354	266

Note: Several Actor Types per Instrument are possible

Table 2: Examples of Grand Challenges Policy Instruments in the Sample

Country	Instrument Name	Description	Objectives	Types of R&I actors targeted
USA	US Global Development Lab	The US Global Development Lab seeks to increase the application of science, technology, innovation and partnerships to accelerate the Agency's development impact in helping to end extreme poverty and promote inclusive economic growth. (…)	The Lab brings together a diverse set of partners to find new innovations, tools and approaches to solve development challenges more effectively and sustainably. The Lab serves as a central hub for shared learning on science, technology, innovation and partnerships, and its works across USAID and (…)	Researchers; Civil society
Sweden	Challenge-Driven Innovation	The Challenge-Driven Innovation (CDI) programme aims to contribute to a significant increase in sustainable growth by transforming and utilising sector-wide innovation in new processes, products and services that meet specific social needs	The programme funds projects of international eminence and develop sustainable solutions to tackle key societal challenges.	Researchers; Firms and Entrepreneurs; Civil Society
Turkey	Healthcare-Related Industries Structural Transformation Program	National transformation program within the scope of the Tenth Development plan, which is dedicated to establishing a production structure that may produce products with high added value, provide products and services to global (…)	This program aims to transform to a production structure that may produce products with high added value, provide products and services to global markets and fulfil a larger portion of the domestic requirement for human medicinal products and medical devices (…)	Researchers; Firms and Entrepreneurs; Capital and Labour

Table 3: Assessing the fit of a five-class model with multinomial logistic regressions

Indicators	Class1	Class2	Class3	Class4	Class5	Wald	p-value	R^2
Researchers	-	-10.809	-7.884	-10.728	-11.284	176.837	<.001	0.558
Firms and Entrepreneurs	-	10.845	4.090	0.912	0.260	204.754	<.001	0.726
Intermediaries	-	-0.071	4.123	0.849	1.051	300.234	<.001	0.384
Government	-	1.165	8.272	15.355	3.057	13.332	0.010	0.739
Capital and Labour	-	3.836	5.109	1.054	4.764	80.652	<.001	0.128
civil society	-	-1.843	2.159	1.019	4.131	250.709	<.001	0.339

Note: The Columns labelled 'Class1'–'Class5' refer to the five latent classes. In the multinomial logistic regression fits presented here, the latent classes are the outcome, with the first latent class as the baseline category. The indicators for the six different types of R&I actors listed in the indicator column are the predictors.

Table 4: The five constellations of R&I actors according to the mean predicted probabilities per class

Class	**Class1**	**Class2**	**Class3**	**Class4**	**Class5**	**Overall**
Class Size	0.4084	0.25	0.1538	0.1121	0.0756	
Label	**'Traditional research constellations'**	**'Traditional firm-led constellations'**	**'Wide constellations'**	**'Government-led constellations'**	**'Civil-society-led constellations'**	
Researchers	0.9999	0.2651	0.8705	0.2812	0.1832	0.6539
Firms and Entrepreneurs	0.0585	0.9997	0.7876	0.1339	0.0745	0.4156
Intermediaries	0.0201	0.0188	0.5592	0.0458	0.0555	0.1083
Government	0.0002	0.0007	0.443	0.9989	0.0043	0.1807
Capital and Labour	0.0022	0.0916	0.2647	0.0062	0.2032	0.0806
Civil society	0.0452	0.0074	0.2906	0.1158	0.7464	0.1344

Table 5: Logistic Regression Coefficients (with Country Fixed Effects)

	Dependent variable:		
	Grand Challenges	Grand Challenges	Grand Challenges
	(1)	(2)	(3)
'Wide constellations'		1.032*** (0.197)	
'Civil-society-led constellations'			0.399* (0.223)
Budget	-0.024 (0.078)	-0.037 (0.078)	-0.021 (0.078)
Measure: Direct Financial Support	0.273*** (0.100)	0.254** (0.100)	0.302*** (0.101)
Measure: Indirect Financial Support	-0.976* (0.529)	-0.943* (0.529)	-0.945* (0.528)
Measure: Collaborative platforms and infrastructure	-0.207 (0.159)	-0.343** (0.166)	-0.187 (0.159)
Measure: Guidance, Regulation and other Incentives	-0.384* (0.199)	-0.436** (0.202)	-0.360* (0.199)
Measure: Governance	0.178*** (0.065)	0.161** (0.069)	0.173*** (0.066)
Reporting Behaviour	Included	Included	Included
Imputed Budget	-0.017 (0.132)	-0.012 (0.132)	-0.020 (0.132)
Observations	3,823	3,823	3,823
Log Likelihood	-1,103.565	-1,090.200	-1,101.992
Akaike Inf. Crit.	2,327.131	2,302.400	2,325.984
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: Average Partial Effects of Logistic Regression

Model	Predictor	Average Partial Effect	Standard Error
2	Wide constellations	0.084	0.015
3	Civil-society-led constellation	0.031	0.018

Table 7: Linear Regression Coefficients (with Country Fixed Effects and Robust Standard Errors)

	Dependent variable:		
	Grand Challenges	Grand Challenges	Grand Challenges
	(1)	(2)	(3)
'Wide constellations'		0.128*** (0.023)	
'Civil-society-led constellations'			0.105*** (0.030)
Budget	-0.005 (0.007)	-0.006 (0.007)	-0.004 (0.007)
Measure: Direct Financial Support	0.025** (0.011)	0.024** (0.011)	0.029*** (0.011)
Measure: Indirect Financial Support	-0.050*** (0.019)	-0.049*** (0.018)	-0.045** (0.018)
Measure: Collaborative platforms and infrastructure	-0.028** (0.012)	-0.039*** (0.012)	-0.025** (0.012)
Measure: Guidance, Regulation and other Incentives	-0.032* (0.019)	-0.038** (0.018)	-0.030 (0.019)
Measure: Governance	0.020* (0.011)	0.015 (0.009)	0.017* (0.010)
Reporting Behaviour	Included	Included	Included
Imputed Budget	0.0001 (0.011)	0.001 (0.011)	0.0002 (0.011)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8: Logistic Regression Coefficients with re-classified grand challenges policy instruments

	Dependent variable:		
	Grand Challenges	Grand Challenges	Grand Challenges
	(1)	(2)	(3)
'Wide constellations'		0.536** (0.214)	
'Civil-society-led constellations'			0.065 (0.235)
Budget	0.034 (0.089)	0.026 (0.089)	0.035 (0.089)
Measure: Direct Financial Support	0.521*** (0.121)	0.503*** (0.124)	0.524*** (0.122)
Measure: Indirect Financial Support	-1.692* (1.025)	-1.688* (1.025)	-1.688* (1.025)
Measure: Collaborative platforms and infrastructure	0.078 (0.186)	-0.008 (0.196)	0.079 (0.186)
Measure: Guidance, Regulation and other Incentives	-0.299 (0.218)	-0.345 (0.222)	-0.297 (0.218)
Measure: Governance	0.093 (0.145)	0.060 (0.153)	0.089 (0.147)
Reporting Behaviour	Included	Included	Included
Imputed Budget	0.022 (0.136)	0.039 (0.137)	0.023 (0.136)
Observations	3,823	3,823	3,823
Log Likelihood	-803.034	-799.999	-802.996
Akaike Inf. Crit.	1,636.068	1,631.998	1,637.992
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix

Note on the Dataset and Replicability

The dataset was downloaded from an OECD Website (stip.oecd.org) in June 2019 and can be made available upon request to the authors. The preparation of the dataset and regression analyses were done using R 3.6.1. The latent class analysis was done using the software Latent Gold (Version 5.1.0.20093). Regarding replication of the results, the dataset analysed and markdown files with the R code are available upon request to the authors. For the analysis with Latent Gold, model specifications and all output generated by the software are available upon request to the authors.

Tables

Table i: Observations per Country

Country	Initial N	N Instruments only (excluding Strategies)	N observations with information about targeted R&I actors	Ratio: N Instruments only / N observations with information about targeted actors
ARG	87	76	76	1
AUS	225	212	175	0.83
AUT	207	195	157	0.81
BEL	261	244	177	0.73
BGR	39	30	20	0.67
BRA	122	116	116	1
CAN	146	139	135	0.97
CHE	93	88	86	0.98
CHL	63	59	57	0.97
CHN	60	56	43	0.77
COL	92	85	84	0.99
CRI	79	73	73	1
CYP	46	42	40	0.95
CZE	57	56	56	1
DEU	163	157	94	0.6
DNK	65	64	64	1
EGY	19	19	2	0.11
ESP	177	166	125	0.75
EST	62	54	53	0.98
FIN	85	80	78	0.98
FRA	138	137	133	0.97
GBR	160	157	111	0.71
GRC	61	59	57	0.97
HRV	74	69	14	0.2
HUN	152	147	123	0.84
IRL	153	150	65	0.43
ISL	21	21	14	0.67
ISR	85	76	51	0.67
ITA	208	185	40	0.22
JPN	79	78	78	1
KOR	97	91	90	0.99
LTU	96	92	92	1
LUX	74	70	63	0.9
LVA	57	47	45	0.96
MAR	56	50	49	0.98
MEX	41	36	36	1
MLT	78	72	70	0.97

NLD	130	125	104	0.83
NOR	130	114	113	0.99
NZL	51	49	47	0.96
PER	75	69	68	0.99
POL	160	146	62	0.42
PRT	135	126	120	0.95
ROU	37	30	4	0.13
RUS	87	77	76	0.99
SVK	33	32	1	0.03
SVN	139	133	133	1
SWE	58	53	52	0.98
THA	85	72	70	0.97
TUR	126	116	112	0.97
USA	24	18	18	1
ZAF	142	129	1	0.01

Initial Median: 85

Median excluding Strategies: 76

Median observations with stakeholder information: 69

Table ii: Coding Types of Actors

Types of Actors (From Survey)	Sub-types of Actors (From Survey)	Coded Types of Actors (in our analysis)	N
Capital and labour	Labour force in general	Capital and Labour	308
	Private investors		
	Workers with tertiary education and above specifically		
	Entrepreneurs	Firms and Entrepreneurs	1589
Firms by age	Established firms (more than 5 years old)		
	Firms of any age		
	Nascent firms (0 to less than 1 year old)		
	Young firms (1 to 5 years old)		
Firms by size	Firms of any size		
	Large firms		
	Micro-enterprises		
	Multinational enterprises		
	SMEs		
Governmental entities	National government	Government	691
	Subnational government		
Intermediaries	Academic societies or academies	Intermediaries	414
	Incubators, science parks or technoparks		
	Industry associations		
	Technology transfer offices		
Research and education institutions	Higher education institutes	Researchers and Education	2.500
	Private research and development lab		
	Public research institutes		
Researchers, students and teachers	Established researchers		
	PhD students		
	Post-doctoral researchers		
	Secondary education students		
	Teachers		
	Undergraduate and master students		
Social groups especially emphasised	Civil society	Civil Society	514
	Disadvantaged and excluded groups		
	Women		

Table iii: Instrument Budgets

Budget Level	Variable Value	No of Observations
Not applicable	0	626
Less than 1M	0.005	423
1M-5M	0.01	420
5M-20M	0.05	283
20M-50M	0.2	202
50M-100M	0.5	112
100M-500M	1	166
More than 500M	5	94
"Don't know" / Field left blank	NA	1497

Note: for NA values, the mean (= 0.347) was imputed.

Table iv: Functional classification of measures (In the final dataset used for the analysis)

Measures	**No. of Instruments**
Direct Financial Support	1.512
Indirect Financial Support	126
Governance	1.121
Guidance Regulation and Incentives	376
Collaboration	532
NA	79
One measure per instrument	*3.344*
Two measures per instrument	*298*
Three or more measures per instrument	*102*

Table v: Sections of the 2017 STIP Survey

Survey Section	No. of Instruments
Governance	624
Public Research System	1116
Innovation in firms and innovative entrepreneurship	983
Public-private knowledge transfers and linkages	646
Human resources for research and innovation	640
Research and innovation for society	648
Digitalisation	234
ERA-related initiatives	286

Note: An instrument may be assigned to more than one survey section

Table vi: Model Selection for Latent Class Analysis

		LL	BIC(LL)	Npar	L^2	df	p-value
Model1	1-Cluster	-10758.6	21566.73	6	5584.264	3207	<0.001
Model2	2-Cluster	-10127.5	20774.58	63	4321.931	3150	<0.001
Model3	3-Cluster	-9734.88	20459.62	120	3536.795	3093	<0.001
Model4	4-Cluster	-9392.72	20245.48	177	2852.467	3036	0.99
Model5	5-Cluster	-9155.44	20241.09	234	2377.896	2979	1
Model6	6-Cluster	-8986.77	20373.95	291	2040.572	2922	1

Table vii: Bivariate Residuals of 5-Class Latent Class Cluster Model

Indicators	Researchers	Firms and Entrepreneurs	Intermediaries	Government	Capital and Labour	Civil Society
Researchers	.					
Firms and Entrepreneurs	0.7603	.				
Intermediaries	0.064	0.066	.			
Government	0.1878	0.4423	0.3684	.		
Capital and Labour	1.0701	5.9373	0.505	0.5128	.	
Civil Society	1.6319	0.2113	3.5875	4.8998	6.7769	.

Note: Values below 3.84 in the bivariate residuals correspond to a significant χ^2 with one degree of freedom (Schreiber 2017). All pairwise associations of actors in the five-class model are significant except for the associations of 'Capital and Labour' with 'Firms and Entrepreneurs' (5.94) and with 'Civil Society' (6.78), and of the association of 'Civil Society' with 'Government' (4.90). Thus, the clusters that the five-class model generates are not helpful for explaining these three associations. According to Schreiber, bivariate residuals values not larger than 2 are desirable from a modelling perspective (Schreiber 2017). The value for the association between 'Civil Society' and 'Intermediaries' is 3.58. Thus, the five-class model might not predict this association well, but the value is still significant. All bivariate residuals except for the ones mentioned above are below 2, so the model has a good fit regarding most pairwise associations of actor types.

Figures

Figure i: ROC Curve for Regression Model 1 (only control variables)

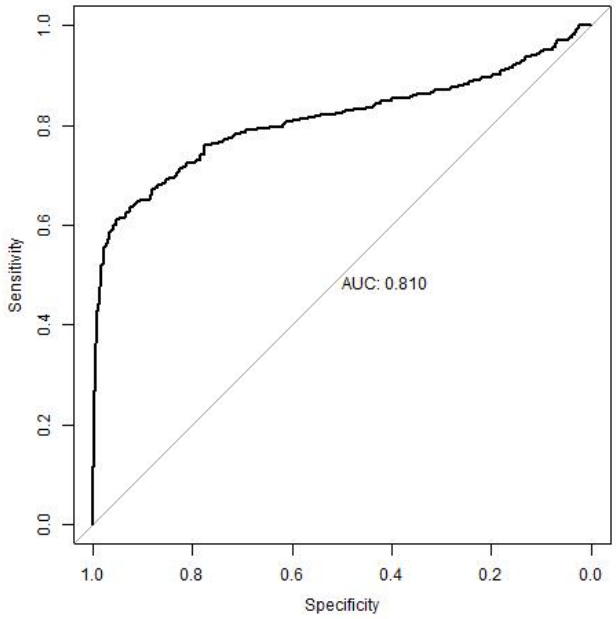

Figure ii: ROC Curve for Regression Model 2 (Predictor: 'Wide constellations')

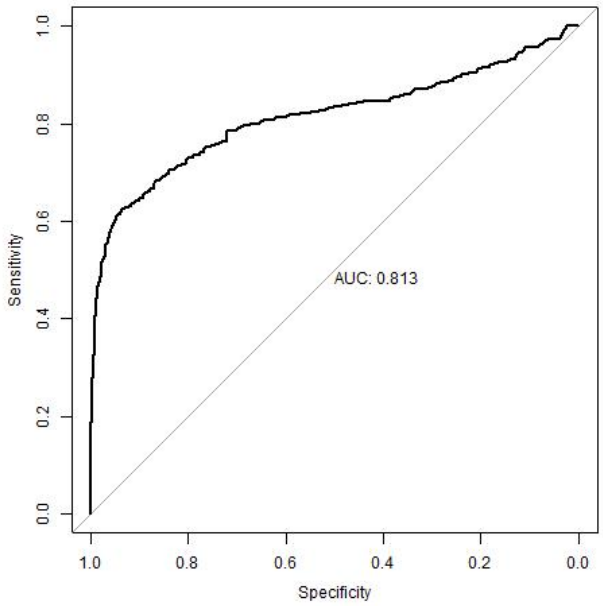

Figure iii: ROC Curve for Regression Model 3 (Predictor: 'Civil-society-led constellations')