Innovation Policy Instrument Mix: Unravelling the Knowns and Unknowns

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Abstract
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Innovation Policy Instrument Mix: Unravelling the Knowns and Unknowns

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Abstract

Governments deploy a mix of different innovation policy instruments to stimulate firm-level innovation additionality. Firms often receive multiple instruments simultaneously, and additionality can depend on interactions within this instrument mix. Depending on how consistent different instruments are with one another in terms of their underlying rationales, goals, and implementation modes, and how stable this consistency is over time, interaction effects can be complementary, substitutive or neutral. Consistency is thus an important means of improving the effectiveness and efficiency of the instrument mix at achieving policy objectives. This has important implications for policymaking. To explore these implications, we build a conceptual framework for the ex-ante and ex-post impact evaluation of innovation policy instrument mixes. Applying this framework, we construct a unique panel dataset capturing the core innovation policy instruments available to firms in Ireland, and employ a novel microeconometric technique to estimate the degree of temporal consistency within the instrument mix. Our results highlight the importance of temporal dynamics when evaluating innovation policy instrument mix consistency.

Keywords: Firm-level innovation, policy mix, instrument mix, temporal consistency, dynamic complementarities

JEL Codes: O38, O33, D04
1. Introduction

Firms often receive multiple innovation policy instruments simultaneously, meaning that the observed impact of innovation policy can depend crucially on interactions within this mix of innovation policy instruments (Martin, 2016; Nauwelaers et al., 2009). The nature of these interaction effects can be complementary, substitutive, or neutral (Rogge and Reichardt, 2016; Lanahan and Feldman, 2015; Howlett and del Rio, 2015). This will depend on the degree of consistency between different innovation policy instruments in terms of their underlying rationales, goals, and implementation modes (Flanagan et al., 2011). Instrument mix consistency can be defined as the alignment of individual innovation policy instruments in the mix with each other in terms of these underlying characteristics (Rogge and Reichardt, 2016). Consistency is important to policymakers as it represents a means of enhancing the effectiveness and efficiency of an instrument mix at achieving policy objectives (OECD, 2015b; OECD, 2010; Howlett and Rayner, 2007). However, the nature of instrument interactions and their eventual impact on policy outcomes cannot be known ex-ante, and therefore represents a challenge for ex-post firm-level evaluation.

Beyond theory, the practice of evaluating instrument interactions is seriously hampered by the fact that innovation policy instrument mixes are emergent in nature and evolve over time, with instruments interacting both within and across multiple levels of government, different policy domains, and geographical spaces (Laranja et al., 2008; Flanagan et al., 2011; Magro and Wilson, 2013). When considering this complex policy system, it is instructive to recall a famous address to the London School of Economics’ Financial Markets Research Group delivered in the midst of the global financial crisis by then Vice-Chairman of the Governing Board of the Swiss National Bank, Philipp Hildebrand. Hildebrand quipped that increasingly complex financial regulation had created a new kind of risk: “Risks about risk assessments”, which he conjectured may be “unknowable unknowns”
(Hildebrand, 2008: 7). That is, things that we know little about, and can never hope to understand. Thinking about innovation policy complexity in this light provokes an important question. Does the level of complexity inherent in innovation policy mix mean that instrument interactions are, to echo Hildebrand, unknowable? To answer this question we must address what is known about policy instrument mix and what remains unknown and in need of unravelling.

At the cornerstone of policy mix theory is a focus on the interactions, interdependencies and trade-offs between different innovation policies as they affect the extent to which policy outcomes are achieved (Cunningham et al., 2016; Flanagan and Uyarra, 2016; Flanagan et al., 2011; Uyarra and Flanagan, 2013). A weight of recent literature has highlighted the crucial underlying role that consistency among policy instrument characteristics plays in moderating policy instrument interactions (Kern et al., 2017; Kivimaa and Kern, 2016; Uyarra et al., 2016; Rogge and Reichardt, 2016; Reichardt and Rogge, 2016). However, to date quantitative empirical evaluations have tended to focus solely on the relative effectiveness of different combinations of policy instruments, leaving consistency unexplored (e.g., Marino et al., 2016; Guerzoni and Raiteri, 2015; Czarnitzki and Lopes-Bento, 2014).

This important cleavage between policy mix theory and evaluation practice exists for three primary reasons. First, though many different aspects of the innovation policy instrument mix are very well conceptualised in the theoretical literature, no unified conceptual framework exists to provide ‘guiding principals’ for impact evaluation. Second, the propensity score matching models typically used to facilitate firm-level impact evaluations can only infer complementary, substitutive, or neutral interaction effects between innovation policy instruments based on the sign and significance of different instrument mix regression coefficients. A direct statistical test for the degree of consistency in the instrument
mix is missing from the literature. Third, no firm-level micro-dataset has heretofore been collected or constructed that captures multiple policy instruments as well as detailed information on their underlying characteristics.

To address these issues, we make three key contributions. First, we establish a conceptual framework for the ex-ante and ex-post impact evaluation of innovation policy instrument mixes. Drawing on policy mix theory, we place consistency between interacting policy instruments at the heart of this framework. We ensure that the framework is truly dynamic by conceptualising feedback loops between ex-post instrument interactions and policy outcomes with ex-ante policy instrument design. In addition, we broaden in a holistic manner the scope for policy impact to include social and political outcomes as well as the economic outcomes typically considered in the literature, and highlight that these outcomes may be unintended as well as intended over the short, medium and long term. Second, we apply a novel microeconometric procedure that is uniquely suited to the direct evaluation of consistency in the innovation policy instrument mix, meaning that we do not need to rely on inference. Following Love et al. (2014), we perform a formal statistical test for static and dynamic complementarity, substitution and neutrality in instrument interactions. Finally, our third contribution is the construction of a wholly novel panel dataset capturing all of the core innovation policy instruments available to firms in Ireland over the period 2006-2014. To date, no other empirical setting we are aware of has provided an impact evaluation of changes to the innovation policy instrument mix over such a long time period, with such precise information on the underlying characteristics of each policy instrument.

By working at the confluence of these theoretical, methodological, and empirical contributions, we are able to ask an important and timely question: How does the temporal consistency of an innovation policy instrument mix affect its observed impact on firm-level
innovation? Our findings strongly suggest that the temporal dynamics play a crucial but underappreciated role in driving the performance of the innovation policy instrument mix.

The rest of the paper is organised as follows. In Section 2 we discuss the conceptual underpinning of the policy mix for innovation, and use this discussion to develop a conceptual framework for the impact evaluation of innovation policy instrument mix. Drawing on this theoretical discussion, we formulate hypotheses to empirically test. Section 3 sets out the paper’s empirical setting and describes the microeconometric method used. Section 4 presents results. Section 5 considers the policy implications of these results. Section 6 concludes and highlights some important avenues for further research.

2. Evaluating the innovation policy instrument mix

Innovation policy studies literature increasingly recognises that policy complexity severely limits the explanatory power of traditional methods of policy evaluation (Laranja et al., 2008; Magro and Wilson, 2013; OECD, 2015b). The concept of policy mix has emerged as a means of understanding and mitigating the limitations brought about by policy complexity (Flanagan et al., 2011). A cornerstone aspect of policy mix theory is to focus on the interactions and trade-offs between different innovation policies as they affect the extent to which policy outcomes are achieved (Flanagan et al., 2011). Rogge and Reichardt (2016: 11) highlight that a “key challenge of any policy mix study concerns the task of setting its boundaries, thereby determining the complexity of the studied policy mix as well as its observable impact”. This necessitates a discussion of the scope of the policy mix to be studied, and the unit of analysis to be used to analyse its impact (Rogge and Reichardt, 2016).

2.1. The policy mix for innovation

At the macro-level of the innovation policy system, broad policy agendas emanate
from a dynamic multi-actor, multi-level and multi-scalar policy process (Matti et al., 2016; Uyarra et al., 2016; Aranguren et al., 2016). The policy process will first give rise to policy strategy at the meso-level (Quitzow, 2015). Policy strategy involves the establishment of policy objectives and the principal plans for achieving them (Rogge and Reichardt, 2016). Taken together, the objectives and plans of policy strategy provide a roadmap for the intended development of the innovation system and thus give important long-term guidance for actors within the system (Rogge et al., 2011; Schmidt et al., 2012). This strategic aspect of the policy mix will be operationalised by a variety of different policy instruments at the micro-level (Veugelers, 2015). Policy instruments are differentiated by type and design feature (Rogge and Reichardt, 2016). In addition, individual policy instruments will be characterised by distinct rationales, goals, and implementation modes (Flanagan et al., 2011).

However, real-world policy mixes also encompass the messy realities of public policy, which does not “pursue a single goal or even a coherent and hierarchical set of goals—rather it pursues a broad and ever-changing range of more or less explicit and implicit, final and intermediate goals and objectives, many of which will conflict in the sense that one can only be obtained at the expense or another” (Flanagan et al., 2011: 708). Therefore, depending on the context, the underlying characteristics of innovation policy may be in need of unravelling to facilitate evaluation.

The point at which policy leads most directly to outcomes is at the micro-level. Therefore, the micro-level is the appropriate level of analysis for quantitative empirical evaluations of the innovation policy instrument mix. There are a wide variety of innovation policy instruments available to firms in numerous different countries (Veugelers, 2015), with a range of different context-dependent underlying characteristics (Kern et al., 2017). Much literature has also described the process of ex-ante policy design to achieve an effective and efficient policy mix (Howlett and del Rio, 2015; Kern and Howlett, 2009; Howlett and
Rayner, 2007). Quantitative empirical evaluations have shed light on the methodological issues involved in the practice of assessing the impact of different combinations of policy instruments at the firm-level (Marino et al., 2016; Guerzoni and Raiteri, 2015).

Therefore, a large body of literature exists that explores different aspects of the innovation policy instrument mix. However, there is a need to synthesise the findings from these literatures into a unified conceptual framework for the ex-ante and ex-post impact evaluation of the policy instrument mix.

2.2. Firm-level innovation

At the micro-level, the appropriate unit of analysis is firm-level innovation (Martin, 2016; Nauwelaers et al., 2009). The wide variety of policy instruments available to firms is indicative of multifaceted policy action governments take to alleviate market and systemic failures that are a major barrier to innovation (Bleda and Del Río, 2013; Dodgson et al., 2011; Lenihan, 2011). Policy action is characterised by information asymmetries between the policymaker and the innovation system which often leads to government failure and the misallocation of scarce public resources (Haapanen et al., 2014). From the seminal work of Schumpeter (1934) to the modern day (e.g., Fagerberg et al., 2012), firm-level innovation has been recognised as an important engine of economic growth (Romer, 1990). Moreover, it has been acknowledged that the dynamic effects of firm-level innovation (Nightingale and Coad, 2013) foster national competitiveness (Griliches, 1986; Carayannis and Grigoroudis, 2014).

In the context of evaluating the impact of innovation policy on firm-level innovation, Metcalfe (1995: 31) notes that an important means of creating effective and efficient innovation policy is “how well policy makers learn and adapt in light of experience”. Evaluations of firm-level innovation are therefore of vital importance in informing this process of policy learning and facilitating informed policy experimentation by providing a
reliable evidence base (Chaminade et al., 2012). However, Lenihan and Hart (2004) draw attention to the fact that policy evaluation is by no means an exact science.

In the field of enterprise policy evaluation, Lenihan (2011) has called for more holistic evaluation practice which incorporates social and political impacts as well as economic impacts, and how these unfold over the short, medium, and long-term. In a similar vein, in the innovation policy studies literature, Edquist and Zabala-Iturriagagoitia (2012) have echoed this call, while also drawing attention to the fact that innovation policy can have unintended as well as intended consequences. Unintended consequences can be both positive and negative. For example, firm-level evaluations have demonstrated that different forms of product, process and organisational innovation are complements (Doran, 2012). Therefore, an innovation policy instrument designed to foster new product development in firms may also lead to process and/or organisational innovation as a positive unintended consequence. In terms of the unintended consequences of a policy instrument mix, it is a-priori unclear how these will unfold or interact. However, it is important to conceptualise unintended consequences into ex-ante policy design and be aware of them in ex-post policy evaluation.

In this regard, Rogge and Reichardt (2016: 1630) note that “widening the system boundaries may allow for a more holistic perspective of the problem – both in terms of policies and politics – and may thereby enable a better achievement of policy objectives”. Give that innovation policy can have social and political as well as economic impacts (Lenihan, 2011), Flanagan et al. (2011: 708) provide an important insight: “Policy also plays rhetorical and performative functions. Policy-making activity can be an end in itself—being seen to have a policy about a problem can play an important political role regardless of whether that policy leads to effective action to solve the problem”. In this case, an economic impact evaluation may find that a policy had been ‘ineffective’ at creating innovation additionality. However, drawing this conclusion would actively hamper policy learning.
Rather, ex-post policy evaluation would benefit from a political science perspective in this instance. Conceptualising impact evaluation in this holistic way addresses Flanagan et al.’s (2011: 705) point that unravelling the underlying characteristics of innovation policy should be “the starting point for any evaluation of the effectiveness of policy action—rather than theoretical rationales retrospectively mapped onto policy actions”.

From this, it is clear that a more holistic approach to policy evaluation, though desirable, brings up a number of methodological problems in terms of conceptualising the impact of policy instrument mix in an ever expanding system of potential interactions and trade-offs. Evaluations of the innovation policy instrument mix can both embrace this more holistic perspective as well as remain within feasible boundaries by specifying the scope of the evaluation along the dimensions of the policy mix.

2.3. The boundaries for evaluation: policy mix dimensions

Policy instrument interactions occur both within and across four different policy mix dimensions: policy space, governance space, geographical space, and time (Flanagan et al., 2011). Specifying the boundaries for impact evaluation around these dimensions makes evaluations both feasible in practice and congruent with theory (Rogge and Reichardt, 2016). In addition, they also allow the evaluator to know and state exactly what aspects of the policy instrument mix are being investigated, what aspects are being held constant, and what aspects are not being captured.

Within the governance dimension, firms can receive policy instruments from national and regional levels of government simultaneously, or from different state agencies operating at the same level of governance. Here, instrument interaction effects will be respectively defined by the degree of vertical and horizontal consistency among instruments. Similarly, policy instruments from many different policy domains can have impacts on firm-level
innovation. In the domain of innovation policy, there are numerous instruments that are available to firms. However, there are also many instruments emanating from other policy domains that have an implicit or explicit focus on festering innovation. Firms may receive enterprise or education policy instruments as well as innovation policy instruments at the same time which, by accident or design, will interact and these interactions will produce unique effects.

Flanagan and Uyarra (2016) have highlighted that time is an under researched policy mix dimension. Even individual policy instruments can have internal inconsistencies where their rationales, goals, and implementation modes are not aligned, or where they drift out of alignment over time (Howlett and Rayner, 2007). In this sense, it is possible to conceptualise a policy instrument mix of a single instrument received by the same actor over time – the same instrument interacts with itself in subsequent periods (Flanagan et al., 2011). As both the instrument and the firm change through time, so will the effects on firm-level innovation (Rogge et al., 2011). More typically, instrument mix means a mix of different innovation policy instruments, differentiated specifically by type and design feature. Firms can receive multiple different instruments simultaneously, and this mix can change over time (Cunningham et al., 2016). As with the same policy instrument interaction with itself over time, the mix of policy instruments firms receive in one period will interact with the mix of policy instruments the same firms receive in the next period (Flanagan et al., 2011; Rogge and Reichardt, 2016). This is where knowing the level of temporal consistency among innovation policy instruments becomes of vital importance (Reichardt and Rogge, 2016).

2.4. Consistency among innovation policy instruments

Depending on the degree of consistency between different policy instruments in terms
of their underlying rationales, goals, and implementation modes, interaction effects can be complementary, substitutive, or neutral (Rogge and Reichardt, 2016; Lanahan and Feldman, 2015). Neutral effects will be the result of ‘weak’ consistency, which involves the simple absence of conflicts between policy instruments, while ‘strong’ consistency entails complementarity and requires policy instruments to mutually reinforce one another’s impact (Howlett and del Rio, 2015). When different policy instruments actively hamper each other they are inconsistent (Kern and Howlett, 2009) and may substitute. Consistency in the instrument mix is therefore an important means of improving the performance of innovation policy, and a large part of the policymaker’s role is to design and coordinate the policy instrument mix to achieve this (OECD, 2010; Borrás and Edquist, 2013).

In this complex policy system, it seems unlikely that consistency will be achieved by simply layering one policy instrument on top of another over time (Kern and Howlett, 2009; Howlett and Rayner, 2007). Therefore, evaluations of the innovation policy instrument mix must take account of the important temporal dimension of instrument mix consistency (Flanagan and Uyarra, 2016; Kern et al., 2017). This requires analysis of the dynamics of how policy instrument mixes are arrived at, as well as the eventual impact these dynamics have on firms’ innovation outcomes (Uyarra, 2010). Given this level of complexity, Rogge and Reichardt (2016: 1627) note that “it may be impossible to actually achieve complete … consistency”. This statement supports Flanagan et al.’s (2011: 702) contention that “it is unrealistic to hope to identify unambiguously ‘good’ mixes”. The multi-actor, multi-level, multi-scalar and dynamic nature of the system means that policy instrument mix evaluations are always going to relative in nature, and never absolute. In addition, as instruments evolve over time the nature and impact of instrument interactions will effect policy design, and thus change the nature of the system through recursive feedback loops. Establishing the
boundaries for impact evaluation provides a conceptual framework within all of this complexity can be managed to effectively foster policy learning.

### 2.5. Impact evaluation: Conceptual framework

Ex-ante, policy makers can create innovation policy instruments on the basis of type and design feature (Rogge and Reichardt, 2016). Additionally, how these instruments will unfold within and across policy mix dimensions can be specified and how they are likely to interact based on their underlying rationales, goals, and implementation modes. However, neither the nature nor the effect of instrument interactions can be known until the policy instrument mix is deployed at firm-level. Flanagan et al. (2011: 708) note that “[t]he impact of a policy depends on when it was implemented and on the path previously followed … [p]ublic policies, just like innovations, display irreversibility and path-dependency: they are adopted not on a tabula rasa but in a context of pre-existing policy mixes”. Policy outcomes achieved with a given policy instrument mix will affect the evolution of the policy instrument mix through time (Hoppmann et al., 2014). Therefore, each ex-ante and ex-post phase of policy instrument mix evaluation is not discrete, but rather will be characterised by feedback loops where ex-post instrument interactions and policy outcomes will inform ex-ante policy instrument design. In this sense, the co-evolution of the policy instrument mix and firms’ innovation outcomes can only be revealed through dynamic analysis (Reichardt et al., 2016).

The conceptual framework for this evaluation of consistency between innovation policy instruments and how this impacts firm-level innovation is summarised in Figure 1.

### 2.6. Operationalising the conceptual framework

Applying this framework in practice brings up an important point highlighted by Rogge and Reichardt (2016: 1631): “This leads us to the need for operationalizing policy mix
Figure 1. A conceptual framework for the ex-ante and ex-post impact evaluation of innovation policy instrument mix

characteristics … which may pose one of the greatest analytical challenge as official databases or documents typically do not capture such characteristics”. To overcome this challenge we can utilise the conceptual framework presented in Figure 1 to demonstrate how an effective instrument mix evaluation can be formulated.

Firstly, evaluators must identify what the key research question is in a given context. Following this, it is necessary to identify the core innovation policy instruments available to firms in the system under examination. These instruments could apply to all firms, or could be specific to a certain sector, industry, or type of actor (i.e. SMEs, etc.). The next important step is to identify is what policy mix dimension an evaluation is examining, what dimensions
are being held constant to facilitate the evaluation, and whether interactions across policy mix dimensions are the important feature.

Once this process is complete, it is necessary to either collect or construct a dataset that captures sufficient information on the underlying rationales, goals, and implementation modes of the relevant instruments to operationalise the evaluation. In addition to this, if the key research question involves temporal dynamic, then a panel dataset will be required as cross-sectional data may obscure the key feature driving observed impact.

In Section 3 we apply this operationalisation of our conceptual framework to the empirical context of Ireland. Temporal dynamics are particularly important in this context. Based on policy mix theory the contextual features on the innovation policy system in Ireland (developed in Section 3), we formulate two hypotheses:

**Hypothesis 1:** When firms receive a combination of two different innovation policy instruments simultaneously, there will be a complementary relationship between them in their impact on firm-level innovation.

**Hypothesis 2:** When firms receive an innovation policy instrument in one year, and then switch to receiving a combination of the initial innovation policy instrument and a new innovation policy instrument in the next year, there will be a complementary relationship between them in their impact on firm-level innovation.

Drawing on the conceptual framework developed in Figure 1, we have specified the effective boundaries for our empirical evaluation. Formulating Hypotheses 1 and 2 facilitates an examination of the important but under-researched time dimension of the policy mix. However, we must make explicit that we are holding policy domain, geographical space and level of governance constant and thus not exploring potential interactions across these
dimensions. This represents an effective application of our conceptual framework, which can serve as a set of ‘guiding principals’ for future evaluations.

3. Data and methods

Having established the effective boundary conditions for empirical analysis, we are able to comprehensively test Hypotheses 1 and 2. In doing so, we unravel some of the unknown aspects of temporal consistency in the innovation policy instrument mix, and, importantly, what affect this has on firm-level innovation. In order to conduct this test in a dynamic context, we construct a unique panel dataset based on merging a large annual survey with three administrative data sources drawn from Ireland.

3.1. Empirical setting

As a small open economy on the periphery of Europe, there has been a sustained policy focus on innovation in Ireland in an effort to achieve and maintain competitive advantage (DJEI, 2015b). As such, government innovation policy intervention has been very active over a long time period. The European Commission (2016: 6) classes Ireland as a “strong innovator”, ranked as the sixth most innovative country in the EU. The 2016 Global Innovation Index ranks Ireland as the seventh most innovative country worldwide (Cornell University et al., 2016). However, gross expenditure on Research and Development (R&D) in Ireland currently accounts for 1.51% of Gross Domestic Product, which lags behind the EU average of 2.04%. An important objective of innovation policy in Ireland is to increase this expenditure to 2% by 2020, which, in combination with other policy initiatives, is planned to transform Ireland into “[g]lobal innovation leader” (DJEI, 2015b: 6). Alongside these features of the innovation policy system, Ireland entered a deep and prolonged economic recession after the 2007 global financial crisis. Among other negative consequences, this

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1 Latest figures available are for 2014, see Eurostat: http://ec.europa.eu/eurostat/statisticsexplained/index.php/R_26_D_expenditure
placed significant pressure on public funding for innovation (DJEI, 2015a) and led to a significant increase in the enterprise mortality rate.²

Ireland’s active innovation policy coupled with the recent macroeconomic turbulence make it a particularly interesting test bed in which to evaluate how the temporal consistency of the innovation policy instrument mix affects its impact on firm-level innovation. However, it must be noted that the implications of our analysis are not specific to Ireland. Rather, we view Ireland as the laboratory in which we test our hypotheses. The findings derived from this analysis unravel the unknown elements of how temporal dynamics within the innovation policy instrument mix drive the performance of overall innovation policy, and as such have broad and generalisable implications.

In order to test our hypotheses in this empirical setting, we must first specify the main innovation policy actors operating in the innovation system under examination.

3.1.1. Enterprise Ireland

Enterprise Ireland (EI) is the state agency responsible for supporting the development of indigenous firms in Ireland, with a particular focus on scaling up business through innovation to compete in the export market. EI was officially launched 1998, but had existed in many different formats since the early 1950s. Indigenous firms in Ireland are predominantly small in size³, meaning that EI’s client firms are typically SMEs⁴. Given that SMEs make up 99.7% of active enterprises in Ireland⁵, it is clear that EI plays an important role in the Irish economy. EI competitively award a wide range of different innovation

⁴ In the Irish context, SMEs are defined as having less than 250 employees. See CSO: http://cso.ie/en/releasesandpublications/ep/p-bii/businessinirelandabridged2012/smallandmediumenterprises/
policy instruments to firms.\(^6\)

### 3.1.2. IDA Ireland

The Industrial Development Authority (IDA) was founded in 1949 with the mission of attracting foreign direct investment into Ireland. It is known as IDA Ireland in the present day. IDA’s client base is mainly large, multinational corporations. In 2015, IDA client companies operating in Ireland employed 187,056 people, 12,600 of which worked in R&D, and had total in-house expenditure on R&D of €1.5bn.\(^7\) Though IDA’s remit expands beyond funding innovation, it is the primary grant awarding agency for innovation in foreign-owned firms operating in Ireland.

### 3.1.3. Science Foundation Ireland

Science policy is a relatively new feature in Ireland’s innovation system. Science Foundation Ireland (SFI) was established in 2003, and is the main funding agency for applied and oriented basic research. At the firm-level, this is implemented through a series of public-private Research Joint Ventures (RJVs). These SFI schemes have been credited with attracting significant R&D investment from foreign-owned multinational corporations into Ireland by building scale and excellence in specific research disciplines (DJEI, 2015a).

### 3.1.4. R&D tax credit

While EI, IDA, and SFI are the three state agencies responsible for the public funding of innovation in firms, a number of reports by the national government (DoF, 2016; DJEI, 2015b) and the OECD (OECD, 2015a; OECD, 2014) have highlighted that innovation policy in Ireland is heavily skewed towards the use of R&D tax credits. The indirect public funding offered by R&D tax credits accounts for approximately 66% of the total public funding for innovation implemented in Ireland (DoF, 2016, p. 17). Therefore, the R&D tax credit is by

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\(^6\) For the full range of EI supports, see: https://www.enterprise-ireland.com/en/funding-supports/

\(^7\) See IDA: http://www.idaireland.com/docs/annual-reports/2015/annual_report_2015.pdf
far the most prominent innovation policy instrument in Ireland in terms of its usage by firms. Though the R&D tax credit is available to all firms in Ireland, it is typically claimed by older, larger, foreign-owned firms (DoF, 2016).

3.2. Construction of the dataset

To capture these four key features of Ireland’s innovation policy system, our empirical analysis is based on firm-level micro-data drawn from a variety of sources. First, the Annual Business Survey of Economic Impact (ABSEI) is a large, annual survey collected by the Department of Jobs, Enterprise and Innovation (DJEI) which captures whether firms received an R&D tax credit in each year, as well as information on R&D expenditure, firm-size, sector, and other important information. Second, we access administrative data holdings from EI, IDA, and SFI. All data sources capture firm-level information on an annual basis. Unlike ABSEI, the administrative data from EI, IDA, and SFI are not surveys, but rather populations of all firms that participated in programmes funded by these agencies.

ABSEI provides a binary indicator of whether firms received an R&D tax credit from the national government in each year. The administrative data from EI and IDA provide information on what years firms received payment of an innovation subsidy. We use this payments data to construct binary variables taking unit value for every year a firm received a subsidy, and zero otherwise. The administrative data from SFI is of a somewhat different structure. Here, firms enter into multi-year RJVs. Therefore, we use this information to construct a binary variable taking unit value for every year the firm participated in the SFI programme, and zero otherwise.

Another important feature of the innovation policy system in Ireland is that while all firms can receive an R&D tax credit and an EI or IDA subsidy or participate in a SFI RJV at the same time, this is not the case with each of the three state agencies. EI supports
indigenous firms while IDA supports foreign-owned firms, so by definition no firm will ever receive funding from both of these agencies. In addition, though in theory firms could participate in SFI programmes and receiving funding from EI or IDA simultaneously, on examination of the data the level of overlap is close to zero. Therefore, in our evaluation of the degree of consistency in the instrument mix, we analyse three pair-wise combinations, R&D tax credits with either: 1) EI subsidies, 2) IDA subsidies, or 3) SFI RJVs.

Administrative data from EI covers the period 2006-2014, while data from IDA and SFI covers the period 2007-2014. As described above, the nature of the data dictates that firms do not receive innovation policy instruments from EI, IDA, or SFI simultaneously. Therefore, we merge each of the three administrative datasets from each state agency with ABSEI separately to make three final datasets to facilitate our evaluation.

The resulting three panel datasets are unbalanced due to entry and exit of firms over the time period. However, we have at least two repeat observations on all firms in the sample, and approximately 50 percent of the firms are observed in all years. In addition, the response rate among surveyed firms in ABSEI is approximately 55-60 percent in each year, meaning that the level of overlap between ABSEI and each of the administrative datasets is very high.

To facilitate the empirical analysis, we must define four discrete innovation policy instrument mix ‘categories’ that account for the interaction effects between each different innovation policy instrument:

1. No EI/IDA/SFI intervention and no R&D tax credit (NEITHER)
2. No EI/IDA/SFI intervention and receives R&D tax credit (R&DTC)
3. Receives EI/IDA/SFI intervention and no R&D tax credit (AGENCY)
4. Receives EI/IDA/SFI intervention and R&D tax credit (BOTH)
Though each pair-wise combination will contain only two different innovation policy instruments, this will result in four innovation policy instrument mix variables representing each of the four categories. Therefore, even though NEITHER contains no innovation policy instrument, and AGENCY and R&DTC contain only innovation one policy instrument each, they are both referred to as instrument mix categories. In addition, these four instrument mix categories are mutually exclusive cases (e.g., an observation in category 4 is not also recorded in category 2 simply because it has received an R&D tax credit, it must receive both EI/IDA/SFI intervention and R&D tax credit together simultaneously to be recorded in category 4).

While these four categories can be used to evaluate the instrument mix consistency at a point in time, we must amend them if we are to capture temporal consistency. As policy mix theory shows, the innovation policy instrument(s) firms have been exposed to in the past will play a key role in determining how a current instrument mix influences firm-level innovation (Flanagan et al., 2011). Therefore, to fully address the dynamics of temporal consistency in the innovation policy instrument mix we use these initial four instrument mix category variables to construct sixteen instrument mix ‘switch’ variables.

In any given year, firms can be in only one of the four instrument mix categories defined above. However, the following year firms in each of these four categories have two options: 1) stay in the same category; or 2) switch to one of the other three categories available. This four by four matrix means that sixteen ‘switch’ variables can be used to define the temporal dynamics of the innovation policy instrument mix. These sixteen instrument switch categories are defined in Appendix 1.

3.3. Innovation outcomes

ABSEI captures firms’ total expenditure on R&D each year. We divide this amount
by the firms’ number of employees to create R&D intensity, and then compute the natural log of this variable to standardise the variance. Using R&D intensity as a measure of firm-level innovation is common in the literature (e.g., Almus and Czarnitzki, 2003; Hussinger, 2008; Czarnitzki and Lopes-Bento, 2014).

3.4. Control variables

To control for other possible influences on firms’ R&D intensity, we include several variables in our econometric analysis that describe firms’ internal characteristics as well as the external business environment in which the firm operates. We include variables indicating the percentage of employees that work on in-house R&D activities within the Republic of Ireland. We also control for firms’ expenditure on formal structured training for employees (divided by number of employees). Based on Eurostat firm-size classifications, we include 4 dummy variables indicating whether a firm is micro (>10 employees), small (10-49 employees), medium (50-249 employees) or large (250+ employees). To control for the sector in which the firm operates, we include 6 dummy variables based on Eurostat sectoral aggregations indicating whether the firm operated in manufacturing (high-technology; medium-high-technology; medium-low-technology; low-technology) or services (knowledge-intensive; less knowledge-intensive). Location variables are included indicating which of Ireland’s three regions the firm is located in: Border, Midlands and Western Region; Southern and Eastern Region; or Dublin (capital city). Outside of these internal firm characteristics, we include dummy variables for each year of the survey to capture information on firms’ external environment. These control variables are the standard ones typically used in the literature (e.g., Roper et al., 2008; Czarnitzki and Lopes-Bento, 2014). Descriptive statistics for these variables are provided in Table 1. All relevant variables are deflated at 2011 prices.
3.5. Description of the dataset

We first consider the cross-sectional characteristics of our three datasets. Table 2 shows the proportion of the sample in each category of innovation policy instrument mix. Overall, approximately three quarters of the sample do not receive any policy intervention, while just under one quarter of the sample receive R&D tax credits.

Table 3 presents a transition matrix which demonstrates how firms switch between different policy instrument mixes through time. The interpretation of Table 3 can be shown by an illustrative example. Take the case of firms in the NEITHER policy instrument mix category for the Enterprise Ireland/ABSEI sample. Of the 13,836 firms that were first observed in this category, 12,789 (92.43%) stay in this category; while, at some point over the time period, 864 (6.24%) switch to receive an R&D tax credit; 160 (1.16%) switch to receive an EI subsidy; and 23 (0.17%) switch to receiving BOTH. As described in Section 3.2, we are using an unbalanced panel of firms with approximately 50% of the sample observed in each time period and at least 2 observations on every firm. Therefore, the transition of an individual firm between different instrument mix categories can be captured a maximum of nine times or a minimum of twice. It is clear from
<table>
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<td>1.2% (240)</td>
<td>1.3% (250)</td>
<td>1.4% (260)</td>
<td>1.5% (270)</td>
<td>1.6% (280)</td>
<td>1.7% (290)</td>
<td>1.8% (300)</td>
<td>1.9% (310)</td>
<td>2.0% (320)</td>
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<td>2.2% (340)</td>
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<tr>
<td>Botswana</td>
<td>0.1% (10)</td>
<td>0.2% (20)</td>
<td>0.3% (30)</td>
<td>0.4% (40)</td>
<td>0.5% (50)</td>
<td>0.6% (60)</td>
<td>0.7% (70)</td>
<td>0.8% (80)</td>
<td>0.9% (90)</td>
<td>1.0% (100)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1.3% (250)</td>
<td>1.4% (260)</td>
<td>1.5% (270)</td>
<td>1.6% (280)</td>
<td>1.7% (290)</td>
<td>1.8% (300)</td>
<td>1.9% (310)</td>
<td>2.0% (320)</td>
<td>2.1% (330)</td>
<td>2.2% (340)</td>
<td>2.3% (350)</td>
</tr>
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</table>

Table 2: Proportions of sample in each policy instrument mix by time period (number of observations in parentheses)
Table 3 that firms that begin in the NEITHER category and the R&DTC category tend to remain in these categories.

Table 3 also highlights a number of important differences between policy instruments administered by SFI and those administered by EI or IDA. Firms that receive an EI or IDA subsidy as their starting category have a tendency to switch to other policy instrument mix categories, particularly NEITHER. This gives an indication of how firms use EI and IDA subsidies: they apply for them, use them for a specific purpose, but do not continue applying for and use them. In contrast to this, firms that receive an SFI RJV as their starting category tend not to switch back to NEITHER, but rather remain in the same category or switch to BOTH. This likely occurs for two reasons. First, because all of the SFI RJVs are
multi-year collaborations (unlike the EI and IDA subsidies) it makes sense that firms would at least stay in the same category. Second, the focus of the SFI policy instrument is on linking firms with the national science base in terms of oriented basic and applied research. Given that firms entering into RJVs facilitated by SFI will be conducting R&D for a sustained period of time, they are a natural complement to R&D tax credits.\(^8\)

As can be seen in Table 4, a clear hierarchy is evident in terms of firms’ R&D intensity in each policy instrument mix category. Firms in the BOTH category achieve the highest level of R&D intensity, with firms in the R&DTC category only marginally behind this. All categories that involve some form of policy instrument outperform firms in the NEITHER category by a large distance. Looking at the AGENCY category, firms that receive IDA subsidies perform the best. Looking at the BOTH category, firms receiving an SFI linkage and an R&D tax credit together have a higher level of R&D intensity than firms that combine an EI or IDA subsidy with an R&D tax credit. It should be noted, however, that the NEITHER category most likely includes firms that do not even attempt to innovate, which may partly explain the much lower levels of R&D intensity of firms in this policy instrument mix category.

While we cannot infer from Table 4 that BOTH causes higher levels of R&D intensity, it is instructive to see the relative innovation performance (as measured by R&D

\(^8\) This point has important implications for the interpretation of our findings, which we highlight in Section 5.
intensity) of firms in each policy instrument mix category. To see whether the identified ‘premium’ associated with BOTH in Table 4 is stable through time, we graph these summary statistics in Figures 2, 3 and 4. With the exception of 2008 for firms receiving IDA innovation subsidies (Figure 3), there is clear evidence of the hierarchy described in Table 4 persisting through time. However, the relative R&D intensity of each group is characterised by a degree of change through time. The R&D intensity of firms receiving EI or IDA subsidies falls significantly in 2011, and never recovers to its previous peak. Firm receiving SFI linkages and R&D tax credits together steadily increase their R&D intensity through time relative to all other categories.

In summary, the data lend support to the contention that receiving any combination of two policy instruments together is associated with higher R&D intensity. To verify this finding from the descriptive statistics, we need to econometrically control for other possible influences on firms R&D intensity, and perform a formal test for the existence of complementarities between R&D tax credits and EI or IDA subsidies or SFI RJV. To do this, we first test for the presence of static complementarities. Following this, we make use of the longitudinal nature of our dataset to test for dynamic complementarities.

3.6. Instrument interactions: Direct test for complementarity, substitution, and neutrality

We can identify complementarity in the policy instrument mix if receiving one policy instrument (i.e. EI subsidy) increases the returns already being achieved with another policy instrument (i.e. R&D tax credit). In order to test for complementarity empirically, we adapt the econometric method specified by Love at al. (2014) and perform a ‘direct’ test for the presence of complementarities, substitution, or neutral instrument interactions by estimating

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9 As was highlighted in Section 3.1, Ireland entered a major economic downturn in 2008 following the 2007 global financial crisis, which placed significantly pressure on public funding for innovation.

10 Given that RJVs are multi-year contracts, they are more insulated from the effects of the recession in Ireland.
Figures 3, 4, and 5. R&D intensity by innovation policy instrument mix ‘category’ by year
an innovation production function (Athey and Stern, 1998; Mohnen and Röller, 2005; Cassiman and Veugelers, 2006). The production function approach works by regressing mutually exclusive instrument mix dummy variables (defined in Section 3.2), as well as a set of control variables, on the natural log of firms’ R&D intensity (the innovation outcome variable). Following this, we apply a formal test for both static and dynamic complementarity, substitution, and neutrality, as described below.

3.6.1. Test for static complementarity, substitution, and neutrality

In Equation (1) below, I represents an innovation outcome indicator for firm i, \( P_i \) is a series of four binary variable indicating which policy instrument mix category firm i belongs to, and \( X_i \) is a vector of control variables. Therefore, we can write:

\[
I_i = \gamma P_i + \beta X_i + \epsilon_i
\]  

(1)

Here, \( P_i \) can indicate each of the four discrete instrument mix categories outlined in Section 3.2. Although there are four potential instrument mix variables, there are only two actual policy instruments, P1 and P2, such that the vectors (00), (01), (10), and (11) define all possible combinations of the two policy instruments.\(^{11}\) To use the example of the R&D tax credit and EI subsidy, (11) represents firms receiving both policy instruments together (i.e. BOTH), while (00) represents firms receiving no policy instrument (i.e. NEITHER). Following common practice in the literature, estimations of Equation (1) are carried out without a constant to display how each of the different policy instrument mix categories impacts firms’ R&D intensity, including that of receiving no policy instrument. Static complementarity between two innovation policy instruments in the innovation production will be observed if Equation (2), below, is satisfied, while static substitution will be observed

\(^{11}\) See Section 3.2. (00): NEITHER; (01): R&DTC; (10): AGENCY; (11): BOTH.
in Equation (3) is satisfied. If neither Equation (2) nor Equation (3) is satisfied, then by definition we have identified a neutral relationship.

\[ I(10, X) + I(01, X) \leq I(00, X) + I(11, X) \]  
\[ I(10, X) + I(01, X) \geq I(00, X) + I(11, X) \]

Static complementarity means that receiving two different innovation policy instruments simultaneously produces a higher level of firm-level innovation output than the sum of the results produced by receiving either innovation policy instrument individually. Following Rogge and Reichardt’s (β016) definition of consistency, we can interpret this as direct evidence of strong instrument mix consistency, and validation of Hypothesis 1. However, if receiving two different innovation policy instruments simultaneously produces a lower level of firm-level innovation output than the sum of the results produced by receiving either innovation policy instrument individually, we can interpret this as evidence of instrument mix inconsistency. If neither static complementarity nor static substitution are identified, then by definition the relationship is neutral, and we can interpret this as direct evidence of weak instrument mix consistency.

3.6.2. Temporal dynamics

Even using panel data, testing for static complementarity involves comparing all of the observations in the dataset to one another in terms of the innovation policy instrument mix they are exposed to at a single point in time. In contrast to this, testing for dynamic complementarities involves utilising the longitudinal nature of the dataset to compare repeat observations to themselves as they are exposed to different policy instrument mix categories through time. Here it is important to bear in mind that testing for complementarities should be inherently dynamic because it involves the addition of something new to something the firm currently has or does (Love et al. 2014).
Similar to Equation (1), we specify Equation (4) to test for dynamic complementarity, substitution and neutrality:

\[ I_i = \gamma_i S_{Wi} + \beta X_i + \varepsilon_i \]  \hspace{1cm} (4)

In Equation (4)\(^1\), \(I\) represents an innovation outcome indicator for firm \(i\), \(S_{Wi}\) is a matrix of 16 different binary variables representing innovation policy instrument mix ‘switch’ variables. See Appendix 1 for the definition of each of these 16 variables.

Dynamic complementarity requires that Equation (5) and (6) are satisfied. Equation (5) states that firms that switch from the R&DTC category in one year to BOTH in the next year have higher level of innovation output than firms that switch from NEITHER in one year to receiving AGENCY in the next year (i.e. adding something new to what the firm currently has or does). Capturing the temporal dynamics, Equation (6) details the opposite sequence.

\[ sw24 \geq sw13 \] \hspace{1cm} (5)

\[ sw34 \geq sw12 \] \hspace{1cm} (6)

Again, echoing Rogge & Reichardt (2016) definition of consistency, if Equations (5) and (6) are verified we can interpret this as evidence of strong instrument mix temporal consistency. Similarly, dynamic substitution requires:

\[ sw24 \leq sw13 \] \hspace{1cm} (7)

\[ sw34 \leq sw12 \] \hspace{1cm} (8)

\(^1\) As Love et al. (2014) point out, the underlying assumption in the dynamic model is different to that of the static model. In the static model, unobserved heterogeneity is assumed to be random. In the dynamic model, the assumption is that intra-firm dynamics in unobserved heterogeneity are random.
Equations (7) and (8) state that firms that switch from receiving one innovation policy instrument in one year to receiving a combination of two innovation policy instruments in the next year\textsuperscript{13} have lower level of innovation output than firms that receive no innovation policy instrument in one year, and then switch to receiving one innovation policy instrument in the next year. We can interpret this as direct evidence of instrument mix temporal inconsistency. If neither dynamic complementarity nor dynamic substitution is identified, then by definition the relationship is neutral. We can interpret this as direct evidence of weak instrument mix temporal consistency.

The dynamic approach allows us to observe how the sequence in which firms receive different policy instruments affects innovation outcomes. For example, does receiving an R&D tax credit first, followed by an EI subsidy, impact firms R&D intensity differently to receiving them in the opposite order? This question has important implications for policy. Though different innovation policy instruments may have been designed to be consistent with one another ex-ante, they may still interact negatively if the temporal aspect of their consistency has not been taken into consideration. Similarly, instrument interactions can evolve in an unintended manner as they unfold across different policy mix dimensions. If this possibility is not built into policy evaluation, the ‘wrong’ policy implications may be drawn. To unravel this issue, we must map out all of the known temporal dynamics in the policy instrument mix and trace the relationship these movements have with firms’ R&D intensity, captured by Hypothesis 2.

3.7. Estimation procedure

We estimate Equation (1) and Equation (2) using OLS based estimation methods. Some literature has highlighted that two-step estimation models (Athey and Stern, 1998;  

\textsuperscript{13} Because we are using an unbalanced panel, the ‘next year’ should be taken to mean the next time period the firm is observed in subsequent to the initial observation.
Cassiman and Veugelers, 2006) or instrumental variables regression methods (Mohnen and Röller, 2005) are superior in terms of accounting for endogeneity and unobserved heterogeneity. However, in a detailed review of this literature, Love et al. 2014 have noted that, in practice, both of these estimation methods are not applicable with secondary data. To be applicable, a primary dataset would have to be designed and collected with the specific estimation procedure in mind. As outlined in Section 3.2, evaluating the innovation policy instrument mix tends to require merging a variety of different secondary data sources together to capture the required number of policy instrument variables, and retain sufficient information on their underlying characteristics. Therefore, these methods are not applicable in this instance. This issue is common in the literature, and we follow the standard practice applied in previous literature (e.g., Bourke and Roper, 2016; Love et al., 2014; Roper and Arvanitis, 2012; Roper et al., 2008).

4. Results

The consistency of an instrument mix can be defined as how well different instrument in the mix are aligned with one another (Reichardt and Rogge, 2016). This can be conceptualised in two different ways: 1) a state of the instrument mix at a point in time, and 2) the process of how this consistency was achieved through time (Rogge and Reichardt, 2016). Below, we first present an evaluation of the state of instrument mix consistency by performing a static test for complementarity, substitution, and neutrality in instrument interactions. Following this, we analyse the process element of consistency by examining temporal dynamics.

4.1. Static instrument mix consistency

Table 5 presents the results from estimating Equation (1) for static complementarity, substitution, and neutrality. When comparing coefficients, as might be expected, all
innovation policy instrument mix categories that involve receiving at least one innovation policy instrument are superior to receiving no innovation policy instrument (i.e. R&DTC, AGENCY, and BOTH). The hierarchy of instrument mixes described in Section 3.5 is maintained in terms of EI and IDA subsidies and SFI RJVs having a lower impact on firms’ R&D intensity in absolute terms. However, unlike the summary statistics provided in
Table 3 above, only firms which receive an R&D tax credit combined with an IDA subsidy (i.e. BOTH) outperform firms that receive an R&D tax credit alone (i.e. R&DTC).

By itself, this result does not indicate that BOTH is a superior innovation policy instrument mix category for IDA sponsored firms, and inferior for those supported by EI and SFI. To determine this, we must perform the formal tests for static complementarity and substitution outlined in Equations (2) and (3). As indicated in the final row of Table 5, the null hypothesis of no complementarity cannot be rejected in any case, including that of firms receiving an R&D tax credit and an IDA subsidy together. In fact, in all cases we find evidence of substitution and thus instrument mix inconsistency. Therefore, we can reject Hypothesis 1, that when firms receive a combination of two different innovation policy instruments simultaneously there will be a complementary relationship between them in their impact on firm-level innovation.

This finding would appear to lend support to Flanagan et al.’s (2011: 708) claim that “[i]t seems highly unlikely that, regardless of theoretical complementarities, complementarities in practice can be achieved by the simple accumulation of instrument after instrument. At some point theoretically complementary instruments may begin to interact in negative or contradictory ways if layered one upon the other”. However, it is important to bear in mind the dynamic nature of complementarity and how this should be incorporated into evaluations of the instrument mix. In this regard, Love et al. (2014: 1174) highlight that “[t]wo discrete activities are (Edgeworth) complementary if adding one activity increases the returns from doing the other. This implies that the benefit of adding a new activity depends not simply on what the firm currently does, but on what it did in the past: it concerns adding something to an existing strategy”. Therefore, we must also test the temporal dynamics of the instrument mix to verify this finding.
4.2. Temporal dynamics of instrument mix consistency

Table 6 presents the results from estimating Equation (4). As described in Section 3.2, we now have sixteen innovation policy instrument mix ‘switch’ variables that represent firms either moving between instrument mix categories or remaining in the same category (for a detailed description, see Appendix 1). The coefficients on each of these instrument mix variables can be interpreted as being relative to the option of remaining in the NEITHER category. However, as highlighted in Table 2, the exception to this is in the case of SFI/ABSEI dataset, where the category SW32 has no observations. Therefore, in this case, we set SW32 as the reference category and include SW11 in the regression. The only negative coefficient is the case of SW11 in the SFI/ABSEI regression. This negative result is as expected, because it captures the impact of firms remaining in the NEITHER category relative to switching from receiving an SFI linkage and no other policy instrument in one year, to receiving an R&D tax credit and no other policy instrument in the following year (i.e. SW32). The coefficients in Table 6 show that there is a universally positive ‘premium’ on receiving any individual policy instrument (i.e. SW22, SW33) or combination of policy instruments (i.e. SW44) relative to remaining in the NEITHER category.

However, as was highlighted in Section 3.6.2, our primary interest is not the absolute values of the policy instrument mix coefficients, but rather to test whether switches between certain policy instrument mixes have a greater impact on firms’ R&D intensity than others. This involves testing for the inequality embodied in Equations (5) and (6) for dynamic complementarity and Equations (7) and (8) for dynamic substitution.
<table>
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<th></th>
<th>Enterprise Ireland</th>
<th>IDA Ireland</th>
<th>SFI</th>
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<tr>
<td></td>
<td>R&amp;D intensity (log)</td>
<td>R&amp;D intensity (log)</td>
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<tr>
<td>sw11</td>
<td>—</td>
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<td>-0.333***</td>
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<tr>
<td></td>
<td>(0.077)</td>
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<tr>
<td>sw22</td>
<td>3.307***</td>
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<td>(0.066)</td>
<td>(0.066)</td>
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<td>(0.417)</td>
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<td>(0.667)</td>
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Dynamic complementarity test
- H0: sw24 ≤ sw13  p = 1.000  p = 1.000  p = 1.000
- H0: sw34 ≤ sw12  p = 0.000  p = 0.000  p = 0.000

Dynamic substitution test
- H0: sw24 ≤ sw13  p = 0.000  p = 0.000  p = 0.000
- H0: sw34 ≤ sw12  p = 1.000  p = 1.000  p = 1.000

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01
Notes: sw11 is displayed in column 3 because sw32 has no observations, therefore sw31 is set as the reference category; Control variables suppressed for brevity; Category dummies: the first number denotes starting category, the second number denotes the next observed category.

1: No EU/IDA/SFI intervention and no R&D tax credit
2: No EU/IDA/SFI intervention and receives R&D tax credit
3: Receives EU/IDA/SFI intervention and no R&D tax credit
4: Receives EU/IDA/SFI intervention and R&D tax credit
In the final six rows of Table 6\textsuperscript{14}, we first test for dynamic complementarity. We find that in the first case (i.e. SW24>SW13) the null hypothesis of no dynamic complementarity is rejected. However, in the second case (i.e. SW34>SW12), the null hypothesis of no dynamic complementarity cannot be rejected. Following this, our tests for dynamic substitution reveal the same pattern of results. These results clearly demonstrate the crucial role temporal dynamics play in the innovation policy instrument mix. This also highlights the important role the sequence in which firms receive the innovation policy instruments plays a moderating role in this complementary relationship.

5. Discussion and implications for policy

The empirical component of this paper serves to demonstrate the applicability of the conceptual framework developed in Section 2.5. Applying this conceptual framework to the empirical setting of Ireland, we were able to investigate how the temporal dynamics of the innovation policy instrument mix affected its impact on firms’ R&D intensity. Our results from testing Hypotheses 1 and 2 highlight the vital role temporal dynamics play in moderating interaction effects within the innovation policy instrument mix. This finding has important implications for policy and the practice of evaluation.

Testing for complementarity and substitution at a point in time, we find strong evidence of static substitution between all instrument mix combinations. However, when taking the temporal dynamics into consideration and testing for dynamic complementarity and substitution, we find evidence that some temporal dynamics lead to complementarity while others lead to substitution. It is important to note that, by themselves, these results do not indicate instrument mix inconsistency and the rejection of Hypothesis 2. Rather, these

\textsuperscript{14} Give that we now have sixteen innovation policy instrument mix ‘switch’ variables instead of the four innovation policy instrument mix ‘category’ variables in Table 5, the control variables have been omitted from Table 6 for brevity. Results from the control variables can be viewed in Appendix 2.
results require a nuanced interpretation based on policy mix theory and the system features of the empirical setting.

As was demonstrated in Table 3, some instrument mix combinations happen very rarely. Firms that receive an EI or IDA subsidy in one year tend not to receive a combination of the EI or IDA subsidy together with an R&D tax credit in the next year. This switch occurs a total of 14 times for EI firms and 3 times for IDA firms. In contrast to this, the opposite sequence is relatively common. This is likely because the R&D tax credit is an automatic innovation policy instrument, while EI and IDA subsidies are awarded on a competitive and selective basis. Therefore, it is understandable that receiving an R&D tax credit in one period and switching to receive a combination of the R&D tax credit with an EI or IDA subsidy or a SFI RJV in the next period is a much more common observation. However, these sequencing effects are not picked up by conducting a static test. Therefore, rather than indicating instrument mix inconsistency, results from the testing Hypothesis 1 (i.e. the static test) should serve to highlight the danger of not taking temporal dynamics into consideration when conducting instrument mix evaluations. Where switches are common, we find direct evidence of dynamic complementarity and thus strong instrument mix consistency, thus supporting Hypothesis 2.

In this sense, the results of any innovation policy instrument mix evaluation should not be treated as ‘absolute’, but rather dependent on context. For example, the time period our dataset corresponds to captures the 2008 global financial crisis, which was particularly acute in the Irish economy and had lasting effects for many years. This means that the temporal dynamics are particularly important to include in the model for evaluation. In this context, our results when testing for dynamic complementarity demonstrate a surprisingly high degree of robustness in the innovation policy system. Despite an unfavourable business environment
characterised by lack of access to credit\textsuperscript{15} and high firm mortality rate\textsuperscript{16}, we still find evidence of a high degree of temporal consistency among innovation policy instruments. Evaluations conducted using cross-sectional data, or not specifically incorporating temporal dynamics into their econometric model, would likely arrive at the ‘wrong’ implication for policy.

Therefore, from a policy perspective, this inaccurate policy implication could be used as evidence to discontinue certain innovation policy instruments. Similarly, state agencies responsible for awarding innovation funding could be instructed not to award funding to a firm already receiving a different innovation policy instrument where an inconsistent relationship had been identified using a static test. This would lower the effectiveness and efficiency of innovation policy overall, as well as hamper policy learning. By using the concept of consistency and testing for directly static and dynamic complementarity and substitution, we are able to directly identify these important temporal dynamics which would be obscured using a different theoretical and econometric method.

6. Conclusion and recommendations for future research

Around the world, significant public finances are devoted to funding firm-level innovation. However, the effective and efficient allocation of these scarce public resources is hampered by the policy complexity inherent in dynamic multi-actor, multi-level, and multi-scalar innovation systems. The concept of policy mix has emerged and gained a prominence in the literature as a means of mitigating or circumventing the limitations imposed by policy complexity. This paper contributed to the literature by synthesising a number of different stranded in the policy mix literature to establish a conceptual framework for the ex-ante and ex-post impact evaluation of innovation policy instrument mixes. Applying this framework to

\textsuperscript{15} See CSO: http://www.cso.ie/en/releasesandpublications/er/atf/accessofinance2014/

a unique empirical setting using a novel microeconometric procedure, we demonstrate its usefulness to the field as a set of ‘guiding principals’ for instrument mix evaluation. However, this application of the conceptual framework only represents the first step towards gaining a more full understanding the nature of real world innovation policy instrument mixes how they leads to firm-level innovation additionality. Therefore, we highlight a number of avenues for future research.

The most immediate extensions are based on data availability. Firstly, though our dataset facilitates a comprehensive analysis of the different innovation policy instruments available to firms, it is limited in that we only have one indicator of firms’ innovation outcomes. We need to move beyond measuring innovation solely as input additionality and examine the impact of the innovation policy instrument mix on output and behavioural additionalities. Secondly, it is not sufficient to only know the impact of the innovation policy instrument mix on firm-level innovation, but rather we also need to know what the impact of this firm-level innovation is on economic indicators such as exports, productivity, and employment growth. As highlighted by Rogge and Reichardt (2016), finding a dataset that is comprehensive enough to conduct this kind of analysis, while still capturing sufficient information on the underlying characteristics of each policy instrument, poses a major challenge to policy mix research. Therefore, it would likely require merging multiple detailed economic surveys to construct a dataset that captures all of this information.

Finally, there are two additional avenues that future research could usefully pursue in terms of extending the econometric method. All of the tests for complementarity we have conducted here have been between pairs of innovation policy instruments available to firms from the national government. However, it is also likely that firms receive innovation policy instruments from the supra-national level of government. For example, firms may be exposed to a policy instrument mix consisting of R&D tax credits and Enterprise Ireland subsidies
from the national government in addition to Horizon 2020 funding from the EU. Theoretically, this would involve a test on the joint inequality of multiple coefficients, as opposed to the pairwise test conducted here. To the authors’ knowledge, joint inequality testing has never been conducted in the policy evaluation literature previously, but it is the next logical methodological step for future research to pursue.

In this paper we have unravelled the much of what is known and the unknown concerning the innovation policy instrument mix. Focusing on the crucial underlying role played by consistency among innovation policy instruments, we have laid out a more holistic set of ‘guiding principals’ for impact evaluation on the instrument mix. While this paper represents the first step towards a more full understanding of the policy mix, future research can build of these foundations to move the field close to fulfilling Flanagan et al.’s (2011: 711) call for innovation policy studies “to move towards substantial empirical innovation policy histories … of policy mixes” (emphasis in original).

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Appendices

**Appendix 1** Sixteen innovation policy instrument mix ‘switch’ categories

<table>
<thead>
<tr>
<th>Category</th>
<th>Switch</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>sw11</td>
<td>Firms in NEITHER category in period t-1, and in NEITHER category in period t</td>
</tr>
<tr>
<td>2</td>
<td>sw22</td>
<td>Firms in R&amp;DTC category in period t-1, and in R&amp;DTC category in period t</td>
</tr>
<tr>
<td>3</td>
<td>sw33</td>
<td>Firms in AGENCY category in period t-1, and in AGENCY category in period t</td>
</tr>
<tr>
<td>4</td>
<td>sw44</td>
<td>Firms in BOTH category in period t-1, and in BOTH category in period t</td>
</tr>
<tr>
<td>5</td>
<td>sw12</td>
<td>Firms in NEITHER category in period t-1, and in R&amp;DTC category in period t</td>
</tr>
<tr>
<td>6</td>
<td>sw13</td>
<td>Firms in NEITHER category in period t-1, and in AGENCY category in period t</td>
</tr>
<tr>
<td>7</td>
<td>sw14</td>
<td>Firms in NEITHER category in period t-1, and in BOTH category in period t</td>
</tr>
<tr>
<td>8</td>
<td>sw21</td>
<td>Firms in R&amp;DTC category in period t-1, and in NEITHER category in period t</td>
</tr>
<tr>
<td>9</td>
<td>sw23</td>
<td>Firms in R&amp;DTC category in period t-1, and in AGENCY category in period t</td>
</tr>
<tr>
<td>10</td>
<td>sw24</td>
<td>Firms in R&amp;DTC category in period t-1, and in BOTH category in period t</td>
</tr>
<tr>
<td>11</td>
<td>sw31</td>
<td>Firms in AGENCY category in period t-1, and in NEITHER category in period t</td>
</tr>
<tr>
<td>12</td>
<td>sw32</td>
<td>Firms in AGENCY category in period t-1, and in R&amp;DTC category in period t</td>
</tr>
<tr>
<td>13</td>
<td>sw34</td>
<td>Firms in AGENCY category in period t-1, and in BOTH category in period t</td>
</tr>
<tr>
<td>14</td>
<td>sw41</td>
<td>Firms in BOTH category in period t-1, and in NEITHER category in period t</td>
</tr>
<tr>
<td>15</td>
<td>sw42</td>
<td>Firms in BOTH category in period t-1, and in R&amp;DTC category in period t</td>
</tr>
<tr>
<td>16</td>
<td>sw43</td>
<td>Firms in BOTH category in period t-1, and in AGENCY category in period t</td>
</tr>
</tbody>
</table>

Note: ‘sw’ denotes ‘switch’. Categories: the first number denotes starting category, the second number denotes the next observed category.

1. No EU/IDA/SFI intervention and no R&D tax credit
2. No EU/IDA/SFI intervention and receives R&D tax credit
3. Receives EU/IDA/SFI intervention and no R&D tax credit
4. Receives EU/IDA/SFI intervention and R&D tax credit

**Appendix 2** Omitted control variables from dynamic test

<table>
<thead>
<tr>
<th></th>
<th>Enterprise Ireland</th>
<th>IDA Ireland</th>
<th>SFI</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D intensity (log)</td>
<td>0.096</td>
<td>0.101</td>
<td>0.102</td>
</tr>
<tr>
<td>Training exp. (log)</td>
<td>0.317***</td>
<td>0.314***</td>
<td>0.316***</td>
</tr>
<tr>
<td>Small (size)</td>
<td>0.008</td>
<td>0.009</td>
<td>0.009</td>
</tr>
<tr>
<td>Medium (size)</td>
<td>0.057</td>
<td>0.009</td>
<td>0.060</td>
</tr>
<tr>
<td>Large (size)</td>
<td>0.157**</td>
<td>0.161**</td>
<td>0.182**</td>
</tr>
<tr>
<td>Sector dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Location dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>1.592***</td>
<td>1.747***</td>
<td>1.692***</td>
</tr>
</tbody>
</table>

Standard errors in parentheses: * p < 0.1; ** p < 0.05; *** p < 0.01
References


