Evaluating the impact of innovation policy instrument mix on firm-level Research and Development intensity

by

Kevin Mulligan, B.A., M.Sc.

A Thesis Submitted to the Kemmy Business School, University of Limerick
In Fulfilment of the Requirements of the Degree of Doctor of Philosophy

Supervisor: Professor Helena Lenihan

External Supervisor: Dr Justin Doran (UCC)

Submitted to the University of Limerick, December 2018
Evaluating the impact of innovation policy instrument mix on firm-level Research and Development intensity

Kevin Mulligan

Abstract: Firm-level innovation is a well-established determinant of national competitiveness and economic growth. Many studies highlight that private firms may under invest in innovation due to market and system failures. This has motivated a large body of research on the role of public funding to support firms’ innovation activities. At the level of the firm, a suite of innovation policy instruments operationalise innovation policy. While impact evaluations traditionally focus on individual innovation policy instruments, such analyses have limitations. Firms often apply to public funding agencies for different innovation policy instruments. Many firms accrue more than one instrument, resulting in an innovation policy instrument mix. Different instruments can have a complementary or substitutive relationship. It is essential to consider how interactions between instruments in the mix influence firms’ innovation outcomes. Despite this imperative, there is lack of empirical research evaluating the impact of innovation policy instrument mix on firm-level innovation.

To address this gap, this thesis develops a novel conceptual framework for evaluating static and dynamic complementarity and substitution between innovation policy instruments. To apply this framework empirically, the analysis creates three unique panel datasets through a series of data merges. Each dataset captures detailed information on the type and source of innovation policy instruments firms in Ireland receive, and contains 16,084 observations of 3,098 firms from 2007 to 2014. This data facilitates pairwise tests for complementarity and substitution between Research and Development (R&D) tax credits and R&D/innovation support from Ireland’s three key national funding agencies: Enterprise Ireland (EI), Industrial Development Agency Ireland (IDA) and Science Foundation Ireland (SFI). The panel nature of the data enables estimating a number of lag-structured models to test for both contemporaneous and longer-term impacts. To control for potential selection bias and endogeneity associated with the allocation and receipt of public funding, the econometric analysis employs an instrumental variable method.

Using R&D intensity as a measure of firm-level innovation, results indicate that firms receiving a combination of R&D tax credits and EI support benefit more than firms that receive the same instruments separately. This static complementary relationship materialises in the same year firms receive this instrument mix, and persists for two years following receipt of the mix. Static complementarity is also identified between a combination of R&D tax credits and IDA or SFI support up to two years after the mix is initially received. The tests for dynamic complementarity reveal that a complex relationship between instruments unfolds over time. The transition from receiving an R&D tax credit in one year to an instrument mix composed of an R&D tax credit and EI support in the next year produces a substitutive relationship. In contrast, dynamic complementarity is identified when firms transition from receiving an R&D tax credit to a mix of the R&D tax credit and IDA support, or when firms transition from receiving SFI support to a combination of the R&D tax credit and SFI support. These results highlight that the sequence in which firms receive different instruments through time plays an important role in driving impact. While this study makes an important academic contribution to the field of innovation policy evaluation, the results also have potential policy implications in the area of public funding for innovation.
Declaration of Originality

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or institute of learning.

I declare that the thesis represents the results of my own work. Following normal academic conventions, I have made due acknowledgements of the work of others. The work has been completed within the specific word limit with 74,285 words, including references and appendices.

Copyright Statement:

Copyright in text of this thesis rests with the author. Copies (by any process), either in full or of extracts, may be made only in accordance with instructions given by the author.

Signed: ______________________

Kevin Mulligan
Acknowledgements

I am very grateful to many people, whom I wish to acknowledge here, for the advice and support they provided me with throughout the long period of researching and writing this thesis.

First and foremost, I wish to sincerely thank my supervisors, Professor Helena Lenihan and Dr Justin Doran. For giving me this opportunity, for their support, encouragement and expertise throughout the process, and for much more, I am genuinely grateful.

I would like to thank the many academics who gave their time to discuss my research along the way: Dr Kieron Flanagan, Professor Mark Lorenzen, Professor Oliver Alexy, Professor Dirk Czarnitzki, Dr Sam Arts, Dr Vera Rocha and Professor Bernadette Andreosso-O’Callaghan.

To Michelle Cunningham and Rebecca Gachet at the Kemmy Business School (KBS) research office, and Josephine O’Sullivan in the Department of Economics, for help over my four years in the KBS Graduate Research Centre, thank you.

I am grateful to Science Foundation Ireland (SFI) and the Irish Research Council (IRC) for the financial support I received during my PhD and the financial support I received from the KBS research office.

I am also grateful for feedback and advice I revived from members of the SFI/IRC International Steering Committee on Science Policy and Innovation.

I am thankful to Dr Jonathan Healy at the Department of Business, Enterprise and Innovation (DBEI) and to Mr Barry Kelleher at the Central Statistics Office (CSO) for help and support in gaining access to the data used in this study. I also gratefully acknowledge the assistance received from other staff members in DBEI and the CSO.

To my friends and colleagues in the KBS Graduate Research Centre for their great support and countless chats and discussions on everything related to ‘doing a PhD’: Mauricio, Maeve, Sarah, Kathryn, Helen, Bunmi, Clodagh, Nuala, Shona, Meredith, Ashley, Naji, Abobaker, Munif, Okezie, Uduakobong, all those who attended the KBS PhD Colloquium.

Finally, I wish to say a very special thank you to my parents, Patrick and Helena Mulligan, and to Aoife Coughlan, for your endless patience, love and support throughout this long journey.
# Table of contents

Abstract: ................................................................................................................................. iii
Declaration of Originality ......................................................................................................... iv
Acknowledgements .................................................................................................................. v
Table of contents ....................................................................................................................... vii
List of tables ............................................................................................................................. xi
List of figures .............................................................................................................................. xiv
List of appendices ...................................................................................................................... xv
List of abbreviations ................................................................................................................ xvi

## Chapter 1: Introduction ........................................................................................................ 1

1.1. Introduction ...................................................................................................................... 1
1.2. Complementarity in the innovation policy instrument mix ................................................. 5
1.2.1. Behavioural and Resource Based Foundations of Policy Effects and Complementarity .. 9
1.3. Econometric Model............................................................................................................. 11
1.3.1. Sources of Selection Bias .............................................................................................. 12
1.3.2. Sources of Endogeneity ................................................................................................. 13
1.4. Empirical setting and data merges .................................................................................... 15
1.4.1. Empirical setting: Ireland ............................................................................................. 16
1.4.2. Description of datasets .................................................................................................. 17
1.4.3. Merging datasets ........................................................................................................... 19
1.5. Rationale for the research ............................................................................................... 21
1.6. Research objectives ......................................................................................................... 22
1.7. Contributions of the current research .............................................................................. 23
1.8. Conclusion ....................................................................................................................... 26

## Chapter 2: A survey of the literature on innovation policy instrument evaluation .......... 29

2.1. Introduction ...................................................................................................................... 29
2.2. Schumpeterian theories of innovation .............................................................................. 30
2.3. The rationale for innovation policy intervention .............................................................. 33
2.3.1. The linear model of innovation ...............................................................34
2.3.2. Neo-classical assumptions of market failure ........................................35
2.3.3. Innovation systems ..............................................................................39
2.3.3.1. Assumptions behind innovation systems ........................................39
2.3.3.2. Codified knowledge, tacit knowledge and learning..........................41
2.3.3.3. Systemic failures ............................................................................42
2.3.3.4. Innovation policy responses to systemic failure ..............................44
2.4. Market failure and systemic failure ..........................................................45
2.4.1. The influence of market failure in innovation policy documents .........45
2.4.2. Influence of market failure in firm-level empirical evaluations ..........46
2.4.3. Market failure’s dominance as the rationale for policy intervention .....48
2.4.4. Co-existence of market failure and systemic failure rationales ..........49
2.5. Evaluating the impact of public funding for innovation ..........................50
2.5.1. Direct and indirect public funding for innovation ..............................51
2.5.2. Systemic forms of public funding for innovation ...............................53
2.5.3. Additionality and crowding-out ..........................................................54
2.5.4. Measures of public funding for innovation in survey data .................55
2.5.5. Direct innovation policy instruments ..................................................57
2.5.6. Indirect innovation policy instruments ...............................................58
2.5.6.1. The effectiveness of R&D tax credits ............................................62
2.5.6.2. Incremental versus volume-based R&D tax credits .......................65
2.5.7. Systemic innovation policy instruments ............................................67
2.5.8. Time lag to additionality ...................................................................70
2.6. Conclusion ..............................................................................................72

**Chapter 3: The innovation policy instrument mix** ......................................75

3.1. Introduction ............................................................................................75
3.2. The policy mix for innovation ...............................................................78
3.2.1. The boundaries for evaluation: policy mix dimensions ....................79
3.2.2. Consistency among innovation policy instruments ..........................81
3.2.3. Conceptual framework .....................................................................86
3.3. The microeconometric literature ............................................................90
3.3.1. Firms receiving a mix of different of innovation policy instruments .............................................. 92
3.3.2. A typology of innovation policy instrument mixes ................................................................. 95
3.3.3. A review of innovation policy instrument mix evaluations ..................................................... 100
3.4. Conclusion ........................................................................................................................................ 115

Chapter 4: Methodology and data ........................................................................................................ 119
4.1. Introduction ........................................................................................................................................ 119
4.2. Microeconometric evaluation ........................................................................................................ 121
4.2.1. Estimating static complementarity and substitution ................................................................. 121
4.2.2. Estimating dynamic complementarity and substitution ............................................................ 124
4.2.3. Microeconometric method: ‘Generated’ instrumental variable estimation ............................... 126
4.3. Empirical setting: Ireland ................................................................................................................. 131
4.3.1. Revenue Commissioner: R&D tax credit .................................................................................. 132
4.3.3. IDA Ireland ................................................................................................................................. 135
4.3.4. Science Foundation Ireland ....................................................................................................... 136
4.4. Description of datasets .................................................................................................................. 137
4.4.1. Annual Business Survey of Economic Impact (ABSEI) ............................................................. 139
4.4.1.1. ABSEI Questionnaire ........................................................................................................ 140
4.4.1.2. Dependent variable: R&D intensity ...................................................................................... 141
4.4.1.2.1. Dependent Variable: Measure Choice, Rationale and Implications ......................... 142
4.4.1.3. Treatment variable: R&D tax credits ................................................................................... 143
4.4.1.4. Control variables ................................................................................................................ 143
4.4.2. Enterprise Ireland, IDA Ireland and Science Foundation Ireland administrative datasets .................................................. 144
4.4.3. Innovation policy instrument variables .................................................................................... 148
4.4.4. Merging datasets ..................................................................................................................... 151
4.4.4.1. R&D active firms and Non-R&D active firms ...................................................................... 151
4.4.4.2. Description of final merged datasets .................................................................................. 152
4.5. Conclusion ........................................................................................................................................ 163
Chapter 5: The impact of innovation policy instrument mix on firms’ R&D intensity: Empirical findings for Ireland

5.1. Introduction ............................................................................................................. 165
5.2. Testing for static complementarity and substitution ............................................... 169
5.2.1. Static tests: ABSEI-Enterprise Ireland sample ................................................ 171
5.2.2. Static tests: ABSEI-IDA Ireland sample ............................................................ 174
5.2.3. Static tests: ABSEI-SFI sample .......................................................................... 178
5.2.4. Specification tests for static Lewbel instrumental variable regressions .............. 181
5.3. Testing for dynamic complementarity and substitution .......................................... 182
5.3.1. Dynamic tests: ABSEI-Enterprise Ireland sample ........................................... 184
5.3.2. Dynamic tests: ABSEI-IDA Ireland sample ....................................................... 188
5.3.3. Dynamic tests: ABSEI-SFI sample .................................................................... 192
5.3.4. Specification tests for dynamic Lewbel instrumental variable regressions .......... 195
5.4. Discussion and interpretation of empirical findings ............................................. 196
5.4.1. R&D tax credits .................................................................................................. 197
5.4.2. National funding agencies: Enterprise Ireland, IDA Ireland and SFI ............... 198
5.4.3. The relationship between R&D tax credits and funding agency support .......... 200
5.4.3.1. Static complementarity tests ......................................................................... 201
5.4.3.2. Dynamic complementarity tests ................................................................... 203
5.5. Conclusion ........................................................................................................... 205

Chapter 6: Conclusion ............................................................................................... 208

6.1. Introduction .......................................................................................................... 208
6.2. Summary and discussion ...................................................................................... 210
6.3. Contributions of the current research ................................................................. 217
6.4. Limitations and suggestions for future research .................................................. 219
6.5. Conclusion ........................................................................................................... 221

References .................................................................................................................. 223
Appendices .................................................................................................................. 251
List of tables

Table 1 Microeconometric evaluations of the innovation policy instrument mix (Part 1)……101

Table 2 Microeconometric evaluations of the innovation policy instrument mix (Part 2)……102

Table 3 Microeconometric evaluations of the innovation policy instrument mix (Part 3)……103

Table 4 Changes in the R&D tax credit scheme since introduction.................................133

Table 5 Enterprise Ireland: Innovation policy instruments..............................................135

Table 6 IDA Ireland: Innovation policy instruments......................................................136

Table 7 Science Foundation Ireland: Innovation policy instruments..............................137

Table 8 Description of sixteen treatment category 'switch' variables..............................150

Table 9 Descriptive statistics on variables used in three final merged datasets.................156

Table 10 Proportion of each sample in each treatment category by year (number of observations in parentheses).................................................................157

Table 11 Transition matrix of the four policy instrument categories..............................159

Table 12 R&D intensity (log) by treatment category......................................................160

Table 13 Testing for static complementarity and substitution between R&D tax credits and Enterprise Ireland R&D/innovation support (results for contemporaneous model).................................................................172

Table 14 Testing for static complementarity and substitution between R&D tax credits and Enterprise Ireland R&D/innovation support (results for one, two and three lag-models).................................................................173
Table 15 Testing for static complementarity and substitution between R&D tax credits and IDA Ireland R&D/innovation support (results for contemporaneous model)………………..175

Table 16 Testing for static complementarity and substitution between R&D tax credits and IDA Ireland R&D/innovation support (results for one, two and three lag-models)…………………………………………………………………………………..176

Table 17 Testing for static complementarity and substitution between R&D tax credits and Science Foundation Ireland linkages (results for contemporaneous model)…………………179

Table 18 Testing for static complementarity and substitution between R&D tax credits and Science Foundation Ireland linkages (results for one, two and three lag-models)………………….180

Table 19 Specification tests for static complementarity regressions………………………………181

Table 20 Testing for dynamic complementarity and substitution between R&D tax credits and Enterprise Ireland R&D/innovation support (results for contemporaneous model)…………………………………………………………………………………………………………………………………………………..186

Table 21 Testing for dynamic complementarity and substitution between R&D tax credits and Enterprise Ireland R&D/innovation support (results for one, two and three lag-models)………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………………….
Table 25 Testing for dynamic complementarity and substitution between R&D tax credits and Science Foundation Ireland linkages (results for one, two and three lag-models)………194

Table 26 Specification tests for dynamic complementarity regressions…………………………196
List of figures

Figure 1.1 Complementarity and substitution in the innovation policy instrument mix.........6

Figure 1.2 Temporal dynamics in the innovation policy instrument mix..........................8

Figure 1.3 Structure of the thesis chapters.................................................................88

Figure 3.1 A conceptual framework for innovation policy instrument mix evaluation.........99

Figure 3.2 A typology of public funding for innovation..................................................99

Figure 4.1 Creating binary measures for whether firms received support from Ireland’s three national funding agencies.................................................................146

Figure 4.2 Data merges to create three final datasets......................................................152

Figure 4.3 R&D intensity by treatment category by year, ABSEI-Enterprise Ireland sample….161

Figure 4.4 R&D intensity by treatment category by year, ABSEI-IDA Ireland sample.........161

Figure 4.5 R&D intensity by treatment category by year, ABSEI-SFI sample....................162
List of appendices

Appendix A Omitted results for control variables in the dynamic complementarity and substitution regressions (Tables 19 and 20)………………………………………………………………………….251

Appendix B Omitted results for control variables in the dynamic complementarity and substitution regressions (Tables 21 and 22)………………………………………………………………………….251

Appendix C Omitted results for control variables in the dynamic complementarity and substitution regressions (Tables 23 and 24)………………………………………………………………………….252
# List of abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABSEI</td>
<td>Annual Business Survey of Economic Impact</td>
</tr>
<tr>
<td>CIS</td>
<td>Community Innovation Survey</td>
</tr>
<tr>
<td>CSAGI</td>
<td>Chief Scientific Adviser to the Government of Ireland</td>
</tr>
<tr>
<td>CSO</td>
<td>Central Statistics Office</td>
</tr>
<tr>
<td>DBEI</td>
<td>Department of Business Enterprise and Innovation</td>
</tr>
<tr>
<td>DoF</td>
<td>Department of Finance</td>
</tr>
<tr>
<td>DPER</td>
<td>Department of Public Expenditure and Reform</td>
</tr>
<tr>
<td>EC</td>
<td>European Commission</td>
</tr>
<tr>
<td>EI</td>
<td>Enterprise Ireland</td>
</tr>
<tr>
<td>EU</td>
<td>European Union</td>
</tr>
<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
</tr>
<tr>
<td>GNP</td>
<td>Gross National Product</td>
</tr>
<tr>
<td>IDA</td>
<td>Industrial Development Agency Ireland</td>
</tr>
<tr>
<td>HEI</td>
<td>Higher Education Institution</td>
</tr>
<tr>
<td>IRC</td>
<td>Irish Research Council</td>
</tr>
<tr>
<td>MNE</td>
<td>Multinational Enterprise</td>
</tr>
<tr>
<td>NACE</td>
<td>Nomenclature generale des Activites economiques dans les Communautes europeennes</td>
</tr>
<tr>
<td>NUTS</td>
<td>Nomenclature of Territorial Units for Statistics</td>
</tr>
<tr>
<td>OCAG</td>
<td>Office of the Comptroller and Auditor General</td>
</tr>
<tr>
<td>OECD</td>
<td>Organisation for Economic Co-operation and Development</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>Research and Development</td>
</tr>
<tr>
<td>SFI</td>
<td>Science Foundation Ireland</td>
</tr>
<tr>
<td>SME</td>
<td>Small and Medium-sized Enterprises</td>
</tr>
</tbody>
</table>
Chapter 1: Introduction

1.1. Introduction

This chapter presents an overview of the thesis to provide context for the subsequent chapters. The chapter will outline the theoretical and empirical backdrop against which the research takes place; introduce the key concepts that will be considered in later chapters; present the rationale for the research and state the research objectives; and highlight the contributions of the research.

Schumpeter's (1934; 1942) path-breaking work established innovation as a key driving force behind the economy. Feldman (2000, p. 373) defines innovation as “the novel application of economically valuable knowledge”. Drawing on Schumpeter’s seminal contributions, Grossman and Helpman (1994, p. 32) argue that innovation constitutes a key “engine of growth” for the economy. Substantial economic theory and empirical evidence support the view that firms’ Research and Development (R&D) investments stimulate innovation activities that in turn play a crucial role in increasing national competitiveness, productivity and economic growth (Romer 1990; Griliches 1992; Hasan & Tucci 2010; Pradhan et al. 2018).

As a means of boosting national and regional economic prosperity, policymakers worldwide have implemented a suite of innovation policies that often involve using public money to subsidise private firms’ R&D and innovation activities (OECD 2017; 2018a). Extensive rationales for this form of innovation policy intervention have centred on the identification of certain market failures (Nelson 1959; Arrow 1962) and systemic failures (Chaminade & Edquist 2006; 2010). As detailed in Chapter 2, these issues prevent firms from engaging in a sufficient level of R&D and innovation, which in turn hinders economic development. Edler and Fagerberg (2017) have recently noted that since the late 1970s, innovation policy and its
impact on firm-level innovation have received increasing attention in the economic literature. However, understanding and explaining the contribution of innovation policy to firms’ innovation performance remain challenging for academics and policymakers alike (Fagerberg 2018).

Broad innovation policies, such as the increasing national expenditure on R&D, are operationalised by different innovation policy instruments at firm level (Martin 2016; Edler et al. 2016). For example, R&D tax credits and R&D grants are two distinct types of innovation policy instruments policymakers implement in an effort to increase firms’ R&D investments (OECD 2018). Each instrument is designed to address different market and systemic failures and influence firm-level innovation in somewhat different ways (European Commission 2016; 2017a; 2017b). In a recent review of the literature, the European Commission (2017a, p. 38) reports that each of these instruments tends to have “significant and large” impacts on firms’ R&D and innovation.

However, since the early 2000s, the concept of the policy mix for innovation (STRATA/ETAN Expert Group 2002; Soete & Corpakis 2003) has gained prominence in the literature (e.g. Rogge & Schleich 2018; Schmidt & Sewerin 2018). In the field of innovation policy evaluation, Flanagan et al. (2011, p. 702) highlight that the policy mix concept “implies a focus on the interactions and interdependencies between different policies as they affect the extent to which intended policy outcomes are achieved”. Many different innovation policies are designed and implemented by policymakers to influence national, regional and firm-level innovation. As noted, firms are a key locus of innovation within the economy (Griliches & Mairesse 1984; Dodgson 2017). Therefore, the focus of this study is on firm-level innovation.

As discussed in Section 1.4.2 and later in Chapter 4, Section 4.2.2.2, firms’ R&D expenditure is used as a proxy for firm-level innovation in the empirical part of this study. This approach is consistent with existing studies on the impact of public funding on firm-level innovation, such as Czarnitzki & Lopes-Bento (2013; 2014) and Aristei et al. (2017).
At the level of the firm, taking a policy mix approach to innovation policy evaluation necessitates evaluating the innovation policy instrument mix (Flanagan et al. 2011; Rogge & Reichardt 2016). The innovation policy instrument mix can be defined as the interactions between innovation policy instruments that a firm receives, and how these interactions influence the firm’s innovation outcomes. Instrument mixes occur as firms often apply for a variety of different innovation policy instruments (Indecon 2017; OECD 2018). The result of these applications is that some firms receive no instrument, other firms receive one instrument, and yet other firms accrue more than one instrument (i.e. an innovation policy instrument mix). The policy mix concept suggests that the impact of innovation policy on firm-level innovation may depend crucially on the specific mix of innovation policy instruments firms receive (Flanagan et al. 2011).

Dumont's (2017) recent empirical research has demonstrated that it is often more common for firms to receive a mix of instruments than one individual instrument. This leads Dumont (2017, p. 1852) to question “whether the different support schemes tend to reinforce or weaken one another” when firms receive a mix. Similarly, Guerzoni and Raiteri (2015) show that evaluations of individual innovation policy instruments that do not control for whether firms receive other instruments at the same time can misattribute the impact of a mix to one instrument in the mix. This can lead to serious under- and over-estimation of the impact of individual innovation policy instruments on firm-level innovation (Guerzoni & Raiteri 2015). Therefore, understanding the innovation policy instrument mix is important for policymakers, both in terms of ensuring accountability for how public money is spent and in fostering policy improvement.

Several key studies that lay the theoretical foundations for the policy mix concept argue that

---

2 A more detailed discussion of the innovation policy instrument mix is provided in Chapter 3, Section 3.2.2.
innovation policy instruments can have a complementary or substitutive relationship (e.g. Rogge & Reichardt 2016; Lanahan & Feldman, 2015; Howlett & del Rio, 2015; Flanagan et al. 2011). Rogge and Reichardt (2016, p. 1625) highlight that understanding the nature of the relationship between different instruments is important because it can allow policymakers to “avoid negative interactions and to strive for positive or complementary interaction outcomes”. This can improve the effectiveness of the innovation policy instrument mix in stimulating firm-level innovation (Flanagan & Uyarra 2016; OECD 2018).

Complementarity between different instruments can be conceived of in a static sense, as the combination of instruments a firm receives at a point in time, and in a dynamic sense, as interactions between different instruments a firm receives through time (Rogge & Reichardt 2016; Schmidt & Sewerin 2018). Flanagan et al. (2011, p. 710) note that it is unlikely that “complementarities in practice can be achieved by the simple accumulation of instrument after instrument … [because] theoretically complementary instruments may begin to interact in negative or contradictory ways if layered one upon the other”. Therefore, theory suggests that the temporal dynamics of the instrument mix can play a key role in driving the effectiveness of the mix at stimulating firm-level innovation (Howlett 2017; Kern & Rogge 2016; Sovacool 2016).

Despite these theoretical developments, the policy mix concept has proven difficult to operationalise empirically at the firm level (Howlett & del Rio 2015; Rogge & Schleich 2018). Notwithstanding the increased importance of policy mix theory within the literature, Schmidt and Sewerin (2018, p. 1) argue that “the debate about policy mixes has reached an impasse” due to lack of empirical research applying the policy mix concept. This mismatch between policy mix theory and empirical practice is the precise issue this thesis addresses.
To help bridge the gap between theory and empirics noted above, this thesis makes three contributions. Firstly, it develops a novel conceptual framework that is presented in Chapter 3. To be commensurate with theory, this framework has at its core the identification of static and dynamic complementarity between different instruments. The framework is introduced in Section 1.2 below, while the theory underpinning it is detailed in Chapters 2 and 3. Secondly, the study applies a novel empirical strategy to directly test for complementarity and substitution between innovation policy instruments (presented in Section 1.3 below, and detailed in Chapter 4). Thirdly, the analysis constructs three unique panel datasets through a series of data merges. Outlined in Section 1.4 below (with a complete description provided in Chapter 4) these datasets capture detailed information on the source and type of innovation policy instruments firms in Ireland received each year from 2007 to 2014. Section 1.5 provides a rationale for the research, followed by a statement of the research objectives in Section 1.6. The contributions of the research are presented in Section 1.7, alongside an outline of the structure of the thesis, while Section 1.8 concludes the first chapter and introduces the review of the pertinent literature.

1.2. Complementarity in the innovation policy instrument mix

As noted in the previous section, a number of authors have argued that the development of policy mix research has been hindered by the lack of empirical analysis (Howlett & del Rio 2015; Rogge & Schleich 2018; Schmidt & Sewerin 2018). Therefore, this study adopts a novel empirical strategy to evaluate whether different innovation policy instruments are complements or substitutes in terms of their impact on firm-level innovation. The primary objective of this evaluation is to test whether firms that receive two distinct innovation policy instruments benefit more than firms that receive the same instruments separately. Figure 1.1 provides an illustrative example of the empirical strategy that this study employs to achieve this objective.
As Milgrom and Roberts (1990) note, the term *complementarity* can have a diverse range of meanings in economics. Following Milgrom and Roberts (1990, p. 514), this study defines complementarity as “a relation among groups of activities … [where] if the levels of any subset of the activities are increased, then the marginal return to increases in any or all of the remaining activities rises”. The concept of complementarity has been applied broadly in innovation studies to test whether firms that undertake two distinct forms of innovation activity benefit more than firms that undertake the same forms of innovation activities separately, such as internal and external knowledge sourcing (e.g. Love & Roper 2009; Schmiedeberg 2008; Cassiman & Veugelers 2006) or different forms of innovation such as product, process and organisational innovation (e.g. Doran 2012; Ballot et al. 2015).

---

3 Milgrom and Roberts (1990, p. 516) also use the term “supermodularity” as equivalent to complementarity. However, in a strict sense, supermodularity only occurs when undertaking two activities generates a larger return than performing the activities separately (e.g. Mohnen & Röller 2005). As detailed in Chapter 4, Section 4.2.1, this thesis applies strict tests for supermodularity and submodularity (i.e. substitution).
This study focuses on the identification of complementarity between different innovation policy instruments. Essentially, as Figure 1.1 shows, this study tests whether the benefit derived from the concurrent combination of two different innovation policy instruments is greater than the sum of its parts. To the best of the author’s knowledge, this is the first study to directly test for complementarity between different innovation policy instruments. In the context of recent theoretical developments, this is an important methodological contribution to the field of innovation policy evaluation.

As detailed in Chapter 3, the empirical literature that evaluates the impact of innovation policy instrument mix on firm-level innovation uses a variety of propensity score matching (PSM) models (e.g. Czarnitzki & Lopes-Bento 2014; Guerzoni & Raiteri 2015; Radas et al. 2015). Based on the results of these models, previous studies have inferred complementarity between different instruments based on whether the magnitude and statistical significance of regression coefficients for instrument mix variables is greater than that of variables representing individual instruments. However, by directly testing for complementarity, this study builds on the foundational studies referred to above so as to provide a clearer picture of the effectiveness of innovation policy instrument mix at stimulating firm-level innovation. This direct test requires the use of a recently developed instrumental variable model (Lewbel 2012; 2018) that is outlined in Section 1.3 and described in detail in Chapter 4.

While testing for complementarity in the innovation policy instrument mix is important, the notion of complementarity heretofore discussed is inherently static, involving the combination of two innovation policy instruments at the same point in time. Recently, Love et al. (2014, p. 1774) highlight that “[t]wo discrete activities are (Edgeworth) complementary if adding one activity increases the returns from doing the other”. This understanding of complementarity “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” (Love
et al. 2014, p. 1774). As noted, policy mix theory places a crucial emphasis on the temporal dynamics of an innovation policy instrument mix in terms of its eventual impact on firm-level innovation (e.g. Rogge & Reichardt 2016). Therefore, applying Love et al.'s (2014) definition, this study tests for both static and dynamic complementarity. Ceteris paribus, Figure 1.2 summarises the conceptualisation of temporal dynamics in the innovation policy instrument mix used in this study.

**Figure 1.2** Temporal dynamics in the innovation policy instrument mix

In Figure 1.2, Instrument B is added to both *Firm i* and *Firm j* in *time period* t (i.e. the current period). The key difference is that *Firm i* is transitioning from receiving *Instrument A* in the last time period (i.e. time period t-1) to receiving an innovation policy instrument mix comprised of *Instrument A* and *Instrument B* in the current period (i.e. time period t). In contrast, *Firm j* transitions from receiving no instrument in the previous period to receiving *Instrument B* in the current period. If the impact of transitioning from *Instrument A* to a mix comprised of *A* and *B* on firm-level innovation is greater than the impact of transitioning from no instrument to *Instrument B*, then there is a dynamic complementary relationship between *Instrument A* and *B* through time. Therefore, the identification of temporal dynamics through
empirical analysis has the potential to aid policymakers. This form of analysis could go some way towards identifying effective ways to implement innovation policy instruments over time.

1.2.1. Behavioural and Resource Based Foundations of Policy Effects and Complementarity

It is important to discuss how complementary or substitutive relationships may arise between different innovation policy instruments. In essence, this thesis considers three distinct forms of innovation policy instrument: 1) direct support, such as R&D grants; 2) indirect support, such as R&D tax credits; and 3) systemic support, such as incentivised collaborations between firms and public research centres. This section introduces the somewhat different intra-firm mechanisms through which each different form of innovation policy instrument operates (if effective) to impact firm-level innovation, considering signalling effects, liquidity effects, behavioural effects and qualitative influences from R&D/innovation support, while Chapter 2, Section 2.5, considers each instrument in much greater detail.

Lerner (1999; 2002) argues that the receipt of public funding certifies the quality of a firm to the external business environment. Recipients of public R&D/innovation support can then leverage this quality signal to gain additional external capital, as well as attract high quality human capital. Using a sample of indigenous Irish firms, Hart & Lenihan (2006) demonstrate that there is a positive externality associated with receiving public sector equity finance, in that it enables firms to raise additional funds from private sector sources. Unlike R&D tax credits which a firm can claim automatically on any eligible R&D investments, receiving direct innovation policy instruments such as R&D grants can have signalling effects (Kleer 2010), given that they are usually awarded on the basis of a competitive application process (Colombo et al. 2011). Firms that have been successful in obtaining public funding have been through a process of due diligence, which, as Hart & Lenihan (2006, p. 340) note, “serves as an important signal to other potential investors by reducing the level of perceived risk associated with the
investment”. In a similar way, participation in research collaborations with public research centres can act as a quality signal about the firm to the market (Scandura 2016). Therefore, the signalling effects of receiving public R&D/innovation support can be leveraged by firms to gain other sources of capital to fund their R&D/innovation activities.

Liquidity constraints often represent a major barrier to firm investment in R&D (Czarnitzki & Hottenrott 2011; Sasidharan et al. 2015). Mohnen (2017) has recently highlighted that R&D tax credits act as an important policy instrument that lowers this constraint for firms. In addition, Brown et al. (2011) demonstrate that firms usually try to smooth their R&D investment schedule through time, and one crucial means of achieving this is the use of external equity finance. Therefore, it may be argued that complementarity could a priori be expected between R&D tax credits and direct/systemic forms of innovation policy instruments. While R&D tax credits allow firms to plan their R&D investments by directly reducing financial constraints, receiving direct/systemic innovation policy instruments provides a quality signal that enables firms to access equity finance. In this way, receiving a combination of indirect and direct/systemic instruments may reinforce the impact of both instruments. This may in turn foster higher levels of R&D intensity than would have been achieved if the firm had received only one instrument.

In addition to the liquidity and signalling effects of innovation policy instruments, receiving public funding for innovation can also have important behavioural effects (Georghiou 2002). Gök & Edler (2012) note that receiving public R&D/innovation support can have intra-firm learning effects that occur in the short term which manifest into increased R&D investment and innovation output in the longer term. With respect to the behavioural effects of public R&D/innovation support, Clarysse et al. (2009, p. 1518) highlight that the role of innovation policy instruments is usually “not to alter a stop-go decision by the firm in respect of the project, but rather to modify the manner in which the project was carried out”. Chapman et al. (2018)
highlight that receiving direct R&D subsidies increases the number of partners with which firms collaborate, which acts as important sources of knowledge in firm R&D and innovation activities. In terms of complementarities within the mix of innovation policy instruments, Neicu et al. (2015) note that (relative to firms receiving an R&D tax credit alone) when firms receive an R&D grant in addition to an R&D tax credit they shift their R&D investments to become more research intensive. Receiving innovation policy instruments can have important qualitative influences on the type of R&D/innovation project that firms engage in (Rosenberg 1990). Firms can leverage the learning effects induced by one innovation policy instrument, and augment their R&D investments using other sources of R&D/innovation support (Neicu et al. 2015).

Having briefly discussed the conceptual underpinnings of static and dynamic complementarity as applied to the innovation instrument mix (which is developed further in Chapters 3 and 4), as well as how complementarities arise between different innovation policy instruments based on the mechanisms through which each individual instrument influences firm-level innovation (discussed in Chapter 2), the next section outlines the precise econometric analysis required for such an evaluation.

1.3. Econometric Model

The empirical strategy described in Section 1.2 is operationalised through the econometric estimation of an innovation production function (Griliches 1979; 1995; Geroski 1990; Love & Roper 1999; Roper et al. 2008) and subsequent tests for supermodularity (complementarity) and submodularity (substitutability) between innovation policy instruments (Mohnen & Röller 2005). The innovation production function was estimated using a recently developed form of instrumental variable model (Lewbel 2012; 2018). This sophisticated econometric method uses so-called generated instrumental variables to control for potential selection bias and endogeneity.
1.3.1. Sources of Selection Bias

As highlighted by Czarnitzki & Lopes-Bento (2013, p. 78), “neither the fact of applying, nor the fact of receiving a public subsidy can be viewed as random”. Rather, firms must apply for public support for their R&D and innovation activities, and, in many cases (e.g. competitively awarded grants), as noted by Busom et al. (2014) funding agencies will decide which firms receive support on the merits of a funding proposal relative to policy objectives. Funding agencies may target encouraging R&D in small firms due to the high fixed cost of R&D investment and inefficiencies in capital markets that are particularly acute for smaller firms (Busom 2000). Alternatively, policymakers may specify that funding be allocated to firms in specific research fields that the government has designated as high importance to the national economy, or where there is a large gap between the private and social returns to investment (Klette & Mohnen 2012; Busom et al. 2015). However, both Cantner & Köster (2012) and Antonelli & Crespi (2013) demonstrate that public funding for R&D and innovation is often allocated to films on the basis of a picking-the-winners strategy by funding agencies. David et al. (2000) note that funding agencies may be under pressure to achieve short term success with the R&D/innovation funding they allocate to firms, and may thus prioritise projects with a high expected rate of return. Cantner & Köster (2012) have pointed out that this strategy can shift the focus of funding agencies away from correcting “malfunctions in markets and systems or funding marginal projects”, and may thus lead to firms substituting public funding for their own private investment.

Therefore, the allocation of innovation policy instruments is characterised by selection bias. Due to this issue, there is likely to be systematic differences in the firms that receive innovation policy instruments and firms that do not. Hall & Maffioli (2008) demonstrate that, as a result of selection bias, a simple comparison on the average differences in innovation outcomes for recipients of public funding for innovation and non-recipient firms may produce misleading
results regarding the effectiveness of public funding. Therefore, appropriate econometric methods must be applied to correct for the issue of selection bias when evaluating the impact of innovation policy instruments on firm-level innovation (see e.g. David et al. 2000).

1.3.2. Sources of Endogeneity

Similar to the issue of selection bias, estimates from a linear regression model considering the receipt of public support for R&D/innovation as an exogenous variable are likely to be biased. Firms that receive the public R&D/innovation support may differ systematically in several characteristics from non-recipients. Actual recipients may have higher absorptive capacity (Clarysse et al. 2009), and thus a greater ability to recognise, assimilate and exploit knowledge through innovation. Recipient firms may also be active in sectors of the economy with a higher “technological opportunity set” (David et al. 2000, p. 509), and thus a higher premium on R&D/innovation. In addition, recipients of public R&D/innovation support may have been more successful in their innovation activities in the past, which suggests they may be more productive with public R&D/innovation support in the present (Czarnitzki & Lopes-Bento 2013).

Due to their inherent characteristics and past performance, even in the hypothetical situation of the absence of any innovation policy instruments, actual recipients are likely to be more innovative than the non-recipients (Georghiou 2002). In addition, and for the same reasons, the former group may also have been more likely than the latter to apply for innovation policy instruments (Busom 2000). Thus, the comparison of recipients and non-recipients is likely to produce biased estimates of the impact of innovation policy instruments on firm-level innovation. Instead, the use of innovation policy instruments has to be considered as an endogenous variable (David et al. 2000; Czarnitzki et al. 2011). To correct for this endogeneity issue, appropriate econometric methods must be applied when evaluating the impact of innovation policy instruments on firm-level innovation.
Therefore, both selection bias and endogeneity must be controlled for in empirical analysis. As noted, PSM models are commonly used in the empirical literature, primarily because they control for these issues. However, as recently highlighted by Papalia et al. (2018), PSM models do not facilitate direct tests for strict complementarity and substitution, and therefore cannot be used to address this study’s primary objective (Mohnen & Röller 2005).

While traditional instrumental variable models control for selection bias and endogeneity, Love et al. (2014, p. 1779) highlight that “this approach has generally proved unsuccessful [in testing for complementarity and substitution] … when highly specific microeconomic datasets are used”. This is important for innovation policy instrument evaluation because available datasets typically lack obvious instrumental variables for receiving an innovation policy instrument (for a discussion, see Aerts & Schmidt 2008). Unless strong and valid instrumental variables are available in the data, attempting traditional forms of instrumental variable estimation may introduce further econometric bias (i.e. in addition to selection bias and endogeneity) and can thus be counterproductive (Love et al. 2014; Mohnen & Röller 2005; Cassiman & Veugelers 2006).

This study overcomes this issue by employing Lewbel’s (2012; 2018) instrumental variable model, which generates strong and valid instrumental variables based on the econometric model’s heteroscedasticity. This econometric model is particularly useful because it enables direct testing for complementarity and substitution between different innovation policy instruments, while controlling for selection bias and endogeneity. In addition, recent studies have found that Lewbel’s (2012; 2018) instrumental variable model produces results that are consistent with other econometric models such as PSM (Czarnitzki et al. 2018; Heim et al. 2017; Liu et al. 2016). Therefore, the estimator is consistent with the most commonly used
estimator in innovation policy instrument evaluations, and provides the added benefit of enabling direct testing for strict complementarity (supermodularity) and substitution (submodularity).

1.4. Empirical setting and data merges

Applying the conceptual framework and empirical strategy discussed above requires a comprehensive dataset that captures detailed information on the innovation policy instruments firms receive over time. However, Rogge and Reichardt (2016, p. 1631) suggest that accessing data with sufficient detail on the innovation policy instruments firms actually receive may pose “the greatest analytical challenge” for empirical research. Indeed, as detailed in Chapters 2 and 3, only cross-sectional datasets with limited information on the innovation policy instruments firms receive have been available to the vast majority of previous studies. Therefore, this study constructs three unique datasets by drawing on multiple administrative data sources. This section introduces the empirical setting for this research and describes how the datasets were constructed (this issue is returned to in much detail later in Chapter 4).

Ireland serves as the locale for this study, and Section 1.4.1 provides some insights into the innovation policy landscape in Ireland (further detail is provided in Chapter 4). Particular focus is placed on Ireland’s three key national funding agencies: Enterprise Ireland, Industrial Development Agency\(^4\) (IDA) Ireland and Science Foundation Ireland (SFI). Together with the R&D tax credit, these three agencies represent the key sources of public funding for innovation in Ireland (DBEI 2018; Department of Finance 2016). Following this, Section 1.4.2 introduces the datasets used and Section 1.4.3 discusses the merging process.

\(^4\) The 1993 Industrial Development Act dissolved the Industrial Development Authority and established the Industrial Development Agency (S.I. No. 19 of 1993). The term Industrial Development Agency is used throughout this thesis.
1.4.1. Empirical setting: Ireland

In Ireland, the two national funding agencies that support the development and growth of firms are Enterprise Ireland and IDA Ireland. Enterprise Ireland support indigenous, Irish-owned firms with a suite of funding programmes aimed at helping them start, grow and innovate, with the end goal being to increase firms' competitiveness in export markets (Enterprise Ireland 2017). Enterprise Ireland-supported firms are typically Small and Medium Sized Enterprises (SMEs)\(^5\). Given that SMEs comprise 99.80% of all firms in Ireland (CSO 2018), Enterprise Ireland has a large and diverse range of client companies.

In contrast to Enterprise Ireland, IDA Ireland’s remit is to bring Foreign Direct Investment (FDI) into Ireland (IDA Ireland 2017). Therefore, IDA Ireland solely targets foreign-owned, Multinational Enterprises (MNEs), which comprise both large firms and SMEs (IDA Ireland 2017). Although MNEs constitute just 1.34% of all firms in Ireland (i.e. SMEs and large firms), they account for 22.25% of total employment (CSO 2018). Therefore, although IDA Ireland’s client base of firms is significantly smaller than that of Enterprise Ireland, the agency performs a very important role in Ireland’s industrial policy landscape. While these two funding agencies support a range of enterprise development functions (e.g. training, capital investment, export growth), in 2017 approximately 30% of total expenditure for Enterprise Ireland and 37% for IDA Ireland was directed at supporting firms’ R&D and innovation activities (DBEI 2018; Enterprise Ireland 2018; IDA Ireland 2018), which is the focus of this study.

The third key funding agency in Ireland is SFI. Unlike Enterprise Ireland or IDA Ireland, SFI’s remit is not to directly fund firms’ R&D and innovation activities. Rather, it is to invest in scientific researchers based at Higher Education Institutions (HEIs) in Ireland (SFI 2012; 2018). However, firms can participate in co-funded projects with SFI research centres based in

---

\(^5\) Eurostat defines SMEs as firms with 1-249 persons employed, while large firms are defined as firms with 250 or more persons employed.
HEIs, which are designed to incentivise academic-industry collaborations oriented to applications that industry needs (SFI 2010; DBEI 2014). Although SFI has a somewhat different remit to Enterprise Ireland and IDA Ireland, as noted by the Chief Scientific Adviser to the Government of Ireland (2016), it can still be considered a key source of innovation policy instruments for firms (see also DBEI 2014; 2018; SFI 2014; 2018; Indecon 2017). Therefore, it is important to include SFI in this study.

In addition to support offered by Enterprise Ireland, IDA Ireland and SFI, firms in Ireland can avail themselves of the R&D tax credit, which was launched in 2004 and is administered by the Revenue Commissioners (Revenue Commissioners 2015). As noted by the Department of Finance (2013; 2014; 2016) and the OECD (2014; 2015) the R&D tax credit is the most prominent innovation policy instrument in Ireland. In 2014, the cost of the scheme was €553 million and approximately 1,600 firms availed themselves of it (Comptroller and Auditor General 2016). To put the scale of the R&D tax credit in perspective, it equates to circa 90% of the combined total expenditure of Enterprise Ireland, IDA Ireland and SFI (Enterprise Ireland 2014; IDA Ireland 2014; SFI 2014), and 75% of the public expenditure on R&D by all government departments and agencies (DBEI 2018). To perform a comprehensive evaluation of the innovation policy instrument mix in Ireland, this study must capture innovation supports available to firms from Enterprise Ireland, IDA Ireland and SFI, in addition to the R&D tax credit. Section 1.4.2 introduces the datasets used in this study, and Section 1.4.3 introduces the data merges that were carried out. A more detailed discussion and analysis of both of these issues is provided in Chapter 4.

1.4.2. Description of datasets

This study draws on four distinct sources of data to capture as complete as possible a set of innovation policy instruments available to firms in Ireland from the national government. The first is the Annual Business Survey of Economic Impact (ABSEI), which is collected by the
Department of Business, Enterprise and Innovation (DBEI). ABSEI serves as the *master* dataset for all the empirical research conducted in this study. Thus, as outlined in Section 1.4.3 and detailed in Chapter 4, all other datasets are merged into ABSEI.

ABSEI records two crucial pieces of information that are required to evaluate the innovation policy instrument mix in Ireland. Firstly, it captures a binary measure indicating whether firms received an R&D tax credit each year. Due to the importance of the R&D tax credit in Ireland, any evaluation would be fundamentally incomplete without this information. Secondly, ABSEI records firms’ annual total R&D expenditure, which can be used as a proxy for firm-level innovation (for a recent discussion, see Baumann & Kritikos 2016). In the analysis, a firm’s R&D expenditure is divided by its number of employees to create R&D intensity. R&D is an important input into the innovation process and is frequently used in the literature as an innovation outcome variable (see e.g. Busom 2000; Almus & Czarnitzki 2003; Cerulli & Poti 2012; Czarnitzki & Lopes-Bento 2013; 2014; Aristei et al. 2017). As Section 1.5 and Chapter 4 detail, increasing firms’ R&D investments is a key innovation policy focus in Ireland (DBEI 2015a; 2018). Therefore, in this study, firm-level innovation is defined as firms’ R&D intensity.

The other three data sources come from the administrative records of Ireland’s three key national funding agencies, Enterprise Ireland, IDA Ireland and SFI. In the case of Enterprise Ireland and IDA Ireland, these administrative datasets record each year firms received any form of R&D/innovation funding. In the case of SFI, the administrative data record the start and end dates for firms that engaged in co-funded research projects with SFI research centres. Each administrative dataset is a census, capturing the full population of the firms that received

---

6 On 26 June 2017, the Irish government changed the name of the Department of Jobs, Enterprise and Innovation (DJEI) to the Department of Business, Enterprise and Innovation (DBEI) (S.I. No. 364 of 2017). The acronym “DBEI” is used throughout this thesis.
While these three administrative datasets capture key information on the innovation policy instruments firms receive, they are not collected with impact evaluation in mind. Rather, their primary function is to record what funding programmes firms participated in and what payments firms received each year. As such, none of the three datasets includes any measure of firm-level innovation. In addition, each dataset records information only on firms that received support. This means that each dataset lacks a control group of firms that received no support to test against. In contrast, ABSEI captures information on firms’ R&D expenditure, which is a commonly used proxy for firm-level innovation. In addition, ABSEI captures information on firms that receive no innovation policy instruments, which can be used as a control group.

### 1.4.3. Merging datasets

Given that Enterprise Ireland supports Irish-owned firms and IDA Ireland supports foreign-owned firms based in Ireland, no firm will ever receive support from both agencies at the same time. In addition, there is almost no overlap between the firms receiving Enterprise Ireland/IDA Ireland support and SFI support⁷ (see Chapter 4). In contrast, firms frequently receive R&D tax credits in addition to support from the three national funding agencies (Indecon 2017; DBEI 2018). Therefore, this study tests for pairwise complementarity between three distinct and mutually exclusive combinations of instruments: 1) R&D tax credit and Enterprise Ireland support; 2) R&D tax credit and IDA Ireland support; and 3) R&D tax credit and SFI linkages. Each of these distinct instrument combinations is mutually exclusive. Therefore, three final datasets are created.

---

⁷ This was confirmed in a discussion with a policymaker in the Department of Business, Enterprise and Innovation’s Science Foundation Ireland Liaison Unit on 12 November 2018.
ABSEI is the master dataset for this study, and each of the three administrative datasets is merged into ABSEI separately to construct the three final datasets. Therefore, the full ABSEI dataset and the part of each administrative dataset that overlaps with ABSEI are usable for the empirical analysis. Firms recorded in the three datasets but not in ABSEI are not usable. The three final panel datasets each contain 16,084 observations of 3,098 firms from 2007-2014, with approximately 2,000 observations in each year of the survey. The panel is unbalanced because not every firm returns a completed survey in every year. However, approximately 50% of the sample is observed every year. These data merges are possible because firms in ABSEI are recorded with the same unique identifier numbers as firms in the Enterprise Ireland, IDA Ireland and SFI administrative datasets, rendering them usable for impact evaluation.

It is important to note that this research uses binary measures indicating each year firms received any financial support for R&D/innovation from Enterprise Ireland or IDA Ireland or had a linkage with SFI. In this way, the innovation policy instruments firms receive from the each funding agency are aggregated into three binary variables. Consequently, this study does not test for complementarity between the R&D tax credit and each individual innovation policy instrument available to firms from Enterprise Ireland, IDA Ireland and SFI. Rather, it tests for complementarity between the R&D tax credit and binary, aggregate measures of R&D/innovation support from the three key sources of funding in Ireland. The decision to measure the innovation policy instrument variables in this way is discussed in detail in Chapter 4.

In addition, the panel nature of the three datasets allows testing for both the contemporaneous and lagged impact of the innovation policy instrument mix on firm-level innovation. Following Keiser and Kuhn (2012), four different lag structures are used. Contemporaneous impact is defined as the effect of the innovation policy instrument(s) a firm receives in the current time period on R&D intensity in the same time period (i.e. no lag). The three lag structured models
estimate the impact of the instrument(s) a firm received one year ago, two years ago and three years ago (i.e. one, two and three lags) on the firm’s R&D intensity in the current period. This is important because, as detailed in Chapter 2, the impact of innovation policy instrument(s) can take time to manifest and can have long-term effects (Hall et al. 1986; Roper & Hewitt-Dundas 2012). However, as Cunningham et al. (2016) highlight, the literature provides very little evidence on the longer term impact of public funding for innovation, primarily because the data available to previous studies was cross-sectional in nature (see also Zúñiga-Vicente et al. 2014). In contrast, the annual panel data available to this study facilitates the estimation of several precise lag structured models, which build on the findings of previous research.

This chapter has provided an overview of the theoretical underpinnings of this thesis and the research question it addresses. In addition, the empirical strategy employed and the data used have been described. Section 1.5 offers a concise outline of the rationale for the research, followed by a discussion of the research objectives.

1.5. Rationale for the research

The importance of firm-level innovation for national competitiveness and economic growth is well established in the literature. Innovation policy, as operationalised by a mix of innovation policy instruments, can play an important role in driving firm-level innovation. Therefore, achieving a more complete understanding of how the innovation policy instrument mix influences firm-level innovation is the underlying rationale for this study.

Maximising the effectiveness of the innovation policy instruments available to firms is particularly important in the case of Ireland, the empirical setting for this research. A small open economy on the periphery of Europe, Ireland has sustained a policy focus on R&D and innovation as a means of achieving competitiveness and sustainable economic growth (see e.g. Irish Government 1963; National Board for Science and Technology 1980; Culliton 1992;
However, government budget allocations for R&D fell by 18% in the years following the 2008 financial crisis (DBEI 2017, p. 4). The European Commission has warned that Ireland risks permanently damaging its competitiveness if this trend continues (European Commission 2016a).

Innovation 2020, the Irish government’s five-year innovation strategy, has set an ambitious goal of transforming Ireland into a “Global Innovation Leader driving a strong sustainable economy and a better society” (DBEI 2015b, p. 6). However, figures from Eurostat demonstrate that Ireland’s gross expenditure on R&D currently accounts for only 1.20% of its gross domestic product (GDP), significantly lower than the European Union average of 2.03% (Eurostat 2017). Therefore, developing a sound evidence base to inform R&D and innovation funding policy decisions is urgent in Ireland. This study aims to assist in the development of this evidence base by taking key insights from policy mix theory and applying them empirically. While particularly important in the context of Ireland, these insights are helpful to similar debates occurring internationally in both academic and policymaking circles. Following the discussion on the rationale for the current research, Section 1.6 describes the study’s research objectives.

1.6. Research objectives

This study poses one key research question: Are different innovation policy instruments complements or substitutes? While the theory underpinning this research question is presented in the subsequent chapters of the thesis, the research objectives of this study can be summarised as follows:

- To construct a conceptual framework that bridges the gap between policy mix theory and empirical practice to enhance the capacity of academics and policymakers to evaluate the impact of innovation policy instruments on firm-level innovation;
• To construct a unique dataset for testing whether different innovation policy instruments are complements or substitutes, both at a point in time (i.e. static complementarity and substitution) and through time (i.e. dynamic complementarity and substitution);

• To empirically estimate whether a complementary or substitutive relationship exists between different innovation policy instruments in terms of their impact on firm-level innovation.

To achieve these objectives, Chapters 2 and 3 present the theory underpinning the research. These theoretical underpinnings help develop a conceptual framework and formulate two hypotheses that are presented in Chapter 3. Section 1.7 alludes to the contributions to knowledge emanating from the findings of this study.

1.7. Contributions of the current research

Using Ireland as a laboratory in which to test the research question, the study builds on earlier evaluations of the impact of public funding on firm-level innovation. In addressing the research question, this study makes a number of contributions to the knowledge base.

○ Theoretical contributions

• The study develops a novel conceptual framework that distils key insights from policy mix theory into a usable format for evaluating the impact of innovation policy instrument mix on firm-level innovation.

• While embracing more traditional models for evaluating the impact of public funding for innovation, the framework of this thesis places the identification of complementarity and substitution between different innovation policy instruments at its core.

• In the conceptual framework, complementarity and substitution between different instruments is conceived of as static (i.e. the combination of instruments a firm receives
at a point in time) and dynamic (i.e. how the instruments a firm received previously interact with the instruments the firm currently receives).

- **Methodological contributions**
  - This research creates three unique panel datasets, capturing a comprehensive set of innovation policy instruments available to firms in Ireland from the national government. Each dataset is constructed by merging one large-scale survey with three administrative datasets drawn from Ireland’s three key national funding agencies. Each dataset is large and covers a comprehensive portion of the Irish economy that engages with the innovation policy system.
  - The data merges are designed to capture the three key innovation policy instrument mixes available to firms in Ireland: 1) R&D tax credit and Enterprise Ireland support; 2) R&D tax credit and IDA Ireland support; and 3) R&D tax credit and SFI linkages. Each innovation policy instrument mix is mutually exclusive. Therefore, this study tests for pair-wise complementarity between each combination.
  - Whereas previous studies have relied on inference, this research performs direct tests for strict complementarity and substitution between innovation policy instruments. A sophisticated econometric method is employed to control for the selection bias and endogeneity associated with innovation policy instruments. Using this econometric method enables the study to deal with these issues in a more robust way than was available to most previous studies that test for strict complementarity and substitution.

- **Empirical contributions**
  - Results from the econometric analysis show the effects of different innovation policy instrument mixes on firm-level innovation. These results provide evidence that some
instruments have a complementary relationship, while other instruments have a substitutive relationship when firms receive a mix.

- The temporal dynamics of the innovation policy instrument mix are shown to be important. The innovation policy instrument(s) firms received in the past are found to influence the impact of the instruments firms receive in the current time period.
- Using a variety of lag structures in different models offers some insights on how long it takes for the impact of some innovation policy instrument(s) to materialise and how persistent this impact is over time.

- **Potential policy contributions**
  - Given the important role firms’ R&D expenditure plays in both the Irish (Georghiou et al. 2017) and wider European innovation ecosystems (European Commission, 2017a), this study offers insights that are potentially important for building comprehensive evidence for policymakers to inform funding policy decisions.
  - This evidence base could facilitate greater accountability of how public money is spent to support firms’ R&D activities, which may help ensure value for investment is achieved.
  - The empirical findings of this study may play a role in fostering policy improvement by alerting policymakers to the presence of more or less effective options when implementing innovation policy instruments. This may help policymakers prioritise particularly effective mixes in a given context.

In the context of these contributions to knowledge, and to answer the research question, this study is structured into five sequential phases, each of which builds on the previous one. Figure 1.3 depicts the structure of this thesis, while Section 1.8 concludes the introduction.
1.8. Conclusion

Substantial literature highlights the importance of firm-level innovation for economic growth and the role public funding plays in driving firms’ innovation performance. More recently, the concept of policy mix has gained prominence within this literature as a means of making innovation policy more effective. An armoury of different innovation policy instruments is available to policymakers that are designed to stimulate firm-level innovation. However, adding new innovation policy instruments to the mix that firms receive will not necessarily be beneficial, and may in fact end up having an “ineffective or even harmful” impact on firms’ innovation performance (Gök 2016, p. 404). This is an important issue for policymakers, because the literature currently does not provide clear guidance on whether different innovation policy instruments tend to reinforce or undermine one another’s impact.

Despite the growth in interest, the field of innovation policy evaluation has yet to distil the insights from policy mix theory into a conceptual framework that is usable for impact evaluation. The policy mix concept has proven difficult to operationalise empirically, leading to a mismatch between theory and empirics. This thesis addresses this issue by building on the literature to create a novel conceptual framework that is usable for innovation policy instrument mix impact evaluation. At the heart of this framework are the notions of complementarity and substitution between different innovation policy instruments, as well as an understanding of how these relationships unfold through time. Theory suggests that these issues are key to understanding the innovation policy instrument mix, but they currently tend to be absent from firm-level evaluations.

To apply the conceptual framework, this study constructs three novel datasets through a series of data merges. These datasets capture the key innovation policy instruments available to firms in Ireland and thus facilitate a comprehensive evaluation of the innovation policy instrument mix. Constructed specifically to address the identified theoretical issues, these datasets
represent an improvement on the data available to previous studies. Therefore, while Lenihan and Hart (2004) draw attention to the fact that policy evaluation can never be an exact science, the current research represents a useful step forward in the field of innovation policy evaluation.

This chapter provided an overview of the key concepts and the empirical setting for the research and the method and data used. In addition, the chapter posed the research question that guides the study, the rationale for the research and key research objectives. The chapter also highlighted that the findings not only contribute to the academic literature by providing a valuable addition to the current debate about the role of innovation policy in driving firm-level innovation, but also the findings have the potential to provide helpful insights in the realm of innovation policy and specifically the evaluation of same. To establish the theoretical backdrop for the study, Chapter 2 reviews the literature on innovation policy evaluation. Chapter 3 reviews the literature on the innovation policy instrument mix. Both chapters will draw on theoretical and empirical literature to provide a firm foundation for the empirical analysis described in Chapter 4.
Figure 1.3 Structure of the thesis chapters.

- Chapter 1: Introduction
- Chapter 2: A survey of the literature on innovation policy instrument evaluation
- Chapter 3: The innovation policy instrument mix
- Chapter 4: Methodology and data
- Chapter 5: The impact of innovation policy instrument mix on firms' R&D intensity: Empirical findings for Ireland
- Chapter 6: Conclusion
Chapter 2: A survey of the literature on innovation policy instrument evaluation

2.1. Introduction

This chapter provides the theoretical foundations for the current research by reviewing literature pertaining to firm-level innovation. In order to evaluate the impact of innovation policy (as operationalised by innovation policy instruments) on firm-level innovation, it is important to begin by establishing the theoretical underpinnings for such an analysis.

Given the large body of research related to innovation, this chapter first discusses the foundational theories of firm-level innovation and how these theories have shaped contemporary understandings of innovation (Section 2.2). This places the current research in context with the wider literature. Building on this discussion and analysis, the chapter turns to current debates about the rationale for innovation policy intervention (Section 2.3). Drawing on neo-classical and systemic theories of innovation, this discussion focuses on the two dominant theoretical rationales, market failure and systemic failure (Section 2.4).

Following this analysis of the justification for innovation policy, the chapter then reviews both the theoretical and empirical literature on the practice of the evaluation of public funding for innovation (Section 2.5). This section details the different forms public funding for firm-level innovation can take. It focuses on direct innovation policy instruments (such as R&D grants), indirect innovation policy instruments (such as R&D tax credits) and systemic innovation policy instruments (such as incentivised firm-university collaborations). The section provides a detailed outline of how these types of instruments are designed to impact firm-level innovation through different mechanisms, which will inform the empirical analysis in Chapter 5.
Section 2.6 concluded the chapter by summarising the key issues discussed. Drawing on these vital themes in the literature pertaining to firm-level innovation, the section highlights the almost exhaustive focus in existing studies on single innovation policy instrument evaluations, and the potential limitations this entails. The section closes by introducing the basis for a more encompassing form of impact evaluation which investigates how interactions between different innovation policy instruments firms receive may influence innovation outcomes (the to which Chapter 3 then turns).

2.2. **Schumpeterian theories of innovation**

Modern theories of innovation, and the fundamental role that firms’ innovation activities play in how the economy and society function, stem from the path-breaking work of Joseph Schumpeter in the first half of the 20th century (McCraw 2007; Fagerberg 2018). In *The Theory of Economic Development*, Schumpeter (1934) presents the view that innovation is due to an economy constantly in flux. Schumpeter’s (1934) view of innovation in the economy comprises four sequential phases:

1) The constant entry of innovative small and young firms into the market;
2) The commercial application of new innovative ideas;
3) The displacement of large incumbent firms;
4) The establishment of a new technological regime with ‘new’ incumbents.

Following these four phases in a never-ending cycle, more new innovative firms enter the market to challenge the ‘new’ incumbents. This turbulent system of economic development through innovation in a competitive market, termed ‘creative destruction’, represents one of the most pervasive theories for how economic growth occurs (Freeman et al. 1982; Archibugi et al. 2013).
Under a system of creative destruction, firms may already have operated for some years before they begin innovating as a response to a market opportunity. Similarly, new innovative firms may appear in response to market opportunities. In Schumpeter’s earlier work (i.e. 1934), small and young firms function as the seedbed of innovation, displacing established firms and leading to economic development; or, as Schumpeter (1934, p. 68) put it: “in general it is not the owner of stage coaches who build railways”. Here, innovation is conceptualised as transformative for the economy, led by entrepreneurs establishing firms or applying new ideas in fiercely competitive new industries that may displace old industries.

Schumpeter (1934) did perceive a role (albeit limited) for large incumbent firms in the process of technological advancement. Describing how new firms drive the innovation process, Schumpeter (1934, p. 136) notes that “[t]he same is true if a new enterprise is started by a producer in the same industry and is connected with his previous production. This is by no means the rule; new enterprises are mostly founded by new men and the old businesses sink into insignificance”. The kernel of this idea—that large incumbent firms play a role in innovation processes—grew into the second major branch of Schumpeter’s later theorising on innovation. In contrast to his earlier (i.e. 1934) work, *Capitalism, Socialism, and Democracy* (Schumpeter 1942) develops the theory that large, established firms chiefly lead innovation by innovating continuously, but on a much more incremental basis. These incumbents have developed market power through innovation, and their competitive advantage lies in the constant development and amelioration of knowledge. In this regard, large incumbent firms function as among the most dynamic firms in the economy, sustaining constant innovation activities and investment as a means of survival.

Schumpeter’s later work (i.e. 1942) suggests that technological advancements emanate from the kind of in-house Research and Development (R&D) laboratories that only large incumbent firms can maintain (Schumpeter 1942). In addition, large firms can exploit economies of scale
in innovation activities, and consistently finance new R&D through existing profits or debt that small and young firms could not access (Schumpeter 1942). Schumpeter (1942, p. 88) also emphasises that processes of innovation are inherently risky: “[l]ong-range investing under rapidly changing conditions, especially under conditions that change or may change at any moment under the impact of new commodities and technologies, is like shooting at a target that is not only indistinct but moving—and moving jerkily at that”. Therefore, the market power that incumbent firms enjoy acts as a form of “insuring or hedging” against the inherent risk associated with innovation (Schumpeter 1942, p. 88).

The phenomenon of ‘creative accumulation’, the continuous incremental innovation leading firms to incumbency and market power, builds high barriers to entry for innovative non-incumbents (Bell & Pavitt 1993; Malerba & Orsenigo 1995; Pavitt 1999). Schumpeter’s (1942) later contributions to theory suggest that under a system of creative accumulation (as opposed to creative destruction), an oligopolistic market structure characterised by a concentration of large innovative incumbent firms may better serve innovation and its consequent economic development: “[a]s soon as we go into details and inquire into the individual items in which progress was most conspicuous, the trail leads not to the doors of those firms that work under conditions of comparatively free competition but precisely to the doors of the large concerns … a shocking suspicion dawns upon us that big business may have had more to do with creating that standard of life than with keeping it down” (Schumpeter 1942, p. 82).

These Schumpeterian models of innovation have come to frame the conceptualisation and understanding of innovation (McCraw 2007; Fagerberg 2018). Freeman et al. (1982) distinguish between these two divergent models of innovation in Schumpeter’s writing by characterising them as ‘Mark 1’, developed by the younger Schumpeter and emphasising the importance of creative destruction; and ‘Mark 2’, developed by the older Schumpeter and emphasising the importance of creative accumulation. More recently, Archibugi et al. (2013,
p. 303) synthesised these two models of innovation with Schumpeter’s (1939) theory on business cycles, noting that “economic cycles are the consequence of innovation, but also that innovative activities and innovative organisations are re-shaped by economic crises”. As the economy is growing steadily and the business cycle is trending up, innovation and technological change occur in the context of creative accumulation, where “cumulative learning processes and path-dependent patterns that are woven into organizational routines”, favour large, established firms that can engage in innovation continuously and use their market power to prevent new innovative firms from entering the market to compete (Archibugi et al. 2013, p. 303). On the other hand, during economic crises, the business cycle trending downward puts significant pressures on established firms, creating technological opportunities for non-incumbent firms to challenge incumbents’ market share, or create new markets through creative destruction (Archibugi et al. 2013).

This discussion of Schumpeterian theories of innovation, and how they have influenced contemporary understanding of the role of firm-level innovation in the economy, sets a broad context for the research undertaken in this thesis. Having established innovation as an important factor in economic dynamics, the next section details the rationale for innovation policy intervention.

### 2.3. The rationale for innovation policy intervention

Building on the seminal contributions of Schumpeter, Archibugi et al. (2013) synthesise how innovation occurs in firms across the business cycle, through processes of creative accumulation and creative destruction, as discussed in Section 2.2 above. Based on this synthesis, Archibugi et al. (2013, p. 311) make the following recommendation for innovation policy: “On the one hand, policies should support the good innovators, and reward the winners under the assumption that those who won in the past are those better equipped to also win in
the future. On the other hand, policies should also encourage the creation of new innovative firms”. However, this policy recommendation contains three implicit assumptions:

1) It assumes that government policy is *necessary* to support innovation;

2) It assumes that policy intervention using public funds to support innovation in private firms is a *legitimate* use of scarce public financial resources;

3) It assumes that any innovation policy intervention will have a *positive* impact on firms as well as the wider economic system within which they operate.

If these three points are the basis for forming innovation policy intervention, then developing a strong rationale for innovation policy intervention must be extremely important.

The most commonly used rationales for innovation policy intervention rely on two different conceptualisations of how innovation takes place: the linear model of innovation, and the theory of innovation systems (i.e. non-linear). These theories legitimise innovation policy intervention, explain how current policy works and guide the design of future policy as well as implementing and revising it (Dodgson et al. 2011; Bleda & Del Rio 2013). Therefore, the following subsections will first describe these theories and then place them within the literature on evaluating innovation policy.

**2.3.1. The linear model of innovation**

In the second half of the 20th century, the ‘linear model’ of innovation (Godin 2006; 2017) became the dominant theory for explaining how innovation works. Kline and Rosenberg (1985) highlight the linear model’s treatment of innovation as a highly technical and scientific process comprising four discrete, sequential phases: 1) basic research; 2) applied research; 3) experimental development; 4) production and diffusion. The linear model stands on neo-classical theories of economics, which assume that firms have perfect information, engage in profit maximisation and have rational preferences (Nelson & Winter 1974). These neo-classical
assumptions naturally imply that free and competitive markets allocate resources at the socially optimal level. Drawing on evidence from large-scale successful public investments in science, technology and innovation in the United States (US) and United Kingdom (UK) during the Second World War, Irvine and Martin (1984) credit Bush (1945) as an early and important source documenting the causal links between investment in scientific research and economic and societal progress.

The next subsection details the neo-classical assumptions that underpin the linear model of innovation, and how this leads to the theory of market failure as a rationale for innovation policy intervention.

2.3.2. Neo-classical assumptions of market failure

Nelson (1959) and Arrow (1962) laid the theoretical foundation for the formal understanding of the linear model. Using neo-classical assumptions, these authors developed a comprehensive theory of innovation, which had at its core the assumption that innovation flows from the creation of new knowledge. The key question addressed in this literature is: If the benefits to the economy and society from investments in R&D and innovation are so high, then why do private firms not invest in R&D and innovation to a sufficient level? Neo-classical assumptions include a ‘socially desirable’ level of investment in innovation by private firms. In this model of innovation, firms will systematically under-invest due to a series of market failures, succinctly defined by Arrow (1962) as: 1) Inappropriability; 2) Indivisibility; and 3) Uncertainty.

Inappropriability is perhaps the most cited of these market failures within the literature. The theory of inappropriability suggests that knowledge has the qualities of a public good. Knowledge it is non-rival (i.e., one firm’s use of a piece of knowledge does not diminish the ability of other firms to use of the same piece of knowledge) and non-excludable (once one

35
firm creates knowledge, that firm cannot easily prevent other firms from accessing and using it). In addition, knowledge is *indivisible*, in that producing any new knowledge has a high minimum cost. Once produced, the producers or any other user can use the new knowledge multiple times, which means that the cost of production is unrelated to the scale of the knowledge’s use (Arrow 1962; 1996; 1999; Lamberton 1996). Due to these characteristics of knowledge, firms that invest in and produce new knowledge cannot appropriate the full economic return on their investment, despite bearing all the cost.

At least some of the new knowledge the firm has created will spill over to other firms (Grossman & Helpman 1990; Jaffe et al. 1993; Audretsch & Feldman 2004). This knowledge spillover is socially desirable because it will raise the overall level of innovation in the economy. However, in the free market, it reduces the incentive for the initial firm to make the investment in producing new knowledge, which may prevent its creation in the first place. *Uncertainty* and risk are inherent features of firms’ innovation activities. At the beginning of an innovation process, firms cannot know that it will succeed and achieve the desired innovation. If the innovation process is successful, firms cannot know if the innovation will bring economic returns from the market. In this regard, Czarnitzki and Lopes-Bento (2013, p. 78) highlight that “the path from a brilliant idea to a technical invention and eventually to a successful market application is long, risky and sinuous”.

The neo-classical model of innovation typically assumes firms to be risk averse (Arrow & Lind 1970). This generally means that they are less likely to undertake projects necessitating risky and uncertain innovation processes. In this context, both Hall (2002) and Hall and Lerner (2010) describe a key difficulty of the innovation process, one that occurs even in the following illustrative example of a ‘successful’ innovation project.
• A firm is willing to bear the inherent risk and uncertainty of innovation and undertake an innovation project (i.e. not risk averse).

• The resultant innovation project is successful (i.e. the production of new knowledge before commercialisation).

• The innovation output was successful in the market (i.e. commercialisation).

Even this ‘successful’ innovation project will likely produce a large gap between the economic return firms can achieve from innovation output and the cost of capital for R&D and innovation activities from external sources (Hall 2002; Hall & Lerner 2010).

Arrow (1962) highlights the high minimal scale for many innovation projects and the uninsurability of the risk and uncertainty associated with these innovation projects. In this regard, Hall (2002, p. 36) points out that “unless an inventor is already wealthy, or firms already profitable, some innovations will fail to be provided purely because the cost of external capital is too high, even when they would pass the private returns hurdle if funds were available at a ‘normal’ interest rate”. This point may be most acute in the case of smaller and younger firms, firms engaging in innovation activities for the first time, and firms located in peripheral regions (Oughton et al. 2002). Such firms likely have more constraints on resources and less access to external finance for R&D and innovation than other firms (Martin & Scott 2000).

The market failure arguments based on the linear model of innovation provide a strong, logical and clearly articulated rationale for government intervention in the market through innovation policy. A policy implication of the linear model of innovation is that Governments should subsidise production of new knowledge, to bring the market as close as possible to the socially optimal equilibrium (Bleda & Del Rio 2013). This is especially the case for large-scale projects with very big social return likely, such as from investments in basic research, but with the acute severity of the market failures also likely (Czarnitzki et al. 2011). Under the neo-classical
assumptions of rational preferences, profit maximisation and perfect information, correcting for market failures in this way will facilitate the economy tending toward equilibrium, thus, achieving the socially desirable level of investment in innovation. Without policy intervention, the economy would be at a sub-optimal level below equilibrium, which entails welfare losses. Under these assumptions, governments intervene to remove or weaken information asymmetries, or the negative externalities associated with the inappropriability, indivisibility and uncertainty inherent in the production of new knowledge.

However, as Fagerberg (2018) has recently noted, though market failure in the linear model of innovation is the most commonly used rational for innovation policy intervention, this rationale has also been critiqued in more recent literature. For example, one critique highlights that focusing exclusively on correcting for market failures underestimates role policymakers can play in “actively shaping and creating markets and systems, not just fixing them” (Mazzucato 2017, p. 15). Another critique holds that there is a “vagueness of the policy advice” emanating from the linear model, where no guidance is provided to policymakers on what the socially optimal level for R&D investment should be raised to after correcting for a market failure (Edler & Fagerberg 2017, p. 7). Critiques such as these have led to an alternative rationale for innovation policy intervention being developed based on innovation systems.

As discussed below in Section 2.4 (specifically subsection 2.4.4), market failure is the dominant rationale which guides innovation policy intervention. Indeed, market failure almost exclusively forms the conceptual basis for innovation policy instrument evaluation at the firm-level (discussed in Section 2.5), which is the focus of this thesis. However, the theory underpinning innovation systems has had an important influence on the development and implementation of innovation policy. Therefore, though market failure is the primary rationale underpinning this thesis, it would be remiss not to analyse innovation systems, and systemic
failure as a rationale for innovation policy intervention that this theory gives rise to. The next section turns to a discussion of the theory underpinning innovation systems.

2.3.3. Innovation systems

The theory of innovation systems is the second dominant theory of innovation, alongside the linear model of innovation (Dodgson et al. 2011; Bleda & Del Rio 2013). Developed by Freeman (1987), Lundvall (1988; 1992), Nelson (1993) and Edquist (1997), innovation systems theory suggests that innovation is inherently non-linear and takes place via complex evolutionary processes involving the behaviour and interactions of a wide variety of economic and societal actors and components within the system. Under the innovation systems framework, the rigid neo-classical assumptions of the linear model of innovation give way to the more flexible assumptions of evolutionary economics (Nelson & Winter 1982; Witt 2003; Woolthuis et al. 2005; Uyarra 2010).

As noted in Section 2.3.2 above (and detailed further in Section 2.4 below), market failure is the primary rationale underpinning this thesis. Therefore, an exhaustive discussion on innovation systems is beyond the scope of this chapter. Thus, the discussion is constrained to the main implications for public support for firm-level innovation. The subsections which follow outline the assumptions underpinning innovation systems theory, discuss the conceptualisation of knowledge in innovation systems and, finally, detail systemic failure as a rationale for innovation policy intervention.

2.3.3.1. Assumptions behind innovation systems

In contrast to the linear model, under the evolutionary and systemic models of innovation, firms are not perfectly rational; rather, bounded rationality guides their decision-making (Lundvall et al. 2002; Carlsson et al. 2002; Foxon 2006). In addition, firms do not have perfect information; rather, information is asymmetric (Hauknes & Nordgren 1999). Information
asymmetry is a virtue in the innovation system because it creates opportunities for entrepreneurs to achieve competitive advantage through innovation, acting as a crucial source of novelty and variety (Barbaroux 2014). Finally, firms engage in profit maximisation through adaptation and interactive learning with other actors and components within the system (Chaminade & Edquist 2006; 2010).

From an innovation systems perspective, the major criticism of the linear model of innovation is that intervention based on correcting for market failures will not be sufficient to foster knowledge production and diffusion into the economy and society (Bleda & del Rio 2013). The primary reason for this is that the linear model of innovation treats ‘knowledge’ and ‘information’ as equivalent concepts (Metcalfe 2005). While the linear model of innovation rarely defines knowledge explicitly, Smith (2000) points out that the linear model implicitly assumes that knowledge has the following characteristics:

- Knowledge is highly technical and research-based;
- Knowledge is codified in nature;
- Knowledge is accessible to all firms and readily adaptable to firm-specific contexts.

For the purposes of economic analysis, Lundvall (2004) defines knowledge within the innovation systems framework as consisting of four multidimensional characteristics: 1) Know-what; 2) Know-why; 3) Know-how; 4) Know-who.

The first of these characteristics, know-what, captures the informational aspects of knowledge, such as easily interpreted and communicated facts. Know-why refers to knowledge about things such as fundamental principles, scientific theorems and laws of nature. Know-how focuses on capabilities, the abilities and skills necessary to carry out an action. In this regard, know-how captures both the theoretical and practical skills required to carry out a task, such as logical computing power combined with intuition, honed through experience. Finally, know-who
relates to information on who knows what to do and how to do it. *Know-who* also captures the socialisation required to work on a co-operative basis and communicate effectively with a diverse system of actors. A combination of skills, knowledge and technology from different fields is often necessary to engage in a process of innovation (e.g. see Pavitt 1998). *Know-who* can facilitate accessing and combining these different capabilities.

### 2.3.3.2. Codified knowledge, tacit knowledge and learning

In Lundvall’s (2004) conceptualisation of innovation systems, knowledge can be both codified and tacit. In this regard, Cohen and Levinthal (1989) highlight that firms’ R&D and innovation efforts effectively have ‘two faces’. The first face enables firms to create new knowledge that is more codified. The second face enhances firms’ ability to assimilate and exploit external knowledge and is thus more tacit. This second face, which captures the tacit quality of knowledge, necessitates learning and is vital for building firms’ “absorptive capacity” (Cohen & Levinthal 1989, p. 569). The learning process that transforms different forms of tacit and codified knowledge into actual innovations is a key feature of the innovation systems framework (Lundvall 1998; 2004).

Jensen et al. (2007) categorise two key modes of learning: ‘Science and Technology to Innovation’ (STI) and ‘Doing, Using and Interacting’ (DUI). The STI mode of learning concerns itself with codified knowledge that is typically scientific in nature and useful for technological development. The DUI mode of learning refers to the more tacit elements of knowledge such as problem-solving and experience. Important agents and components within the innovation system include private sector firms, universities, institutions, public-sector organisations and consumers (Lundvall 1988; 1992; 2004; 2007). Innovation is a dynamic process involving interactions between these system agents and components to facilitate knowledge sharing and learning (Kline & Rosenberg 1986; Soete et al. 2010). In addition, the
nature and importance of these system agents and components will vary across sectors, regions and countries (Chaminade et al. 2012).

2.3.3.3. Systemic failures

As alluded to earlier, in the linear model, neo-classical assumptions require policy intervention when the market does not reach equilibrium to produce the socially optimum level of knowledge and innovation (Chaminade & Edquist 2006; 2010). The implicit understanding is that policymakers have access to all the necessary information to detect and remedy market failures, thus returning the economy to optimum equilibrium (Metcalfe 1995a; 1995b).

However, much evolutionary and systemic theory explicitly rejects the notion of equilibrium and a socially optimum level of innovation, and therefore rejects the notion that correcting for market failures will return the economy to equilibrium. Rather, innovation systems are in a constant state of dynamic evolution (Nelson & Winter 1982). Thus, according to this branch of theory, identifying an optimal level or equilibrium may not be possible. Here, some interdependent features of the innovation system do not function effectively, hampering or blocking production and diffusion of new knowledge and innovation in the economy, requiring policy intervention (Edquist 1997; Lundvall 1992). In contrast to market failure, this rationale for government intervention is referred to as system failure (Dodgson et al. 2011; Bleda & del Rio 2013).

Chaminade and Edquist (2006) isolate five potential system failures that can hamper or block firms’ innovation activities: 1) infrastructure failures; 2) capability failures; 3) network failures; 4) institutional failures; and 5) transition or lock-in failures.

*Infrastructure failures* relate to general physical infrastructure such as transportation networks and internet access, as well as specific research infrastructure such as public R&D centres. *Capability failures* occur where firms lack the absorptive capacity to recognise, assimilate and
exploit knowledge produced elsewhere in the innovation system. *Network failure* addresses the nature and intensity of linkages between actors that facilitate the dissemination of knowledge and learning within the system. Strong network linkages can greatly enhance this process, but if network linkages are too intense, they can blind the firms involved to other opportunities and developments outside of the network. Alternatively, where the cognitive distance between actors is too high, network linkages can be weak or non-existent (Chaminade et al. 2012), which may negate the incentives for actors to share knowledge (Nootenboom 2000).

Chaminade and Edquist’s (2006) fourth form of systemic failure is *institutional failure*. This captures poorly developed or missing aspects of the governance, bureaucratic, regulatory and legal aspects of the innovation system, which establish the formal rules for how the system functions (e.g. laws), as well as less formal rules such as political culture, social norms and values (Johnson et al. 2003; Oyelaran-Oyeyinka 2006; Lundvall et al. 2006). The final form of systemic failure listed above is the presence of *transition or lock-in failure* due to the path-dependent nature of innovation within the system. A firm’s ability to learn, develop new knowledge and innovate is a path-dependent process, in the sense that it relies on what the firm has done in the past (Dosi 1988). If a firm’s path-dependent trajectory constrains its knowledge capacity, then the firm may be unable to transition its innovation activities to take advantage of new opportunities to respond to challenges. Conversely, firms may have a high concentration of knowledge capabilities in one area, but this can lead to being locked in to that area and similarly unable to respond to opportunities and challenges (Smith 2000; Narula 2002).

Following this discussion of different forms of systemic failure, the next outlines the chief policy responses to address failures in innovation system.
2.3.3.4. Innovation policy responses to systemic failure

Any of the system failures discussed above can block or hamper the important interactive learning process that connects different actors and components in the innovation system and creates the dynamics necessary to produce new knowledge and innovation (Woolthuis et al. 2000). As Edler and Fagerberg (2017) have recently highlighted, market failures typically conceived of as universal features in the production of new knowledge, which require a universal policy response. In contrast, system failures only require a policy response when they play an important role in preventing the innovation system from functioning in a specific context (Chaminade et al. 2012). Therefore, though a systemic failure may exist in a certain country, region or sector at a point in time, if this is not important to the overall functioning of the innovation system, then it does not require a policy response.

In this context, Metcalfe (1995a, p. 31) highlights one of the key issues for policymakers as “how well policymakers learn and adapt in the light of experience”. Chaminade et al. (2012, p. 1477) take this notion a step further, noting that policymakers must recognise the degree to which they can “analyse and interpret the (limited) information that they have on their innovation system”. In this light, Bleda and del Rio (2013) have argued that policy responses with a systemic failure rationale tend to focus on deeper issues regarding how the innovations system functions, while policy responses to market failure tend to transpire at the surface or operational level of the innovation system. However, as detailed below in Section 2.4.4, the systemic failure rationale difficult to operationalise at the firm-level. The market failure rationale is perhaps more appropriate for this micro-level of the innovation system (Georghiou 2002). Thus, the market failure approach has tended to dominate, both as a rationale guiding firm-level innovation policy intervention, and as the conceptual basis for innovation policy instrument evaluations.
2.4. Market failure and systemic failure

Market failure remains the dominant rationale in both the academic literature (e.g. Laursen & Salter 2014; Jacobsson et al. 2017; Raven & Walrave 2018; Hewitt-Dundas & Roper 2018) and policy documents (e.g. European Commission 2016; 2017a; 2017b; 2018; OECD 2017; 2018) for innovation policy and its associated policy interventions. However, though market failure tends to dominate, insights from innovation systems theory, and the systemic failure rationale, have influenced both the formulation and implementation of innovation policy at the firm-level. To give a context for the research undertaken in this thesis, this section discusses the application of market failure and systemic failure in innovation policy documents, empirical evaluations of public funding for innovation, the tensions between both rationales and how they co-exist in the field of innovation policy evaluation.

2.4.1. The influence of market failure in innovation policy documents

Two recent high-level reports from the European Commission exemplify the dominance of the market failure theory and its influence among policymakers. *The Economic Rationale for Public Research & Innovation Funding and its Impact* (European Commission 2017a) is set to act as an overarching guide for innovation policy in the European Union (EU) for years to come, while *R&D tax incentives: How to make them most effective?* (European Commission 2017b) is an extensive report on one specific form of public funding for firm-level innovation.

Neither report uses systemic failure arguments to motivate the necessity of innovation policy intervention. Instead, both reports rely exclusively on strictly market failure arguments. It is interesting to note that the former report (European Commission 2017a, p. 30) does use the ‘language’ of innovation systems, saying, for example “[a]mbitious reforms of national [research and innovation] systems are often needed to increase the capacity to obtain the most value from these investments”. However, despite the ideas of innovation systems informing
this report, the report does not cite systemic failure as the specific rationale for diverting public funding to private firms in an effort to enhance their innovation performance (European Commission 2017a).

**2.4.2. Influence of market failure in firm-level empirical evaluations**

In addition to high-level international policy reports, most empirical evaluations of the impact of public funding on firm-level innovation rely on the market failure rationale for policy intervention over the systemic failure rationale. An instructive recent example is Czarnitzki et al. (2018, p. 1), who state that “[g]overnments sponsor private research and development (R&D) activities in a number of ways and theoretical justifications for these public interventions are well understood in the literature”. Czarnitzki et al. (2018) conclude by citing two highly influential references used to build the market failure rationale, but which are unrelated to systemic failure: Arrow (1962) and Hall and Lerner (2010). Any reference or allusion to systemic failure as a rationale for public funding for private firms’ innovation activities is absent. This illustrative recent example is emblematic of the wider literature that can use the *language* of innovation systems without basing the need for innovation policy intervention on systemic failure.

As discussed in Section 2.4.4, this is perhaps because the market failure approach is more applicable to firm-level evaluations, while the systemic failure rationale is difficult to operationalise at firm-level. However, a number of tensions exist between market and systemic failure rationale in innovation policy evaluations. This section outlines the basis of these tensions.

Since its inception, the market failure rationale for innovation policy intervention at the level of the firm has become pervasive among policymakers who design and implement innovation policy instruments, as well as academics and policy analysts who evaluate the impact of
innovation policy instruments on firm-level innovation (e.g. see OECD 2010; European Commission 2017a). However, the dominant theory driving the nature of these innovation policy instruments comes from addressing broader failures in the innovation system (Bleda & Del Rio 2013).

Chaminade et al. (2012, p. 1477) may best exemplify the central divide between the market and systemic failure rationales for innovation policy intervention when they note that “[t]he scholars in the [innovation systems] and evolutionary economics traditions reject the notion of optimality (and thus that of equilibrium or failure). Innovation process is path-dependent and context-specific, and it is not possible to specify an ideal or optimal [innovation system]”. Following this logic, policymaking that uses the language and theory of innovation systems to inform policy design and implementation but intervenes on the basis of correcting for market failures is not consistent with theory. This is a key tension between market and systemic failure rationales. Following this logic, equally inconsistent are academics and policy analysis evaluating the impact of innovation policy instruments on firm-level innovation, who formulate their evaluations on an inconsistent basis. Rather than correcting for market failure at firm-level, this line of theory suggests they should investigate whether innovation policy addresses systemic failure that hampers functioning of the entire innovation system.

However, if firms are the locus of innovation within the overall innovation system, then it becomes very difficult to imagine an innovation policy intervention that does not target the specific problems firms face in engaging in innovation activities. Each of these firm-level interventions will have a market failure rationale, even though an overall systemic failure rationale may guide their design and implementation. For example, a wide range of different forms of public funding for innovation targeting different aspects of an identified systemic failure may become available to firms. Here, both market and systemic failure rationales work
hand in glove to legitimise and guide a broad suite of innovation policy interventions that may have a systemic effect, but are operationalised at the firm-level.

While this section has outlined the chief tensions between the theory underlying market and systemic failure, the next section discusses the dominance of market failure as a rationale for innovation policy intervention.

### 2.4.3. Market failure’s dominance as the rationale for policy intervention

Edler and Fagerberg (2017) argue that the appeal of the market failure rationale and its success in influencing policymakers lies in its simplicity, clarity and ready applicability to policy decisions relative to systemic failure. Despite this, as alluded to earlier, some authors have suggested that the market failure rationale’s weakest point is its inability to provide specific guidance to policymakers about the design and implementation of innovation policy outside of a general rationale for intervention (Metcalf & Georghiou 1998; Mazzucato & Semieniuk 2017). Dodgson et al. (2011, p. 1145) identify this trend, noting that although the theory of innovation systems is having an important influence on innovation policy, “the predominant logic behind policy choices still remains one of addressing market failure”.

In addition, although systemic failures manifest only partially at the firm-level, allocation of public funding for private firms’ innovation activities occurs at the firm-level (Georghiou 2002). Georghiou (2002, p. 60) notes that when evaluating how public funding for innovation addresses systemic failures, “with no attempt at optimality, the desired effects are less clearly specified … the effects looked for include structural changes and enhancements of firms’ capabilities. For innovation policies such as R&D subsidies where the main aim is to provide resources to the firm it seems reasonable to expect both kinds of effect to be evident”. This suggests that it is legitimate to investigate how firm-level interventions impact firm-level outcomes, and then how these outcomes arrive at having a systemic effect.
2.4.4. Coexistence of market failure and systemic failure rationales

A third recent high-level report from the European Commission (2016) titled *Science, Research and Innovation performance of the EU* emphasises the point that both market and systemic failure rationale can co-exist as a basis for innovation policy intervention, but market failure will usually be more applicable at firm-level. European Commission (2016) use the systemic failure rationale alongside the market failure rationale. This report argues that either rationale (or both rationales together) may apply, *depending on the context*, when intervening with innovation policy, stating that “policies should take into account the specific market failures (framework conditions) and specific systemic failures (creation of new opportunities, interaction of different actors in the innovation system or the entrepreneurship ecosystem)” (European Commission 2016, p. 269).

Even the most systemic forms of public funding for innovation, such as incentivising collaborations between the public research system and private firms to link the industry with the publicly funded science-base, have their root in market failure (e.g. see Beck et al. 2016). The main reason this form of systemic policy intervention exists is to enhance science-based elements of firms’ innovation performance, even though they also will enhance firms’ absorptive capacity (Kaiser & Kuhn 2012). Though they have systemic elements and the logic of innovation systems guides them to a large degree, they remain rooted in market failure. Therefore, market failure remains the most pervasive and dominant rationale for innovation policy intervention. However, the logic of innovation systems has influenced the policy recommendations that come from market failure based interventions. This occurs in the sense that many innovation policy instruments target increasing firms’ absorptive capacity and attempt to link the recipient firm with other firms or innovation actors, such as universities and research centres (European Commission 2016; OECD 2016). These criteria may add up to a systemic effect, even though the basis for the intervention is market failure.
In summary, there are two distinct major strands in the literature on the rationale for innovation policy intervention. On the purely theoretical side of the literature, the systemic failure rationale pervades, and often explicitly rejects the conceptual foundations for the market failure rationale. However, the application of innovation policy by policymakers and the evaluation of innovation policy by both policy analysts and scholars almost universally relies upon the market failure rationale. In contrast, innovation systems theories act as the guiding elements in policy design and implementation. Therefore, in this regard the literature appears more nebulous, with no clear consensus emerging, but market failure and systemic failure co-existing in practice. As noted above, this thesis relies more heavily on the market failure approach. Given that the empirical part of this thesis focuses evaluating the impact of innovation policy instruments on firm-level.

To account for market and systemic failures, policymakers intervene with a broad range of innovation policies. At the level of the firm, innovation policies are operationalised by specific forms of public funding for innovation, known as innovation policy instruments, that subsidise firms’ innovation activities. Following the largely theoretical discussion of the rationale for innovation policy intervention above, the next section draws on both the theoretical and empirical literature to set out key issues for evaluating the impact of public funding on firm-level innovation. This section focuses on the different forms of public funding for innovation available to firms, the mechanisms through which public funding impacts firm-level innovation, and how public funding for innovation is evaluated in practice.

2.5. Evaluating the impact of public funding for innovation

In terms of evaluating the impact of public funding for innovation on firms’ innovation performance, Czarnitzki et al. (2011, p. 219) note that “[s]tudies of the impact of government programs in support of R&D or more broadly defined innovation activities typically investigate
the program’s impact on innovation inputs and outputs”. In relation to this point, Aerts and Schmidt (2008, p. 807) highlight that the key issue surrounding innovation policy evaluation is for policymakers to “allocate public funding only to those projects that are socially beneficial and would not be carried out in the absence of a subsidy”.

However, an incentive always exists for firms to apply for public funding for innovation to reduce the marginal cost of undertaking an innovation project, even when the innovation project may have been undertaken without the public funding (David et al. 2000). In this case, the public funding would merely replace or crowd out private investment in innovation activities without stimulating additional investment (David et al. 2000; Czarnitzki & Fier 2002; Almus & Czarnitzki 2003). In this context, a key question when evaluating the impact of public funding for innovation on firms’ innovation activities is whether public funding stimulates additional R&D and innovation activities (Georghiou 2002; Aerts & Schmidt 2008; European Commission 2017a).

Since the European Commission’s Lisbon Agenda of 2000, most EU and OECD countries, as well as many developing countries, have significantly increased the quantity, type and level of support for financial innovation policy instruments to firms (Lundvall & Borrás 2004; OECD 2017). Regarding the different forms that innovation policy interventions can take, Martin & Scott (2000, p. 439) note that “[t]he forces leading to private underinvestment in innovation differ from sector to sector across the economy, and policy design should take these differences into account”.

2.5.1. Direct and indirect public funding for innovation

In an important recent review of the literature evaluating the effectiveness of innovation policy instruments, Castellacci and Lie (2015) undertake the most comprehensive meta-evaluation of the literature to date. Based on this review, Castellacci and Lie (2015, p. 820) state that
innovation policy instruments “can basically take two distinct forms”, which can be listed as follows:

1) Direct innovation policy instruments in the form of grants, loans and public procurement contracts for R&D and innovation

2) Indirect innovation policy instruments in the form of fiscal incentives for innovation activities such as R&D tax credits

However, it is important to note that other forms of categorisation for innovation policy instruments are possible. Rogge and Reichardt (2016) categorise innovation policy instruments as technology-push and demand-pull. Guerzoni and Raiteri (2015) use the terminology of supply-side and demand-side technology policies. In both categorisations, direct and indirect instruments, such as R&D grants and R&D tax credits, would fall under the technology-push/supply-side categories because firms receive them in an effort to ‘push’ them to develop new technologies. The main exception is public procurement contracts for innovation, where the government creates demand for new products or services that require innovation to come into existence (i.e. they do not currently exist in the form required) and are thus categorised as demand-pull/demand-side instruments. However, given that direct and indirect innovation policy instruments are by far the most common forms of public financial support available to firms (OECD 2016), it makes sense to separate them into different classes. In addition, the terms ‘direct’ and ‘indirect’ are the most commonly used in the literature (e.g. see a recent review of the literature by Beck et al. (2016)). Therefore, this research classifies innovation policy instruments as direct and indirect, following the definition by Castellacci and Lie (2015).

Having discussed the two most common forms of innovation policy instrument, the next section turns to a less-studied form of public funding for innovation that does not fall strictly within the direct and indirect classification: systemic innovation policy instruments.
2.5.2. Systemic forms of public funding for innovation

In a similar vein to Castellacci and Lie (2015), a previous review by Zúñiga-Vicente et al. (2014, p. 61) highlighted that “[t]here are several public policy instruments to boost R&D. The most important ones are direct subsidies (i.e. grants, loans or procurements), fiscal incentives (i.e. tax credits), public research performed in public institutions, and R&D consortia”. The last two forms of policy instrument noted here are somewhat different from the first two, and do not fall into the strict classification of direct or indirect innovation policy instruments.

Beck et al. (2016) note that public research institutes and R&D consortia are forms of policy instruments that play an important role within the wider suite of different forms of innovation policy instrument available to firms, but have received very little attention in the literature. This form of public support, termed systemic innovation policy instruments (Rogge & Reichardt 2016), link different parts of the innovation system to improve its functioning by directly targeting multiple interdependent market failures, as well as systemic failures identified within a given innovation system (Smits & Kuhlmann 2004; Wieczorek & Hekkert 2012). Systemic instruments typically take the form of incentivised research joint ventures of public-private research collaborations between public research centres or universities and private firms (Kaiser & Kuhn 2012).

This section has, thus far, introduced the theory underlying evaluations of public funding for innovation, and categorised the main forms of public funding for innovation into three distinct categories: direct, indirect and systemic innovation policy instruments. The next section provides a discussion and analysis of the literature concerning the policy objectives these instruments aim to achieve: stimulating firm-level innovation. The next section is designed to provide a broad context for the objectives of innovation policy instrument evaluations, to establish a backdrop for the research undertaken in this thesis.
2.5.3. Additionality and crowding-out

When evaluating the impact of innovation policy instruments on different forms of firm-level innovation, policymakers’ primary concern is whether the instruments are effective in terms of stimulating ‘additionality’ (European Commission 2017a). Additionality is defined as the additional (or induced) innovation activities, beyond what firms were already doing, which can be attributed to receiving some form of public funding for innovation (Buisseret et al. 1995; Georghiou 2002; Zúñiga-Vicente et al. 2014). The opposite side of the coin to additionality is ‘crowding-out’, which occurs where firms substitute public funding for innovation for their own private investments. If crowding-out occurs, policymakers will have subsidised innovation activities that would have occurred even in the absence of the subsidy, thus replacing private investment with public funding—an important issue for policymakers.

Clarysse et al. (2009) point out the three most common forms of additionality: 1) input additionality, which captures additional R&D investments as an input into the overall innovation process; 2) output additionality, which captures actual innovations such as new products and processes; and 3) behavioural additionality, which captures short- and long-term learning effects that modify the way firms carry out innovation projects.

The issues discussed above are intended to provide a broad context for innovation policy instrument impact evaluations. However, as highlighted in Chapter 1, the primary objective of this thesis is to evaluate whether firms that receive two distinct innovation policy instruments benefit more than firms that receive the same instruments separately (i.e. to test for complementarity and substitution). To understand how this this specific objective can be operationalised within the broader context discussed above, the next section focuses on empirical evaluations of public funding. This section gauges how public funding is measured in empirical evaluations, and the details the issues encountered in the literature when using real-world data.
2.5.4. Measures of public funding for innovation in survey data

Following the largely theoretical discussion above, this section focuses on empirical issues related to firm-level data. Powell et al. (1996) demonstrate that networks of learning among firms provide the locus of innovation within the economy. More recently, Dodgson (2017, p. 85) has argued that firms are “the central mechanism for converting innovation into economic action”. Much literature examines the effect of public funding for innovation at country- and region- and industry-level. However, due to the crucial importance of firms in the innovation process, and the fact that this thesis is concerned with firm-level innovation, this section focuses solely on firm-level studies and highlights important issues surrounding firm-level data.

The microeconometric (i.e. empirical studies using firm-level data) literature evaluating whether different forms of public funding for innovation produce additionality or lead to crowding-out vary in the way they define public funding. While some research has focused on evaluating specific innovation policy instruments, other research has aggregated all forms of innovation policy instrument into a ‘general’ variable capturing public funding for innovation. Instructive examples of the latter case include Hewitt-Dundas and Roper (2010), Martinez-Covarrubias et al. (2017) and Aristei et al. (2017).

Hewitt-Dundas and Roper (2010) aggregate firms’ responses to a number of questions capturing information on whether firms received government support of greater than £5,000 for product development, process development or R&D, into one variable capturing whether the firm received public support for innovation. Martinez-Covarrubias et al. (2017, p. 1798) collect a primary micro-dataset and define public funding for innovation as “any type of policy instrument used by policy-makers to increase business innovation”. Similarly, in the work of

---

Aristei et al. (2017, p. 559), firms that receive both R&D tax credits and direct R&D subsidies fall into the same category, as the authors note that “we consider as ‘untreated’ units those firms that did not benefit from any kind of public support”.

The literature typically uses this more general definition for public funding for innovation, for two reasons. First, the way the data is collected may not allow for the identification of specific types of innovation policy instrument (i.e. direct, indirect and systemic). Second, an aggregate measure of public funding may be appropriate to addressing the research question under examination. For instance, a more general research question may ask about the overall impact of public funding for innovation. However, as highlighted by Edler and Fagerberg (2017), the policy recommendations that stem from addressing this form of research question will tent to be somewhat non-specific. If general public funding for innovation leads to additionality, it will be unclear if all innovation policy instruments are effective, or if some are very effective while others are ineffective (or less effective). Therefore, it is important, where possible, to distinguish between different forms of innovation policy instrument.

This section offered an analysis of how public funding is usually measured in the datasets available to previous empirical literature, providing some illustrative examples of research that has used ‘general’ measures of public funding. The next three subsections focus primarily on the empirical literature (with some insights from the theoretical literature where appropriate) which has examined the three specific forms of public funding discussed above: direct, indirect and systemic innovation policy instruments. As noted in Chapter 1, and detailed in Chapter 4, the R&D tax credit is the most prominent innovation policy instrument in Ireland, and thus a key focus of this thesis. Therefore, a somewhat more detailed discussion of the R&D tax credit is provided, as compared to direct and systemic innovation policy instruments. While the next subsection turns to direct innovation policy instruments, the following section considers R&D tax credits and the section after that focuses on systemic instruments.
2.5.5. Direct innovation policy instruments

A rich body of academic literature evaluates the impact of direct innovation policy instruments on firms input, output and behavioural additionalities. This stands in contrast to indirect instrument evaluations that focus almost universally on input additionality and systemic instruments, generally much less studied. Recent reviews of microeconometric literature evaluate the impact of direct instruments, including Cunningham et al. (2013), Becker (2014), Zúñiga-Vicente et al. (2014), Dimos and Pugh (2016) and Beck et al. (2017). The overarching message of these reviews is that direct forms of innovation policy instrument do not fully crowd out firms’ private investment in innovation. However, the evidence is not clear with regard to the precise impacts of direct instruments. Estimated results range from large additionalities, particularly evident in the most recent literature (Dimos & Pugh 2016) to no effect where firms simply added the subsidy onto their existing innovation expenditure, and on to partial crowding-out, where some of the subsidy is substituted for private investment (Becker 2014; Dimos & Pugh 2016).

The findings of the microeconometric literature seem to depend heavily on the design of the innovation policy instrument under examination, its implementation by innovation funding agencies and the country context as well as the dataset and econometric method used for estimation (Zúñiga-Vicente et al. 2014).

For policymakers, the main advantage of direct innovation policy instruments, such as grants, loans and public procurement contracts, is that they allow policymakers to target forms of firm-level innovation they view as important, or where they perceive market and systemic failures to be most acute (Fagerberg et al. 2016). Some innovation projects only have the potential for a low private rate of return on investment because they involve more high-risk, radical, long-term forms of innovation (David et al. 2000; Czarnitzki & Lopes-Bento 2011). However, these forms of innovation also have the potential for a high social rate of return (OECD 2014).
Radical innovations can produce the largest knowledge spillovers and the greatest systemic impact by enhancing firms’ absorptive capacity (Beck et al. 2016; Braunerhjelm et al. 2018). An innovation funding agency at regional, national or supra-national levels of governance on a competitive basis typically awards this form of public funding, based on the merits of the firm’s application (OECD 2010; 2013). Direct innovation policy instruments facilitate policymakers targeting this form of innovation project by specifying in open calls for proposals that this is what they seek and evaluating the funding proposals they receive in this light (Edler & Boon 2018; Boon & Edler 2018).

If effective, direct innovation policy instruments boost firm-level innovation by raising the marginal rate of return on firms’ R&D and innovation investments that may have a high social rate of return, but a low private rate of return (David et al. 2000; Hall & Van Reevan 2000; Czarnitzki et al. 2011; Aristei et al. 2017). The literature refers to this as the ‘directionality’ of innovation policy instruments (Edler & Boon 2018). Directionality is important to policymakers as it allows them to engage in “[p]roactively stimulating and thus prioritizing specific innovation activities in order to exploit opportunities that could contribute to moving in the direction of desired long-term transformative change” (Weber & Rohracher 2012, p. 1042).

Having considered the theory behind direct innovation policy instruments, empirical evidence on their effectiveness at stimulating firm-level innovation, the next section focuses on indirect innovation policy instruments, primarily the R&D tax credit.

2.5.6. Indirect innovation policy instruments

The early literature evaluating the impact of R&D tax credits on firm-level innovation focuses predominantly on input additionality in samples of firms in the US and Canada, both of which had established programmes of fiscal incentives to encourage private R&D investment since
the 1980s. Hall & Van Reevan (2000) and David et al. (2000) provide the seminal reviews of the early literature; Parsons and Phillips (2007) and Mairesse and Mohnen (2010) update reviews of the literature; and Cerulli and Poti (2012) and Rao (2016) present reviews of econometric methods used in the most recent literature.

As of 2016, 29 of the 35 OECD countries and 22 of the 28 EU Member States offer different forms of R&D tax credit (OECD 2017; European Commission 2017b). In many developed countries (e.g. France, Ireland, Korea, Australia, Canada, the Netherlands, Japan, Portugal and Greece), fiscal incentives such as the R&D tax credit, targeted at stimulating private-firm R&D expenditure, have become more prominent over more traditionally prominent direct forms of innovation policy instruments, such as R&D and innovation grants (OECD 2016). This dominance comes in terms of the number of firms that claim R&D tax credits and the amount of funding provided (OECD 2016; 2018). As discussed below, the two primary reasons for this shift are that R&D tax credits are thought to: 1) lack bias in their allocation process because any firm can claim them as eligible R&D expenditures; and 2) facilitate firms’ using the funding in the way they feel is most effective (IMF 2016).

The growth in popularity of R&D tax credits throughout the world has led to a corresponding growth, in a wide range of countries, in the number of firm-level evaluations of their impact on firms’ R&D investments (e.g. see Castellacci & Lie (2015) and Gaillard-Ladinska et al. (2015)) for the most up-to-date reviews of the literature). As noted by Castellacci and Lie (2015), the vast majority of microeconometric evaluations of the effectiveness of R&D tax credits typically estimate one of two items: 1) whether there was an increase (additionality) or decrease (crowding-out) in firms’ R&D investments due to receiving the R&D tax credit; and 2) whether the marginal cost of investment in R&D decreased due to receiving the R&D tax credit (elasticity). Given that the focus of the present research is on the impact of innovation
policy instruments on firm-level innovation, this section will focus on the former issue (i.e. point two).

R&D tax credits incentivise firms to engage in more R&D by allowing them to claim deductions from their annual tax bill, thus enabling firms to increase their R&D-related innovation activities (IMF 2016; European Commission 2017b). In contrast to direct innovation policy instruments that increase the marginal rate of return on firm-level innovation, R&D tax credits operate through a different mechanism by reducing the marginal cost of R&D and innovation investments (David et al. 2000; Hall & Van Reevan 2000; Czarnitzki et al. 2011; Aristei et al. 2017). In addition, all firms in the economy can potentially avail themselves of R&D tax credits. Firms can automatically claim them after they apply for the deduction for eligible R&D expenditures. This differs from direct forms of innovation policy instruments, typically awarded on a competitive and selective basis. Therefore R&D tax credits are thought of as a ‘neutral’ innovation policy instrument because there is no sectoral or regional bias in their allocation and they can be claimed on all qualifying R&D expenditures (Castellacci & Lie 2015; IMF 2016).

The neutrality of R&D tax credits constitutes an advantage, given that direct grants fall prey to ‘government failure’ such as political pressure, misaligned policy objectives and strategic priorities, corruption, incompetence and costly bureaucratic procedures (Winston 2006). In addition, information asymmetries that can lead to a mismatch between policy problem and policy response that may exacerbate pre-existing market and systemic failures (Lenihan 2011; Haapanen et al. 2014). In this way, direct innovation policy instruments function as ‘top-down’ forms of public funding, in that policymakers who decide what kind of innovation projects will be funded dictate the use of the funding (Castellacci & Lie 2015; Gaillard-Ladinska et al. 2015).
R&D tax credits are designed as ‘bottom-up’ innovation policy instruments, in that the funding is spent based on firms’ decisions about what R&D and innovation activities will be pursued (Castellacci & Lie 2015; Gaillard-Ladinska et al. 2015). On one hand, this neutral aspect of R&D tax credits advantageously limits the potential for government failure; on the other hand, R&D tax credits lack the directionality inherent in direct and systemic innovation policy instruments. Therefore, while R&D tax credits may stimulate an increase in total R&D expenditures and innovation activities, they may not address specific market and systemic failures in as targeted a way as direct and systemic forms of innovation policy instruments. In this regard, Czarnitzki et al. (2011, p. 218) note that there is the potential that R&D tax credits may primarily incentivise “activities promising the largest short term profits”, while riskier projects, projects with a long time-horizon, and projects with a high social rate of return but lower private return may be less incentivised.

As highlighted in Section 2.4. above, different innovation policy instruments are designed to address different market and systemic failures which can act as barriers to firm R&D and innovation activities. R&D tax credits act to reduce firms marginal cost of R&D capital investment, thus making R&D expenditure less expensive (Czarnitzki et al. 2011). Given that R&D is a key input into many firm innovation activities, Busom et al. (2015) note that the source of market failure R&D tax credits address is to lower firms financial constraints to innovation. In contrast to R&D tax credits, direct innovation policy instruments such as R&D grants increase the marginal rate of return firms can achieve from R&D investment (Czarnitzki & Lopes-Bento 2013). Policymakers can target direct R&D grants at riskier, more radical forms of R&D/innovation projects which may have a high potential for knowledge spillovers (and thus a high social rate of return) but only a marginal private rate of return (Boon & Edler 2018). By operating through this mechanism, direct R&D grants compensate firms for the financial loss associated with the inappropriability of investments in R&D/innovation (Busom et al.
2015). However, systemic forms of innovation policy instrument, such as incentivised research collaborations between private firms and public research centres, operate through a somewhat different mechanism to impact firm R&D and innovation activities. As discussed in Section 2.5.7. below, systemic innovation policy instruments target systemic failures, as opposed to the more traditional direct and indirect instruments, which target specific market failures (Rogge & Reichardt 2016). Systemic instruments function by linking up different actors in the economy, such as firms and research centres, where policymakers have identified a potential weakness in the innovation system, such as the transfer of knowledge (Smits & Kuhlmann 2004).

While this section focused largely on the design of R&D tax credits and the mechanism through which they influence firms R&D and innovation activities, the next section presents the empirical evidence on the impact of R&D tax credits on firm-level innovation.

2.5.6.1. The effectiveness of R&D tax credits

However, more recent literature controls for these issues using a variety of different robust estimation methods (e.g. Cerulli & Poti 2012; Rao 2016). Overall, this research suggests that R&D tax credits do lead firms to increase their private investments in R&D (Gaillard-Ladinska et al. 2015). The only major caveat is that in some instances, €1 of R&D tax credit stimulates less than an additional €1 of private R&D investment (Castellacci & Lie 2015). Therefore, the literature leads to two main conclusions: 1) full crowding-out, where public funding in the form of the R&D tax credit completely substitutes for private investment, is rejected; and 2) partial crowding-out is possible, but the overall level of private R&D investment would have been lower had the R&D tax credit not been in place.

Castellacci and Lie (2015), Ientile and Mairesse (2009) and Cerulli and Poti (2012) all note that an important limitation of this literature is that almost universally, it only considers the impact of R&D tax credits on firms’ R&D investments (i.e. input additionality). This is primarily due to lack of data on other forms of additionality in the administrative datasets drawn from government departments or state funding agencies, used for this form of evaluation. For example, Clarysse et al. (2009) undertook their own survey of firms to construct reliable measures of behavioural additionality, because of the lack of theoretically valid proxies for behavioural additionality available in administrative datasets or publicly available datasets. Examples of this type of analysis are rare within the microeconometric literature, with notable exceptions being Czarnitzki et al. (2011) and Cappelen et al. (2012). These papers evaluate the impact of R&D tax credits on output additionality, as measured by patenting and the market success of firms’ product innovations in cross-sectional samples of firms in Canada and Norway, respectively.

By considering output additionality, the work of Czarnitzki et al. (2011) and Cappelen et al. (2012) make an important contribution to the literature. However, these papers consider output additionality only, because the datasets used in both papers do not contain any reliable measure
of input additionality. Drawing on theory (e.g. Bilbao-Osorio & Rodríguez-Pose (2004); Mairesse & Mohnen (2004)), the chain of events that should link R&D tax credits to output additionality necessitates an initial phase of input additionality. This is because the R&D tax credit should stimulate new R&D investments; in turn, the firm should use these new R&D investments as an input in the innovation process that leads to output additionality. Also, as opposed to other forms of innovation policy instrument, which often target a range of different innovation activities, R&D tax credits specifically target firms’ R&D investments. Therefore, it makes logical sense to evaluate R&D tax credits in terms of input additionality, at least in the first instance, before moving on to output and behavioural additionality.

As outlined in Chapter 1, and detailed in Chapter 4, the innovation outcome measure used in this thesis is firms R&D expenditure. The discussion above highlighted that having a more complete spectrum of innovation outcome measures available for empirical analysis would be advantageous. Notwithstanding this, datasets containing this information have not available to most previous studies. As noted above, R&D expenditure is a key outcome variable to test against when considering R&D tax credits. The R&D tax credit is the most prominent innovation policy instrument available to firms in Ireland (Department of Finance 2016), the empirical context for this study. Therefore, R&D expenditure is an important and valid innovation outcome variable to use in the empirical analysis. This section has discussed the empirical literature that evaluates the effectiveness of R&D tax credits at stimulating firm-level innovation. The next section highlights a key distinction between volume-based and incremental forms of R&D tax credit, which may affect how they influence firms’ R&D and innovation activity.
2.5.6.2. Incremental versus volume-based R&D tax credits

An issue that has received less attention in the literature is whether the R&D tax credit programme available to firms represents an ‘incremental’ or ‘volume-based’ system (IMF 2016; European Commission 2017; Mohnen et al. 2017). Incremental R&D tax credit programmes apply to additional R&D investments above a certain baseline of R&D investment the firm was already making. In contrast, volume-based R&D tax credits are deductible from all eligible R&D investments the firm undertakes, regardless of whether the firm engages in additional R&D investment.

Small and Medium-sized Enterprises (SMEs), firms that do not currently engage in R&D, firms that only engage in R&D occasionally or engage in R&D regularly but not intensively, tend to favour incremental programmes (Gaillard-Ladinska et al. 2015). These firms typically find the transition from a low baseline level of R&D investment to qualify for the R&D tax credit on additional investments more manageable and worthwhile (Castellacci & Lie 2015). In contrast, the firms that benefit most from volume-based schemes are typically larger, more R&D-intensive firms and multinational enterprises (DBEI 2016), meaning that any increase in R&D investment among these firms will have a larger impact on the overall level of R&D expenditure in the economy (Mohnen 2017).

The IMF (2016, p. 36) notes that an important advantage of the incremental R&D tax credit is that firms “avoid a windfall gain for existing R&D below the baseline”. This may explain the finding of partial crowding-out in some of the literature reviews noted above (Mohnen 2017). However, though the literature highlights partial crowding-out as a feature of some volume-based R&D tax credit programmes, Mohnen (2017, p. 47) notes that despite the advantages of incremental R&D tax credits, they have “proved to be costly to administer, for the firms and for the government, and limited in their ability to generate a lot of new R&D”. Therefore, two different trade-offs exist in the choice between incremental and volume-based R&D tax credit.
programmes. First, does the efficiency of incremental programmes outweigh the fact that they are not hugely impactful? Second, are the inefficiencies of volume-based programmes, in terms of partial crowding-out, more important than the higher level of overall additional R&D investment that is generated? (IMF 2016; Mohnen 2017; Mohnen et al. 2017).

Two important caveats are important to note alongside each of these trade-offs. First, firms’ R&D investments are persistent over time (Peters 2009; Arqué-Castells & Mohnen, 2015); or, put differently, “once in the R&D game, firms tend to remain in the R&D game” (Mohnen 2017, p. 46). Therefore, encouraging small and non-R&D-intensive firms to begin investing in R&D or increase their R&D investments from a low baseline could have a greater long-term impact (Gaillard-Ladinska et al. 2015). This would lend support to the use of an incremental R&D tax credit. Secondly, volume-based R&D tax credits can serve an important industrial policy function. In addition to their role as an innovation policy instrument, R&D tax credits may attract R&D-intensive foreign direct investment (FDI) to a country, and keep firms’ R&D facilities located in a country rather than moving them to other countries (DBEI 2016; Mohnen 2017). In practice, most EU Member States that implement R&D tax credits adopt a volume-based programme, though both incremental and volume-based programmes are available to firms in Spain (European Commission 2017).

This section has reviewed the pertinent theoretical and empirical literature on indirect innovation policy instruments, focusing on R&D tax credits. In the discussion, the design and objectives of R&D tax credits were set against direct forms of innovation policy instruments, such as grants or loans. While direct and indirect instruments are most common forms of public funding for innovation, the next section turns to a form of public funding that has received less consideration in the literature: systemic innovation policy instruments.
2.5.7. Systemic innovation policy instruments

In contrast to direct and indirect innovation policy instruments which are based more on correcting for market failures, systemic innovation policy instruments represent the most cogent attempt to intervene in the market with based on a systemic failure rationale (Rogge & Reichardt 2016). Smits and Kuhlmann (2004) introduce the idea of the systemic innovation policy instrument, analysing what they consider to be the three overarching trends in innovation theory: 1) The end of the linear model of innovation; 2) The rise of the innovation systems approach; and 3) The inherent uncertainty of innovation and the need for experimentation and learning.

Based on their analysis of these three trends, Smits & Kuhlmann (2004, p. 25) state that “present day innovation processes are in need of instruments that support functions operating at system level”. Smits & Kuhlmann (2004) distinguish between systemic functions on which systemic instruments should particularly focus: 1) The management of interfaces; 2) The building and organising systems; 3) The provision of a platform for learning and experimenting; 4) Providing strategic intelligence; and 5) Demand articulation.

Building on the work of Smits and Kuhlmann (2004), more recently Rogge and Reichardt (2016) highlight that the most important systemic instruments applicable at the firm-level are different forms of cooperative R&D incentives. Of particular note are incentivised research joint ventures and public-private research collaborations between private firms and public research institutes (Kaiser & Khun 2012; Scandura 2016; Beck et al. 2016).

Firms’ linkages with universities and public research centres have long been a potentially important source of knowledge for firm-level innovation (Roper et al. 2004; Roper et al. 2008). Research centres designed to facilitate academic-industry collaborations on innovation projects may be designed as systemic instruments, in that they address potential infrastructure failures
(dedicated sector-specific research centres), capability failures (increase firms’ absorptive capacity by linking them with science system), and network failures (facilitate the transfer of complex knowledge). However, a systemic instrument could itself lead to lock-in problems where all infrastructure, capabilities and networks concentrate in one area, prevent firms from taking advantage of new opportunities (e.g. see Smith 2000; Narula 2002), leading to government failure (Lenihan 2011).

In a recent study that reviewed the literature on the types of partners firms’ collaborate with on R&D projects, Beck et al. (2016) differentiate between other private firms and public research centres. This review demonstrates that the academic literature emphasises the perceived importance to the innovation system of private firms’ collaboration with public research institutes on R&D and innovation projects. However, there is a major gap in the literature in terms of actual evaluations of what impact these collaborations have on firm-level innovation (Beck et al. 2016). The empirical part of the research by Beck et al. (2016) uses five pooled cross-sections of the Swiss version of the Community Innovation Survey from 1999 to 2011. Based on this data, the authors can control for whether firms that received a direct R&D subsidy also collaborated with universities or public research centres, rather than whether the academic-industry collaboration was itself incentivised through a systemic innovation policy instrument. Therefore, even in the most advanced literature that considers systemic forms of innovation policy instruments, as outlined in Section 2.5.4 above, available datasets do not facilitate a more detailed analysis.

This is an important point in the context of the current research. As outlined in Chapter 1 (and detailed in Chapter 4), one of the innovation policy instruments considered in the empirical analysis is a form of incentivised research collaboration between firms and research centres. As such, this instrument has many systemic features. Therefore, discussing the theory behind systemic instruments, and reviewing the empirical literature that has evaluated their
contribution to firm-level innovation, provides necessary context for the empirical part of this study.

Kaiser and Khun (2012) and Scandura (2016) are two exceptions within the literature that focus on incentivised academic-industry collaborations. Drawing on a panel of firms in Denmark from 1990-2007, Kaiser and Khun (2012) demonstrate that firms participating in subsidised research joint ventures, specifically designed to link the science and industrial bases, increase their patent applications immediately after receiving the systemic instrument. Using the panel structure of their data, Kaiser and Khun (2012) also demonstrate that this indicator of output additionality remains significant for the following three years and loses significance thereafter. These findings were significant for SMEs, but not large firms, primarily driven by firms active in patent applications prior to receiving the systemic instrument (Kaiser & Khun 2012).

Scandura (2016) uses a pooled cross-sectional dataset of firms in the UK from 1997-2007, which captures whether firms participated in funded university-industry collaborations. Scandura’s (2016) results indicate that participating in this programme increased firms’ R&D intensity and the share of R&D-based employees in the firms’ total employee base. Therefore, while only scant evidence exists on the impact of systemic forms of innovation policy instruments on firm-level innovation, there is some evidence that this form of public funding produces both input and output additionality.

As a whole, this section and the sections that have preceded it, have focused on the theory underpinning the design of different forms of innovation policy instruments, as well as the findings from empirical studies that estimate the impact of direct, indirect and systemic forms of innovation policy instruments. However, if effective, the impact of innovation policy instruments on firm-level innovation may take time to materialise. Therefore, the next section concentrates on theory and empirical evidence regarding the time lag between firms receiving public funding and achieving greater innovation performance.
2.5.8. Time lag to additionality

Kaiser and Khun (2012) demonstrate that both a contemporaneous impact as well as a lagged impact of innovation policy instruments on firm-level innovation are likely, and that this lagged impact will dissipate over time. However, in an extensive review of the literature, Zúñiga-Vicente et al. (2014) demonstrate that the vast majority of the literature evaluates the contemporaneous or short-term impact of a variety of different R&D subsidies on private R&D expenditures. Cunningham et al. (2013, p. 16) state that “little of the evaluation evidence concerns longer term impacts”. This is primarily because the datasets available to previous microeconometric literature have been cross-sectional in nature, capture firms’ innovation performance and whether they received innovation at one point in time.

Hall et al. (1986, p. 265) identify the potential for contemporaneous and lagged impacts of public funding for innovation on firms’ innovation performance, noting that there will be “gestation lags in knowledge production”. In a recent study evaluating the impact of direct R&D subsidies on firms’ output additionality, Le and Jaffe (2017, p. 434) highlight that “firms’ R&D investment take different gestation periods of up to three years to produce output”. However, an important point from Le and Jaffe’s (2017, p. 435) study is that “there is no definite gestation period between when a grant is received and when an output is observed”. In this light, Cunningham et al. (2013, p. 15) review the literature on the impact of direct innovation policy instruments and note that “it will generally take little time for some of the intended consequences of support such as concrete R&D projects undertaken, increased R&D expenditures, additional employment generated, etc, to be demonstrated”. In contrast to this, the output and behavioural additionality of R&D subsidies may take a longer time to materialise (Cunningham et al. 2013).

This form of lag is typically built into innovation surveys that ask firms whether they received public funding for innovation in the last 12, 24 or 36 months, thus allowing time for the
additionality effects to become manifest, while measuring the indicators of firm-level innovation in the current period. Research by Dimos and Pugh (2016) and Klette and Møen (2012) highlights that in the limited evidence that does exist, the effectiveness of different forms of innovation policy instrument at stimulating firm-level innovation tends to increase over time. Similarly, Roper and Hewitt-Dundas (2012) evaluate the input, output and behavioural additionality effects of receiving public funding for innovation in firms in Northern Ireland and the Republic of Ireland over the period 1991 to 2011. These authors find strong evidence that output and behavioural additionality (and somewhat weaker evidence for input additionality) persist long after the public funding was initially received (Roper & Hewitt-Dundas 2012).

While the panel data available for Roper and Hewitt-Dundas’ (2012) study covers a significant time period (i.e. 1991-2011), is structured in three-year waves. This means that the authors’ ability to identify precisely when an innovation policy instrument was received in the three-year wave, and when additionality manifests and disappears, is somewhat more limited than would be the case if annual data were available. In contrast, Kaiser and Khun (2012) have access to annual data that raises the precision of their analysis. However, unlike Roper and Hewitt-Dundas (2012), Kaiser and Khun (2012) only have access to one measure of output additionality (firms’ patent applications) rather than the full range of input, output and behavioural additionalities. Therefore, in the most advanced literature examining the lagged effects of innovation policy instruments, a trade-off exists between the range of available innovation outcome measures available and the precision of the lag-structured models that can be estimated.

As detailed in Chapter 4, this study has access to eight years of annual panel data recording the innovation policy instruments firms in Ireland received each year. Similar to Kaiser and Khun (2012), this annual data enables the study to test both the contemporaneous impact of
innovation policy instruments (i.e. the impact the instruments have the same year firms receive them), as well as the lagged impact of these instruments (i.e. the impact the instruments have one, two and three years firms receive them). However, only one innovation outcome measure is available in the data: firms’ R&D expenditure. As discussed above, this measure of firm-level innovation is appropriate to for the current research given that the R&D tax credit is a key innovation policy instrument in the analysis. Although the data used in this study compare favourably to the data used elsewhere in the literature, an ideal situation in terms of data access would entail having access to annual panel data with a broad spectrum of innovation outcome measures such as those used by Roper and Hewitt-Dundas (2012).

This section has presented a detailed discussion of the key issues concerning the impact of public funding on firm-level innovation, and the evaluation of same. Placing a dual focus on both the theoretical and empirical literature, the section provides the conceptual basis for the empirical evaluation that will be described in Chapter 4. In addition, the section places this study within the broader context of the field of innovation policy evaluation. The next section offers a summary and conclusion of this chapter. In the context of the literature reviewed above, the next section also introduces the key issue that is analysed in the next chapter: the relationship between different innovation policy instruments firms receive, and the influence of this relationship on firm-level innovation.

2.6. Conclusion

This chapter reviewed the literature on the theory of innovation, paying particular attention to the role of firm-level innovation as a driving force behind economic development. Beginning with the foundational theories of Joseph Schumpeter (1934; 1942), Section 2.2 provided a review of innovation studies that have informed contemporary innovation theory (e.g. Archibugi et al. 2013). Though much research has studied innovation at the macro-level (i.e.
country- and region-level), there is widespread agreement that firms are the key locus of innovation within the wider economy. Therefore, studying innovation at the micro-level (i.e. firm-level) allows for a focussed analysis of this study’s key concern: The impact of public funding on firms’ innovation performance.

Given the focus of this study, Section 2.3 provided a review of the theoretical literature on the rationale for innovation policy intervention in the context of different theories of innovation. Analysing both neo-classical and systemic theories of innovation, this section provided a context for how innovation in firms takes place and outlined the factors that can hinder firm-level innovation. Building on this review, Section 2.4 detailed the two dominant rationales that guide innovation policy: market failure and systemic failure. While market failure deals with firm-specific issues in the innovation process, such as uncertainty and the inappropriability of knowledge, the systemic failure approach takes a more broad view, focusing on interactions between many actors in the economy. The discussion in this regard concluded that the market failure approach is more appropriate for firm-level analysis, such as that conducted in this thesis. However, it would be remiss not to acknowledge the role of firms within wider innovation systems and the influence that the innovation systems theory has on innovation policy.

Drawing on the discussion of market and systemic failure, Section 2.5 reviewed the theory and empirical application of evaluations of public funding for firm-level innovation. Based on a review of the literature, this section categorised different forms of public funding for innovation into direct, indirect and systemic innovation policy instruments. These forms of public funding are designed to influence firm-level innovation in somewhat different ways. Direct instruments, such as R&D grants, enable governments to directly support innovation activities that they perceive as having the highest potential social benefit. Indirect instruments, such as R&D tax credits, reduce the cost of conducting R&D for firms. In contrast, systemic instruments are
designed to incentivise firms to engage with publicly funded research institutions on R&D and innovation projects. Empirical evaluations of each of these individual types of innovation policy instruments suggest that they have positive and significant effects on a variety of measures of firm-level innovation.

However, the fact that a suite of different innovation policy instruments is available to firms prompts a potentially important question: What happens if firms receive a combination of instruments? The issue of firms receiving multiple innovation policy instruments could have important ramifications for the evaluation of public funding for innovation. Edler and Fagerberg (2017, p. 13) have recently suggested that “different policy instruments may interact, making it difficult to distinguish their individual effects … [which] raises serious questions regarding the usefulness of evaluations of individual policy instruments”. Therefore, the next chapter reviews the small but growing literature on the so-called policy mix for innovation (Flanagan et al. 2011). This chapter will concentrate on the interactions between different instruments and the influence these interactions have on firms’ innovation outcomes (Nauwelaers et al. 2009; Rogge & Reichardt 2016). Building on the literature reviewed in the current chapter, the chapter which follows constructs a theoretical framework to underpin this study. The framework developed in the next chapter draws on the established theory and empirical approaches discussed in this chapter, but extends upon this by also incorporating the emerging literature on policy mix which is discussed in detail in Chapter 3.
Chapter 3: The innovation policy instrument mix

3.1. Introduction

Understanding firm-level innovation is crucial when considering fundamental economic issues such as growth, competitiveness and productivity (Romer 1990; Pradhan et al. 2018). However, firms face many market and systemic failures that hinder their innovation activities (Arrow 1962; Chaminade et al. 2012). Therefore, understanding the role public funding for innovation plays in overcoming these issues and driving firm-level innovation is also vitally important (Almus & Czarnitzki 2003; European Comission 2017a; OECD 2018). Chapter 2 presented a review of the literature on innovation, which focused specifically on firms as the locus of innovation within the economy, as well as the theory and empirical evidence which underpins the contemporary understanding of public funding for innovation. The current chapter will present a review of the literature on the policy mix for innovation, a recently-developed concept that has implications for the debate on public funding for innovation (Flanagan et al. 2011). The chapter focuses on how this concept is operationalised at firm-level, from both a theoretical and empirical perspective, through the innovation policy instrument mix (Rogge & Reichardt 2016). In doing so, this chapter continues to build the conceptual framework on which this thesis is based.

The policy mix for innovation is the term used by economists and other social scientists to refer to the interactions, interdependencies and trade-offs between different public policies that, intentionally or unintentionally, have an influence on whether (and to what extent) innovation policy objectives are achieved (Flanagan et al. 2011; Rogge & Reichardt 2016; Nauwelaers et al. 2009; Guy et al. 2009). As discussed in Chapter 2, innovation policy targeted at firms is operationalised by a suite of innovation policy instruments, such as R&D tax credits and R&D grants. Firms frequently receive a mix of different instruments (Dumont 2017; Indecon 2017).
Policy mix theory suggests that these interactions can be complementary or substitutive in nature, and may influence the impact the instruments have on firm-level innovation (Howlett & del Rio 2015).

Therefore, at the level of the firm, the policy mix for innovation can be applied by evaluating whether complementarity or substitution exists between innovation policy instruments (Rogge & Reichardt 2016). Disentangling the observed impact of each individual innovation policy instrument on firm-level innovation from that of the wider mix of instruments that firms receive can be very challenging, because interactions between instruments within the mix drive this impact (Flanagan et al. 2011; Rogge & Reichardt 2016; Nauwelaers et al. 2009). Therefore, this chapter develops a conceptual framework for evaluating the impact of innovation policy instrument mix on firm-level innovation.

The concept of an innovation policy instrument mix, and its potential influence on firms’ innovation outcomes, has existed in the innovation literature since the early 2000s (STRATA/ETAN Expert Group 2002; Soete & Corpakis 2003). However, this approach has had limited transition into the empirical literature evaluating the impact of innovation policy instruments on firm-level innovation (as discussed below). While often recognising that a range of innovation policy instruments exists, and firms may receive more than one instrument at the same time, the literature focuses almost exhaustively on single innovation policy instruments (e.g. Zúñiga-Vicente et al. 2014; Dimos & Pugh 2016).

Some empirical evaluations of individual instruments note that considering the broader policy mix may be potentially useful in providing a greater depth of analysis (Cappelen et al. 2012; Czarnitzki & Lopes-Bento 2013). However, previous literature tends to view policy mix as an add-on to the main focus of one specific instrument. For example, in their evaluation of R&D tax credits, Cappelen et al. (2012, p. 334) noted that “[e]valuation of the incentives in various
countries may help determine which policies or policy mixes work well”. Similarly, when evaluating direct R&D grants, Czarnitzki and Lopes-Bento (2013, p. 78) specify that “[a] detailed overview of the existing policy mix and its potential effects on R&D activities would however be beyond the scope of this study, since we are merely interested in direct subsidies”. In contrast, policy mix theory suggests that the mix of instruments a firm receives may be an essential feature driving the observed impact of each individual innovation policy instrument (Flanagan et al. 2011; Flanagan & Uyarra 2016). The focus of this chapter is to build on previous studies such as Cappelen et al. (2012) and Czarnitzki and Lopes-Bento (2013) by incorporating policy mix theory into evaluations of public finding for innovation.

The notion of different instruments interacting to produce distinct effects, and the possibility of harnessing these interactions to maximise the effectiveness of each instrument has been recognised in the most recent literature (Cunningham et al. 2016; Edler et al. 2016; Beck et al. 2017; Edler & Fagerberg 2017). For example, Beck et al. (2017, p. 15), when reviewing the literature on the impact of individual innovation policy instruments on firm-level innovation, conclude that despite little being known about how the innovation policy instrument functions, “a policy mix composed of tax incentives and direct subsidies should be coordinated in an effective way to optimally stimulate additional R&D investment”. This chapter reviews the literature on the innovation policy instrument mix, building on the information provided in Chapter 2, to develop a conceptual framework for the evaluation of innovation policy instrument mix.

The remainder of this chapter is organised as follows. The next section (3.2) outlines the overarching concept of the policy mix for innovation, and how this can be applied at firm-level through the innovation policy instrument mix. This section also focuses on the nature of the relationship between different innovation policy instruments (i.e. complementarity and substitution), and how this relationship influences firms’ innovation outcomes. Building on this
review of the theoretical literature, Section 3.3 turns to the empirical issues encountered when examining the innovation policy instrument mix. This section outlines a typology of different instrument mixes, and reviews previous empirical studies that have estimated the impact of different instrument mixes on firm-level innovation. Drawing on both the theoretical and empirical literature, Section 3.4 presents the conceptual framework that is used to guide the empirical analysis in Chapters 4 and 5, while Section 3.5 concludes this chapter.

3.2. The policy mix for innovation

At the macro-level of the innovation policy system, broad policy agendas emanate from a complex and dynamic multi-actor, multi-level policy process (Matti et al. 2016; Uyarra et al. 2016; Aranguren et al. 2016). The policy process will first give rise to policy strategy (Quitzow 2015), the establishment of policy objectives and the principal plans for achieving them (Rogge & Reichardt 2016). Taken together, the objectives and plans in policy strategy provide a roadmap for the intended development of the innovation system, and thus important long-term guidance for actors within the system (Rogge et al. 2011; Schmidt et al. 2012). For example, the EU’s current (2016) policy document sets out its overarching innovation policy goals. Entitled Open Innovation, Open Science, Open to the World—A Vision for Europe, it articulates a vision to guide the design and implementation of innovation policy throughout the EU. At the micro- or firm-level, a mix of different innovation policy instruments operationalises the broader innovation policy.

Flanagan et al. (2011, p. 708) posit real-world policy mixes, encompassing the messy realities of public policy, rarely “pursue a single goal or even a coherent and hierarchical set of goals”. Indeed, public policy tend to pursue “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 of another” (Flanagan et al. 2011, p. 708).
Therefore, even the presence of a clear roadmap for innovation policy does not guarantee achieving innovation policy goals (Rogge et al. 2017).

Evaluating the impact of innovation policy instrument mix on firm-level innovation necessitates a somewhat more complex evaluation framework relative to single innovation policy instruments. Adam et al. (2018, p. 270) note that a key challenge more complex forms of evaluation face is that they “create a trade-off between the need for increasing methodological sophistication on one side, and the decreasing political impact of more fine-grained and conditional findings of evaluation results on the other”. In one of the key conceptual contributions to the literature, Rogge and Reichardt (2016, p. 1627) observe 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”. Therefore, establishing a conceptual framework that facilitates evaluating the innovation policy instrument mix impact, firmly rooted in policy mix theory and applicable to empirical evaluation, is crucial to enabling its use in informing policy.

This section has outlined the broad context of the policy mix for innovation to establish a theoretical backdrop for this chapter. The next section specifies how the policy mix concept can be operationalised to evaluate the impact of public funding on firm-level innovation.

3.2.1. The boundaries for evaluation: policy mix dimensions

Interactions within the policy mix for innovation 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 & Reichardt 2016). In addition, specifying policy mix dimensions allows the evaluator to know
and state exactly the aspects of the policy mix subject to investigation, remaining constant, or going uncaptured.

Policy mix dimensions represent a means of accounting for policy complexity in practice. The governance dimension of the policy mix for innovation captures the fact that innovation policies and policy instruments flow from three primary sources: sub-national (i.e. regional, local), national, and supra-national (i.e. EU) levels of government. A policy mix can contain policies from each governance level separately, or from different state agencies operating at the same level of governance. Here, the degree of vertical and horizontal alignment among instruments will define policy mix interaction effects respectively. Similarly, implementation of innovation policies occurs on different geographical scales—national, regional or local, or as defined to purpose, as the pan-European scale was in the case of Horizon 2020 (European Commission 2016).

Public policies from many different policy domains can impact firm-level innovation. In the domain of innovation policy, impact focuses directly on various aspects of the innovation system. However, public policies also emanate from other policy domains that have an implicit or explicit agenda to promote innovation, as well as direct or indirect impacts on the innovation system. For example, Antonioli et al. (2014, p. 65) note that “[i]nfrastucture and competition policies … can encourage innovation”. Similarly, enterprise or education policies may complement innovation policies and, either by accident or design, could interact in the policy mix to produce unique impacts on the innovation system (Guy et al. 2009).

The focus of the current research is on evaluating the impact of innovation policy instrument mix on firm-level innovation, which is one sub-set of the much larger and more complex policy mix for innovation. While it would be remiss not to acknowledge the policy complexities that
the policy mix concept highlights and provides guidance on, it is important to clearly note that this study concentrates on the relationship between innovation policy instruments.

Schmidt and Sewerin (2018), Flanagan and Uyarra (2016) and Rogge and Reichardt (2016) have addressed the vital importance of time, a thoroughly under-researched dimension of the policy mix for innovation and, by extension, the innovation policy instrument mix. Even individual innovation policy can have internal inconsistencies where their rationales, goals, and implementation modes are unaligned or drift out of alignment over time (Howlett & Rayner 2007). In this sense, it is possible to conceptualise a ‘mix’ of ‘the same’ innovation policy over time, in which the same policy interacts with itself in subsequent periods (Flanagan et al. 2011). As both the policy and the innovation system change through time, so will the effects on firm-level innovation (Rogge et al. 2011). More typically, policy mix means a mix of different innovation policies operationalised by a mix of different innovation policy instruments.

3.2.2. Consistency among innovation policy instruments

The crux of how innovation policy instrument mix differs from individual instruments in their impact on firm-level innovation resides in the interactions between instruments. Nauwelaers et al. (2009, p. 4) note that “the influence of one policy instrument is modified by the co-existence of other policy instruments”. Moreover, Rogge and Reichardt (2016, p. 1625) highlight that this influence comes from the “direct or indirect effect that the operation or outcomes of instruments have on each other”. The combined effect of an instrument mix on firm-level innovation is influenced by these interdependences, and thus the effectiveness of more broad innovation policy at achieving policy objectives can be dependent on the specific mix of instruments a firm receives (Flanagan et al. 2011).

The nature of interactions between innovation policy instruments in the mix can be complementary, substitutive, or neutral (Rogge & Reichardt 2016; Lanahan & Feldman 2015;
Howlett & del Rio (2015). This will depend on the degree of ‘consistency’ between different innovation policy instruments in terms of their underlying rationales, goals, implementation modes (Flanagan et al. 2011), type, design features (Rogge & Reichardt 2016) and source (Czarnitzki & Lopes-Bento 2014). Instrument mix consistency is the alignment of individual innovation policy instruments in the mix with each other, with respect to these underlying characteristics (Rogge & Reichardt 2016).

Looking at innovation policy instruments targeted at German offshore wind power, Reichardt & Rogge (2016) identify that consistency between feed-in tariffs and grid access regulation (i.e. two different instruments) enhanced innovation activity in the sector. In contrast, Del Río et al. (2011) draw on evidence from innovation policy instruments targeted at renewable energy sectors across a number of different countries, showing that inconsistent instrument mixes combine voluntary compliance with command-and-control regulation, inducing contrary responses from the policy targets.

Consistency potentially matters to policymakers because it represents a means of enhancing the effectiveness and efficiency of an instrument mix at achieving policy objectives (OECD 2015; OECD 2010; Howlett & Rayner 2007). However, the nature of instrument interactions and their eventual impact on policy outcomes are unknown ex-ante, and therefore represent a challenge for ex-post firm-level evaluation.

A body of recent literature surveys the crucial underlying role that consistency among characteristics of innovation policy instruments plays in moderating policy instrument interactions (Kern et al. 2017; Kivimaa & Kern 2016; Uyarra et al. 2016; Rogge & Reichardt 2016; Reichardt & Rogge 2016). However, to date, the econometric research has focused solely on individual instruments in appraising the effectiveness of various combinations of innovation policy instruments at stimulating firm-level innovation. This leaves unexplored the degree of
consistency between instruments and the extent to which that drives their effectiveness. The current research evaluates the degree of consistency between different innovation policy instruments by testing whether they have a complementary or substitutive relationship in terms of their impact on firm-level innovation. As noted by Rogge and Reichardt (2016, p. 1625), consistency in the instrument mix should manifest itself as “positive or complementary interaction outcomes”. This suggests Hypothesis 1, that:

**H1.** A complementary relationship exists between different innovation policy instruments in their impact on firm-level innovation.

Guy et al. (2009, p. 1) suggest that the impact of an instrument mix on firm-level innovation can occur by “design or fortune”. However, Flanagan et al. (2011, p. 709) note that “the intentional combination of two or more instruments” in a designed mix rarely if ever occurs in reality. At the firm-level, a designed mix means policymakers targeting firms with a specific mix of instruments calibrated to meet the firms needs and maximise innovation outcomes. However, instrument mixes usually occur as firms apply for a variety of different innovation policy instruments (Indecon 2017; OECD 2018). The result of these applications is that some firms receive no instrument, other firms receive one instrument, and yet other firms accrue more than one instrument (i.e. an innovation policy instrument mix).

Importantly for the current research, the concept of designed mixes under-conceptualises the time dimension of the policy mix, so that an instrument the firm receives in a given year can interact with an instrument the firm receives the following year (Rogge & Schleich 2018). The impact of this mix may be a function of these temporal dynamics (Rogge & Reichardt 2016; Schmidt & Sewerin 2018). Temporal dynamics must figure at the heart of evaluations of the innovation policy instrument mix. This suggests Hypothesis 2, that:
**H2.** A complementary relationship exists between different innovation policy instruments through time in their impact on firm-level innovation.

In this regard, quoting Flanagan et al. (2011, p. 710) at length bears out this important point:

> The implications of this for policy mixes are, first, that it 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. In other words these characteristics of interactions are relative (an instrument is only complementary or negative in relation to another instrument or mix of instruments) and potentially transient. Policy instruments are flexible and evolve over time, and, because the wider institutional and actor environment in which they operate can also change, the kinds of interaction seen may change over time, and from context to context, place to place. If complementarity is not a simple matter, then nor is substitution. It seems difficult to imagine that two different policy instruments could ever be perfect substitutes—and the extent to which instruments might substitute for one another will change over time.

(Flanagan et al 2011, p. 710)

Depending on the degree of consistency between policy instruments in terms of their underlying characteristics, interaction effects can occur in complementary, substitutive, or neutral fashion (Rogge & Reichardt 2016; Lanahan & Feldman 2015). Neutral effects result from ‘weak’ consistency, involving the simple absence of conflicts between instruments; while ‘strong’ consistency entails complementarity and requires instruments to mutually reinforce each other’s impact (Howlett & del Rio 2015). When policy instruments actively hamper each other, inconsistency results (Kern & Howlett 2009) and one may substitute for the other.

In this complex policy system, achieving consistency by simply layering one policy instrument on top of another over time seems unlikely (Kern & Howlett 2009; Howlett & Rayner 2007). Therefore, evaluations of the innovation policy instrument mix must take account of the important temporal dimension of instrument mix consistency (Flanagan & Uyarra 2016; Kern et al. 2017). This requires analysing the dynamics of how policy instrument mixes form, as well as the eventual impact of these dynamics 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”.

84
Innovation policy instruments can be implemented across multiple policy levels. Since the Lisbon Treaty of 2000, there has been a steady decentralisation in the governance of innovation policies from national to regional and local levels in the EU (Magro & Wilson 2013). This is in line with the theoretical evolution in innovation system analysis from national to regional systems (Uyarra 2010). On the other hand, there has also been an extension of policy competences at certain supra-national levels, for example the European Union (Vītola 2015). Therefore, the mix of innovation policy instruments available to any given set of firms in the EU can be implemented from different policy levels (i.e. EU, national, regional, local). Lanahan & Feldman (2015, p. 1388) point out that innovation policy initiatives at each level of governance hold a “shared imperative of bolstering economic activity”, which in turn “ties these multiple systems together into a policy mix”. However, Kuhlmann (2001) highlights that a ‘governance gap’ can emerge between different policy levels, where scarce public resources wastefully overlap across levels due to lack of integration and coordination (see also Vītola 2015). Flanagan et al. (2011) refer to regions as ‘policy spaces’, where innovation policy instruments from EU, national, regional and local levels can interact to have impacts on firm- and regional-level innovation. Magro & Wilson (2013) note that the presence of multi-level governance of innovation policy instruments adds to the complexity of evaluating the impact of the policy mix for innovation.

This statement supports the contention of Flanagan et al. (2011, p. 702) that “it is unrealistic to hope to identify unambiguously ‘good’ mixes”. The multi-actor, multi-level and dynamic nature of the system destines policy instrument mix evaluations to be always relative in nature, never absolute. In addition, as instruments evolve over time, the nature and impact of instrument interactions will affect policy design, thus changing the nature of the system through recursive feedback loops. Establishing the boundaries for impact evaluation provides a conceptual framework within which to manage all this complexity, to effectively foster policy
learning. As noted, this research focuses on evaluating the impact of innovation policy instrument mix on firm-level innovation. In doing so, the research tests for complementarity between the instruments firms receive at a given point in time, as well the relationship between instruments through time.

*Ex-ante*, policy makers can create innovation policy instruments on the basis of type and design feature (Rogge & Reichardt 2016), implementing them through different sources. Additionally, they can specify how these instruments will unfold within and across policy mix dimensions and how they are likely to interact, considering their underlying rationales, goals and implementation modes. However, neither the nature nor the effect of instrument interactions can be known precisely before deployment of the policy instrument mix at firm-level.

These issues are drawn together in the next section to develop and present the conceptual framework that will guide the empirical evaluation in this thesis. The two hypotheses which test for complementarity between innovation policy instruments are incorporated into this framework, along with the alternative hypotheses of substitution and neutrality.

### 3.2.3. Conceptual framework

*Ex-ante*, policymakers can create innovation policy instruments on the basis of type and design feature (Rogge & Reichardt 2016) and implement them through different sources. Additionally, they can specify how these instruments will unfold within and across policy mix dimensions, along with their likely interactions 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, p. 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). In this sense, only dynamic analysis can reveal the co-evolution of the innovation policy instrument mix and firms’ innovation outcomes (Reichardt et al. 2016).

The important lacuna between policy mix theory and evaluation practice identified above exists for three primary reasons. First, though the theoretical literature conceptualises very well the many different aspects of the innovation policy instrument mix, no unified conceptual framework exists to provide a set of ‘guiding principles’ for impact evaluation. Second, as discussed in Section 3.3.4, 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. The literature is missing a direct statistical test for the degree of consistency in the instrument mix. Third, as detailed in Section 3.3.3 and 3.3.4, a paucity of firm-level datasets to capture detailed information on the full mix of innovation policy instruments available to firms, as well indicators of firms’ innovation outcomes. This data limitation hinders the evaluation of innovation policy instrument mix.

Based on the theoretical and empirical literature reviewed, there is a clear need to translate policy mix theory into a usable conceptual framework for ex-post impact evaluation of the innovation policy instrument mix on firm-level innovation. As highlighted by Rogge and Reichardt (2016), to establish the effective boundaries for impact evaluation, the key research question is in a given context must first be identified. Then, 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 (e.g. SMEs).
Figure 3.1 A conceptual framework for innovation policy instrument mix evaluation
The next important step is to identify what policy mix dimension an evaluation is examining, what dimensions are 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. Given that temporal dynamics are a crucial aspect of the innovation policy instrument mix, a panel dataset will be required, as cross-sectional data may obscure the key feature driving observed impact. Based on this, a conceptual framework for innovation policy instrument mix evaluation is summarised in Figure 3.1.

The conceptual framework developed in Figure 3.1 specifies the effective boundaries for empirical evaluation of the innovation policy instrument mix that will guide the empirical analysis in this thesis. Testing Hypotheses 1 and 2 facilitates an examination of the nature of the relationship between different innovation policy instruments when firms receive a mix. By testing for complementarity and substitution between different instruments, both at a point in time and through time, the hypotheses enable an analysis of consistency in the instrument mix.

The theoretical literature suggests consistency and temporal dynamics are important issues driving the impact of innovation policy instruments on firm-level innovation. However, as detailed in the next section, these theoretical points have not been considered to date in the empirical literature.

This section has analysed the broad policy mix for innovation concept, and how this concept may be applied at firm-level through an examination of the innovation policy instrument mix. The next section reviews the small but growing empirical literature which evaluates the impact of different forms of innovation policy instrument mixes on firms’ innovation performance. As noted, firm-level innovation is the key focus of this thesis. Therefore, the following section
deals exclusively with firm-level studies, and thus refers to these studies as the microeconometric literature.

3.3. The microeconometric literature

Building on the theoretical literature discussed above, this section reviews empirical applications of the policy mix concept at the firm-level. Since the early 2000s, the literature has well understood the fact that an innovation policy instrument mix exists and can have important effects at firm-level (STRATA-ETAN Expert Group 2000; Soete & Corpakis 2003). However, the empirical literature has taken a variety of different approaches when dealing with multiple different innovation policy instruments. This section first outlines the main approaches to include multiple instruments empirical evaluations, which involves estimating the relative impact of different instruments or using other instruments as control variables in the study of one specific instrument. The section then discusses why firms apply for different innovation policy instruments. Following this, the section focuses on studies that specifically evaluate the impact of the mix of instruments firms receive, which is the key issue for the current research.

Colombo et al. (2011) and Grilli and Murtinu (2012) compare the relative effectiveness of public funding for innovation that firms can claim automatically (such as R&D tax credits) to that public funding awarded on a selective basis, for which applicants compete, such as R&D grants. Similarly, Becker et al. (2016) evaluate the relative impact on firm-level innovation of public funding for innovation from EU, national or regional sources. Though implicitly acknowledging an instrument mix for which accounting in some way is important, these studies look only at the relative impacts of composite instruments, rather than the mix itself.

In their study of R&D grants from the government in Flanders, Czarnitzki and Lopes-Bento (2013) take a somewhat different approach by, using the presence of R&D subsidies from other
sources a control variable in their econometric model. Using a sample of firms in Norway, Hægeland and Møen (2007) show that firms receiving R&D tax credits are more likely to apply for and receive direct innovation policy instruments than firms that do not receive R&D tax credits. Hægeland and Møen (2007) interpret these results to mean that direct and indirect innovation policy instruments are complements, in the sense that firms using one as a source of finance tend to use both. However, Hægeland and Møen (2007) do not test whether firms that receive a mix of direct and indirect instruments are more innovative than firms that receive one or the other, as they focus solely on the relative effectiveness of each type of instrument.

Based on an extensive review of the literature evaluating individual innovation policy instruments, Zúñiga-Vicente et al. (2014) find that firms do receive multiple subsidies through different time periods. The impact of public funding for innovation on firm-level innovation can differ for first-time recipients, compared with the impact on repeat recipients (Zúñiga-Vicente et al. 2014). Based on this observation, Zúñiga-Vicente et al. (2014, p. 55) propose two alternative research assumptions to guide evaluations of public funding for innovation, emphasising that either the additionality or crowding-out effects “of public subsidies on private R&D investment might be stronger in firms that are frequent recipients of public subsidies than in first-time recipients”. The authors do not comment on whether (and under what circumstances) crowding-out or additionality is more likely. However, the research assumptions make clear that the authors anticipate that the instrument mix may have some form of distinct impact on firm-level innovation relative to individual innovation policy instruments. In addition, the focus on repeat recipients emphasises the potential influence of temporal dynamics in the instrument mix.

In summary, no clear empirical evidence exists on whether receiving a mix of innovation policy instruments is generally more effective at stimulating firm-level innovation than receiving individual instruments. However, it is important to note that although Zúñiga-Vicente et al.
(2014) provide many important insights based on their review of the literature, they comment on the general case of repeat recipients, and not on the type, design features, source or sequencing in which firms receive these instruments. Policy mix theory would suggest that these are key features of any mix, which drive the interaction effects within the mix and, thus, its eventual impact (Flanagan et al. 2011). Therefore, building on the research of Zúñiga-Vicente et al. (2014) is important to attempt to transform the conceptualisation or practical execution of innovation policy instrument evaluations.

3.3.1. Firms receiving a mix of different of innovation policy instruments

Firms apply for and receive a mix of innovation policy instruments, either from the same source or from different sources; both at the same point in time and over time. Firms might not need public money to reduce the marginal cost of capital and increase their marginal rate of return on investment in R&D and innovation (Wallsten 2000). Rather, firms might just be highly proficient at applying for subsidies (Lööf & Hesmati 2005), due to having successfully applied in the past and built-up administrative knowledge of the process and requirements (Aschhoff 2009). This will allow firms to tailor their future applications to maximise their chance of receiving public funding for innovation. Firms applying for and receiving a mix of innovation policy instruments for these reasons will likely lead to what the enterprise evaluation literature calls deadweight spending (Lenhian 1999; Lenihan 2004; Lenihan & Hart 2004; Lenihan 2011), “the degree to which projects would have gone ahead without assistance” (Lenihan 2004, p. 231).

Busom et al. (2015) demonstrate that many firms tend to become dependent on different forms of public funding for their innovation activities. However, Busom et al. (2015) also find some important differences in the type of firm that receives different forms of innovation policy instruments. Highly productive firms tend to receive direct R&D grants, while the use of R&D tax credits is completely unrelated to firm productivity (Busom et al. 2015). Theoretically, this
finding is understandable. As detailed in Chapter 2, policymakers can target specific R&D/innovation projects they perceive as desirable (i.e. with a high social rate of return) with direct R&D grants. In this respect, the government agencies responsible for the implementation of direct R&D subsidies allocate them to the most ‘deserving’ innovation projects after a competitive and selective application process. Such awards function by raising the marginal rate of return on high risk, radical innovation projects with a high social rate of return (Czarnitzki & Lopes-Bento 2013). R&D tax credits apply automatically and function by lowering the marginal cost of capital for innovation projects (Czarnitzki et al. 2011). Busom et al. (2014) argue that R&D tax credits address one source or market failure (financial constraints), while direct innovation subsidies address a different source (the inappropriability of knowledge). Accordingly, both direct and indirect innovation policy instruments present as complements when firms receive a mix of both, as they address different sources of market failure (Busom et al. 2014).

However, the government funding agency responsible for funding firm-level innovation through direct innovation policy instruments may try to maximise the ‘success’ of the agency’s innovation funding by cherry-picking winners with high levels of R&D and innovation in the past, and thus greater likelihood of engaging in these activities in the future (Aerts & Schmidt 2008). These firms may receive preferential treatment in current and future funding applications. A picking-the-winner funding strategy would only yield a ‘true’ success if the funded firms invested in more innovation on top of what they already do, after being subsidised (i.e. additionality) (Guerzoni & Raiteri 2015). Funding agencies may give preference to innovation projects from firms with the highest perceived innovation capabilities. However, in firms with high innovation capabilities, subsidised innovation projects may have occurred anyway, even without the subsidy (i.e. crowding-out) (Czarnitzki et al. 2011). As mentioned
above, this may also lead to deadweight spending in the public funding for innovation (Lenihan 2004).

In addition, innovation projects publicly funded under a picking-the-winners strategy may represent the innovation projects with the highest potential of success and financial return in the short term (David et al. 2000). However, the kind of innovation projects policymakers often seek to fund ‘in theory’ are more risky forms of investment in radical innovation projects that may have a low private rate of return, but a high social rate of return (Czarnitzki et al. 2011). In this case, firms may apply for as many different subsidies as possible in the current period, and in multiple time periods for the same form of subsidy for which they had successfully applied in the past, simply to reduce their risk and cost of investing in innovation (Wallsten 2000; Lööf & Hesmati 2005).

Firms applying for and receiving subsidies merely to reduce their marginal cost of capital do not necessarily imply that they would not engage in innovation without the subsidies, or that they would engage in less innovation or less risky forms of innovation (i.e. with a higher social rate of return) (Aschhoff 2009; Czarnitzki et al. 2011). Under both market and systemic failure rationales for policy intervention, these would be among the primary reasons to intervene (Bleda & Del Rio 2013). However, firms that receive multiple subsidies from the same or different sources on this basis have a higher likelihood of crowding out additional R&D and innovation expenditure and, perhaps more importantly, divert scarce public financing away from other firms that would put it to more productive use (Wallsten 2000). This would concur with the finding by Clarysse et al. (2009, p. 1517) that the behavioural additionality induced by R&D subsidies decreases “with the number of subsidized projects that are undertaken by the company”.

94
However, in contrast to the situation outlined above, firms may apply for and receive multiple innovation policy instruments from the same or different sources because: 1) They would not engage in any innovation without the subsidy; or 2) They would engage in some innovation without the subsidy, but to a lesser extent (i.e. intensity) or at a slower rate, with a less risky or radical form of innovation, and thus have a lower social rate of return (as discussed in Chapter 2). In addition, innovation projects may last for many years and require subsidies for each of these years, so the firm may have to reapply each year for a new subsidy from the same source, or multiple subsidies from different sources. Receiving subsidies on this basis would be a stable form of necessary finance for innovation activities. In this case, receiving a mix of different innovation policy instruments at a point in time, receiving a mix of ‘the same’ innovation policy instrument through time, or receiving a mix of different innovation policy instruments through time would less likely lead to crowding-out and more likely lead to additionality if the subsidies are effective.

This section has considered the reasons why firms may apply for different innovation policy instruments and the impact that accruing a mix may have on firm-level innovation. The next section builds on this analysis to set out a typology of different innovation policy instrument mixes. The typology draws on the information that is usually available in firm-level datasets used in the empirical literature to suggest how the innovation policy instrument mix concept can be applied in practice.

3.3.2. A typology of innovation policy instrument mixes

Rogge and Reichardt (2016, p. 1631) discuss “the need for operationalizing policy mix characteristics … which may pose one of the greatest analytical challenge as official databases or documents typically do not capture such characteristics”. This section outlines how different innovation policy instrument mixes can be categorised to facilitate an evaluation of their impact. The section draws on datasets that are currently used in the empirical literature to
specify a typology of instrument mixes based on the type and source of each instrument in the mix.

The literature that Chapter 2 reviews demonstrates that the literature well understands and accepts the idea of innovation policy instrument ‘type’. This review outlines the three primary types of innovation policy instrument: tax credits, direct subsidies and systemic instruments (such as incentivised firm-university research collaborations). However, the ‘source’ of the innovation policy instruments firms receive can also play an important role in driving different forms of innovation outcomes.

Hægeland and Møen (2007) note that different funding agencies have can have different rationales and goals when implementing what are nominally ‘the same’ type of innovation policy instrument. Using a sample of firms in Norway to examine the impact of direct R&D grants implemented by two different national funding agencies (i.e. the Norwegian Research Council and Innovation Norway), these authors note that subsidised R&D projects “differ with respect to private returns depending on their source of financing” (Hægeland & Møen 2007, p. 29). Therefore, this section considers both the type and source of innovation policy instruments. What is nominally ‘the same’ type of innovation policy instrument can differ greatly, depending on the source implementing it. Research by Radicic and Pugh (2017), Becker et al. (2017) and Czarnitzki and Lopes-Bento (2014) has clearly demonstrated that public funding for innovation implemented at the EU, national and regional levels of governance impacts firms’ innovation performance very differently.

To illustrate the complexity behind the source of innovation policy instruments, it is instructive to consider three examples of the way firm-level surveys define innovation policy instruments. The Community Innovation Survey (CIS) and the Business Environment and Enterprise Performance Survey (BEEPS) are two of the most common firm-level innovation surveys used
throughout the world. Both the CIS and the BEEPS gauge firms’ innovation performance, such as R&D investment, innovation output and collaborative behaviours, as they collect information on firms’ innovation-related characteristics, such as size, sector and location. In the Irish context, the Annual Business Survey of Economic Impact (ABSEI) also surveys firms, collecting similar information to that collected by the CIS and BEEPS.

The BEEPS focuses on firms in less-developed countries. For all countries surveyed in South America and Central America, the 2010 edition of the BEEPS asks firms the following question: “Over the last three years, did this establishment receive any public support (financial or other types of assistance) for innovation-related activities?” Firms answering “yes” to this question received at least one innovation policy instrument in the last three years. However, it is not clear whether this “yes” captures an aggregate of many different types of innovation policy instruments from different sources received in each of the three years, or one specific type of instrument from one source received in one year. The criterion of “public support” is an aggregate measure.

Referring to this innovation policy instrument is only possible in the most general sense. Evaluating the impact of this innovation policy instrument on firm-level innovation can reveal the effects of innovation policy instruments in general, but cannot provide information on specific innovation policy instruments or specific policy recommendations regarding the innovation policy instrument mix. Therefore, an aggregate measure of public funding for innovation such as this can help answer an important general question about the effectiveness of public innovation funding for stimulating firms-level innovation. However, this form of aggregate measure also runs the risk of capturing both effective and ineffective instruments within one measure. Some instruments may target a specific form of additionality, and may be effective at stimulating that form, but no others.
Similarly to the BEEPS, the 2014 edition of the Irish CIS asks firms: “During the three years 2012 to 2014, did your enterprise receive any public financial support for innovation activities from the following levels of government?”. The question provides three options for firms to indicate: a) Local or regional authorities; b) Central government (including central government agencies or ministries); c) The European Union. This provides more useful detail by differentiating the ‘general’ public funding for innovation, measured in the BEEPS by the specific source of the funding. However, likely within each of these sources is a range of different innovation policy instrument types.

In contrast to the BEEPS and Irish CIS, the ABSEI has asked firms in Ireland (since the 2009/2010 edition) the following question every two years: “Please indicate whether your organisation has availed of the R&D tax credit in the following years: 2007; 2008; 2009”. The user has the advantage of knowing the type of innovation policy instrument that firms received. However, an important disadvantage of the ABSEI relative to the BEEPS and CIS is that it offers no indication of whether firms received any other innovation policy instruments. While ABSEI contains specific information on one innovation policy instrument (i.e. the R&D tax credit), it does not capture whether firms received any other instrument(s). In contrast, the aggregate measures of public funding for innovation used in Irish CIS and BEEPS capture whether firms received any innovation policy instrument(s), but not which specific instrument(s). Accordingly, a typology of the different forms that public funding for innovation can take, summarised in Figure 3.2.

This section has discussed the different forms of innovation policy instrument mix that can exist, as well as the datasets that evaluators can employ to evaluate the effectiveness of the mix on firm-level innovation. Next, it is important to review the current academic literature on innovation policy instrument mix evaluations at the firm-level to gauge the level of congruence between theory and practice.
This section discussed how public funding for innovation is measured in the datasets available in the literature. Different datasets provide a different levels of information about the specific type and source of the innovation policy instruments they collect information on. Based on this analysis, the section constructed a typology of innovation policy instrument mixes. The next section turns to the empirical literature that evaluates the impact of innovation policy instrument mix on firm-level innovation.

**Figure 3.2** A typology of public funding for innovation
3.3.3. A review of innovation policy instrument mix evaluations

A small but growing literature evaluates the impact of different forms of innovation policy instrument mix on firm-level innovation. This literature is summarised below in Table 1, Table 2 and Table 3. This section’s primary goal is to lay out the forms that innovation policy instrument mix evaluations have taken in the literature, as well as presenting the key findings and empirical methodologies from this literature.

Overall, the studies reviewed in this section represent the first empirical research to directly estimate the impact of receiving a mix of different innovation policy instruments on firms innovation outcomes. As such, these studies provide important foundational insights into the impact of different forms of instrument mix on firm-level innovation. In addition, they provide important information on how innovation policy instrument mix evaluations can be carried out in practice.

Notwithstanding these important contributions, as noted briefly in Section 3.1, these studies represent the first steps in applying developments in policy mix theory. This issue has led Howlett and del Rio (2015, p. 1234) who comment that “the cumulative impact of empirical studies has not been great, theorization has lagged and understanding of the mix phenomena, despite many observations of its significance, has not improved very much”. Issues which theory identifies as important, such as testing for consistency among innovation policy instruments (Rogge & Reichardt 2016; Rogge et al. 2017), or examining the role that sequencing plays in their eventual impact (Flanagan et al. 2011; Matti et al. 2017), have been left unexplored in the empirical literature. Therefore, this section analyses the current empirical literature in an effort to understand its important strengths, while also highlighting some limitations. Addressing these limitations could help to bridge the gap between policy mix theory and empirical application.
<table>
<thead>
<tr>
<th>Year</th>
<th>2009</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Authors</td>
<td>Bérubé; Mohnen</td>
<td>Czarnitzki; Lopes-Bento</td>
</tr>
<tr>
<td>Country</td>
<td>Canada</td>
<td>Germany</td>
</tr>
<tr>
<td>Sample</td>
<td>2,784 firms (all firms); 2,468 firms (innovators only); 3,292 firms that do not receive any instrument are dropped</td>
<td>8,734 observations (6,106 unique firms)</td>
</tr>
<tr>
<td>Dataset</td>
<td>Cross-sectional; Firms in manufacturing and logging; firms with &lt;10 employees; firms with &lt;250k revenue</td>
<td>Pooled cross-section</td>
</tr>
<tr>
<td>Outcome variable</td>
<td>Product and process innovation (world first; North America first; Canada first; province/territory first); Number of new product innovations (new to market and new to firm); % revenue from new products (new to market and new to firm)</td>
<td>R&amp;D intensity; innovation intensity (total innovation expenditure/sales); patenting; % of sales from new products; forward citation of patents</td>
</tr>
<tr>
<td>Treatment variable</td>
<td>1) Research and development (R&amp;D) tax credits AND Government research and development (R&amp;D) grants 2) Research and development (R&amp;D) tax credits ONLY</td>
<td>1) no support; 2) national R&amp;D grant; 3) EU R&amp;D grant; 4) Both</td>
</tr>
<tr>
<td>Number of observations</td>
<td>1) R&amp;D tax credit only: 2,200 2) R&amp;D tax credit + grant: 536</td>
<td>1) no support: 6,272 2) national R&amp;D grant: 1,535 3) EU R&amp;D grant: 140 4) Both: 787</td>
</tr>
<tr>
<td>Method</td>
<td>Propensity Score Matching (nearest neighbour)</td>
<td>Propensity Score Matching (nearest neighbour)</td>
</tr>
<tr>
<td>Time lag</td>
<td>Up to a 3-year time lag</td>
<td>Implicit 0-3-year time lag in each cross-section</td>
</tr>
<tr>
<td>Main findings</td>
<td>Higher additionality among for firms receiving 2 instruments</td>
<td>EU, National, and Both lead to input additionality; Both lead to the highest level of input additionality</td>
</tr>
<tr>
<td><strong>Table 2</strong>: Microeconometric evaluations of the innovation policy instrument mix (Part 2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td><strong>Year</strong></td>
<td>2015</td>
<td>2015</td>
</tr>
<tr>
<td><strong>Authors</strong></td>
<td>Guerzoni; Raiteri</td>
<td>Neicu; Teirlinck; Kelchtermans</td>
</tr>
<tr>
<td><strong>Country</strong></td>
<td>EU 27; Switzerland; Norway</td>
<td>Belgium</td>
</tr>
<tr>
<td><strong>Period</strong></td>
<td>2006-2008</td>
<td>2006-2010</td>
</tr>
<tr>
<td><strong>Sample</strong></td>
<td>5,238 firms</td>
<td>177 firms</td>
</tr>
<tr>
<td><strong>Dataset</strong></td>
<td>Pooled cross-section across all countries; Firms with &lt;20 employees</td>
<td>Cross-sectional</td>
</tr>
<tr>
<td><strong>Outcome variable</strong></td>
<td>Increase in innovation spending</td>
<td>Scale, speed of execution, the ratio of ‘R’ (research) versus ‘D’ (development) and the number of R&amp;D projects</td>
</tr>
<tr>
<td><strong>Treatment variable</strong></td>
<td>1) Public procurement for innovation 2) R&amp;D tax credits 3) Direct subsidies</td>
<td>1) Research and development (R&amp;D) tax credits AND Government research and development (R&amp;D) grants 2) Research and development (R&amp;D) tax credits ONLY</td>
</tr>
<tr>
<td><strong>Method</strong></td>
<td>Propensity Score Matching (nearest neighbour; exact matching; kernel density)</td>
<td>Propensity Score Matching (nearest neighbour)</td>
</tr>
<tr>
<td><strong>Time lag</strong></td>
<td>Up to a 3-year time lag</td>
<td>Implicit 0-4 year time lag</td>
</tr>
<tr>
<td><strong>Main findings</strong></td>
<td>Hidden treatment problem if instrument mix not accounted for when evaluating individual instruments; instrument mixes produce higher additionality than individual instruments</td>
<td>Firms receiving both have higher additionality across all outcome indicators</td>
</tr>
<tr>
<td>Year</td>
<td>2016</td>
<td>2017</td>
</tr>
<tr>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Authors</td>
<td>Marino; Lhuillery; Parrotta; Sala</td>
<td>Radicic; Pugh</td>
</tr>
<tr>
<td>Country</td>
<td>France</td>
<td>EU 28</td>
</tr>
<tr>
<td>Sample</td>
<td>10,091 observations; 9,634 observations</td>
<td>671 firms</td>
</tr>
<tr>
<td>Dataset</td>
<td>Unbalanced panel data; firms with over 20 employees</td>
<td>SMEs (fewer than 250 employees and an annual turnover of less than 50 million euros)</td>
</tr>
<tr>
<td>Outcome variable</td>
<td>Growth in R&amp;D expenditure</td>
<td>Input additionality; output additionality</td>
</tr>
<tr>
<td>Treatment variable</td>
<td>1) R&amp;D subsidy 2) R&amp;D tax credit + R&amp;D subsidy</td>
<td>1) no support; 2) national R&amp;D grant; 3) EU R&amp;D grant; 4) Both</td>
</tr>
<tr>
<td>Continuous</td>
<td>Binary</td>
<td>Continuous</td>
</tr>
<tr>
<td>Number of observations</td>
<td>1) R&amp;D subsidy only: 2,536 2) R&amp;D tax credit + subsidy: 2,078 3) no instrument: 7,556</td>
<td>1) no support: 281 2) national R&amp;D grant: 205 3) EU R&amp;D grant: 50 4) Both: 135</td>
</tr>
<tr>
<td>Method</td>
<td>Differences-in-differences; Propensity Score Matching</td>
<td>Propensity Score Matching (inverse probability of treatment weighting regression adjustment)</td>
</tr>
<tr>
<td>Time lag</td>
<td>1 year</td>
<td>Lag of 0-5 years</td>
</tr>
</tbody>
</table>

Bérubé and Mohnen (2009) compare firms that received an R&D tax credit only to firms that received both R&D tax credit and an R&D grant. The evaluations of single innovation policy instruments reviewed in Chapter 2 compare firms that received the instrument (i.e. treatment group) and similar firms that did not receive it (control group). In contrast, Bérubé and Mohnen (2009) remove all firms that received neither an R&D tax credit nor an R&D subsidy (i.e. the sample contains only firms that received an R&D tax credit and/or and R&D grant). In the econometric model, firms that only received the R&D tax credit are the control group, and
firms that received a mix comprising both the R&D tax credit and the R&D subsidy are the treatment group. As discussed later in this section, the methodology that Bérubé and Mohnen (2009) applied has also appeared in much of the later empirical research.

However, it is important to highlight that the cross-sectional nature of the dataset used by Bérubé and Mohnen (2009) limits the scope of the empirical analysis somewhat. The survey questionnaire used to capture the data asks the following question: “Did your firm use any of the following types of programs sponsored by the federal government or provincial/territorial governments during the three years, 2002 to 2004?”.9 Firms may receive an R&D tax credit and/or an R&D grant at any point over this 36-month period. This limits the precision of the possible analysis. For example, firms that are recorded as having received both instruments in the empirical analysis may have received the R&D tax credit in 2002 and the R&D grant in 2004, or they may receive both instruments in the same year, or a number of other possible sequences. The nature of the dataset rules out evaluating the impact of these potential sequencing effects.

The literature reviewed in Chapter 2, Section 2.5.8, highlighted that there can be a time lag between when firms receive public funding for innovation and when the impact of this funding materialises (e.g. Hall et al. 1986; Le & Jaffe 2017). A large time-period gap between when a firm received the first instrument and the second instrument may weaken the interaction effects between them, leading to a lower impact on firm-level innovation. Alternatively, if the first instrument allowed the firm to build up absorptive capacity over two years and then the second instrument allowed the firm to capitalise on this, the interaction effects could be stronger. From a theoretical perspective, it is a priori unclear whether one should expect weaker or stronger interaction effects depending on the gap between firm receipt of instruments. Ideally, the

---

survey would have recorded whether the firms received an R&D tax credit and/or an R&D subsidy in each of the subject years (i.e. in 2002, 2003 and 2004) to enable such distinctions. However, this insight is only readily apparent when viewing the problem through the lens of policy mix, which places an emphasis on the influence sequencing and temporal dynamics have on the observed impact of the innovation policy instrument mix. This issue is returned to in the next chapter, which outlines the dataset used in the current research.

In addition, as noted above, removing all firms that received no innovation policy instrument from the dataset facilitates a direct test for whether firms receiving a mix of R&D tax credits and direct subsidies had higher levels of innovation output than firms that received R&D tax credits alone. An alternative empirical strategy which other studies have employed, which is discussed below, involves keeping the full data sample (i.e. not removing firms that received no instrument); then splitting the full sample into three sub-samples and removing certain firms from each:

1) Keep only firms that received only a direct R&D subsidy and firms that received no instrument;
2) Keep only firms that received only an R&D tax credit and firms that received no instrument;
3) Keep only firms that received a mix comprised of both a direct R&D subsidy and an R&D tax credit, and firms that received no instrument.

In each of the three sub-groups listed above, the firms that received no instrument would serve as the control group in econometric analysis. Then, comparing the results of each model would show which treatment group had the highest impact on firm-level innovation.

Czarnitzki and Lopes-Bento (2014) estimate the relative impacts of receiving R&D funding from two distinct sources, focusing on the following treatment categories: 1) the EU; 2) the
national government; and 3) a R&D funding from both sources (i.e. an instrument mix). This study compares firms receiving funding from each of these sources, as well as the mix, with firms that receive no R&D funding.

As noted in Section 3.1, innovation policy instruments operationalise innovation policies (Flanagan et al. 2011). By focusing on the source of R&D funding, rather than specific instrument types (due to lack of data) Czarnitzki and Lopes-Bento (2014) use two aggregate measures that capture all forms of R&D funding from EU and national governance sources, respectively. These two measures are aggregate measures of EU innovation policy instruments and national innovation policy instruments. As discussed in Section 3.3.3, measures of public funding for innovation such as these capture an aggregate measure of all R&D funding from the EU and national levels of governance, not a specific instrument. However, the literature tends to treat this kind of measure as a specific instrument in empirical analyses. As highlighted in the next chapter, the current research uses a mixture of instrument types (i.e. R&D tax credits) and sources of innovation policy instruments (i.e. Ireland’s three key national funding agencies). Therefore, it is important to highlight the distinction between instrument type and source in existing empirical literature.

There are many specific innovation policy instruments available from the EU. Firms could conceivably receive a mix of instruments from EU sources. However, in the aggregate measure of EU R&D funding that is available in the data Czarnitzki and Lopes-Bento (2014) use, this intra-EU instrument mix would appear as a firm having received an EU innovation policy instrument. The data set or the sample size often requires using this form of summary measure in terms of the definition and measure of the instrument variables in empirical analysis. For example, even if a dataset distinguishes between all the different types of innovation policy instrument available to firms from EU and national sources, too few firms may receive each
individual instrument to enable an empirical analysis. Therefore, in an empirical model, all instruments from each source may require aggregation into one overall category.

Czarnitzki and Lopes-Bento’s (2014) empirical findings demonstrate that the source of R&D funding matters greatly in terms of the impact of subsidies from each source on firm-level innovation, and the interaction between subsidies from both sources when firms receive a mix. Applying the policy mix concept, Czarnitzki and Lopes-Bento (2014) built the empirical foundation which enables further study into the drivers of this relationship.

The key contribution of Guerzoni and Raiteri (2015) is to highlight the potential for a hidden treatment problem in evaluations that focuses on the impact of individual innovation policy instruments on firm-level innovation. This emphasises the necessity to include all innovation policy instruments that firms receive when evaluating impact. The authors’ empirical results demonstrate the vital importance of accounting for whether firms received a mix of instruments at the same point in time. For example, when the authors test the impact of direct subsidies on whether firms increased their innovation expenditure, but do not account for whether firms received any other form of innovation policy instrument, they find that firms are 7.8% more likely to increase their innovation spending. However, when the authors account for whether firms received any other form of innovation policy instrument, the result becomes insignificant. This is evidence of the hidden treatment problem. In addition, all treatment variables capturing the innovation policy instrument mix lead to much higher levels of additionality when compared to the individual instruments. However, the dataset available to Guerzoni and Raiteri (2015) has three limitations which it are important to discuss.

Similar to the studies of Bérubé and Mohren (2009) and Czarnitzki and Lopes-Bento (2014) discussed above, these data limitations hinder the level of detail Guerzoni and Raiteri (2015)
can use in their analysis. For example, the dataset contains two variables\(^\text{10}\) that serve as proxies for innovation policy instruments, where firms are asked:

- “Did at least one of the public procurement contracts that you have won since 2006 include the possibility to sell an innovation (i.e. new or significantly improved products or services)?”
- “Have significant changes in the following policy-related areas introduced since 2006 had a positive effect on innovation in your company? (a) Changes in tax environment (e.g. R&D or innovation tax credits) (b) Changes in public financial support (grants, loans, support for recruiting new staff)”

These questions are limited in the sense that they do not directly gauge whether the firm received a specific innovation policy instrument. Rather, they are indirect measures. They gauge whether the firm received some form of public money that the firm perceives as having induced an innovation.

There is a potential inherent bias in this form of questioning, because firms may receive different forms of innovation policy instrument that they feel have led to no innovation (i.e. they were ineffective). If this is the case, then the firm would answer “no” to the above questions and go on record in the study as having received no innovation policy instrument. On the other hand, if the firm felt a different form of public support had been effective at inducing innovation—for example, an employment support scheme that helped the firm bring in new employees with high innovative human capital—then it would answer “yes” to the above questions, despite the award being an employment support and not an innovation policy.

instrument. This would become a problem if an employment policy instrument that had induced innovation was used as evidence that innovation policy instruments had been effective.

It is also important to note that the data available to Guerzoni and Raiteri (2015) is cross-sectional in nature, capturing information on firms pooled across 27 EU Member States, as well as Switzerland and Norway. These are added into the econometric model as 29 separate control variables. However, the three innovation policy instruments under investigation—public procurement, direct subsidies and tax credits—are likely to have very different design features across different countries.

For example, the R&D tax credit available to firms in France during this time period was incremental in nature, meaning that it could only be claimed on additional R&D expenditure above a baseline (as detailed in Chapter 2). However, in Ireland, firms could claim a volume-based R&D tax credit that is applicable to all eligible R&D investments (Revenue Commissioners 2015). Despite this inherent difference in the designs of what appear as nominally the same instrument, firms in both Ireland and France that answered “yes” to this question will go into the same treatment category. In addition, it is important to note that firms in Germany have no access to R&D tax credits (Czarnitzki & Lopes-Bento 2014). Therefore, any firm located in Germany that answered “yes” to this question in the survey may have interpreted the question as a reference to a different change in the German tax system that they perceived as having induced an innovation, as opposed to having received an R&D tax credit. Both of these data important limitations are inherent when using this form of pooled cross-sectional data across many countries.

A final data limitation in Guerzoni and Raiteri (2015) which it is important to discuss centres the time period used in defining the outcome and treatment variables. The outcome variable, an increase in innovation spending, appears in the question, “Compared to 2006, has the
amount spent by your firm on all innovation activities in 2008 increased, decreased, or stayed approximately the same (adjust for inflation)?” (Guerzoni & Raiteri 2015, p. 733). There is an implicit two-year time lag here. However, the treatment variables qualification is “since 2006”. This means that firms could have received the innovation policy instrument(s) at any point from 2006 to 2008. This is a feature of how many datasets define innovation policy instrument variables, which significantly lowers the level of precision in innovation policy instrument evaluations.

As noted, Guerzoni and Raiteri (2015) make important contributions to the field of innovation policy evaluation by clearly demonstrating the powerful role the instrument mix can play in driving firm-level innovation. In addition, these authors highlight the potential bias engendered by not accounting for firms that receive a mix of instruments when evaluating single innovation policy instruments. The data limitations outlined above serve to inform future empirical research than can build on Guerzoni and Raiteri (2015).

Also clear from the empirical framework used by Guerzoni and Raiteri (2015) is that even in a very large cross-section of firms, as the number of instruments included in each instrument mix category increases, the sample size in that category decreases. For example, only 84 firms receive a mix of public procurement contracts, direct subsidies and tax credits, out of a full sample of 5,238 firms. If this pooled sample were split up into the 29 distinct countries that compose it in an effort to account for country context, this number may drop to single figures, or even to zero, making evaluation of this form of innovation policy instrument mix impossible. This is an important point that will be returned to in Chapter 4, when setting out the data used in the current research.

Neicu et al. (2015) follow the same empirical approach as Bérubé and Mohnen (2009), except that they look at the behavioural additionality of R&D subsidies and R&D tax credits, as
opposed to output additionality. Neicu et al. (2015, p. 231) find that “subsidies enforce behavioural effects that tax credits might have on specific dimensions of firm decision-making in R&D … firms that obtain R&D subsidies are more likely to further adjust their approach to R&D using funds made available through tax credits than when they benefit from tax credits alone”.

In addition to this empirical contribution, in an important theoretical contribution, Neicu et al. (2015, p. 222) argue that “subsidized firms direct the financial resources freed up by the tax exemption toward the subsidized project(s), and as such provide direction for the use of the R&D tax credit. In other words, those financial resources may find a ‘productive home’ within the context of the subsidized project. More specifically, the subsidized R&D projects may serve as a roadmap, pointing to a more productive way for allocating additional R&D resources”.

This argument provides a rationale for why one would expect *a priori* that firms receiving a mix of R&D tax credits and direct R&D subsidies engage in more innovation in general and, specifically, more radical forms of innovation in particular. The latter point occurs because direct R&D subsidies likely target more risky, radical forms of innovation (Czarnitzki et al. 2011). Allocating the discretionary financial support from the R&D tax credit to the directional support of the direct R&D subsidy will support this form of innovation even more firmly (Edler & Boon 2018; Boon & Edler 2018).

However, in terms of the mechanism for how this works, two important issues are inherent in this argument, but not explicitly made clear by Neicu et al. (2015). First, the direct R&D subsidy may be a necessary antecedent to the R&D tax credit. In this mechanism, firms receive the direct R&D subsidy, which increases the marginal rate of return (MRR) on the subsidised innovation project, thus incentivising the firm to engage in it (e.g. see David et al. 2000). Following this, using the R&D tax credit to further finance this project reduces the marginal
cost of capital and incentivises further investment in the same project. However, this could only happen after the firm has already received the direct R&D subsidy.

The second potential mechanism relates to the assumption that firms receive a constant stream of R&D tax credits, so their marginal cost of capital for innovation projects is at a constant low rate. Moreover, as these firms apply for and receive direct R&D subsidies for specific projects, they simply divert the finance from the R&D tax credit to these new projects. Given that firms’ R&D investments tend to be smooth through time (i.e. firms do not stop and start R&D spending), it is plausible that R&D active firms receive a steady supply of R&D tax credits every year. However, in this second mechanism, the R&D tax credit is the necessary antecedent to the direct R&D subsidy, as it enables firms to have a low marginal cost of capital (MCC), which the direct R&D subsidy augments by raising the MRR. A third option for the firm receiving both the R&D tax credit and the R&D grant at the same time seems unlikely, because the firm claims the R&D tax credit on R&D investment that has already taken place, while an R&D subsidy funds a new R&D project that has not yet begun.

Radas et al. (2015) run the same form of analysis as Bérubé and Mohnen (2009) and Neicu et al. (2015), in terms of focusing on a mix of direct R&D subsidies and R&D tax credits. An interesting contribution of Radas et al. (2015) is that they use a dataset that captures SMEs only. This contrasts with Bérubé and Mohnen (2009) and Neicu et al. (2015), who use datasets that capture the full spectrum of firm types. Given that SMEs more commonly use direct R&D grants, Radas et al. (2015) compare the effects of receiving direct R&D subsidies only with those of receiving a mix of direct R&D subsidies and R&D tax credits. This contrasts with the method Bérubé and Mohnen (2009) and Neicu et al. (2015) use to compare the impact of the mix of direct R&D subsidies and R&D tax credits on firm-level innovation with R&D tax credits only. Also, in contrast to Bérubé and Mohnen (2009) and Neicu et al. (2015), Radas et al. (2015) find differences in the impact of receiving an R&D subsidy only, versus the mix of
R&D subsidies and R&D tax credits on firm-level innovation for SMEs. However, one limitation of using this sub-sample of firms in the economy (i.e. SMEs) is that the sample size is small (i.e. 175 firms).

Radicic and Pugh (2017) follow the same empirical approach as Czarnitzki and Lopes-Bento (2014), but use a smaller pan-European dataset and can test the effect of EU and national R&D subsidies on both output and input additionality. This greater span of innovation outcomes is an advantage of this study, relative to Czarnitzki and Lopes-Bento (2014). However, it is important to note that while R&D tax credits are available in most EU countries, they are not accounted for in the national and EU subsidy variables that Radicic and Pugh (2017) use. Czarnitzki and Lopes-Bento (2014) overcome this issue by using a dataset of firms in Germany, where the R&D tax credit is not available. Therefore, it is reasonable to assume that the national and EU subsidy sources they use only capture direct R&D subsidies. Despite the contribution this study makes in terms of using a dataset that expands the range of innovation outcomes studied, using a pan-European dataset presents the same issues discussed above in relation to Guerzoni and Raiteri’s (2015) work. Therefore, a trade-off appears between controlling for as many of the issues that policy mix theory considers important, while still carrying out empirical analysis with large-scale firm-level datasets.

Recent work by Dumont (2017) and Marino et al. (2016) address some of the data issues that are common in the literature, constructing large panel-datasets by merging several different data sources that capture a comprehensive set of the innovation policy instruments available to firms in Belgium and France, respectively. Both authors present robust evidence that receiving a mix of innovation policy instruments has a weaker impact on firm-level innovation when compared to the individual instruments that compose the mix.
While both Dumont (2017) and Marino et al. (2016) use panel data, they consider the instrument mixes in static terms as that mix of different direct grants and tax credits that firms received in each year (i.e. at a single point in time). Neither study considers the sequence in which the instruments were received through time, and the role this may play in influencing their impact on firm-level innovation. Theoretically, temporal dynamics such as these can have a crucial influence on how the instrument mix functions (e.g. see Rogge & Reichardt 2016). Indeed, much theoretical literature has highlighted the lack of empirical research focusing on this issue (Rogge et al. 2011; Schmidt et al. 2012), particularly at the firm-level (Rogge & Schleich 2018). Dumont (2017) and Marino et al. (2016) make important empirical contributions in terms of the quality of the datasets they construct and the sophistication of the econometrics they use. Despite this sophistication, neither study considers the temporal dynamics of the instrument mix. This emphasises the mismatch between theory and empirical practice in the literature.

In addition to this, all the microeconometric literature that this section reviews, with the exception of Bérubé and Mohnen (2009) and Neicu et al. (2015), interpret econometric results as direct evidence of either complementarity or substitution between different innovation policy instruments in the mix. However, the researchers base these claims on the observation that receiving a mix of innovation policy instruments leads to higher or lower additionally, than would occur if receiving either instrument on its own. Though the literature this section reviews provides important indicators of complementarity and substitution, future literature would benefit from using a formal definition of complementarity and substitution. It is possible that the additionality of the instrument mix is greater than that of each individual instrument, but the instruments may still be substitutes.

Directly testing for complementarity and substitution is difficult in the current literature, because formal statistical tests for strict supermodularity and submodularity between
innovation policy instruments cannot use the propensity score matching (PSM) techniques (Papalia et al. 2018). PSM is common in the literature because it addresses important issues of selection bias and endogeneity. However, based on the econometric method most of the literature uses, there is no means of directly testing for complementarity, so at best it is only an inference. This is an important issue for the literature, which would benefit from the introduction of a direct test for whether instruments are complements or substitutes, both in a static sense at a point in time and in a dynamic sense through time. A means of overcoming this issue is presented and discussed in Chapter 4.

3.4. Conclusion

The role of innovation policy instrument mix in driving firm-level innovation was the focus of this chapter. Traditionally, empirical evaluations have focused on single innovation policy instruments (e.g. Beck et al. 2017). However, the theoretical literature reviewed in this chapter suggests that innovation policy instrument evaluations may benefit from being viewed through the lens of the policy mix for innovation (Flanagan & Uyarra 2016). At the cornerstone of policy mix theory is a focus on the interactions, interdependencies and trade-offs between different innovation policy instruments, as they affect the extent to which innovation policy outcomes are achieved (Cunningham et al. 2016; Uyarra & Flanagan 2013). Firms often receive a mix of different innovation policy instruments, such as R&D tax credits and R&D grants (Dumont 2017; Indecon 2017). Policy mix theory suggests the need for evaluations to consider the nature of the relationship between the instruments in the specific mix firms receive (Flanagan et al. 2011; Nauwelaers et al. 2009; Guy et al. 2009).

However, empirical application of the policy mix for innovation concept has lagged behind the development of theory. Howlett and del Rio (2015) and Schmidt and Sewerin (2018) argue that the lack of empirical studies which operationalise the policy mix concept has hindered its
development as a means of understanding the effects of innovation policy. This mismatch between theory and empirical practice is the precise issue the current research seeks to address.

The literature reviewed in this chapter highlights that applying the policy mix concept to the evaluation of public funding for innovation has proved difficult in practice. In order to address this issue, this chapter developed a conceptual framework for the evaluation of public funding for innovation that takes a policy mix approach and places firms at its centre. To construct this framework, the chapter draws on the literature reviewed in Chapter 2 on the theory and practice underpinning traditional innovation policy instrument evaluations, and combines it with insights from policy mix theory.

The relationship between different innovation policy instruments can be complementary, substitutive or neutral (Howlett & del Rio 2015; Flanagan et al. 2011). The literature reviewed suggested that interaction effects are governed by the degree of consistency between different instruments (Rogge & Reichardt 2016). A consistent instrument mix can lead to complementarity, where different instruments mutually reinforce one another and have a greater impact when received separately. In contrast, substitution occurs where different instruments weaken one another’s effectiveness at stimulating firm-level innovation. Complementarity and substitution can be conceptualised as the relationship between different instruments a firm receives: 1) at a point in time; and 2) through time (Reichardt & Rogge 2016).

Therefore, when evaluating the impact of innovation policy instruments on firm-level innovation, it is important to consider the set of instruments a firm receives in a given year, as well as the instruments the firm received in previous years. In addition, the sequence in which firms receive different instruments through time may have a crucial role determining their
eventual impact on firms’ innovation performance. Two hypotheses are develop to address these issues.

Following the theoretical discussions, the chapter turns to the small but growing empirical literature which evaluates the impact of innovation policy instrument mix on firm-level innovation. In the main, these studies find that receiving a mix of different instruments (or R&D/innovation support from different sources) has a positive and statistically significant impact on a variety of different innovation outcomes. While these studies provide foundational insights on the evaluation of innovation policy instrument mix, the review highlighted that they have some limitations. These limitations are primarily due to the datasets that are available to apply the policy mix concept at firm-level. Commonly available datasets are cross-sectional in nature and do not capture detailed information on the specific mix of innovation policy instruments firms receive. This has hindered the empirical application of many aspects of policy mix theory, particularly the temporal dynamics of the innovation policy instrument mix which requires panel data.

This chapter provides a rationale for extending traditional evaluations of public funding for innovation to encompass the mix of innovation policy instruments firms can receive. Such evaluations are necessarily more complex than single instrument evaluations and more demanding in terms of requiring panel data capturing detailed information on the specific mix of innovation policy instruments firms receive through time. Though such evaluations present challenges, taking a policy mix approach to the evaluation of public funding for innovation mitigates the “risk that complexity is simply ‘black boxed’ and rendered unproblematic” within the literature (Flanagan et al. 2011, p. 702). While no evaluation can be ‘perfect’, there is always scope for incremental improvements. This study takes a step towards more fully integrating policy mix theory into the evaluation of innovation policy instruments.
The next chapter builds on this review of the theoretical and empirical literature on the innovation policy instrument mix in two respects. Firstly, drawing on theory, it identifies an empirical method that facilitates direct testing for complementarity and substitution between different innovation policy instruments. Secondly, to overcome the data issues discussed above, it constructs three unique panel datasets through a series of data merges. These datasets enable the study to evaluate the relationship between different instruments a firm receives at a point in time and through time, and how these static and dynamic interactions influence firm-level innovation.
Chapter 4: Methodology and data

4.1. Introduction

The previous chapter established the conceptual basis for evaluating the impact of innovation policy instrument mix on firm-level innovation. Continuing directly from this analysis, this chapter details the empirical methodology and data used to address the research question: Are different innovation policy instruments complements or substitutes?

Chapter 3 noted that the relationship between different innovation policy instruments can be conceptualised in two ways. The first hypothesis deals with the static interaction between the instruments a firm receives at a point in time, and the influence this interaction has on innovation outcomes. Testing this hypothesis necessitates estimating whether the innovation performance of firms that receive a mix of instruments is greater than the performance of firms that received each instrument separately. Hypothesis 2 focuses on the interaction between instruments a firm receives through time. Policy mix theory emphasises that the sequence in which firms’ receive different instruments may play a key role in determining the eventual impact of these instruments on firm-level innovation. To test the second hypothesis, this chapter examines the transitioning from receiving one innovation policy instrument in a given year to receiving a mix of instruments in the next year.

The chapter outlines a recently-developed form of instrumental variable estimation procedure which controls for selection bias and endogeneity associated with innovation policy instruments. This econometric model facilitates conducting direct tests for static and dynamic complementarity between instruments. As noted in Chapter 3, the previous empirical literature relies on inference when evaluating whether the relationship between different innovation policy instruments is complementary or substitutive, rather than directly testing for complementarity and substitution. The direct tests conducted in this study will determine
whether the empirical analysis supports the hypothesised complementary relationship between different innovation policy instruments.

To operationalise this econometric procedure, the study creates three distinct datasets based on a series of data merges. Using Ireland as a locale, the empirical analysis focuses on testing for pairwise complementarity between Research and Development (R&D) tax credits and innovation policy instruments implemented by Ireland’s three key national funding agencies: Enterprise Ireland, Industrial Development Agency (IDA) Ireland and Science Foundation Ireland (SFI). Therefore, each of the three datasets constructed for this analysis captures a different, mutually exclusive combination of instruments: 1) R&D tax credit and Enterprise Ireland R&D/innovation support; 2) R&D tax credit and IDA Ireland R&D/innovation support; and 3) R&D tax credit and SFI linkages. The innovation outcome variable used in this study is firms R&D intensity.

The remainder of this chapter is organised as follows. Section 4.2 details the econometric estimation procedure and the testing for static and dynamic complementarity. Section 4.3 outlines Ireland’s innovation policy landscape to provide a context for the current research. This section provides details on Ireland’s R&D tax credit programme, as well as the innovation policy instruments implemented by Enterprise Ireland, IDA Ireland and SFI. Following from this discussion of the empirical setting, Section 3.4 outlines the specifics of the datasets, how they are merged together and the nature of the key innovation policy instrument variables measured and used in the empirical analysis. This section provides key descriptive statistics on each of the three datasets, while Section 4.5 concludes the chapter and introduces Chapter 5, which presents and analyses the empirical results.
4.2. Microeconometric evaluation

As noted in Chapters 2 and 3, propensity score matching (PSM) models commonly applied in innovation policy instrument evaluations. However, PSM models do not facilitate a direct test for complementarity between innovation policy instruments. Therefore, this study applies a recently-developed instrumental variable model uniquely suited to the direct evaluation of consistency in the innovation policy instrument mix, eliminating the need to rely on inference. Following Love et al. (2014), this analysis includes a formal statistical test for static and dynamic complementarity, substitution and neutrality between combinations of innovation policy instruments in the mix. This chapter adopts the following definition of complementarity: two distinct innovation policy instruments are complements if receiving one increases the additionality of the other. This echoes the definition used by Love et al. (2014, p. 1774), which states “[t]wo discrete activities are (Edgeworth) complementary if adding one activity increases the returns from doing the other”.

4.2.1. Estimating static complementarity and substitution

In the microeconometric literature reviewed in Chapters 2 and 3, it is common to categorise firms that receive any form of public funding for innovation as ‘treated’ and any firms that do not receive public funding for innovation as ‘untreated’. Facilitating a direct test for static complementarity between two innovation policy instruments that a firm receives at the same point in time requires defining four discrete ‘treatment categories’ that capture all potential combinations of innovation policy instruments that firms can receive. In the case of R&D/innovation support from a funding agency and R&D tax credits as an illustrative example, these four treatment categories are:

1) No agency R&D/innovation support and no R&D tax credit (neither; 00)

2) No agency R&D/innovation support intervention and receives R&D tax credit (R&D
tax credit only; 10)

3) Receives agency R&D/innovation support intervention and no R&D tax credit (agency R&D/innovation support only; 01)

4) Receives agency R&D/innovation support intervention and R&D tax credit (both; 11)

The terminology of treatment categories functions well in this context because it continues the commonly used language of the earlier literature reviewed in Chapters 2 and 3, and captures the possible cases completely. Therefore, even though the category ‘Neither/untreated’ contains no innovation policy instrument, and ‘R&D tax credit only’ and ‘agency R&D/innovation support only’ contain only one innovation policy instrument each, both are treatment categories. In addition, these four treatment categories are mutually exclusive cases. An observation in category 4 is not also recorded in category 2 simply because it includes an R&D tax credit; this observation must receive both instruments together at the same point in time to appear in category 4.

A common approach within the literature is to perform a direct test for static complementarity by estimating a traditional innovation production function (Athey & Stern, 1998; Mohnen & Röller 2005; Cassiman & Veugelers 2006; Schmiedeberg 2008; Carree et al. 2011; Doran 2012; Love et al. 2014). Here, the production function approach operates by taking an indicator of the firm’s innovation output as the dependent variable, and taking the treatment category variables defined above (i.e. 00, 10, 01, and 11) and control variables (outlined in Section 4.4.1.4) as independent variables, and preforming regression analysis. This is outlined in Equation (1):

\[ RD_{it} = \gamma_0 0_{0it} + \gamma_1 1_{0it} + \gamma_2 0_{1it} + \gamma_3 1_{1it} + \beta X_{it} + \epsilon_{it} \] (1)
Here, $RD$ represents a measure of innovation outcomes for firm $i$ in time period $t$. Time period $t$, in this analysis, is defined as annual. $X_{it}$ is a vector of control variables, while $\varepsilon_{it}$ is the error term. The key focus variables are $00_{it}$, $10_{it}$, $01_{it}$ and $11_{it}$, which represent each of the four mutually exclusive instrument mix category variables described above. Here, $00_{it}$ captures firms that received no policy instrument (neither/untreated), $10_{it}$ captures firms that received a direct R&D grant only, $01_{it}$ captures firms that received an R&D tax credit only, and $11_{it}$ captures firms that received both instruments together in a mix. Each of these treatment categories is a discrete option available to the firm, with the potential for each treatment category to produce different levels of additionality.

In addition, as Chapter 2 describes, innovation policy instruments may have both a contemporaneous and a lagged impact on firm-level innovation. Therefore, the analysis runs four separate econometric models, each with a different lag specification, as in Equation (2):

$$RD_{it} = \gamma_0 00_{it-k} + \gamma_1 10_{it-k} + \gamma_2 01_{it-k} + \gamma_3 11_{it-k} + \beta X_{it-k} + \varepsilon_{it}$$ (2)

The lag structure models range from no lag (i.e. in Equation (2) set $k = 0$) to three lags (i.e. in Equation (2) set $k = 1, 2$ and 3). This means running four distinct econometric models for each test, each with a different lag structure. For example, for firms in treatment category 2, when $k = 0$, this model will evaluate the impact of receiving a direct R&D grant only in time period $t$, on firm-level innovation in time period $t$. When $k=3$, this model will evaluate the impact of receiving a direct R&D grant only in time period $t$, on firm-level innovation in three years.

To formally test for static complementarity and substitution between different innovation policy instruments, this analysis tests a series of inequalities proposed by Mohnen and Röller.

---

11 As noted in Section 4.1, and detailed in Section 4.4.1.2, the dependent variable used in this analysis is firms R&D intensity. Therefore, the $RD$ is used to indicate firm-level innovation in Equation (1).
Complementarity between two innovation policy instruments in a firm’s innovation production function requires that:

$$RD(10, X) + RD(01, X) \leq RD(00, X) + RD(11, X)$$

(3)

That is, receiving both agency support and an R&D tax credit together ($11_{it}$) stimulates more R&D intensity than the sum of the R&D intensity stimulated by either innovation policy instrument individually. Similarly, substitution between two innovation policy instruments requires that:

$$RD(10, X) + RD(01, X) \geq RD(00, X) + RD(11, X)$$

(4)

Equation (3) and Equation (4) respectively represent tests for strict supermodularity and submodularity. If neither of these equations are satisfied, then by definition a neutral relationship between innovation policy instruments exists.

4.2.2. Estimating dynamic complementarity and substitution

While conceiving of complementarity between innovation policy instruments as occurring at a point in time, the dynamics of how firms arrive at a given innovation policy instrument mix will play an important role in determining the impact that the innovation policy instrument mix has on a firm’s innovation outcomes. Empirical tests for complementarity have typically treated the four key focus variables—i.e. $00_{it}$, $10_{it}$, $01_{it}$ and $11_{it}$ in Equation (1)—as comparative statics (Cassiman & Veugelers 2006; Cozzarin & Percival 2006; Love & Roper 2009; Doran 2012). This involves the comparison of all firms in each category at a point in time. However, Love et al. (2014, p. 1780) point out that the concept of complementarity is “inherently dynamic” in that it involves adding something new to what the firm already has.

Understanding the dynamics of the instrument mix requires mapping out the actual transitions that individual firms make from one treatment category to another each year and determine the
impact that these transitions have on firm-level innovation. This facilitates a comparison of the relative impact of ‘intra-firm’ treatment category transitions on firm-level innovation through time, by directly comparing the coefficients on each transition variable in regression analysis.

Testing for dynamic complementarity and substitution in this way necessitates a move beyond the static comparison of the four treatment category variables outlined in Section 4.2.1 above. Now the evaluation must account for the additionality of the transition from one treatment category in one time period to any of the three other categories, or of remaining in the same category, in the next time period. This involves sixteen possible transitions, twelve of which involve some form of change in instrument mix category, and four of which involve staying in the same category, as outlined in Equation (5):

$$RD_{it} = \gamma_{00}00_{it-k} + \gamma_{00}10_{it-k} + \gamma_{00}j11_{it-k} + \gamma_{10}01_{it-k} + \gamma_{10}10_{it-k} + \gamma_{10}j01_{it-k} + \gamma_{10}j10_{it-k} + \gamma_{11}00_{it-k} + \gamma_{11}10_{it-k} + \gamma_{11}j01_{it-k} + \gamma_{11}j10_{it-k} + \beta X_{it} + \epsilon_{it}$$  (5)

In Equation (5) all of the variables are as in Equation (1), but sixteen transition variables have replaced the four treatment category variables. For example, $\gamma_{11}1_{it-k}$ captures firms that received an R&D tax credit in time period $t-k$ and transitioned to receiving both an R&D tax credit and an agency support in time period $t-j$. To evaluate the contemporaneous impact of this transition variable requires setting $k=1$ and $j=0$. In this example, the $k$ represents one year ago, while the $j$ represents the current year. To evaluate the impact of this transition variable with one time lag calls for setting $k=2$ and $j=1$, and so on.

The coefficients on all of these sixteen transition variables will provide information on the differential effects of all potential dynamics within the innovation policy instrument mix. However, the key focus of this study is not just the absolute value of each transition variable, but rather whether certain transitions lead to more additionality than others. Therefore, testing
for dynamic complementarities requires testing two further inequalities.

First, whether the transition from receiving an agency support in one period to receiving both an R&D tax credit and agency R&D/innovation support together in the next period has a greater impact on firm-level innovation than the transition from receiving no policy instrument to receiving an R&D tax credit only requires:

\[ 1_{it}0_{it-1} \geq 0_{it}0_{it-1} \]  \hspace{1cm} (6)

Second, the test of the opposite transition—whether the transition from receiving an R&D tax credit only to receiving both an R&D tax credit and agency support together has a greater impact on firm-level innovation than the transition from receiving no innovation policy instrument to receiving an direct support only—requires:

\[ 1_{it}0_{it-1} \geq 1_{it}0_{it-1} \]  \hspace{1cm} (7)

As Section 4.4.4.2 below demonstrates in describing the data, some transitions are much more common than others. The most important transition to highlight is that on the left-hand side of Equation (7), where a firm receives an R&D tax credit only in one period and then transitions to receiving both an R&D tax credit and agency R&D/innovation support together in the next period. This is likely due to the nature of the different types of innovation policy instrument under consideration. Firms can claim R&D tax credits automatically on eligible R&D expenditure, while they must apply for agency R&D/innovation support awarded on a competitive basis.

4.2.3. Microeconometric method: ‘Generated’ instrumental variable estimation

As Chapter 2 emphasises, a well-established finding in the innovation policy instrument evaluation literature is that research should not view as random processes neither the act of firms applying for public funding for innovation, nor the fact of receiving it, can be viewed as
random processes (e.g. see David et al. 2000). Firms that apply for public support for their innovation activities will likely differ systemically from firms that do not apply, in many characteristics such as having higher absorptive capacity and past success with innovation (Czarnitzki et al. 2011). Here, even in the absence of any innovation policy instruments, applicant firms would likely be more innovative than non-applicants, due to these inherent characteristics. For the same reasons, but also due to the potential for innovation funding agencies to cherry pick winners, certain firms may also be more likely to receive public funding (Czarnitzki & Lopes-Bento 2013). Therefore, the use of innovation policy instruments must be considered as both endogenous and characterised by selection bias.

As highlighted by David et al. (2000), R&D intensive firms are usually more likely to apply for public support for their R&D activities, and funding agencies are usually more likely to grant R&D support to R&D intensive firms. For these reasons, linear regression models such as Ordinary Least Squares (OLS) can lead to biased estimates of the impact of public R&D/innovation support on firm-level innovation. A number of econometric methods have been developed to correct for issues of endogeneity and selection bias (for a discussion see Cerulli & Poti 2012). The most common methods are matching techniques (e.g. propensity score matching), difference-in-differences (DiD) estimations, and instrumental variable models. While each of these econometric methods have merits, the core issue of concern in this thesis is whether a complementary relationship exists between different innovation policy instruments in terms of their impact on firm R&D intensity. Of the econometric methods listed above, only the instrumental variable method would facilitate this form of evaluation. The other methods are appropriate for evaluating the additionality of public R&D/innovation support, but do not facilitate tests for strict super- and sub-modularity (i.e. complementarity and substitution).

While instrumental variable modelling would control for both endogeneity and selection bias,
strong and valid instrumental variables usually cannot be found when using highly specific micro-datasets, and the inclusion of anything other than truly exogenous instruments may actually be counterproductive (Mohnen & Röller 2005; Love et al. 2014).

Lacking obvious instrumental variables for receiving an innovation policy instrument or instrument mix in the dataset, accounting for the selection bias and endogeneity occurs by employing the heteroscedasticity-based instrumental variable approach developed by Lewbel (2012; 2018).

For Lewbel-instruments to be valid, they must be relevant and exogenous, as is the case with standard instrumental variable methods (Arellano & Bond 1991). In the case of evaluating the impact of innovation policy instruments on firm R&D, the relevance requirement will be met if there is heteroscedasticity between the innovation policy instrument variable and other independent variables in the model. The exogeneity assumption is equivalent to the standard requirement that the instruments and the second stage-error term are uncorrelated. A sufficient condition is the standard assumption of homoscedasticity in the unobserved variable. In the standard unobserved variable model, this assumption is usually implied. However, in overidentified models, this exogeneity assumption can be tested empirically as well. The test results for this thesis (presented in Chapter 5, alongside the estimation results) indicate that the Lewbel-instruments also meet the exogeneity assumption.

Essentially, the method proposed by Lewbel (2012) builds on second moment restrictions, not unlike well-known General Method of Moments (GMM) dynamic panel data estimators (e.g. Arellano & Bond 1991; Arellano & Bover 1995). Though it has only come to prominence recently, Lewbel’s (2012) approach extends a literature with a long tradition.

The possibility of identifying causal relationships through heteroscedasticity was already mentioned in Wright’s (1928) seminal work on instrumental variables. More recently, Rigobon
(2003) and Lewbel (2012) developed estimators that facilitate the identification of causal relationships through heteroscedasticity (see also Lewbel 2018). Rigobon (2003) demonstrated that it is possible to identify causal relationships by exploiting the existence of discrete regimes with different levels of heteroscedasticity. Building of the work of Rigobon (2003), Lewbel (2012) constructs an estimator that does not require the use of discrete regimes, and can be applied generally in research using econometrics.

Though identification through heteroscedasticity is becoming more prominent in applied economic research (Arcand et al. 2015; Comin et al. 2019), it is still not widely employed given how recently it has been developed (e.g. Lewbel 2012; 2018). Therefore, it is important to provide the intuition for how this econometric estimation method works (full details and derivations are provided in Lewbel 2012):

- Assume a research question that requires estimating the following model: \( Y_1 = a + \beta_1 X + \gamma_1 Y_2 + \epsilon_1 \)
- This model is characterised by an endogeneity problem: \( Y_2 = a + \beta_2 X + \gamma_2 Y_1 + \epsilon_2 \)
- Assume that \( E(X\epsilon_1) = E(X\epsilon_2) = \text{cov}(X,\epsilon_1\epsilon_2) = 0 \); We know that \( \text{cov}(X,\epsilon_1\epsilon_2) = 0 \) holds, because then \( E(\epsilon_1\epsilon_2X) = E(\epsilon_1) E(\epsilon_2X) = 0 \)
- Further assume that there is heteroscedasticity in the data (i.e. \( \text{cov}(X,\epsilon_2^2) \neq 0 \))
- Based on this assumption of heteroscedasticity, \( X\epsilon_2 \) can be used as an instrument for \( Y_2 \) (note that Lewbel (2012) uses \( [X-E(X)]\epsilon_2 \))
- \( X\epsilon_2 \) will be a good instrument because the assumption that \( \text{cov}(X,\epsilon_1\epsilon_2) = 0 \) guarantees that \( X\epsilon_2 \) is uncorrelated with \( \epsilon_1 \), and the presence of heteroscedasticity (\( \text{cov}(X,\epsilon_2^2) \neq 0 \)) guarantees that \( X\epsilon_2 \) is correlated with \( \epsilon_2 \) and thus with \( Y_2 \)
- If \( X \) includes more than one variable, the condition \( \text{cov}(X, \epsilon_2^2) \neq 0 \) needs to hold only for a subset \( Z \) of the \( X \) matrix
Note that the assumptions $E(X\varepsilon_1) = E(X\varepsilon_2) = \text{cov}(X,\varepsilon_1\varepsilon_2) = 0$ are standard and their validity can be tested with Hansen’s J test. The only non-standard assumption required for identification is the presence of heteroscedasticity ($\text{cov}(X, \varepsilon_2^2) \neq 0$). As noted above, all diagnostic tests for models using Lewbel-instruments are presented in Chapter 5, alongside the results.

Here, a series of instruments are generated based on functions of the model’s data. In the linear relationship set out in Equation (8) below, $I_i$, an outcome variable representing a measure of firm i’s innovation outcomes, is determined by a vector of control variables, $X_i$, and $Z_i$ an indicator of whether firm i received an innovation policy instrument:

$$Y_i = X_i\beta + Z_i\gamma + \varepsilon_{i1}$$ (8)

Equation (8) will estimate the parameter $\gamma$. Equation (9) below determines whether firm i receives an innovation policy instrument:

$$Z_i = X_i\alpha + \varepsilon_{i2}$$ (9)

In Equation (9), no instruments can be excluded, as in the empirical setting. While this estimator was initially developed for use with a continuous endogenous variable (Lewbel 2012), it also applies in the case of a binary endogenous variable (Lewbel 2018), as is the case here. Innovation policy instrument evaluations have applied this estimator and found it to produce results consistent with other estimation methods (e.g. see Liu et al. 2016; Heim et al. 2017; Czarnitzki et al. 2018).

The rationale for employing the Lewbel-instrumental variable methods is clear: It facilitates addressing the study’s core research question (i.e. testing for complementarity in the innovation policy instrument mix), while correcting for the important econometric issues of selection bias and endogeneity. However, the reliance on one form of econometric method is not without limitations. Freeman (1980, p. xi) highlights that in research using econometric methods, “the more sophisticated the econometrics, the greater the danger the results derive from the model
than from the world. In economics it is the accumulation of disparate lines of evidence, not the
elegance of the statistical technology for a single estimator, that is compelling”. Therefore,
while every effort has been made in this thesis to carefully employ robust econometric methods,
it should be noted that the reliance on one, relatively recently developed estimator is a limitation
of the current study. Future research would benefit from access to a dataset that contained truly
exogenous instrumental variables, as well as detailed information on the innovation policy
instruments firms receive through time. This would facilitate testing the robustness of results
derived from the Lewbel-instrumental variable method.

4.3. Empirical setting: Ireland

As a small open economy on the periphery of Europe, Ireland has sustained a policy focus on
innovation in an effort to achieve and maintain competitive advantage (Forfás 2000; 2010;
DBEI 2015b; 2018). As such, the government has actively engaged in innovation policy
classes Ireland as a “strong innovator” alongside Austria, Belgium, France, Germany and
Slovenia, ranked as the ninth most innovative EU Member State. The 2018 Global Innovation
Index ranked Ireland as the tenth most innovative country worldwide (Cornell University et al.
2018). As noted in Section 4.1, Ireland’s three key national funding agencies that have a focus
on R&D/innovation are: Enterprise Ireland, IDA Ireland, and Science Foundation Ireland
(SFI)12. In addition, since 2004, firms in Ireland have been able to claim R&D tax credits. R&D
tax credits have since become the dominant innovation policy instrument in Ireland in terms of
the cost of the scheme and the number of firms claiming it (Department of Finance 2013; 2016).

12 As defined below in Section 4.4.2, this research uses binary measures indicating each year firms received any
financial support for R&D/innovation from Enterprise Ireland or IDA Ireland or had a linkage with SFI. In this
way, the innovation policy instruments firms receive from the each funding agency are aggregated into three
binary variables. Consequently, this study tests for complementarity between the R&D tax credit and binary,
aggregate measures of R&D/innovation support from the three key sources of funding in Ireland.
While this section has introduced the empirical setting of Ireland, the next four sections detail, in turn, the key features of Ireland’s innovation policy system. First, the analysis focuses on the R&D tax credit scheme, followed by Enterprise Ireland, IDA Ireland and SFI.

4.3.1. Revenue Commissioner: R&D tax credit

The Irish Revenue Commissioners administer the R&D tax credit, which is available to all firms in Ireland that are undertaking qualifying R&D activities in Ireland or within the European Economic Area (Revenue Commissioners 2015). Firms submit R&D tax credit claims to the Irish Revenue Commissioners as part of their annual corporation tax return (known as the CT1 form).

Firms can claim the R&D tax credit at a rate of 25% of qualifying R&D expenditure if they undertake in-house R&D within Ireland, as well as expenditure on buildings and structures used for R&D. Claiming the R&D tax credit can accompany claiming the standard 12.5% corporation tax deduction. Therefore, the R&D tax credit effectively reduces the real cost of R&D for firms in Ireland by up to 37.5% (Comptroller and Auditor General 2016).

The Finance Act of 2004 introduced the R&D tax credit in Ireland. The number of firms claiming the R&D tax credit increased from 73 in 2004 to approximately 1,600 in 2014 (Department of Finance 2015). Over the same period, the cost of the R&D tax credit to the Irish Exchequer increased from €71 million to €553 million (Department of Finance 2015). A number of reports by the national Government (Department of Finance 2016; DBEI 2015b) and the OECD (OECD 2015a; OECD 2014) have highlighted innovation policy in Ireland as heavily skewed toward the use of R&D tax credits. The indirect public funding that R&D tax credits offer accounts for approximately 66% of the total public funding for innovation implemented in Ireland (Department of Finance 2016, p. 17). Therefore, the R&D tax credit is by far the most prominent innovation policy instrument in Ireland, in terms of firm usage.
Table 4 Changes in the R&D tax credit scheme since introduction

<table>
<thead>
<tr>
<th>Finance Act</th>
<th>Amendment made</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>• Introduction of the R&amp;D tax credit – 20% credit on R&amp;D expenditure in excess of R&amp;D expenditure incurred in 2003 (the base year).</td>
</tr>
</tbody>
</table>
| 2006        | • An apportionment of the R&D related share of plant and machinery costs is eligible for the tax credit.  
                        • Allows Revenue to consult with experts when determining if claimed expenditure was incurred in the carrying on of R&D activities. |
| 2007        | • Base year fixed at 2003 until 2009.  
                        • Amendment to relief on expenditure to subcontractors (allowed the use of third parties, subject to a 10% ceiling, previously third level institutions only). |
| 2008        | • Base year fixed at 2003 until 2013. |
| No 2. 2008  | • Increase in the rate of relief from 20% to 25%.  
                        • Introduction of the payable credit.  
                        • Proportion of expenditure on mixed used buildings and structures allowable for tax credit (subject to minimum 35% use for R&D activities).  
                        • Base year fixed at 2003 indefinitely. |
| 2010        | • Amended calculation of qualifying expenditure in base year where company closes one of its R&D centres on a permanent basis. |
| 2011        | • Excluded expenditure on specified intangible assets from the credit where this expenditure is already covered under a separate tax relief regime. |
| 2012        | • First €100,000 of R&D expenditure eligible for the credit regardless of expenditure in base year.  
                        • Key employee provision introduced. |
| 2013        | • First €200,000 of R&D expenditure eligible for the credit regardless of expenditure in base year (increased from €100,000 in 2012).  
                        • Key employee eligibility criteria reduced to 50% of working time on R&D activities (75% when introduced in 2012). |
| No 2. 2013  | • First €300,000 of R&D expenditure eligible for the credit regardless of expenditure in base year (increased from €200,000 in 2013).  
                        • Outsourcing limits increased. |
| 2014        | • Removal of the base year with effect from 1 January 2015. |

Though the R&D tax credit is available to all firms in Ireland, it is typically older, larger, foreign-owned firms that claim it (Department of Finance 2016). Most Finance Acts have amended and enhanced the R&D tax credit regime since its introduction, as Table 4 below shows. The most important of these changes was the shift from a mainly incremental-based R&D tax credit scheme in 2004 to a volume-based R&D tax credit scheme completed in 2012.
This important change did not occur in one year specifically, but rather was an evolution over time that culminated in the change in 2012.

4.3.2. Enterprise Ireland

Significantly, the R&D tax credit is available to all firms in Ireland, distinguishing it from Ireland’s two main enterprise funding agencies: Enterprise Ireland and IDA Ireland. While both Enterprise Ireland and IDA Ireland fund a range of different enterprise development schemes, a significant portion of their spending is directed at firm R&D and innovation activities. This section introduces Enterprise Ireland, while the next section turns to IDA Ireland.

Enterprise Ireland is the national funding 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. Officially launched 1998, Enterprise Ireland had existed in many different forms since the early 1950s. Indigenous firms in Ireland are predominantly micro firms with fewer than 10 employees, and small and medium-sized enterprises (SMEs) with between 10 and 249 employees (CSO 2018). This means that Enterprise Ireland’s client firms are typically micro firms and SMEs. Given that micro firms and SMEs make up 99.8% of active enterprises in Ireland and account for 68.9% of all employment (CSO 2016), Enterprise Ireland clearly plays a prominent role in the Irish economy.

Enterprise Ireland competitively awards firms a wide range of innovation policy instruments. Table 5 provides the names and descriptions of the innovation policy instruments available to firms from Enterprise Ireland. The information in Table 5 is from an extensive DBEI (2015) inventory of all R&D and innovation funding schemes.
Table 5 Enterprise Ireland: Innovation policy instruments

<table>
<thead>
<tr>
<th>Innovation policy instrument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Research, Technology and Innovation (RTI) Scheme</td>
<td>Assistance to Irish owned firms for investment in R&amp;D as part of a company’s strategic development.</td>
</tr>
<tr>
<td>R&amp;D Advocates</td>
<td>Aimed at increasing awareness of, and activity in, RD&amp;I by inactive Irish owned companies through the use of Advocates</td>
</tr>
<tr>
<td>Commercialisation Fund</td>
<td>Supports academic researchers to bring research with commercial potential to a point of technology transfer to industry (via licensing or spinout).</td>
</tr>
<tr>
<td>Intellectual Property Assistance Scheme (IPAS)</td>
<td>Advice &amp; financial assistance for patent protection.</td>
</tr>
<tr>
<td>Innovation Partnerships</td>
<td>Aimed at harnessing the strengths of the third level sector to work in partnership with companies on specific R&amp;D projects.</td>
</tr>
<tr>
<td>Business Partners</td>
<td>Facilitates entrepreneurs to identify research with commercial potential and to connect with research groups, in order to speed up the process of company creation.</td>
</tr>
<tr>
<td>Technology Gateways</td>
<td>Funding of manager and up to three researchers. Governed by industry, Gateways provide technology solutions for the close-to-market needs of Irish industry.</td>
</tr>
<tr>
<td>Innovation Vouchers</td>
<td>Support small companies to engage with HEI researchers in order to explore a business opportunity or solve problems.</td>
</tr>
<tr>
<td>Campus Incubation</td>
<td>A capital/infrastructure programme, where EI invested to develop on-campus space for start-up companies, including specialised biotech facilities.</td>
</tr>
</tbody>
</table>

4.3.3. IDA Ireland

Similar to Enterprise Ireland, IDA Ireland does not make financial support available to all firms in the economy. While Enterprise Ireland supports only indigenous Irish firms, IDA Ireland concentrates solely on foreign-owned firms. Attracting Foreign Direct Investment (FDI) to Ireland as a means stimulating economic growth is a pillar of industrial policy in Ireland (IDA 2017; DBEI 2015a).

IDA Ireland, was founded in 1949, and its mission evolved over many years to one focused on attracting FDI into Ireland. IDA’s client base is mainly large multinational corporations. Though large firms with 250 or more employees account for just 0.2% of all firms in Ireland,
they also account for 31.1% of all employment (CSO 2016). In 2015, IDA client companies operating in Ireland employed 187,056 people, 12,600 of whom worked in R&D and had total in-house R&D expenditure of €1.5bn (IDA, 2015). Though IDA’s remit expands beyond funding innovation, it is the primary grant-awarding agency for innovation in foreign-owned firms operating in Ireland.

IDA Ireland competitively awards funding for R&D and innovation projects to firms via the IDA R&D fund described in Table 6 below. Similar to Section 4.3.2. and Section 4.3.3 above, the information in Table 6 is drawn from an extensive inventory by DBEI (2015a) of all R&D and innovation funding schemes.

<table>
<thead>
<tr>
<th>Table 6 IDA Ireland: Innovation policy instruments</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Innovation policy instrument</strong></td>
</tr>
<tr>
<td>IDA R&amp;D Fund</td>
</tr>
</tbody>
</table>

4.3.4. Science Foundation Ireland

Established in 2003, Science Foundation Ireland (SFI) was and is the main funding agency for applied and oriented basic research in Ireland. In contrast to the R&D tax credit scheme and innovation policy instruments available from by Enterprise Ireland and IDA Ireland, Science Foundation Ireland (SFI) does not fund innovation in firms. SFI’s primary remit is to invest in academic researchers and research teams in the public research system that are most likely to generate new knowledge and leading-edge technologies in the fields of science, technology, engineering and mathematics (STEM). However, SFI does fund a series of Research Centres based on the campuses of Higher Education Intitules (HEIs) in Ireland. Firms are incentivised to participate in research projects based in these Research Centres as a means of enhancing their applied and oriented-basic research activities, as described in Table 7.
<table>
<thead>
<tr>
<th>Innovation policy instrument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Centres for Science Engineering and Technology (CSETs)</td>
<td>Funding of joint academic-industry research centres located within HEIs focused on longer term user-oriented basic research.</td>
</tr>
<tr>
<td>Strategic Research Clusters (SRCs)</td>
<td>Funding of research clusters to support multi-disciplinary internationally leading investigations with industry engagement.</td>
</tr>
</tbody>
</table>

### 4.4. Description of datasets

Evaluating the impact of the innovation policy instrument mix on firm-level innovation crucially requires using a dataset that includes three key pieces of information on firms. First, for studies where the main focus is the innovation policy instrument mix, the analysis would benefit from a dataset that captures a comprehensive set of the key innovation policy instruments available to firms. Second, this dataset must also contain at least one appropriate outcome indicator of firm-level innovation. Without an innovation outcome indicator, any firm-level dataset is not usable for the evaluation of the innovation policy instrument mix. Thirdly, this dataset must capture detailed information on firms’ characteristics associated with innovation, such as the firm’s size and human capital, usable as control variables in any evaluation.

The first point above on using a dataset that captures the full, complete mix of innovation policy instruments is not a trivial matter. As the literature Chapters 2 and 3 review bears out, publicly available datasets typically capture only a summary measure of whether firms received any public funding for innovation in general. This kind of summary measure will mean that firms receiving one innovation instrument from one source go into the same category as firms receiving a mix of instruments from different sources. Where studies do capture information
on the specific instruments firms have received, they typically do not go beyond the individual instrument because their dataset was not designed to capture any other forms of public funding for innovation.

Addressing this important limitation in the current literature in the empirical context of Ireland requires using a dataset that captures information on whether firms received the R&D tax credit or any other innovation policy instruments from Enterprise Ireland, IDA Ireland or Science Foundation Ireland. In addition, as Chapter 2 emphasises, the temporal dynamics of the innovation policy instrument mix will likely play a key role in the eventual impact the mix has on firm-level innovation. For this reason, the dataset used must have a panel structure which surveys the same firms over a number of time periods. Only merging a number of different data sources will result in the required dataset.

To address this issue, this study merges one secondary data source, the Annual Business Survey of Economic Impact (ABSEI), and three administrative data sources. ABSEI is a large-scale survey the Department of Business, Enterprise and Innovation (DBEI) collects, which captures information on whether firms received an R&D tax credit as well as an innovation outcome indicator, firms’ R&D expenditure, and other information on firm characteristics usable as control variables. The three primary data sources are administrative datasets held by Enterprise Ireland, IDA Ireland and Science Foundation Ireland, which contain information on whether firms received innovation policy instruments from these funding agencies in any given year. All datasets are available for eight years, from 2007-2014. This facilitates the construction of a panel dataset and, thus, an investigation of the effects of temporal dynamics in the innovation policy instrument mix at the firm level. Once merged, these data sources provide a final dataset that fulfils the three criteria set out above, to sufficiently evaluate the impact of the innovation policy instrument mix of firm-level innovation.
4.4.1. Annual Business Survey of Economic Impact (ABSEI)

The master dataset for this research is the Annual Business Survey of Economic Impact (ABSEI). ABSEI is a large-scale survey collected every year since 2000 by the Department of Business, Enterprise and Innovation (DBEI). Approximately 2,000 firms respond to the survey each year. Approximately 50% of these 2,000 firms have responded to the survey in every year (detailed further below).

ABSEI is an annual postal survey of client firms of Ireland’s national enterprise funding agencies. Telephone follow-up and validation by experts within each funding agency working in each sector augment the postal survey. The aim of ABSEI is to track a number of variables relating to the output of firms that state agencies assist and to measure expenditure by these companies in the economy. The information from the survey is a key input into a framework of performance indicators designed to assess the economic contribution of agency-assisted client companies. The agencies concerned also use the data on individual companies in their day-to-day working relationship with their clients.

DBEI collects ABSEI in partnership with all of the state agencies and research consultants. The role of DBEI in survey collection is primarily to coordinate the survey across the state agencies, to ensure that it produces comparable statistics relating to the base of all agency-assisted firms and to address issues of quality, reliability and validity. The role of each of the funding agencies is more hands-on and based on their existing relationship with client firms. Each agency has a main contact person for the survey who can act as a link person to others within the agency. Agency executives, who work on a day-to-day basis with a portfolio of client firms, act as a resource to encourage survey responses from their clients.

An interagency group consisting of DBEI and a representative from each of the participating agencies manages the implementation of the survey in a harmonised manner. The group meets
on a regular basis to review progress with respect to survey fieldwork and to consider issues of methodology, coverage and questionnaire content.

4.4.1.1. ABSEI Questionnaire

ABSEI covers the client base of all of Ireland’s enterprise funding agencies, and the population comprises all manufacturing and internationally traded services firms in Ireland with 10 or more employees, approximately 4,000 client firms. The population that the survey covers is a selection from each year’s client base of the funding agencies, including:

- Existing client firms with 10+ employees
- Existing client firms that fall below employees
- New client firms with 10+ employees
- Previously surveyed client firms (even if they now have less than 10 employees)

The survey excludes client firms that have ceased to trade. In addition, since 2004, ABSEI has included a cohort of what it terms High Potential Start Ups (HPSUs), each with less than 10 employees, in the survey population (DBEI 2004). HPSUs are those firms that demonstrate considerable potential for growth (DBEI 2004), and regarded as capable of introducing a new or innovative product or service to international markets, involved in manufacturing or internationally traded services, capable of creating 10 jobs in Ireland and realising €1 million in sales within three to four years of starting up, led by an experienced management team, headquartered and controlled in Ireland and less than six years old (DBEI 2004).

Therefore, ABSEI covers the full range of large firms (more than 250 employees), medium firms (50-249 employees), small firms (10-49 employees) and micro firms (fewer than 10 employees) as Eurostat defines them. However, the majority of micro firms surveyed in ABSEI will be HPSUs.
Each of the national funding agencies provides DBEI with a list of clients that includes their identification number, name, address, telephone number, NACE sector code, nationality of ownership and number of employees. The Annual Employment Survey, also undertaken by DBEI and the agencies, provides an up-to-date population listing for the survey. This is a complete listing of firms within the remit of each agency. The annual response rate for ABSEI is circa 60%.

The data recorded in the previous year’s survey is pre-printed on questionnaires, and respondents are asked to revise these data (if necessary) and to update the same fields for the current year. The ABSEI questionnaire is posted each year on a phased basis between January and May. Each agency uses a similar questionnaire with a common set of core variables. However, each agency also has the scope to add questions for its own specific requirements.

4.4.1.2. Dependent variable: R&D intensity

ABSEI captures a firm’s total expenditure on R&D each year. To use this outcome variable in this research, this amount is divided by the number of firm employees to create R&D intensity, and then the natural log of this R&D intensity variable is computed to standardise the variance.

Using R&D intensity as a measure of firm-level innovation is common in the literature.

It is a long-established tenet in this field that firms’ R&D intensity and innovation activity are positively related to one another (Levin et al. 1987; Czarnitzki et al. 2011; Le & Jaffe 2017). While R&D often feeds directly into firms’ innovation activities, firms also must invest in R&D to foster and maintain absorptive capacity so they can assimilate knowledge that higher education institutions or public research centres produce (Pavitt 1998; Nightingale 1997; Roper et al. 2008; Roper & Arvanitis 2012) and other firms (Cohen and Levinthal 1989, 1990; Zahra and George 2002; Love et al. 2010; Lucena & Roper 2016).
Several studies have evaluated the impact of different forms of R&D subsidies on the total R&D intensity of firms in a wide variety of countries, using a variety of different microeconometric methods to control for selection bias and endogeneity. The results of this literature indicate that the R&D subsidies either did not lead to full crowding-out (Busom 2000; Almus & Czarnitzki 2003; González et al. 2005; Czarnitzki & Licht 2006; González & Pazó 2008; Alecke et al. 2011; Barbieri et al. 2012; Cerulli & Poti 2012a; Cerulli & Poti 2012b; Czarnitzki & Lopes-Bento 2013; 2014; Aristei et al. 2017), or stimulated additional R&D investment on top of what the firm was already spending (Duguet 2004; Hussinger 2008; Carboni 2011; Hud & Hussinger 2015).

4.4.1.2.1. Dependent Variable: Measure Choice, Rationale and Implications

As highlighted by Morbey and Reithner (1990), R&D intensity is defined in two ways in the literature: 1) R&D expenditure divided by sales; and 2) R&D expenditure divided by employees. Both of these approaches standardise the variance of the data. This is a common practice when evaluating the impact of public funding for innovation on firm-level R&D (for a discussion, see e.g. Crepon et al. 1998). Castellani et al. (2019) note that a large firm may invest more in R&D than a small firm in absolute terms. However, relative to its size (in terms of sales or employees), the large firm’s expenditure may in fact be less substantial than that of the small firm. Both measures of R&D intensity are commonly used in the literature. For example, Czarnitzki & Lopes-Bento (2013; 2014) define R&D intensity as R&D expenditure divided by sales, while Castellani et al. (2019), Baumann & Kritikos (2016), Hall et al. (2009) and Görg and Strobl (2007) use R&D expenditure divided by employees. When considering which measure of R&D intensity to use, Morbey and Reithner (1990, p. 12) note that “[b]ecause the number of employees tends to have less short-term variability than sales, the R&D per employee ratio may be more robust in determining a long-term commitment to innovation”. In a recent study of the impact of firm-university collaborations on firm-level R&D, Scandura
(2016, p. 1910) favours using R&D expenditure per employee, highlighting that this “provides a measure of companies’ effort taking into account both capital and labour input factors”. Therefore, this research defines firm-level R&D intensity as a firm’s total R&D expenditure divided by the firm’s number of employees.

4.4.1.3. Treatment variable: R&D tax credits

Since the 2009/2010 edition, ABSEI has asked firms in Ireland every two years to respond to this item, as updated: “Please indicate whether your organisation has availed of the R&D tax credit in the following years: 2007; 2008; 2009”. Therefore, ABSEI is a vitally important survey that provides information on the most prominent innovation policy instrument available to firms in Ireland. ABSEI captures the R&D tax credit variable in binary form, where firms answer a yes-or-no question on whether they received it in any given year.

However, ABSEI provides no indication of whether firms received any other innovation policy instruments (i.e. from Enterprise Ireland, IDA Ireland or Science Foundation Ireland). Were a study to use ABSEI to evaluate the impact of the R&D tax credit against similar firms that did not receive the R&D tax credit, it could in fact test them against firms that did not receive the R&D tax credit but did receive other forms of innovation policy instrument. Therefore, to make ABSEI usable for an evaluation of the innovation policy instrument mix requires linking it with other datasets that capture the full mix.

4.4.1.4. Control variables

To control for other possible influences on firms’ R&D intensity, the microeconometric analysis that describe firms’ internal characteristics as well as the external business environment in which the firm operates includes several variables: a variable indicating the percentage of employees that work on in-house R&D activities within the Republic of Ireland; a variable indicating firm expenditure on formal structured training for employees (divided by
number of employees); four dummy variables (based on Eurostat firm-size classifications) indicating whether a firm is micro (>10 employees), small (10-49 employees), medium (50-249 employees) or large (250+ employees); and a variable indicating the natural log of the Euro-amount of firms’ exports divided by number of employees (i.e. exporting intensity). Outside of these internal firm characteristics, other control variables include dummy variables for each year of the survey, to capture information on firms’ external environment. These control variables are among the standard ones the literature typically cites (e.g. Roper et al. 2008; Czarnitzki and Lopes-Bento 2014). All relevant variables are deflated at 2011 prices using the Consumer Price Index deflators published by the CSO. In addition, all models estimated include fixed effects which incorporate unobserved heterogeneity not captured in the vector of control variables.

4.4.2. Enterprise Ireland, IDA Ireland and Science Foundation Ireland administrative datasets

Unlike ABSEI, the administrative datasets from Enterprise Ireland, IDA Ireland and Science Foundation Ireland are not surveys, but rather populations of all firms that participated in programmes these agencies funded. ABSEI provides a binary indicator of whether firms received an R&D tax credit in each year. However, the administrative data from Enterprise Ireland and IDA Ireland provide information on the Euro-amounts that firms received from these agencies for their innovation activities in each year. In years where the firms received no payment, this amount shows a zero.

The four innovation policy instrument variables used across the analyses are binary measures capturing each year firms received: 1) an R&D tax credit; 2) any R&D/innovation support from IDA Ireland; 3) any R&D/innovation support from Enterprise Ireland; and 3) engaged with a

13 The CSO’s guide to deflating prices using the Consumer Price Index can be found here: https://www.cso.ie/multiquicktables/quickTables.aspx?id=cpm02_cpa04_8
SFI research centre on a collaborative R&D project. In the case of Enterprise Ireland, two innovation policy instruments compose the aggregate binary variable, Innovation Vouchers and Innovation Partnerships. In the final dataset, 80% of the cases where firms received R&D/innovation support from Enterprise Ireland represent firms receiving Innovation Vouchers, while 20% of the cases represent firms engaging in Innovation Partnerships. For IDA Ireland, the binary variables includes two supports from the IDA Ireland R&D fund, 75% R&D Innovation and 25% Research, Development and Innovation (RD&I) Feasibility. While for SFI the binary variable is composed of 75% Strategic Research Clusters (SRCs), 25% Centres for Science, Engineering & Technology (CSETs). This is a summary of the three binary measures representing innovation policy instrument variables from Ireland’s key national funding agencies, based on the final merged datasets (described below in Section 4.4.4.2). The process of creating there three binary variables is illustrated in Figure 4.1.

Enterprise Ireland’s Innovation Voucher initiative was developed to build links between Ireland’s public knowledge providers (i.e. higher education institutes, public research bodies) and small businesses (Enterprise Ireland 2018a). Innovation Vouchers worth €5,000 are available to assist firms to explore a business opportunity or problem with a registered knowledge provider (Enterprise Ireland 2018). Similar to the Innovation Voucher, Innovation Partnerships aim to assist firms with gaining access to the most up-to-date skills and expertise public knowledge providers in Ireland, such as Higher Education Institutions (DBEI 2015). The Innovation Partnership scheme operates on a higher level of funding to the Innovation Voucher initiative, providing up to 80% of the cost of research work to develop new and improved products, processes or services, or generate new knowledge (Enterprise Ireland 2018b).
Figure 4.1 Creating binary measures for whether firms received support from Ireland’s three national funding agencies

Enterprise Ireland administrative data

IDA Ireland administrative data

Science Foundation Ireland administrative data

Binary measure (1/0), capturing each year firms received any R&D/innovation support from Enterprise Ireland

Binary measure (1/0), capturing each year firms received any R&D/innovation support from IDA Ireland

Binary measure (1/0), capturing each year firms had a linkage with a Science Foundation Ireland-funded research centre
Both of these IDA Ireland innovation policy instruments target increasing firm engagement in R&D/innovation activities, assisting firms to develop innovative products, processes and services, with the overall target of increasing the number of firms performing R&D in Ireland and the scale of those R&D investments (DBEI 2015).

SFI’s CSETs programme is designed to link scientists and engineers in partnerships across academia and industry to address crucial research questions and foster the development of new and existing Irish-based technology companies (SFI 2010; 2014). The CSETs programme funds joint academic-industry research centres located within Universities focused on longer term user-oriented basic research (DBEI 2014). Similarly to CSETs, the SFI SRC programme aims to link scientists and engineers in partnerships across academia and industry to address crucial research questions, foster the development of new and existing Irish-based technology companies, and grow partnerships with industry that could make an important contribution to the Irish economy (SFI 2010). The SRC programme has been designed to facilitate the clustering of researchers to carry out joint research activities in areas of strategic importance to Ireland, while also giving the time and resources to attract and cultivate strong industry partnerships that can inform and enhance their research programmes (SFI 2010).

The overarching research question this thesis seeks to address is whether there is a complementary relationship between different innovation policy instruments in their impact on firm-level R&D intensity. The dataset constructed to address this question contains information on the €-amount (i.e. continuous data) that firms received for R&D/innovation support from Enterprise Ireland or IDA Ireland. However, as noted above, the study does not use this continuous data. Instead, the study uses binary indicators that take the value of one each year a firm receives any R&D/innovation support from Enterprise Ireland or IDA Ireland, and zero otherwise. The reason for using binary measures as opposed to continuous measures is that, from a theoretical perspective (see e.g. Papalia et al. 2018), addressing the research question
requires an econometric method that facilitates direct tests for super- and sub-modularity (i.e. complementarity and substitution). Existing methods that facilitate these tests require binary measures of the variables under examination (Athey & Stern 1998; Mohnen & Röller 2005; Cassiman & Veugelers 2006; Love & Roper 2009). In the case of this thesis, these variables capture whether firms received an R&D tax credit as well as financial R&D/innovation support from Enterprise Ireland or IDA Ireland, or have a linkage with a SFI research centre. Therefore, given that only binary measures of whether firms received a R&D tax credit or has a SFI linkage are available in the data, the decision was taken to also use binary measures of financial R&D/innovation support from Enterprise Ireland and IDA Ireland.

This payments data is the basis for constructing binary variables, taking unit value for every year a firm received any payment from Enterprise Ireland or IDA Ireland, and zero otherwise. The administrative data from Science Foundation Ireland is of a somewhat different structure. Here, firms enter into multi-year collaborations with SFI-funded Research Centres. Therefore, this information supports construction of a binary variable taking unit value for every year the firm participated in the SFI programme at an SFI Research Centre, and zero otherwise. Creating binary variables indicating whether firms received innovation funding from Enterprise Ireland, IDA Ireland and Science Foundation Ireland is necessary in this analysis of the innovation policy instrument mix, because the R&D tax credit variable available from ABSEI is in binary form. Therefore, the Enterprise Ireland, IDA Ireland and Science Foundation Ireland innovation policy instrument variables indicate that firms received one or more innovation policy instruments from these sources in any given year.

4.4.3. Innovation policy instrument variables

As noted above, all firms in Ireland can receive an R&D tax credit in combination with an Enterprise Ireland or IDA Ireland innovation support or participate in an SFI Research Centre at the same time. However, this kind of overlap does not exist among the three state agencies.
Enterprise Ireland supports indigenous firms, while IDA Ireland supports foreign-owned firms. Therefore, 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 Enterprise Ireland or IDA Ireland simultaneously, on examination of the data the level of overlap is close to zero.\textsuperscript{14} In addition, internal approximate estimates provided to the researcher by SFI indicate that there is a near-zero level of overlap in which firms that received support from the IDA also co-funded projects with SFI.\textsuperscript{15}

Therefore, the econometric analysis studies three pair-wise combinations: the R&D tax credit combined with either: 1) Enterprise Ireland; 2) IDA Ireland; or 3) SFI. Facilitating the empirical analysis requires defining four discrete treatment categories:

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).

Each of these treatment categories are mutually exclusive cases. 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.

Administrative data from EI covers the period 2006-2014, while data from IDA and SFI covers the period 2007-2014. Therefore, to make the datasets as comparable as possible, all datasets used ran from 2007-2014. As described above, the nature of the data dictates that firms not receive innovation policy instruments from Enterprise Ireland, IDA Ireland, or Science

\textsuperscript{14} As noted in Chapter 1, this was confirmed in a discussion with a policymaker in the Department of Business, Enterprise and Innovation’s Science Foundation Ireland Liaison Unit on 12 November 2018.

\textsuperscript{15} The information was provided to the researcher on request in private email correspondence on July 10, 2018.
Foundation Ireland simultaneously. Therefore, this study merges each of the three administrative datasets from each state agency with ABSEI separately to make three final datasets to facilitate the evaluation.

Table 8 Description of sixteen treatment category 'switch' variables

<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 EI/IDA/SFI intervention and no R&D tax credit
2: No EI/IDA/SFI intervention and receives R&D tax credit
3: Receives EI/IDA/SFI intervention and no R&D tax credit
4: Receives EI/IDA/SFI intervention and R&D tax credit

While an evaluation of the instrument mix at a point in time can use these four treatment categories, using them to capture temporal dynamics requires amending them. As policy-mix theory shows, the innovation policy instrument(s) to which firms have been exposed in the past will play a key role in determining how a current instrument mix influences firm-level innovation (Flanagan et al. 2011). Therefore, addressing temporal dynamics in the innovation policy instrument mix means using these initial four treatment categories to construct sixteen ‘switch’ variables that capture what treatment category firms were in during one year and the treatment category to which they transitioned in the next year. Table 8 defines these sixteen switch categories.
In any given year, firms can be in only one of the four treatment 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 define the temporal dynamics of the innovation policy instrument mix.

4.4.4. Merging datasets

To create the three final datasets for this analysis, ABSEI served as the master dataset, and the three state agency datasets were merged into it separately. The three state agency datasets are large, covering the full population of firms that received support from Enterprise Ireland, IDA Ireland and Science Foundation Ireland. However, none of these datasets are usable for impact evaluation on their own because they lack any innovation outcome variables. Therefore, the final three merged datasets contain all firms that ABSEI surveyed each year, as well as the firms in each state agency dataset also in ABSEI. The firms in the state agency datasets that did not overlap with ABSEI had to be dropped from the analysis. A description of the process follows.

4.4.4.1. R&D active firms and Non-R&D active firms

A number of firms in ABSEI indicate that they did not invest in R&D in any year from 2007-2014. Including a sample of firms that never invest in R&D in any year likely could bias the results. Therefore, firms that do not invest in R&D in any year drop out of the analysis. Lach (2002) and Neicu et al (2015) took similar measures, using only R&D active firms in their studies; as did Bérubé and Mohnen (2009), Czarnitzki et al. (2011) and Love et al. (2014), who use sub-samples of firms that are innovation active as robustness tests, for their main sample that includes both innovation-active and non-innovation-active firms. Dropping all non-R&D-
active firms from ABSEI reduced the sample size from 21,474 observations over the period 2007-2014 to 16,084 observations.

4.4.4.2. Description of final merged datasets

As noted above, ABSEI is the master dataset for this study. Therefore, the full ABSEI dataset, as well as the part of the administrative datasets that overlap with ABSEI, are usable for the empirical analysis in this study. The merging process to create the final three datasets is outlined in Figure 4.2. In Figure 4.2, the oval marked as ‘ABSEI’ on the right hand side (including the overlap with the second oval) is used in the final analysis.

Figure 4.2 Data merges to create three final datasets

After cleaning the administrative datasets from Enterprise Ireland, IDA Ireland and Science Foundation Ireland to put them in a usable format, the final three state-agency datasets had the following number of unique firms and observations from 2007-2014:
• Enterprise Ireland: 1,408 firms; 11,257 observations
• IDA Ireland: 161 firms; 1,281 observations
• Science Foundation Ireland: 142 firms; 1,129 observations

As noted above, each of these datasets was then merged into ABSEI separately. Only observations from the three state-agency datasets that were also in ABSEI could remain. This necessitated dropping the following data from each merged ABSEI-state agency dataset:

• ABSEI-Enterprise Ireland sample: 903 firms; 7,224 observations
• ABSEI-IDA Ireland sample: 42 firms; 336 observations
• ABSEI-Science Foundation Ireland sample: 40 firms; 320 observations

The final number of firms and observations in the assisted and non-assisted categories in each sample is as follows:

**ABSEI-Enterprise Ireland sample**

• Number of firms assisted by Enterprise Ireland in the final dataset: 505
• Number of observations assisted by Enterprise Ireland in the final dataset: 4033
• Number of firms not assisted by Enterprise Ireland in the final dataset: 2593
• Number of observations not assisted by Enterprise Ireland in the final dataset: 12051

**ABSEI-IDA Ireland sample**

• Number of firms assisted by IDA Ireland in the final dataset: 119
• Number of observations assisted by IDA Ireland in the final dataset: 945
• Number of firms not assisted by IDA Ireland in the final dataset: 2979
• Number of observations not assisted by IDA Ireland in the final dataset: 15139

**ABSEI-Science Foundation Ireland sample**

• Number of firms that have an SFI linkage in the final dataset: 102
• Number of observations that have an SFI linkage in the final dataset: 809
• Number of firms that do not have an SFI linkage in the final dataset: 2996
• Number of observations that do not have an SFI linkage in the final dataset: 15275

After the data-merge process, the resulting three panel datasets are unbalanced due to entry and exit of firms over the time period. However, the sample includes at least two repeat observations on all firms, and approximately 50% of the firms observed in all years. This subsection describes each of the three datasets in detail. Table 9 provides descriptive statistics on the variables used in each dataset.

As noted in Section 4.4.1.4., this thesis uses the Eurostat firm-size classifications, which defines micro enterprises as having less than 10 employees, small firms have between 10 and 49 employees, medium firms have 50 to 249 employees and large firms have 250 employees or more. Using these Eurostat classifications, Table 9 demonstrates that 25.1% of the firms in the sample are micro enterprises, 42.7% of the firms are small, 24.1% are medium and 8.1% of the firms are large. CSO (2018) show that business demography is heavily skewed towards SMEs, which make up 99.80% of the firms in Ireland. On this basis, it could be argued that large firms are over-represented in the sample. However, CSO (2017) highlights that large firms account for 55% of the business expenditure on R&D in Ireland, with small and medium firms accounting for 45% (micro enterprises are not surveyed by the CSO when collecting business expenditure on R&D data). In addition, unlike the CSO figures which seek to present a representative picture of the overall Irish economy, the ABSEI survey collects information on firms that have engaged with national funding agencies in the past. As the Department of Finance (2016) highlight, large firms are often more likely to receive innovation policy instruments. Further, as described in Section 4.4.4.1., this study includes only R&D active firms. Given that this thesis is concerned with R&D intensity, all firms that have no expenditure on R&D from 2007-2014 are excluded from the sample. Therefore, the fact that large firms are
over-represented in the sample relative to the overall Irish economy may reflect the fact that they are more R&D intensive and more likely to engage with national funding agencies.

Other control variables include the percentage of staff firms have engaged in R&D activities, firm expenditure on formal structured training for employees as well as firm export intensity. Table 9 shows that on average 20.2% of employees work on in-house R&D. While this figure is high, as noted above, the ASBEI sample used in this study contains only R&D active firms. In addition, in the ABSEI sample firms have a high average level of expenditure on training. However, the variance of this figure is almost 50% of the mean, reflecting that even among a sample of R&D active firms, there is still a wide range of different business strategies in terms of where firms invest their resources. Finally, there is also a high level of export intensity within the sample. ABSEI surveys firms that have engaged with national funding agencies in the past. Given that both IDA Ireland and Enterprise Ireland target export intensive firms, the high level of exporting in the sample is reasonable for this sample, and reflective of the firms that are target of R&D/innovation support.

It is important to describe the cross-sectional characteristics of the three datasets. Table 10 shows the proportion of the sample in each treatment category. 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>
<thead>
<tr>
<th>Table 9 Descriptive statistics on variables used in three final merged datasets</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ABSEI-Enterprise Ireland sample</strong></td>
</tr>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>R&amp;D tax credit (1/0)</td>
</tr>
<tr>
<td>Enterprise Ireland (1/0)</td>
</tr>
<tr>
<td>R&amp;D intensity (log)</td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
</tr>
<tr>
<td>Exporting intensity (log)</td>
</tr>
<tr>
<td>Micro (&gt;10 employees)</td>
</tr>
<tr>
<td>Small (10-49 employees)</td>
</tr>
<tr>
<td>Medium (50-249 employees)</td>
</tr>
<tr>
<td>Large (250+ employees)</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Firms</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ABSEI-IDA Ireland sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>R&amp;D tax credit (1/0)</td>
</tr>
<tr>
<td>IDA Ireland (1/0)</td>
</tr>
<tr>
<td>R&amp;D intensity (log)</td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
</tr>
<tr>
<td>Exporting intensity (log)</td>
</tr>
<tr>
<td>Micro (&gt;10 employees)</td>
</tr>
<tr>
<td>Small (10-49 employees)</td>
</tr>
<tr>
<td>Medium (50-249 employees)</td>
</tr>
<tr>
<td>Large (250+ employees)</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Firms</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ABSEI-Science Foundation Ireland sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>R&amp;D tax credit (1/0)</td>
</tr>
<tr>
<td>SFI (1/0)</td>
</tr>
<tr>
<td>R&amp;D intensity (log)</td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
</tr>
<tr>
<td>Exporting intensity (log)</td>
</tr>
<tr>
<td>Micro (&gt;10 employees)</td>
</tr>
<tr>
<td>Small (10-49 employees)</td>
</tr>
<tr>
<td>Medium (50-249 employees)</td>
</tr>
<tr>
<td>Large (250+ employees)</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Firms</td>
</tr>
<tr>
<td>Table 10</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>Neither</td>
</tr>
<tr>
<td>R&amp;D tax credit</td>
</tr>
<tr>
<td>Enterprise Ireland</td>
</tr>
<tr>
<td>Both</td>
</tr>
<tr>
<td>Total</td>
</tr>
<tr>
<td>ABSEI-IDA Ireland sample</td>
</tr>
<tr>
<td>Neither</td>
</tr>
<tr>
<td>R&amp;D tax credit</td>
</tr>
<tr>
<td>IDA Ireland</td>
</tr>
<tr>
<td>Both</td>
</tr>
<tr>
<td>Total</td>
</tr>
<tr>
<td>ABSEI-Science Foundation Ireland sample</td>
</tr>
<tr>
<td>Neither</td>
</tr>
<tr>
<td>R&amp;D tax credit</td>
</tr>
<tr>
<td>SFI</td>
</tr>
<tr>
<td>Both</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>
In contrast to Table 10 above, Table 11 below presents a transition matrix that demonstrates how firms switch between different treatment categories through time. As described above, the dataset consists of an unbalanced panel of firms with approximately 50% of the sample observed in each time period and at least two observations on every firm. Therefore, the transition of an individual firm between different treatment categories can occur a maximum of eight times, or a minimum of twice. It is clear from Table 11 that firms that begin in the ‘Neither’ category and the ‘R&D tax credit only’ category tend to remain in these categories.

Table 11 above also highlights important differences between innovation policy instruments Science Foundation Ireland administered and those Enterprise Ireland or IDA Ireland administered. Firms that receive an Enterprise Ireland or IDA Ireland 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 Enterprise Ireland and IDA Ireland subsidies: They apply for them, use them for a specific purpose, but do not continue applying for and using them. In contrast, firms that participate in SFI Research Centres 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 the SFI programmes are multi-year collaborations (unlike the Enterprise Ireland or IDA Ireland R&D/innovation support), 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 SFI-facilitated collaboration will conduct R&D for a sustained period, it is a natural complement to R&D tax credits.
Table 11 Transition matrix of the four policy instrument categories

ABSEI-Enterprise Ireland sample

<table>
<thead>
<tr>
<th>Starting category</th>
<th>End category</th>
<th>Neither</th>
<th>R&amp;D TC only</th>
<th>EI only</th>
<th>Both</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neither</td>
<td></td>
<td>88.14%</td>
<td>9.70%</td>
<td>1.81%</td>
<td>0.35%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7044)</td>
<td>(775)</td>
<td>(145)</td>
<td>(28)</td>
<td>(7992)</td>
</tr>
<tr>
<td>R&amp;D TC only</td>
<td></td>
<td>11.52%</td>
<td>84.06%</td>
<td>0.42%</td>
<td>4.01%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(497)</td>
<td>(3627)</td>
<td>(18)</td>
<td>(173)</td>
<td>(4315)</td>
</tr>
<tr>
<td>EI only</td>
<td></td>
<td>64.49%</td>
<td>13.55%</td>
<td>18.69%</td>
<td>3.27%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(138)</td>
<td>(29)</td>
<td>(40)</td>
<td>(7)</td>
<td>(214)</td>
</tr>
<tr>
<td>Both</td>
<td></td>
<td>6.80%</td>
<td>64.00%</td>
<td>2.00%</td>
<td>27.20%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(17)</td>
<td>(160)</td>
<td>(5)</td>
<td>(68)</td>
<td>(250)</td>
</tr>
</tbody>
</table>

ABSEI-IDA Ireland sample

<table>
<thead>
<tr>
<th>Starting category</th>
<th>End category</th>
<th>Neither</th>
<th>R&amp;D TC only</th>
<th>IDA only</th>
<th>Both</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neither</td>
<td></td>
<td>89.45%</td>
<td>9.92%</td>
<td>0.50%</td>
<td>0.12%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7278)</td>
<td>(807)</td>
<td>(41)</td>
<td>(10)</td>
<td>(8136)</td>
</tr>
<tr>
<td>R&amp;D TC only</td>
<td></td>
<td>11.62%</td>
<td>86.50%</td>
<td>0.18%</td>
<td>1.70%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(514)</td>
<td>(3826)</td>
<td>(8)</td>
<td>(75)</td>
<td>(4423)</td>
</tr>
<tr>
<td>IDA only</td>
<td></td>
<td>44.29%</td>
<td>22.86%</td>
<td>24.29%</td>
<td>8.57%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(31)</td>
<td>(16)</td>
<td>(17)</td>
<td>(6)</td>
<td>(70)</td>
</tr>
<tr>
<td>Both</td>
<td></td>
<td>7.75%</td>
<td>49.30%</td>
<td>2.82%</td>
<td>40.14%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(11)</td>
<td>(70)</td>
<td>(4)</td>
<td>(57)</td>
<td>(142)</td>
</tr>
</tbody>
</table>

ABSEI-Science Foundation Ireland sample

<table>
<thead>
<tr>
<th>Starting category</th>
<th>End category</th>
<th>Neither</th>
<th>R&amp;D TC only</th>
<th>SFI only</th>
<th>Both</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neither</td>
<td></td>
<td>89.73%</td>
<td>9.98%</td>
<td>0.25%</td>
<td>0.05%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7214)</td>
<td>(802)</td>
<td>(20)</td>
<td>(4)</td>
<td>(8040)</td>
</tr>
<tr>
<td>R&amp;D TC only</td>
<td></td>
<td>12.05%</td>
<td>86.61%</td>
<td>0.12%</td>
<td>1.22%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(513)</td>
<td>(3686)</td>
<td>(5)</td>
<td>(52)</td>
<td>(4256)</td>
</tr>
<tr>
<td>SFI only</td>
<td></td>
<td>11.45%</td>
<td>3.61%</td>
<td>68.67%</td>
<td>16.27%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(19)</td>
<td>(6)</td>
<td>(114)</td>
<td>(27)</td>
<td>(166)</td>
</tr>
<tr>
<td>Both</td>
<td></td>
<td>0.32%</td>
<td>14.89%</td>
<td>5.83%</td>
<td>78.96%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(46)</td>
<td>(18)</td>
<td>(244)</td>
<td>(309)</td>
</tr>
</tbody>
</table>
Table 12 below shows a clear hierarchy in terms of firms’ R&D intensity in each treatment category. Firms in the BOTH category achieve the highest level of R&D intensity, with firms in the R&DTC category only marginally behind them. 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.

**Table 12 R&D intensity (log) by treatment category**

<table>
<thead>
<tr>
<th>Treatment category</th>
<th>Observations</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEITHER</td>
<td>10,143</td>
<td>6.49</td>
<td>3.77</td>
<td>0</td>
<td>14.92</td>
</tr>
<tr>
<td>R&amp;DTC</td>
<td>5,358</td>
<td>9.19</td>
<td>1.98</td>
<td>0</td>
<td>15.63</td>
</tr>
<tr>
<td>AGENCY</td>
<td>274</td>
<td>7.60</td>
<td>3.35</td>
<td>0</td>
<td>12.84</td>
</tr>
<tr>
<td>BOTH</td>
<td>309</td>
<td>9.77</td>
<td>1.90</td>
<td>0</td>
<td>13.51</td>
</tr>
</tbody>
</table>

While Table 12 does not imply that BOTH causes higher levels of R&D intensity, it is instructive to see the relative innovation performance (as measured by R&D intensity) of firms in each treatment category. To see whether the identified ‘premium’ associated with BOTH in Table 12 is stable through time, these summary statistics are graphed over the years 2007-2014 in Figures 4.3, 4.4 and 4.5 below.
Figure 4.3 R&D intensity by treatment category by year, ABSEI-Enterprise Ireland sample

Figure 4.4 R&D intensity by treatment category by year, ABSEI-IDA Ireland sample
With the exception of firms receiving only IDA innovation subsidies, there is clear evidence that the hierarchy described in Table 12 persists through time. However, the relative R&D intensity of each group reflects a degree of change through time. The R&D intensity of firms receiving Enterprise Ireland or IDA Ireland subsidies falls significantly in 2011, and never recovers to its previous peak. Firms receiving SFI linkages and R&D tax credits together steadily increase their R&D intensity through time, relative to all other categories.

4.5. Conclusion

In summary, the data lends support to the contention that receiving a combination of two policy instruments together is associated with higher R&D intensity, relative to receiving either of the instruments separately. To verify this finding from the descriptive statistics requires econometrically controlling for other possible influences on firms’ R&D intensity, as well as
selection bias and endogeneity, and performing a formal test for the existence of complementarities between R&D tax credits and R&D/innovation support from Enterprise Ireland, orIDA Ireland or SFI linkages. To do this, the next chapter applies the method and data described above, and first tests for the presence of static complementarities. Following this, it utilises the panel nature of the dataset to test for dynamic complementarities. Results from this analysis are analysed and interpreted in the context of the previous literature and the innovation policy landscape of Ireland.

Testing for static and dynamic complementarity in the innovation policy instrument mix is an important contribution to the literature for two main reasons. First, the temporal dynamics of the instrument mix constitute an important issue in the theoretical literature that the empirical literature has never, to the best of the author’s knowledge, applied his concept at the firm-level. Second, though a limitation of the current microeconometric literature is that it has inferred static complementarity and substitution between different instruments at a point in time, at least it has considered this issue. As emphasised above, dynamic complementarity and substitution are theoretically important issues, but always inferred. Therefore, by directly testing for dynamic complementarity and substitution, this research pushes the literature forward and attempts to bridge the gap between theory and empirical practice.
Chapter 5: The impact of innovation policy instrument mix on firms’ R&D intensity: Empirical findings for Ireland

5.1. Introduction

The previous chapter was concerned with detailing the econometric method and datasets used in this thesis. The current chapter presents the findings of the empirical analysis based on this method and data. Drawing on the results of the econometric analysis, the chapter offers a discussion and of these findings in the context of the previous literature and how they may be interpreted in the empirical setting of Ireland.

This thesis has one overarching research question: Are different innovation policy instruments complements or substitutes? Therefore, the focus of this chapter is to investigate whether receiving a combination of different innovation policy instruments has a greater impact on firms’ Research and Development (R&D) intensity\(^{16}\) than receiving the same instruments separately. By using firm R&D intensity as the outcome indicator for the analysis, this thesis focuses specifically on input additionality (as discussed in Chapter 2). R&D is considered to be an input into firm innovation processes, and input additionality can be defined as the extra R&D expenditure firms make as a result of receiving innovation policy instruments (i.e. additional R&D expenditure on top of what the firm was already spending).

The literature on innovation policy instrument mix, reviewed and analysed in Chapter 3, demonstrates that complementarity and substitution between innovation policy instruments can be conceptualised in two different ways:

\(^{16}\) The natural log of R&D intensity is the dependent variable used in all regression analyses presented in this chapter. R&D intensity is defined as a firm’s total R&D expenditure divided by the firm’s number of employees.
1) The relationship between different instruments a firm receives at a point in time (i.e. static);

2) The relationship between different instruments a firm receives through time (i.e. dynamic).

Therefore, to address the research question, this study tests two distinct hypotheses (presented in Chapter 3). Hypothesis 1 deals with static complementarity between innovation policy instruments, while Hypothesis 2 concentrates on how the temporal dynamics of the innovation policy instrument mix influence firms’ innovation outcomes.

In testing Hypothesis 1, the primary objective is to evaluate whether firms that receive two distinct innovation policy instruments benefit \(^{17}\) more than firms that receive the same instruments separately. To examine this hypothesis, this chapter performs strict tests for supermodularity (i.e. complementarity) and submodularity (i.e. substitution) based on the results of estimating firms’ innovation production functions (Mohnen & Röller 2005). To test the dynamic relationship between instruments through time (i.e. Hypothesis 2), a similar estimation procedure is performed. However, the dynamic tests investigate the added benefit (in terms of increased R&D intensity) of transitioning from receiving one instrument last year (i.e. in time period \(t-1\)) to receiving a combination of two instruments in the current year (i.e. time period \(t\)) (Love et al. 2014).

The three panel datasets that capture information on firms in Ireland over the period 2007 to 2014 were created for this analysis through a series of data merges (detailed in Chapter 4). The study draws on the Annual Business Survey of Economic Impact (ABSEI), which serves as the master dataset for all of the empirical analyses, as well as three administrative datasets from Ireland’s

---

\(^{17}\) The word *benefit* is used here because both hypotheses test for *complementarity* between innovation policy instruments, which implies a beneficial relationship (i.e. where receiving two instruments together produces a greater R&D intensity than receiving the instruments separately). This is not to assume, *a priori*, that receiving any form of public funding for R&D/innovation will *necessarily* have a positive impact on firms’ R&D intensity. Public funding could have *no impact* or a *negative impact*, where *ceteris paribus* subsidy recipients have the same or lower R&D intensity relative to unsubsidised firms. In the empirical tests for complementarity, if the null hypothesis of no complementarity cannot be rejected then a substitutive relationship will be identified.
three key national funding agencies: Enterprise Ireland, Industrial Development Agency (IDA) Ireland and Science Foundation Ireland (SFI). ABSEI is the master dataset, and each administrative dataset is separately merged into ABSEI to create the three final datasets. These datasets are referred to in this chapter as the ABSEI-Enterprise Ireland sample, the ABSEI-IDA Ireland sample and the ABSEI-SFI sample. Using these datasets, the empirical analyses test for complementarity and substitution between the following combinations of instruments: 1) R&D tax credit and Enterprise Ireland support; 2) R&D tax credit and IDA Ireland support; and 3) R&D tax credit and SFI linkages.18

As described in Chapter 4, the four innovation policy instruments variables used across the analyses are binary (i.e. 1/0) measures capturing each year firms received: 1) an R&D tax credit; 2) any R&D/innovation support from Enterprise Ireland; 3) any R&D/innovation support from IDA Ireland; and 3) engaged with a SFI research centre on a collaborative R&D project, referred to as an SFI linkage. While the R&D tax credit measure represents one individual innovation policy instrument, the Enterprise Ireland, IDA Ireland and SFI measures are aggregate measures capturing whether firms received any R&D/innovation support from these key sources of funding. When this chapter refers to R&D/innovation support from Ireland’s three national funding agencies, it means these three binary variables. As such, the tests for complementarity are between one innovation policy instrument (i.e. the R&D tax credit) and three sources of R&D/innovation support (i.e. Enterprise Ireland, IDA Ireland and SFI).

The impact of innovation policy instrument(s) on firm-level innovation can take time to manifest and can have long-term effects (Hall et al. 1986; Roper & Hewitt-Dundas 2012). However,

18 The rationale for using three separate datasets is detailed in Chapter 4, Section 4.4.2.
primarily due to the cross-sectional nature of the data available to previous studies, little empirical
evidence exists which considers these potential temporal effects (Zúñiga-Vicente et al. 2014;
Cunningham et al. 2016). The panel nature of the three datasets used in this study facilitates testing
for both the contemporaneous and lagged impact of the innovation policy instrument mix on firm-
level innovation. Following Keiser and Kuhn (2012), four different lag structures are used.
Contemporaneous impact is defined as the effect of the innovation policy instrument(s) a firm
receives in the current time period \( t \) on R&D intensity in the same time period (i.e. no lag). The
three lag-structured models estimate the impact of the instrument(s) a firm received one year ago
\( (t-1) \), two years ago \( (t-2) \) and three years ago \( (t-3) \) (i.e. one, two and three lags) on the firm’s R&D
intensity in the current period. Each alternative lag process is estimated in a separate regression
model.

A critical issue identified in the literature reviewed in Chapters 2, 3 and 4 is the need to correct for
possible selection bias and endogeneity in the empirical analysis which evaluates the impact of
innovation policy instruments on firm-level innovation (e.g. David et al. 2000; Czarnitzki 2011;
Cerulli & Poti 2012; Czarnitzki et al. 2018). However, as recently highlighted by Papalia et al.
(2018), the most commonly used estimation procedure that controls for these issues, propensity
score matching (PSM), does not facilitate direct testing for strict complementarity
(supermodularity) and substitution (submodularity). Love et al. (2014, p. 1779) suggest that the
most pragmatic way of dealing with these issues when testing for complementarity is “to apply
some form of instrumental variable approach”. However, Love et al. (2014) also note that suitable
instrumental variables are usually not available in the highly specific firm-level datasets typically
available for such analyses, and using weak instruments may prove counterproductive (see also
Mohnen & Röller 2005; Cassiman & Veugelers 2006). The econometric analysis presented in this
thesis overcomes this issue and controls for selection bias and endogeneity by using a recently developed form of instrumental variable method that generates strong and valid instrumental variables based on the econometric model’s heteroscedasticity (Lewbel 2012; 2018).

The remainder of this chapter is structured as follows. Section 5.2 outlines the tests for static complementarity and substitution, while the subsections which follow (i.e. 5.2.1, 5.2.2 and 5.2.3) present the findings from, respectively, the ABSEI-Enterprise Ireland, ABSEI-IDA Ireland and ABSEI-SFI datasets. Each of these subsections begins by presenting the findings for the contemporaneous impact of innovation policy instrument mix on firms’ R&D intensity, followed by findings from the lag-structured models. In Section 5.3, the chapter turns to the analysis of temporal mix dynamic complementarities between innovation policy instruments. Sections 5.3.1, 5.3.2 and 5.3.3 present the results from the tests for dynamic complementarity in each dataset. As with the static tests, each subsection begins by presenting the results from the contemporaneous models, followed by the lag-structured models. Sections 5.2 and 5.3 primarily concentrate on presenting the econometric results, and, as such, offer only a limited discussion of the findings. Section 5.4 offers a more comprehensive discussion of the findings from both static and dynamic tests in the context previous studies, and how they can be interpreted in the empirical setting of Ireland. Section 5.5 summarises the key contributions of the empirical analysis and concludes this chapter.

5.2. Testing for static complementarity and substitution

This section presents the results from empirically testing Hypothesis 1, which states that there will be a complementary relationship between different innovation policy instruments in firms’ innovation production functions. As noted above, the outcome variable used in this analysis is firm R&D intensity. R&D is an input into firm innovation processes, rather than an innovation output
(i.e. product, process or organisational innovation). Therefore, the results presented in this section can be interpreted as the input additionality of receiving innovation policy instruments. Testing for static strict complementarity (supermodularity) and substitution (submodularity) between two different innovation policy instruments necessitates setting up four treatment categories, which are listed below:

1) No agency R&D/innovation support\(^{19}\) and no R&D tax credit (\textit{neither}; 00)

2) No agency R&D/innovation support intervention and receives R&D tax credit (\textit{R&D tax credit only}; 10)

3) Receives agency R&D/innovation support intervention and no R&D tax credit (\textit{agency R&D/innovation support only}; 01)

4) Receives agency R&D/innovation support intervention and R&D tax credit (\textit{both}; 11)

The category \textit{neither} (00) is used as the reference category in all econometric models. Therefore, all results from the econometric models can be interpreted as relative to firms that received no innovation policy instrument. A complementary relationship will be identified if the impact of receiving \textit{both} (11) on firms’ R&D intensity is greater than the joint impact of receiving the \textit{R&D tax credit} (10) and \textit{agency R&D/innovation support} (01) separately. Essentially, this would mean that the impact of receiving a combination of two distinct innovation policy instruments is greater than the sum of its parts.

The next section presents the results of the estimated innovation production functions for the ABSEI-Enterprise Ireland sample and subsequent tests for static complementarity and substitution. This is followed by the results for the ABSEI-IDA Ireland sample and the ABSEI-SFI sample.

\(^{19}\)“Agency support” refers to R&D/innovation support from Enterprise Ireland, IDA Ireland or SFI.
Results from the contemporaneous models and lag-structured models are presented in separate tables. As lag length increases, sample size diminishes. In each dataset, the three-lag model has approximately 9,000 fewer observations than the contemporaneous model. This means that each econometric model tests a somewhat different sample, and results from the lag-structured models should be interpreted with this caveat in mind.

5.2.1. Static tests: ABSEI-Enterprise Ireland sample

Table 13 presents the results from estimating the contemporaneous impact of R&D tax credits and R&D/innovation support from Enterprise Ireland on firms’ R&D intensity. When the coefficients on the treatment categories in first three rows of Table 13 are compared, it is clear that firms receiving either R&D tax credits or a combination of both R&D tax credits and Enterprise Ireland R&D/innovation support at the same time (i.e. both) are more R&D intensive than firms that receive no innovation policy instrument. However, relative to the base category of firms that receive no innovation policy instrument, receiving R&D/innovation support solely from Enterprise Ireland has no statistically significantly impact on firms’ R&D intensity.

The descriptive statistics presented in Chapter 4 highlight that, on average, firms in the treatment categories both or R&D tax credit only have higher levels of R&D intensity than firms that receive Enterprise Ireland R&D/innovation support only. The findings from the regression analysis presented in Table 13 support this observation from the descriptive statistics. The final section of Table 13 presents the tests for static complementarity and substitution. Based on the results of the econometric analysis, the null hypothesis of no complementarity is rejected. This finding provides empirical support for Hypothesis 1, that a complementary relationship exists between R&D tax credits and Enterprise Ireland support in terms of their impact on firms’ R&D intensity. As noted, these results are discussed and interpreted in Section 5.4.
Table 13 Testing for static complementarity and substitution between R&D tax credits and Enterprise Ireland R&D/innovation support (results for contemporaneous model)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-Enterprise Ireland sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 lags</td>
</tr>
<tr>
<td>R&amp;D tax credit (10)</td>
<td>1.52***</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
</tr>
<tr>
<td>Enterprise Ireland (01)</td>
<td>-0.14</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
</tr>
<tr>
<td>Both (11)</td>
<td>1.87***</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
<td>4.73***</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
</tr>
<tr>
<td>Export intensity (log)</td>
<td>0.10***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
<td>0.17***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>Small</td>
<td>0.43***</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
</tr>
<tr>
<td>Medium</td>
<td>0.86***</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
</tr>
<tr>
<td>Large</td>
<td>1.13***</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
</tr>
<tr>
<td>Year dummies</td>
<td>yes</td>
</tr>
<tr>
<td>n</td>
<td>16084</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.15</td>
</tr>
<tr>
<td>F-statistic</td>
<td>129.93***</td>
</tr>
</tbody>
</table>

Static complementary test (p-values of t-test):
H0: 11 ≥ 10 + 01
p = 1.000

Static substitution test (p-values of t-test):
H0: 11 ≤ 10 + 01
p = 0.000

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Note: Dependent variable is R&D intensity; All results are relative to the reference category of receiving no innovation policy instrument (i.e. 00)

Building on the analysis of the contemporaneous impact of public support for R&D/innovation, Table 14 presents the results from the three lag-structured models using the ABSEI-Enterprise Ireland dataset. Table 14 highlights that the impact of receiving an R&D tax credit persists for up to two years following its receipt. Similar to the results reported in Table 13, receiving R&D/innovation support from Enterprise Ireland alone has no statistically significantly impact on
firms’ R&D intensity in any of the lag-structured models. However, receiving Enterprise Ireland support combined with an R&D tax credit has a positive and statistically significant impact on firms’ R&D intensity.

The tests for static complementarity at the base of Table 14 reveal that a complementary relationship exists between the R&D tax credit and Enterprise Ireland support in both the one- and
two-lag models. These results suggest that both instruments reinforce one another’s effectiveness in stimulating firm R&D expenditure. These results are consistent with those presented in Table 13 and lend further support to Hypothesis 1. As noted, there can be a time lag between when a firm receive an innovation policy instrument and when that instrument (if effective) impacts firm-level innovation. The lag-structured models in Table 14 enable this study to test for this lagged effect.

In the model using three lags (i.e. three years after the firm initially received support) presented in the third column of Table 14, none of the coefficients representing the three treatment categories is statistically significant. This means that three years after the firms received an R&D tax credit or a combination of Enterprise Ireland R&D/innovation support and an R&D tax credit, these instruments ceased to influence R&D intensity. While the test for static complementarity is passed in this instance, given that none of the coefficients are statistically significant it is difficult to interpret this result. Therefore, where all of the relevant treatment category variables lack statistical significance in the remaining regression analyses presented in this chapter, the results will not be interpreted and instead marked as ‘n/a’ (i.e. not applicable).

5.2.2. Static tests: ABSEI-IDA Ireland sample

Tables 15 and 16 present the results from estimating the impact of IDA Ireland R&D/innovation support and R&D tax credits on firms’ R&D intensity. These results tell a somewhat different story than those obtained with the ABSEI-Enterprise Ireland sample. Results from the contemporaneous model presented in Table 15 demonstrate that R&D/innovation support from IDA Ireland has no statistically significant effect, while R&D tax credits have a positive and significant impact on firms’ R&D intensity.
Table 15 Testing for static complementarity and substitution between R&D tax credits and IDA Ireland R&D/innovation support (results for contemporaneous model)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-IDA Ireland sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 lags</td>
</tr>
<tr>
<td>R&amp;D tax credit (10)</td>
<td>1.47***</td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
</tr>
<tr>
<td>IDA Ireland (01)</td>
<td>-1.41</td>
</tr>
<tr>
<td></td>
<td>(1.10)</td>
</tr>
<tr>
<td>Both (11)</td>
<td>1.08</td>
</tr>
<tr>
<td></td>
<td>(0.71)</td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
<td>4.69***</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
</tr>
<tr>
<td>Export intensity (log)</td>
<td>0.10***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
<td>0.16***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>Small</td>
<td>0.45***</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
</tr>
<tr>
<td>Medium</td>
<td>0.92***</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
</tr>
<tr>
<td>Large</td>
<td>1.28***</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
</tr>
<tr>
<td>Year dummies</td>
<td>yes</td>
</tr>
<tr>
<td>n</td>
<td>16084</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.14</td>
</tr>
<tr>
<td>F-statistic</td>
<td>130.39***</td>
</tr>
</tbody>
</table>

Static complementary test (p-values of t-test):
H0: 11 ≥ 10 + 01  
p = 0.000

Static substitution test (p-values of t-test):
H0: 11 ≤ 10 + 01  
p = 1.000

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Note: Dependent variable is R&D intensity; All results are relative to the reference category of receiving no innovation policy instrument (i.e. 00).

Relative to the base category of firms that receive no innovation policy instrument, firms receiving a combination of both IDA Ireland R&D/innovation support and an R&D tax credit do not have higher R&D intensity. Unlike the results obtained with the ABSEI-Enterprise Ireland sample (presented in Table 13), results from tests for static complementarity between IDA Ireland support and the R&D tax credit fail to reject the null hypothesis of no complementarity. This suggests that
R&D tax credits and IDA Ireland R&D/innovation support have a substitutive relationship in terms of their contemporaneous impact on R&D intensity. Therefore, findings from the contemporaneous model using the ABSEI-IDA Ireland sample do not support Hypothesis 1. However, as noted above, it may take time for the impact of some forms of public funding for R&D/innovation to manifest. Table 16 presents the results from three lag-structured models.

Table 16  Testing for static complementarity and substitution between R&D tax credits and IDA Ireland R&D/innovation support (results for one, two and three lag-models)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-IDA Ireland sample</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1 lag</td>
<td>2 lags</td>
<td>3 lags</td>
</tr>
<tr>
<td>R&amp;D tax credit (10)</td>
<td>1.46***</td>
<td>1.43***</td>
<td>-0.29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.51)</td>
<td>(0.56)</td>
<td></td>
</tr>
<tr>
<td>IDA Ireland (01)</td>
<td>1.37</td>
<td>0.06</td>
<td>-0.43</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.99)</td>
<td>(1.13)</td>
<td>(1.38)</td>
<td></td>
</tr>
<tr>
<td>Both (11)</td>
<td>2.25***</td>
<td>0.44</td>
<td>0.35</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.83)</td>
<td>(0.88)</td>
<td>(0.91)</td>
<td></td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
<td>5.08***</td>
<td>5.78***</td>
<td>5.91***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.22)</td>
<td>(0.27)</td>
<td></td>
</tr>
<tr>
<td>Export intensity (log)</td>
<td>0.05***</td>
<td>0.06***</td>
<td>0.06***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.2)</td>
<td></td>
</tr>
<tr>
<td>Training intensity (log)</td>
<td>0.14***</td>
<td>0.14***</td>
<td>0.14***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>0.49***</td>
<td>0.39**</td>
<td>0.48***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.14)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>1.01***</td>
<td>1.02***</td>
<td>1.17***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.20)</td>
<td>(0.20)</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>1.27***</td>
<td>1.38***</td>
<td>1.78***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.27)</td>
<td>(0.31)</td>
<td>(0.32)</td>
<td></td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>12771</td>
<td>9852</td>
<td>7610</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.1</td>
<td>0.07</td>
<td>0.11</td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>79.4***</td>
<td>63.8***</td>
<td>46.75***</td>
<td></td>
</tr>
</tbody>
</table>

Static complementary test (p-values of t-test): H0: 11 ≥ 10 + 01
p = 1.000    p = 0.000    n/a

Static substitution test (p-values of t-test): H0: 11 ≤ 10 + 01
p = 0.000    p = 1.000    n/a

Standard errors in parentheses; * p < 0.1;  ** p < 0.05;  *** p < 0.01; Note: Dependent variable is R&D intensity; All results are relative to the reference category of receiving no innovation policy instrument (i.e. 00). In the tests for dynamic complementarity and substitution, n/a indicates that the relevant treatment category variables lack statistical significance and are thus not interpreted.
The results presented in Table 16 demonstrate that receiving a combination of IDA Ireland R&D/innovation support and an R&D tax credit has a large, positive and statistically significant impact on firms’ R&D intensity, but this impact materialises one year after the instruments are received. Based on tests for static complementarity presented at the base of Table 16, the null hypothesis of no complementarity for the one-lag model is rejected. In contrast to the ABSEI-Enterprise Ireland sample, for the ABSEI-IDA Ireland sample, the impact of receiving IDA Ireland support and an R&D tax credits takes one year to manifest, but when it does, it is of a large magnitude. Section 2.4 below offers a discussion and interpretation of this result, alongside results from the ABSEI-Enterprise Ireland and ABSEI-SFI samples, as well as the dynamic complementarity analysis.

It is important to note that the magnitude of the impact of receiving both instruments on R&D intensity in the one-lag model is almost twice as large as that of receiving R&D tax credits only. The impact of both instruments is relative to the R&D intensity of firms that receive no innovation policy instrument. As discussed in Chapter 4, the sample used in this analysis only contains firms that had positive R&D expenditure during at least one year from 2007 to 2017. As noted by Czarnitzki et al. (2011), firms that do not receive any public support for R&D/innovation may have no intention to invest in R&D or engage in innovation activities. Such firms would form a less representative reference group for evaluating the impact of innovation policy instruments in comparison to firms that receive no public funding for innovation but are R&D-active (see also Love et al. 2014). The large magnitude of the impact of receiving a combination of IDA Ireland support and an R&D tax credit on firms’ R&D intensity is particularly noteworthy given that it is relative to unsubsidised but R&D-active firms.

The results from both the contemporaneous model (Table 15) and the lag-structured models (Table
16) highlight that receiving the R&D tax credit has a positive and significant impact on firms’ R&D intensity which persists for up to two years.

5.2.3. Static tests: ABSEI-SFI sample

As discussed in Chapter 4, SFI do not directly fund firms R&D and innovation activities in the manner of Enterprise Ireland and IDA Ireland. Rather, SFI provide funding to research centres based at Irish Higher Education Institutions (HEIs) that incentivise firms to participate in collaborative R&D projects. While SFI facilitate this collaboration, it is not a direct form of funding. The firm collaborates with the research centre, not SFI. Therefore, in the analysis below SFI support is referred to as an SFI linkage. This term denoted that the firm does have a collection with SFI that may have an impact of their R&D/innovation activities, but it is not a direct link in the way that Enterprise Ireland and IDA Ireland provide R&D/innovation funding directly to firms.

Results from estimating the contemporaneous impact of SFI linkages and R&D tax credits on firms’ R&D intensity are presented in Table 17. These results indicate that R&D tax credits have a positive and significant impact on firms’ R&D intensity, and that this impact materialises the same year that firms receive the instrument. However, in the contemporaneous model, firms that have an SFI linkage only or a combination of both an R&D tax credit and SFI linkage at the same time do not invest significantly more in R&D relative to the base category of receiving no support.

As noted, SFI linkages involve firms engaging in incentivised joint research partnerships with research centres. The initial phase of any research collaboration may involve set-up costs and some disruption to current R&D activities while firms explore new opportunities with an academic partner. Therefore, the impact of SFI linkages, and the joint impact of an SFI linkage with an R&D tax credit, may take some time to manifest. Results from the lag-structured models presented in Table 18 indicate that this is the case.
Table 17 Testing for static complementarity and substitution between R&D tax credits and Science Foundation Ireland linkages (results for contemporaneous model)

<table>
<thead>
<tr>
<th>ABSEI-Science Foundation Ireland sample</th>
<th>0 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D tax credit (10)</td>
<td>1.40***</td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
</tr>
<tr>
<td>SFI (01)</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>(0.74)</td>
</tr>
<tr>
<td>Both (11)</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
<td>4.69***</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
</tr>
<tr>
<td>Export intensity (log)</td>
<td>0.10***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
<td>0.16***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>Small</td>
<td>0.45***</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
</tr>
<tr>
<td>Medium</td>
<td>0.93***</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
</tr>
<tr>
<td>Large</td>
<td>1.31***</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
</tr>
<tr>
<td>Year dummies</td>
<td>yes</td>
</tr>
<tr>
<td>n</td>
<td>16084</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.14</td>
</tr>
<tr>
<td>F-statistic</td>
<td>130.38***</td>
</tr>
</tbody>
</table>

Static complementary test (p-values of t-test):

H0: 11 ≥ 10 + 01  p = 0.000

Static substitution test (p-values of t-test):

H0: 11 ≤ 10 + 01  p = 1.000

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Note: Dependent variable is R&D intensity; All results are relative to the reference category of receiving no innovation policy instrument (i.e. 00)

Receiving a combination of an SFI linkage and an R&D tax credit has a positive and significant impact on firms’ R&D intensity in both the one- and two-lag models (i.e. one and two years after the firm initially received the instrument mix). Results of tests for static complementarity presented at the base of Table 18 reveal that the SFI linkages and R&D tax credits substitute one another in the one-lag model. However, a complementary relationship is identified between these two
instruments in the two-lag model. Therefore, while the impact of receiving this instrument mix materialises after one year, a complementary relationship only occurs after a two-year gestation period. These findings provide partial support for Hypothesis 1 and demonstrate the importance of considering the time lag involved between receiving public support for innovation and the impact of that support becoming manifest.

### Table 18

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-Science Foundation Ireland sample</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 lag</td>
<td>2 lags</td>
<td>3 lags</td>
<td></td>
</tr>
<tr>
<td>R&amp;D tax credit (10)</td>
<td>1.45***</td>
<td>1.17**</td>
<td>-0.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.50)</td>
<td>(0.53)</td>
<td></td>
</tr>
<tr>
<td>SFI (01)</td>
<td>0.59</td>
<td>0.62</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.82)</td>
<td>(0.90)</td>
<td>(1.01)</td>
<td></td>
</tr>
<tr>
<td>Both (11)</td>
<td>1.27**</td>
<td>1.21*</td>
<td>-0.18</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.68)</td>
<td>(0.81)</td>
<td></td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
<td>5.09***</td>
<td>5.76***</td>
<td>5.90***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.22)</td>
<td>(0.27)</td>
<td></td>
</tr>
<tr>
<td>Export intensity (log)</td>
<td>0.05***</td>
<td>0.06***</td>
<td>0.06***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.015)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>Training intensity (log)</td>
<td>0.14***</td>
<td>0.14***</td>
<td>0.14***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>0.48***</td>
<td>0.42**</td>
<td>0.48***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.14)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>1.01***</td>
<td>1.07***</td>
<td>1.17***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.12)</td>
<td>(0.20)</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>1.31***</td>
<td>1.44***</td>
<td>1.79***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.27)</td>
<td>(0.31)</td>
<td>(0.32)</td>
<td></td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>12771</td>
<td>9852</td>
<td>7610</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.1</td>
<td>0.08</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>79.55***</td>
<td>64.22***</td>
<td>46.96***</td>
<td></td>
</tr>
</tbody>
</table>

Static complementary test (p-values of t-test):

H0: 11 ≥ 10 + 01

<p>| |</p>
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>p</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>0.000</td>
</tr>
<tr>
<td>1.000</td>
</tr>
<tr>
<td>n/a</td>
</tr>
</tbody>
</table>

Static substitution test (p-values of t-test):

H0: 11 ≤ 10 + 01

<p>| |</p>
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>p</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>1.000</td>
</tr>
<tr>
<td>0.000</td>
</tr>
<tr>
<td>n/a</td>
</tr>
</tbody>
</table>

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Note: Dependent variable is R&D intensity; All results are relative to the reference category of receiving no innovation policy instrument (i.e. 00). In the tests for dynamic complementarity and substitution, n/a indicates that the relevant treatment category variables lack statistical significance and are thus not interpreted.
The models estimated above facilitated testing for static complementarity and provided some support for Hypothesis 1. This section focused on the impact of receiving a combination of two different innovation policy instruments (i.e. an R&D tax credit combined with R&D/innovation support from Enterprise Ireland, IDA Ireland of a SFI linkage) at the same time. The next section investigates the temporal dynamics of the innovation policy instrument mix by conducting tests for dynamic complementarity.

5.2.4. Specification tests for static Lewbel instrumental variable regressions

As noted in Chapter 4, for Lewbel-instruments to be valid, they must be relevant and exogenous, as is the case with standard instrumental variable methods (see e.g. Arellano & Bond 1991). Table 19 reports the standard specification tests for instrumental variable regression analysis in the static models using Lewbel’s (2012) method of heteroscedasticity-based instruments.

<table>
<thead>
<tr>
<th>Table 19 Specification tests for static complementarity regressions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enterprise Ireland-ABSEI sample</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Underidentification test</td>
</tr>
<tr>
<td>-------------------------</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Hansen's J statistic</td>
</tr>
<tr>
<td>IDA Ireland-ABSEI sample</td>
</tr>
<tr>
<td>Underidentification test</td>
</tr>
<tr>
<td>Hansen's J statistic</td>
</tr>
<tr>
<td>Science Foundation Ireland-ABSEI sample</td>
</tr>
<tr>
<td>Underidentification test</td>
</tr>
<tr>
<td>Hansen's J statistic</td>
</tr>
</tbody>
</table>

* p < 0.1; ** p < 0.05; *** p < 0.01
The results reported in Table 19 show that all regressions, across all lag-structured models, reject the null of no first order autocorrelation (i.e. the underidentification test), and that all models do not reject the null of no second order autocorrelation (i.e. the Hansen’s J statistic). The Hansen tests of the overidentifying restrictions never reject the null. The general pattern of these results indicates that all model specifications meet the sufficient validity criteria.

5.3. Testing for dynamic complementarity and substitution

As highlighted in Section 5.2 above, in each of the datasets used in this analysis, two innovation policy instruments are available to firms: R&D/innovation support from a national funding agency and an R&D tax credit. In any given year, firms can fall into one of the following four treatment categories: 1) Receives no agency R&D/innovation support or R&D tax credit; 2) Receives an R&D tax credit only; 3) Receives agency R&D/innovation support only; or 4) Receives both agency R&D/innovation support and an R&D tax credit.

Even when using panel data, testing for static complementarity involves comparing all of the observations in the dataset to one another in terms of the treatment category they fall into at a single point in time. In contrast, testing for dynamic complementarities involves utilising the panel nature of the dataset to compare repeat observations to themselves as they transition between treatment categories through time. As noted by Love et al. (2014), testing for complementarities has an inherently dynamic quality because it involves the addition of something new to what the firm currently does. Therefore, as opposed to the static tests which involve four treatment categories, the dynamic tests necessitate 16 treatment categories. Each of the 16 treatment categories represents a ‘switch’ variable. In the estimation results presented below, the switch variables are identified by the prefix ‘sw’. The numerical indicators in each of the switch variables listed below represent the four treatment categories discussed in Section 5.2 for the static
complementarity analysis. The switch variables capture firms either moving between treatment categories from one year to the next or remaining in the same category (for a detailed description, see Table 5 in Chapter 4). The tests for dynamic complementarity focus on four key switch variables:

1) sw24: Transition from R&D tax credit to both;
2) sw13: Transition from neither to agency R&D/innovation support;
3) sw34: Transition from agency R&D/innovation support to both;
4) sw12: Transition from neither to R&D tax credit.

How the tests for static complementarity work can be shown by example. If the impact of sw24 on a firm’s R&D intensity is greater than that of sw13, this can be interpreted as evidence of a dynamic complementary relationship between the two different instruments. Given that the dynamic tests focus on adding something new to what the firm already has, in both sw13 and sw24, the ‘new’ instrument that is being added is agency R&D/innovation support. Firms in the sw13 category transition from receiving no support to agency R&D/innovation support only. In contrast, firms in the sw24 category transition from receiving an R&D tax credit one year to receiving both an R&D tax credit and agency R&D/innovation support the next year. The coefficients of each of the 15 switch variables in the regression analysis can be interpreted as being relative to firms that receive no R&D/innovation support in one year and no R&D/innovation support in the next year (i.e. firms that remain in the neither category, or sw11).

---

20 These treatment categories are as follows: 1) No agency R&D/innovation support and no R&D tax credit (neither; 00); 2) No agency R&D/innovation support intervention and receives R&D tax credit (R&D tax credit only; 10); 3) Receives agency R&D/innovation support intervention and no R&D tax credit (agency R&D/innovation support only; 01); and 4) Receives agency R&D/innovation support intervention and R&D tax credit (both; 11)
Testing for dynamic complementarity in this way will shed light on Hypothesis 2, which states that there will be a complementary relationship between the innovation policy instrument(s) a firm received in the past and the innovation policy instrument(s) that the firm receives in the present in the firm’s innovation production function. To test this hypothesis, the empirical analysis focuses on firms’ transition from one year to the next.

In addition, by examining the coefficients of all of the 15 switch variables in the results from the dynamic approach, it is possible to observe how the sequence in which firms receive different innovation policy instruments affects innovation outcomes. For example, does receiving an R&D tax credit one year, followed by receiving both an R&D tax credit and R&D/innovation support from Enterprise Ireland the next year, impact firms’ R&D intensity differently from receiving them in the opposite sequence? The following subsections seek to shed light on this question. As in the tests for static complementarity and substitution presented above in Section 5.2, it is important to highlight that the outcome variable used in each regression analysis in this section is firm R&D intensity. Therefore, the results presented in this section represent the input additionality of receiving innovation policy instruments.

5.3.1. Dynamic tests: ABSEI-Enterprise Ireland sample

Tables 20 and 21 present the results from estimating the impact of the 15 switch variables on firms’ R&D intensity in the ABSEI-Enterprise Ireland sample. As noted, all results are relative to the base category of receiving no innovation policy instrument in two consecutive years (i.e. sw11). In both the contemporaneous and lagged models, remaining in the R&D tax credit category from one year to the next (i.e. sw22) has the most consistent positive and significant impact on firms’ R&D intensity. This result concurs with that of the static complementarity analysis in Section 5.2.,
which found that firms receiving an R&D tax credit had a positive and significant impact on firms’ R&D intensity.

In Table 20 (i.e. the contemporaneous model), the coefficient of the switch variable sw42, representing firms that transition from receiving both instruments to R&D tax credits only, is positive and significant and of a slightly larger magnitude than that of sw22. However, this impact is only statistically significant in the contemporaneous model and loses its significance in the one, two- and three-lag models presented in Table 21. Therefore, this result can be interpreted as the lagged impact of receiving an instrument mix one year ago (i.e. the transition from ‘4’ to ‘2’).

However, as highlighted in Chapter 4, the primary interest of the current study is not the absolute values of the switch variable coefficients, but rather whether switches between certain treatment categories have a greater impact on firms’ R&D intensity than others. As noted, the key switch variables of interest are sw24 and sw34. While sw24 captures firms that transition from an R&D tax credit to a combination of Enterprise Ireland R&D/innovation support and an R&D tax credit, sw34 captures firms that transition from Enterprise Ireland support one year to a combination of Enterprise Ireland R&D/innovation support and an R&D tax credit the next year.

The only statistically significant coefficient of the key switch variables is sw12 in the contemporaneous model (i.e. Table 20), indicating that there is a dynamic substitutive relationship between R&D tax credits and Enterprise Ireland R&D/innovation support. These findings do not support Hypothesis 2.
Table 20  Testing for dynamic complementarity and substitution between R&D tax credits and Enterprise Ireland R&D/innovation support (results for contemporaneous model)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-Enterprise Ireland sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 lags</td>
</tr>
<tr>
<td><strong>sw22</strong></td>
<td>0.90*** (0.28)</td>
</tr>
<tr>
<td><strong>sw33</strong></td>
<td>0.1 (0.68)</td>
</tr>
<tr>
<td><strong>sw44</strong></td>
<td>1 (0.66)</td>
</tr>
<tr>
<td><strong>sw12</strong></td>
<td>0.66*** (0.20)</td>
</tr>
<tr>
<td><strong>sw13</strong></td>
<td>0.001 (0.40)</td>
</tr>
<tr>
<td><strong>sw14</strong></td>
<td>1.05 (0.77)</td>
</tr>
<tr>
<td><strong>sw21</strong></td>
<td>0.28 (0.24)</td>
</tr>
<tr>
<td><strong>sw23</strong></td>
<td>-0.81 (0.79)</td>
</tr>
<tr>
<td><strong>sw24</strong></td>
<td>0.69 (0.46)</td>
</tr>
<tr>
<td><strong>sw31</strong></td>
<td>-0.1 (0.39)</td>
</tr>
<tr>
<td><strong>sw32</strong></td>
<td>0.68 (0.98)</td>
</tr>
<tr>
<td><strong>sw34</strong></td>
<td>0.38 (0.77)</td>
</tr>
<tr>
<td><strong>sw41</strong></td>
<td>1.43 (0.95)</td>
</tr>
<tr>
<td><strong>sw42</strong></td>
<td>0.92** (0.45)</td>
</tr>
<tr>
<td><strong>sw43</strong></td>
<td>-0.85 (0.94)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
</tr>
<tr>
<td>n</td>
<td>16084</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.14</td>
</tr>
<tr>
<td>F-statistic</td>
<td>73.81***</td>
</tr>
</tbody>
</table>

Dynamic complementary test (p-values of t-test):

H0: sw24 ≥ sw13  n/a
H0: sw34 ≥ sw12  p = 1.000

Dynamic substitution test (p-values of t-test):

H0: sw24 ≤ sw13  n/a
H0: sw34 ≤ sw12  p = 0.000

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Notes: Dependent variable is R&D intensity. For brevity, the control variables have been omitted; see Appendix A for the results for control variables. In the tests for dynamic complementarity and substitution, n/a indicates that the relevant treatment category variables lack statistical significance and are thus not interpreted.
Table 21 Testing for dynamic complementarity and substitution between R&D tax credits and Enterprise Ireland R&D/innovation support (results for one, two and three lag-models)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-Enterprise Ireland sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 lag</td>
</tr>
<tr>
<td>sw22</td>
<td>0.83***</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
</tr>
<tr>
<td>sw33</td>
<td>-0.16</td>
</tr>
<tr>
<td></td>
<td>(0.65)</td>
</tr>
<tr>
<td>sw44</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>(0.60)</td>
</tr>
<tr>
<td>sw12</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
</tr>
<tr>
<td>sw13</td>
<td>-0.1</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
</tr>
<tr>
<td>sw14</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
</tr>
<tr>
<td>sw21</td>
<td>-0.22</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
</tr>
<tr>
<td>sw23</td>
<td>1.02</td>
</tr>
<tr>
<td></td>
<td>(0.90)</td>
</tr>
<tr>
<td>sw24</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
</tr>
<tr>
<td>sw31</td>
<td>-0.09</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
</tr>
<tr>
<td>sw32</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>(0.97)</td>
</tr>
<tr>
<td>sw34</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>(0.77)</td>
</tr>
<tr>
<td>sw41</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td>(1.12)</td>
</tr>
<tr>
<td>sw42</td>
<td>0.74</td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
</tr>
<tr>
<td>sw43</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>(1.10)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
</tr>
<tr>
<td>n</td>
<td>12771</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.11</td>
</tr>
<tr>
<td>F-statistic</td>
<td>45.3***</td>
</tr>
</tbody>
</table>

Dynamic complementarity test (p-values of t-test):
H0: sw24 ≥ sw13  n/a  n/a  n/a
H0: sw34 ≥ sw12  n/a  n/a  n/a

Dynamic substitution test (p-values of t-test):
H0: sw24 ≤ sw13  n/a  n/a  n/a
H0: sw34 ≤ sw12  n/a  n/a  n/a

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Notes: Dependent variable is R&D intensity. For brevity, the control variables have been omitted; see Appendix A for the results for control variables. In the tests for dynamic complementarity and substitution, n/a indicates that the relevant treatment category variables lack statistical significance and are thus not interpreted.
Results from the three lag-structured models presented in Table 20 highlight that firms in the four key switch categories do not invest more in R&D relative to the base category of receiving no public support for R&D/innovation from one year to the next (i.e. sw11). However, as noted above, as the number of lags increases in each model, the sample size reduces. This reduction in sample size, coupled with the fact that firms are distributed among 15 treatment categories involving at least one innovation policy instrument, may explain non-significant results.

It is important to note that there are 15 treatment category variables listed in all of the dynamic regressions, as opposed to four in the static regressions. This makes the regression tables (i.e. Table 20 above) very long and difficult to read. Therefore, for reasons of brevity and ease of presentation, the control variables have been omitted from the table. However, these variables were included in each dynamic regression model (in addition to fixed effects), and results are listed in Appendix A.

### 5.3.2. Dynamic tests: ABSEI-IDA Ireland sample

Results of the estimation using the ABSEI-IDA Ireland sample and subsequent tests for dynamic complementarity differ significantly from those of the ABSEI-Enterprise Ireland sample. Results for the contemporaneous model, presented in Table 22, highlight that there is a dynamic complementary relationship between R&D tax credits and IDA Ireland R&D/innovation support. The transition from receiving an R&D tax credit one year to receiving a combination of an R&D tax credit and IDA Ireland R&D/innovation support in the next year (i.e. sw24) has a positive and significant impact on firms’ R&D intensity. In contrast, the impact of transitioning from no R&D/innovation support to IDA Ireland R&D/innovation support only (i.e. sw13) is not significantly different from receiving no R&D/innovation support in either year (i.e. the reference category sw11). This finding provides support for Hypothesis 2.
However, receiving these instruments in the opposite sequence (i.e. sw34) does not have a statistically significant impact on firms’ R&D intensity. Given that the transition from no R&D/innovation support to receiving an R&D tax credit only (i.e. sw12) has a positive and significant impact on firms’ R&D intensity, the tests for dynamic complementarity at the base of Table 22 fail to reject the null hypothesis of no complementarity. Therefore, in the contemporaneous model, the two key inequality tests lend partial support for Hypothesis 2.

The statistically non-significant finding for the variable sw34 should be viewed alongside the fact that each of the other switch variables that involve a transition towards receiving both instruments (i.e. sw14, sw24 and sw44) produces a positive, statistically significant coefficient. The magnitude of each of these coefficients is large in size. In the case of firms that receive both instruments in two consecutive years (i.e. sw44), the impact (in both the contemporaneous and one-lag models) is over double that of firms that receive an R&D tax credit in two consecutive years (i.e. sw22).

It is also instructive to consider the results for firms that transition away from receiving both an R&D tax credit and IDA Ireland R&D/innovation support (i.e. sw41, sw42 and sw43). In the contemporaneous model (Table 21), the coefficients for each of these variables are statistically significant, large in magnitude and positive. However, the results presented in Table 23 demonstrate that in the three years following this transition away from receiving an instrument mix, firms either: 1) cease to have R&D intensity above that of firms that received no innovation policy instrument (i.e. sw11); or 2) have a large and statistically significant reduction in their R&D intensity. In summary, although dynamic substitution is identified when firms transition from IDA Ireland R&D/innovation support to a combination of IDA Ireland R&D/innovation support and an R&D tax credit, there is a high premium associated with all other treatment categories that involve receiving an instrument mix.
Table 22 Testing for dynamic complementarity and substitution between R&D tax credits and IDA Ireland R&D/innovation support (results for contemporaneous model)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-IDA Ireland sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 lags</td>
</tr>
<tr>
<td>sw22</td>
<td>0.79***</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
</tr>
<tr>
<td>sw33</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
</tr>
<tr>
<td>sw44</td>
<td>1.86***</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
</tr>
<tr>
<td>sw12</td>
<td>0.40**</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
</tr>
<tr>
<td>sw13</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>(0.62)</td>
</tr>
<tr>
<td>sw14</td>
<td>1.54*</td>
</tr>
<tr>
<td></td>
<td>(0.86)</td>
</tr>
<tr>
<td>sw21</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
</tr>
<tr>
<td>sw23</td>
<td>-0.91</td>
</tr>
<tr>
<td></td>
<td>(1.04)</td>
</tr>
<tr>
<td>sw24</td>
<td>1.19**</td>
</tr>
<tr>
<td></td>
<td>(0.52)</td>
</tr>
<tr>
<td>sw31</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>(0.64)</td>
</tr>
<tr>
<td>sw32</td>
<td>0.78</td>
</tr>
<tr>
<td></td>
<td>(1.22)</td>
</tr>
<tr>
<td>sw34</td>
<td>1.32</td>
</tr>
<tr>
<td></td>
<td>(1.46)</td>
</tr>
<tr>
<td>sw41</td>
<td>2.45***</td>
</tr>
<tr>
<td></td>
<td>(0.95)</td>
</tr>
<tr>
<td>sw42</td>
<td>1.06**</td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
</tr>
<tr>
<td>sw43</td>
<td>2.74***</td>
</tr>
<tr>
<td></td>
<td>(1.06)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
</tr>
<tr>
<td>n</td>
<td>16084</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.13</td>
</tr>
<tr>
<td>F-statistic</td>
<td>74.87***</td>
</tr>
</tbody>
</table>

Dynamic complementary test (p-values of t-test):
H0: sw24 ≥ sw13  p = 0.000
H0: sw34 ≥ sw12  p = 1.000

Dynamic substitution test (p-values of t-test):
H0: sw24 ≤ sw13  p = 1.000
H0: sw34 ≤ sw12  p = 0.000

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Notes: Dependent variable is R&D intensity. For brevity, the control variables have been omitted; see Appendix B for the results for control variables.
### Table 23

Testing for dynamic complementarity and substitution between R&D tax credits and IDA Ireland R&D/innovation support (results for one, two and three lag-models)

<table>
<thead>
<tr>
<th></th>
<th>1 lag</th>
<th>2 lags</th>
<th>3 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ABSEI-IDA Ireland sample</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sw22</td>
<td>0.61***</td>
<td>0.17</td>
<td>-0.41*</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.23)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>sw33</td>
<td>-0.31</td>
<td>-0.79</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.86)</td>
<td>(0.90)</td>
<td>(1.10)</td>
</tr>
<tr>
<td>sw44</td>
<td>1.69***</td>
<td>0.14</td>
<td>-0.77</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.67)</td>
<td>(0.63)</td>
</tr>
<tr>
<td>sw12</td>
<td>0.27</td>
<td>0.07</td>
<td>-0.23</td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.19)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>sw13</td>
<td>1.06</td>
<td>-0.17</td>
<td>-0.14</td>
</tr>
<tr>
<td></td>
<td>(0.65)</td>
<td>(0.74)</td>
<td>(0.79)</td>
</tr>
<tr>
<td>sw14</td>
<td>1.05</td>
<td>0.96</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>(0.90)</td>
<td>(0.96)</td>
<td>(0.97)</td>
</tr>
<tr>
<td>sw21</td>
<td>-0.06</td>
<td>0.42</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.26)</td>
<td>(0.29)</td>
</tr>
<tr>
<td>sw23</td>
<td>-0.006</td>
<td>0.46</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>(1.03)</td>
<td>(1.22)</td>
<td>(1.51)</td>
</tr>
<tr>
<td>sw24</td>
<td>0.7</td>
<td>-0.91</td>
<td>-0.2</td>
</tr>
<tr>
<td></td>
<td>(0.50)</td>
<td>(0.58)</td>
<td>(0.63)</td>
</tr>
<tr>
<td>sw31</td>
<td>0.88</td>
<td>0.087</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
<td>(0.84)</td>
<td>(1.01)</td>
</tr>
<tr>
<td>sw32</td>
<td>0.07</td>
<td>-0.54</td>
<td>-0.32</td>
</tr>
<tr>
<td></td>
<td>(1.31)</td>
<td>(1.30)</td>
<td>(1.25)</td>
</tr>
<tr>
<td>sw34</td>
<td>1.87</td>
<td>0.76</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td>(1.44)</td>
<td>(1.43)</td>
<td>(3.10)</td>
</tr>
<tr>
<td>sw41</td>
<td>-2.80****</td>
<td>0.99</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(1.15)</td>
<td>(1.52)</td>
</tr>
<tr>
<td>sw42</td>
<td>0.55</td>
<td>0.12</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>(0.58)</td>
<td>(0.63)</td>
<td>(0.91)</td>
</tr>
<tr>
<td>sw43</td>
<td>0.21</td>
<td>-2.24</td>
<td>-3.88***</td>
</tr>
<tr>
<td></td>
<td>(1.10)</td>
<td>(1.58)</td>
<td>(1.46)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>n</td>
<td>12771</td>
<td>9852</td>
<td>7610</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.11</td>
<td>0.11</td>
<td>0.1</td>
</tr>
<tr>
<td>F-statistic</td>
<td>45.42***</td>
<td>38.37***</td>
<td>27.28***</td>
</tr>
</tbody>
</table>

**Dynamic complementary test (p-values of t-test):**
- H0: sw24 ≥ sw13  n/a  n/a  n/a
- H0: sw34 ≥ sw12  n/a  n/a  n/a

**Dynamic substitution test (p-values of t-test):**
- H0: sw24 ≤ sw13  n/a  n/a  n/a
- H0: sw34 ≤ sw12  n/a  n/a  n/a

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Notes: Dependent variable is R&D intensity. For brevity, the control variables have been omitted; see Appendix B for the results for control variables. In the tests for dynamic complementarity and substitution, n/a indicates that the relevant treatment category variables lack statistical significance and are thus not interpreted.
5.3.3. Dynamic tests: ABSEI-SFI sample

Tables 24 and 25 present the estimation results and tests of dynamic complementarity for the ABSEI-SFI sample. These results demonstrate some noteworthy differences from the ABSEI-Enterprise Ireland and ABSEI-IDA Ireland samples. Focusing first on the key transition variables for the dynamic complementarity tests, the transition from having an SFI linkage in one year to having both an SFI linkage and an R&D tax credit (i.e. sw34) has a positive and statistically significant impact on firms’ R&D intensity. This result is in direct contrast to that found for the variable sw34 in the ABSEI-IDA Ireland sample, as discussed above. Taken together, these findings suggest that the sequence in which firms receive different innovation policy instruments plays an important role in determining their eventual impact on firms’ R&D intensity.

Based on the results of the econometric analysis, the tests for dynamic complementarity presented at the base of Table 24 reject the null hypothesis of no complementarity. This finding provides empirical support for Hypothesis 2, that a dynamic complementary relationship exists between R&D tax credits and SFI linkages through time in terms of their impact on firms’ R&D intensity.

Another result presented in Table 24 is also noteworthy due to its unique nature among all results from either static or dynamic models across all datasets. Receiving an SFI linkage only in one year, and remaining in this category in the next year (i.e. sw33), has a positive and statistically significant impact on firms’ R&D intensity. In the static models presented in Section 2.2, receiving R&D/innovation support solely from Enterprise Ireland, IDA Ireland or SFI did not have an impact on firms’ R&D intensity that was greater than that of receiving no R&D/innovation support (i.e. the reference category).
Table 24 Testing for dynamic complementarity and substitution between R&D tax credits and Science Foundation Ireland linkages (results for contemporaneous model)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-Science Foundation Ireland sample</th>
<th>0 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>sw22</td>
<td>0.69***</td>
<td>(0.25)</td>
</tr>
<tr>
<td>sw33</td>
<td>1.13**</td>
<td>(0.51)</td>
</tr>
<tr>
<td>sw44</td>
<td>0.59</td>
<td>(0.37)</td>
</tr>
<tr>
<td>sw12</td>
<td>0.31</td>
<td>(0.20)</td>
</tr>
<tr>
<td>sw13</td>
<td>-0.37</td>
<td>(0.90)</td>
</tr>
<tr>
<td>sw14</td>
<td>0.86</td>
<td>(1.12)</td>
</tr>
<tr>
<td>sw21</td>
<td>0.1</td>
<td>(0.23)</td>
</tr>
<tr>
<td>sw23</td>
<td>0.45</td>
<td>(2.46)</td>
</tr>
<tr>
<td>sw24</td>
<td>0.4</td>
<td>(0.61)</td>
</tr>
<tr>
<td>sw31</td>
<td>0.83</td>
<td>(0.76)</td>
</tr>
<tr>
<td>sw32</td>
<td>0.43</td>
<td>(1.12)</td>
</tr>
<tr>
<td>sw34</td>
<td>1.31**</td>
<td>(0.64)</td>
</tr>
<tr>
<td>sw41</td>
<td>0.77</td>
<td>(1.44)</td>
</tr>
<tr>
<td>sw42</td>
<td>0.35</td>
<td>(0.74)</td>
</tr>
<tr>
<td>sw43</td>
<td>0.66</td>
<td>(0.80)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>16084</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>73.93***</td>
<td></td>
</tr>
</tbody>
</table>

Dynamic complementary test (p-values of t-test):
H0: sw24 ≥ sw13  n/a
H0: sw34 ≥ sw12  p = 0.000

Dynamic substitution test (p-values of t-test):
H0: sw24 ≤ sw13  n/a
H0: sw34 ≤ sw12  p = 1.000

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Notes: Dependent variable is R&D intensity. For brevity, the control variables have been omitted; see Appendix B for the results for control variables.
Table 25 Testing for dynamic complementarity and substitution between R&D tax credits and Science Foundation Ireland linkages (results for one, two and three lag-models)

| Table 25 Testing for dynamic complementarity and substitution between R&D tax credits and Science Foundation Ireland linkages (results for one, two and three lag-models) |
|---------------------------------|-----------------|-----------------|-----------------|
|                                | 1 lag            | 2 lags          | 3 lags          |
| sw22                            | 0.82***          | 0.19            | M0.39***        |
|                                 | (0.24)           | (0.23)          | (0.22)          |
| sw33                            | 0.44             | 0.52            | 0.57            |
|                                 | (0.55)           | (0.55)          | (0.55)          |
| sw44                            | 0.61*            | 0.11            | -0.26           |
|                                 | (0.36)           | (0.38)          | (0.38)          |
| sw12                            | 0.32             | 0.13            | -0.22           |
|                                 | (0.20)           | (0.20)          | (0.20)          |
| sw13                            | -0.1             | 0.36            | 0.4             |
|                                 | (0.94)           | (0.89)          | (0.85)          |
| sw14                            | 0.76             | 0.11            | -0.02           |
|                                 | (1.06)           | (1.03)          | (1.02)          |
| sw21                            | -0.07            | 0.41            | 0.02            |
|                                 | (0.26)           | (0.27)          | (0.29)          |
| sw23                            | -0.39            | 0.47            | 0.78            |
|                                 | (2.36)           | (2.31)          | (2.31)          |
| sw24                            | 0.62             | 0.04            | -0.23           |
|                                 | (0.60)           | (0.59)          | (0.60)          |
| sw31                            | 0.87             | 0.51            | 0.64            |
|                                 | (1.63)           | (1.04)          | (0.69)          |
| sw32                            | M0.15            | 0.35            | 0.15            |
|                                 | (1.08)           | (1.04)          | (1.06)          |
| sw34                            | 0.56             | 0.46            | 0.15            |
|                                 | (0.69)           | (0.64)          | (0.79)          |
| sw41                            | 2.13             | 0.53            | M0.50           |
|                                 | (2.31)           | (1.31)          | (1.33)          |
| sw42                            | 0.89             | 1.28            | 0.66            |
|                                 | (1.17)           | (2.18)          | (0.64)          |
| sw43                            | 0.71             | 0.48            | 0.09            |
|                                 | (0.87)           | (0.84)          | (1.01)          |
| Fixed effects                   | yes              | yes             | yes             |
| n                               | 12771            | 9852            | 7610            |
| R-squared                       | 0.11             | 0.11            | 0.1             |
| F-statistic                     | 45.12***         | 38.09***        | 27.94***        |

Dynamic complementary test (p-values of t-test):
H0: sw24 ≥ sw13                   n/a              n/a              n/a
H0: sw34 ≥ sw12                   n/a              n/a              n/a

Dynamic substitution test (p-values of t-test):
H0: sw24 ≤ sw13                   n/a              n/a              n/a
H0: sw34 ≤ sw12                   n/a              n/a              n/a

Standard errors in parentheses; * p < 0.1; ** p < 0.05; *** p < 0.01; Notes: Dependent variable is R&D intensity. For brevity, the control variables have been omitted; see Appendix B for the results for control variables. In the tests for dynamic complementarity and substitution, n/a indicates that the relevant treatment category variables lack statistical significance and are thus not interpreted.
In the dynamic tests presented above for the ABSEI-Enterprise Ireland and ABSEI-IDA Ireland samples, remaining in the *Enterprise Ireland only* or *IDA Ireland only* categories (i.e. sw33) has no impact on R&D investments. Although this variable loses its significance in the lag-structured models presented in Table 25, it is worthwhile to highlight the unique nature of this finding. As noted, an analysis of the results from each of the three datasets is provided in Section 2.4.

The results presented from the tests for dynamic complementarity across each of the three datasets, as well as the contemporaneous and lag-structured models, reveal a complex picture of how innovation policy instruments impact firms’ R&D intensity. Similar to the tests for Hypothesis 1, the empirical tests lend some support for Hypothesis 2. However, this support is not universal across the datasets and lag-structured models.

While the preceding sections have presented the results of the econometric analysis, the next section discusses and interprets the findings of the econometric analysis in the context of previous literature and the empirical setting of Ireland.

**5.3.4. Specification tests for dynamic Lewbel instrumental variable regressions**

Table 26 reports the standard specification tests for instrumental variable regression analysis in the dynamic models. In the same way as the specification tests for the static regressions reported in Table 19, all regressions reject the null of no first order autocorrelation (i.e. the underidentification test), and all models do not reject the null of no second order autocorrelation (i.e. the Hansen’s J statistic). Following the pattern established in Table 19, the results presented in Table 26 indicate that all regression models meet the specification requirements.
Table 26 Specification tests for dynamic complementarity regressions

<table>
<thead>
<tr>
<th>Enterprise Ireland-ABSEI sample</th>
<th>0 Lag</th>
<th>1 Lag</th>
<th>2 Lag</th>
<th>3 Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underidentification test</td>
<td>872.743***</td>
<td>835.376***</td>
<td>803.508***</td>
<td>669.173***</td>
</tr>
<tr>
<td>Hansen's J statistic</td>
<td>174.128</td>
<td>151.193</td>
<td>149.502</td>
<td>107.181</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>IDA Ireland-ABSEI sample</th>
<th>0 Lag</th>
<th>1 Lag</th>
<th>2 Lag</th>
<th>3 Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underidentification test</td>
<td>1045.534***</td>
<td>926.656***</td>
<td>830.238***</td>
<td>796.335***</td>
</tr>
<tr>
<td>Hansen's J statistic</td>
<td>260.257</td>
<td>211.88</td>
<td>222.604</td>
<td>174.909</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Science Foundation Ireland-ABSEI sample</th>
<th>0 Lag</th>
<th>1 Lag</th>
<th>2 Lag</th>
<th>3 Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underidentification test</td>
<td>984.358***</td>
<td>885.668***</td>
<td>833.649***</td>
<td>782.642***</td>
</tr>
<tr>
<td>Hansen's J statistic</td>
<td>162.49</td>
<td>120.127</td>
<td>159.154</td>
<td>99.858</td>
</tr>
</tbody>
</table>

* p < 0.1; ** p < 0.05; *** p < 0.01

5.4. Discussion and interpretation of empirical findings

The primary objective of this thesis is to evaluate whether different innovation policy instruments are complements or substitutes in their impact on firm-level R&D intensity. This section provides a summary and analysis of the empirical results this chapter presents, as they pertain to the research question. Using Ireland’s innovation policy landscape as a laboratory to operationalise and study the innovation policy instrument mix, the econometric analysis yields mixed results. However, it is clear that receiving a mix of innovation policy instruments can have a significant impact on firms’ R&D intensity. The section first considers results for the R&D tax credit (Section 5.4.1), followed by a discussion of R&D/innovation support from Enterprise Ireland and IDA Ireland, as well as SFI linkages (Section 5.4.2). Finally, Section 5.4.3 turns to the relationship between R&D
tax credits and support from the three Irish national funding agencies, discussing these results in relation to the study’s two research hypotheses.

5.4.1. R&D tax credits

As detailed in Chapter 4, the R&D tax credit is the dominant innovation policy instrument in Ireland, both in terms of the cost of the scheme and the number of firms availing themselves of it. National policy reports highlight the large cost of the R&D tax credit programme in terms of corporation tax forgone (Department of Finance 2013; 2016). Indeed, the OECD (2015a, p. 13) suggest that policymakers in Ireland should “[r]ebalance innovation support towards direct grants” to curb the R&D tax credit’s prominent position.

Employing a generated instrumental variable estimator to control for selection bias and endogeneity associated with the allocation and receipt of public funding, results from this study suggest that the R&D tax credit plays an important role in driving firm R&D investment in Ireland. Across all econometric estimations, the most consistent finding is that receiving an R&D tax credit has a positive and statistically significant impact on firms’ R&D intensity, compared to that of firms receiving no innovation policy instrument. These findings tally with previous studies (e.g. Rao 2016; IMF 2016; Gaillard-Ladinska et al. 2015; Castellacci & Lie 2015; Cappelen et al. 2012; Czarnitzki et al. 2011).

Results from the contemporaneous and lag-structured models in the static regressions reveal that such impact manifests in the same year that firms receive the R&D tax credit and persists for up to two years following its receipt. Indeed, the impact of receiving an R&D tax credit increases slightly one year following its receipt (i.e. in the one-lag models). The dynamic regressions
confirm these findings, showing that receiving an R&D tax credit in two consecutive years (i.e. the variable sw22) has a positive and significant impact on firm R&D.

In a recent audit of the R&D tax credit programme in Ireland, the Comptroller and Auditor General (2016, p. 187) note that the “primary objective of the tax credit is to incentivise Business Expenditure on Research and Development”. The findings detailed above suggest that the R&D tax credit meets this objective. On this basis, the policy recommendation from OECD (2015b) noted above may require nuancing to recognise the important role the R&D tax credit currently plays in Ireland’s innovation policy landscape, while still envisaging a larger role for Ireland’s key national funding agencies that implement a broader range of innovation policy instruments.

5.4.2. National funding agencies: Enterprise Ireland, IDA Ireland and SFI

In contrast to the findings for R&D tax credits, results across all regression models demonstrate that firms receiving R&D/innovation support solely from Enterprise Ireland or IDA Ireland, or with SFI linkage, do not show higher R&D intensity than firms receiving no innovation policy instrument. This section discussed these somewhat surprising results in the context of the previous literature, interpreting them within the empirical context of Ireland.

In their extensive review of the empirical literature on direct forms of R&D subsidy, Dimos and Pugh (2016) categorically demonstrate that subsidised firms do not invest less in R&D than they did before receiving the subsidy (i.e. crowding out). However, these authors find little evidence that firms substantially increase their own private R&D expenditure on top of the R&D subsidy (i.e. additionality). While the literature on more systemic forms of innovation policy instruments
is scant, relative to that focusing on direct and indirect instruments, Scandura (2016) finds that funded university-industry collaborations have a positive impact on firms’ R&D intensity.

However, as detailed in Chapter 2, direct and systemic forms of innovation policy instrument (such as those offered by Enterprise Ireland, IDA Ireland and SFI) differ from indirect innovation policy instruments (such as the R&D tax credit) in two key respects: 1) directionality; and 2) the mechanism through which they influence firm-level innovation. In terms of directionality, direct and systemic instruments enable policymakers to target R&D/innovation projects with a low private rate of return but with potential for a high social rate of return (Edler & Boon 2018). While policymakers may view these private investments as crucial for long-term transformative change, little benefit may accrue to the firm in the short term (Weber & Rohracher 2012). These projects are typically riskier and less likely to take place in the absence of a subsidy (Buisseret et al. 1995; Georghiou 2002; Zúñiga-Vicente et al. 2014). Therefore, the government compensates firms by increasing the marginal rate of return on these investments, through different forms of targeted innovation policy instruments (Aristei et al. 2017).

Conversely, with indirect instruments such as R&D tax credits, the mechanism that policymakers utilise to induce more R&D is to reduce the marginal cost of capital for R&D/innovation (David et al. 2000; Hall & Van Reevan 2000). In Ireland and internationally, R&D tax credits can be claimed on any qualifying R&D expenditure (Department of Finance 2013; OECD 2017). As such, when claiming R&D tax credits, firms tend to prioritise R&D investments with the highest private rate of return (Czarnitzki et al. 2011; Rao 2016). This has led Hægeland and Møen (2007, p. 29) to suggest that “projects should differ with respect to private returns depending on their source of financing”. Using a sample of firms in Norway, Hægeland and Møen (2007) find that R&D tax
credits have a positive and significant impact on firm R&D, direct forms of R&D and innovation support from Norway’s key funding agencies.

Viewed in the context of previous literature, the non-significant results for receiving R&D/innovation support from Enterprise Ireland or IDA Ireland, or having an SFI linkage, while somewhat surprising, are not inconsistent with theory or previous empirical findings. In addition, as noted in Chapters 2 and 3, the vast majority of previous studies examining individual instruments did not control for whether firms received a mix of innovation policy instruments. Guerzoni & Raiteri (2015) highlight that not controlling for whether firms receive a mix of instruments can lead to serious over-estimation of the impact of individual instruments. As shown in the descriptive statistics in Chapter 4, in the data used in this empirical analysis it is actually more common for firms to receive an R&D/innovation support from Enterprise Ireland or IDA Ireland, or an SFI linkage, in combination with the R&D tax credit, than to receive support solely from the funding agencies. Therefore, the next section discusses the nature of the relationship between R&D tax credits and R&D/innovation support from Enterprise Ireland, IDA Ireland or SFI linkages.

5.4.3. The relationship between R&D tax credits and funding agency support

The key empirical focus of this thesis is to test for complementarity between different innovation policy instruments. To examine Hypothesis 1, the analysis first defines the relationship between the innovation policy instruments that a firm receives at the same point in time (i.e. static complementarity). Examining Hypothesis 2 depends upon analysing the temporal dynamics of the instrument mix by focusing on firms that transition from receiving one instrument in a given year to receiving a combination of two instruments in the next year (i.e. dynamic complementarity). Findings from the econometric analysis reveal a complex picture that provides partial support for
both hypotheses. This section focuses first on the tests for static complementarity before turning to the tests for dynamic complementarity.

5.4.3.1. Static complementarity tests

In many instances, receiving an R&D tax credit in combination with R&D/innovation support from Enterprise Ireland, IDA Ireland or an SFI linkage stimulates firms’ R&D intensity to a greater degree than receiving the R&D tax credit alone. These findings concur with previous empirical studies on the innovation policy instrument mix. Using cross-sectional firm-level data from a range of country contexts, these previous studies find that R&D tax credits combined with R&D grants boost firm R&D investment, as well as other innovation outcome measures, to a greater degree than receiving an R&D tax credit alone (Bérubé & Mohnen 2009; Neicu et al. 2015; Radas et al. 2015; Guerzoni & Raiteri 2015).

However, studies using panel datasets drawn from administrative sources present more mixed results (Marino et al. 2016; Dumont 2017). These studies show that receiving a combination of R&D tax credits and direct R&D/innovation support can have a positive impact on firms’ R&D intensity. Nonetheless, instrument mixes more often have no impact or a lower impact than each of the individual instruments that compose the mix. However, neither of these studies estimates the lagged impact of innovation policy instruments under examination. As discussed in Chapters 2 and 3, cross-sectional datasets usually have an implicit time-lag of up to 36 months for the impact of innovation policy instruments to take effect (i.e. firms are asked in the survey whether they received an instrument in the previous 36 months). In contrast, the annual panel data used in the current research facilitates estimating a number of lag-structured models, such that the innovation policy instrument mix can effectively stimulate firms’ R&D intensity, but it takes one to two years for this impact to materialise.
An instructive example of the time-lag to impact is the case of firms receiving R&D tax credits and SFI linkages. During the year in which firms receive this mix of instruments (i.e. the contemporaneous model), it has no impact on firm R&D intensity. After one year, this instrument mix does have a positive and significant effect, but it is less than the impact of receiving an R&D tax credit alone. In this case, the instruments are in a substitutive relationship. However, two years after firms receive an R&D tax credit combined with an SFI linkage, the impact is larger than that of receiving either instrument individually. Statistical tests reveal a complementary relationship between R&D tax credits and SFI linkages, but it takes two years for the complementarity to manifest. This finding recalls the theory of Hall et al. (1986, p. 265), that there will be “gestation lags” in in the production of new knowledge. Given the nature of the SFI linkages, which involve multi-year collaborations with academics in research centres, it is perhaps unsurprising that the impact of this instrument in combination with the R&D tax credit occurs over a longer time horizon than receiving an R&D tax credit alone.

While the findings for SFI linkages and R&D tax credits lend partial support to Hypothesis 1, the analysis using the ABSEI-Enterprise Ireland dataset provides strong support. Static complementarity between R&D tax credits and Enterprise Ireland R&D/innovation support is identified in the contemporaneous model, as well as in the one- and two-lag models. A static complementary relationship is also identified between R&D tax credits and R&D/innovation support from IDA Ireland in the one-lag model (i.e. one year following receipt of the instrument mix). This finding is noteworthy because of the magnitude of the instrument mix coefficient (2.25), relative to the coefficient on receiving an R&D tax credit only (1.46).

To interpret this result, it is instructive to consider it in the context of the literature and the innovation policy landscape of Ireland. Busom et al. (2017) find that firms with the greatest ability
to finance R&D investments (i.e. with their own internal funds or external funds) will benefit the most under a volume-based R&D tax credit system, where the credit is deducted from the firm’s coronation tax liability. As highlighted by the Irish Department of Finance (2016), large foreign-owned multinational enterprises (MNEs) are the main type of firm to claim R&D tax credits in Ireland. Such firms tend to face fewer financial constraints and try to keep R&D investments steady through time (Brown et al. 2012; Mohnen 2017). Therefore, MNEs in Ireland may claim R&D tax credits in most years and apply for R&D/innovation support from IDA Ireland for specific projects. Therefore, when the joint impact of the R&D tax credit and IDA Ireland support manifests, the resultant R&D investment is larger.

Given that a static complementary relationship is identified between R&D tax credits in combination with R&D/innovation support from Enterprise Ireland, IDA Ireland or SFI linkages across a number of the lag-structured models, overall findings partially support Hypothesis 1.

5.4.3.2. Dynamic complementarity tests

The tests for dynamic complementarity present a similar pattern to the analysis of static complementarity. However, this analysis is necessarily more complex because it involves 16 treatment category variables rather than the four used in static tests. In the ABSEI-IDA Ireland sample, dynamic complementarity is identified when firms transition from receiving an R&D tax credit in one year to receiving a combination of the R&D tax credit and R&D/innovation support from IDA Ireland. Dynamic complementarity is also identified between R&D tax credits and SFI linkages, but only when firms receive them in the opposite sequence. This issue of sequencing highlights the importance of augmenting the static approach discussed above, by operationalising the temporal dynamics of instrument mix.
These results suggest that firms use R&D/innovation support from IDA Ireland and SFI linkages somewhat differently in terms of their R&D investments. MNEs appear to apply for the IDA Ireland support on top of the R&D tax credit they are already using to subsidise their R&D expenditure. Results suggest that R&D-active MNEs use the IDA Ireland support for specific projects, and this amplifies the impact of the R&D tax credit they already receive. Conversely, results from the ABSEI-SFI sample suggest that firms use the SFI linkage as their ‘base’ instrument. Once the research collaborations with an SFI-funded research centre are established and up-and-running for a year, then the firms claim the R&D tax credit on top of the SFI linkage. This notion of using the SFI linkage as a base instrument is supported by the finding that receiving this instrument in two consecutive years (i.e. sw33) has a positive and significant impact on firms’ R&D intensity. This is the sole finding across all econometric models of support from any of the national funding agencies (i.e. not in combination with the R&D tax credit) that shows a significant impact.

While Hypothesis 2 is partially supported by the findings from the ABSEI-IDA Ireland and ABSEI-SFI samples, no dynamic complementarity is identified in the R&D tax credits and Enterprise Ireland R&D/innovation support. Therefore, Hypothesis 2 is not supported in the ABSEI-Enterprise Ireland sample. However, outside of the key treatment category variables, it is important to highlight the positive and statistically significant impact of receiving a combination of instruments in two consecutive years in the ABSEI-IDA Ireland and ABSEI-SFI samples (i.e. sw44). This finding shows that the innovation policy instrument mix can have an important impact on firms’ R&D intensity, and the value of testing for dynamic as well as static complementarity.

Overall, the results bear out the importance of using a more encompassing evaluation framework that includes the mix of innovation policy instruments and sources of R&D/innovation support.
that firms receive. In addition, the results highlight the limitations of evaluations that focus on single innovation policy instruments. While this econometric analysis can only begin to infer what is driving these results, and any potential importance they may have for policymaking, it does take a useful step toward evaluating the impact of innovation policy instrument mix on firm-level innovation. In the main, the results suggest that there is no ‘one size fits all’ or ‘perfect’ innovation policy instrument mix for stimulating firms’ R&D intensity. Drawing on the above analysis, the next section offers a conclusion to this chapter.

5.5. Conclusion

Until recently, firm-level studies have been limited to the use of aggregate measures of public funding for innovation or individual innovation policy instruments. However, both the theoretical literature and empirical evidence presented in Chapter 3 demonstrate that firms often receive a mix of different innovation policy instruments. It can be very challenging at times to disentangle the observed impact of each individual innovation policy instrument on firm-level innovation from that of the wider mix of instruments firms receive, because interactions between instruments within the mix drive this impact (Martin 2016; Rogge & Reichardt 2016; Flanagan et al. 2011; Nauwelaers et al. 2009). The core contribution of this thesis is to operationalise the concept of the innovation policy instrument mix and estimate its impact on firm-level innovation. In doing so, this chapter presents the results from a number of econometric models, and tests based on these results, to determine whether different innovation policy instruments are complements or substitutes.

The findings of this analysis suggest that receiving a mix of different innovation policy instruments can have a positive and significant impact on firms’ R&D intensity. Complementarity between different instruments can be conceived of in a static sense, as the combination of instruments a
firm receives at a point in time; and in a dynamic sense, as interactions between different instruments a firm receives through time (Rogge & Reichardt 2016; Schmidt & Sewerin 2018). Based on analyses of three separate datasets, results reveal that pairwise complementarity exists between R&D tax credits and R&D/innovation support from Enterprise Ireland or IDA Ireland or SFI linkages.

These results partly support the two hypotheses, particularly in the static complementarity tests between R&D tax credits and Enterprise Ireland R&D/innovation support and in the dynamic tests between IDA Ireland R&D/innovation support and R&D tax credits. The dynamic tests also highlight that the sequence in which firms receive different innovation policy instruments through time can have an important influence on their eventual impact on firm-level innovation (defined as R&D intensity in this study).

This chapter builds on the theoretical and methodological contributions of the previous chapters by presenting the results of the econometric analysis which evaluates whether different innovation policy instruments are complements or substitutes. Discussing the empirical findings in the context of previous literature, and interpreting them in relation to Ireland’s innovation policy landscape, reveals that the innovation policy instrument mix can have important impacts on firm-level innovation. The findings suggest that it is important to test for the effects of the innovation policy instrument mix, in as much as is possible, when evaluating the impact of public funding for innovation. In summary, this chapter contributes to knowledge by providing by operationalising the innovation policy instrument mix concept, and highlighting its potential usefulness for innovation policy evaluation. The next chapter summarises the findings from the entire study and highlights the contribution to existing knowledge about firm-level innovation, public funding and
innovation policy. In addition, the chapter clarifies the limitations of the research and proposes topics for future research.

As noted in Chapter 2, evaluations of public funding for innovation are usually concerned with the concept of additionality, defined as the additional (or induced) innovation activities, beyond what firms were already doing, which can be attributed to receiving some form of public funding for innovation (Georghiou 2002). R&D is considered to be an input into firm innovation processes (Clarysse et al. 2009). Input additionality deals with the question regarding to what extent innovation policy instruments lead to more continued efforts in the R&D process by the firms that receive them. Alternatively, firms could substitute public funding for their own private funding for R&D that would have taken place even in the absence of the R&D/innovation support. The latter case would represent public funding crowding-out private investment. The most recent research (e.g. European Commission 2017a; Aristei et al. 2017) converge on the conclusion that there is no crowding-out effect. In the dataset constructed for the current research, R&D expenditure is the only outcome variable available to measure the impact of public funding for innovation. Therefore, this thesis focused on evaluating the input additionally of innovation policy instruments. Future research would benefit from access to datasets which capture the full spectrum of additionalities, including measures of innovation output (i.e. product, process and organisational innovation as well as sales from new products) and behavioural changes induced by receiving public support. However, as noted in Chapter 4, constructing a dataset which captures a comprehensive set of the innovation policy instruments firms receive over time as well as a range of measures of innovation additionalities (i.e. input, output and behavioural) represents a major challenge for the evaluation of public funding for innovation.
Chapter 6: Conclusion

6.1. Introduction

This chapter presents a summary of the research conducted in this thesis and reflects on the study’s contributions to the knowledge base from theoretical, methodological, empirical and policy perspectives. Finally, the chapter reviews the limitations of this research and outlines suggestions for future research in the field of innovation policy evaluation.

The main objective of this study was to evaluate the impact of innovation policy instrument mix on firm-level innovation. At the level of the firm, a suite of innovation policy instruments, such as R&D tax credits and R&D grants, operationalise innovation policy. A review of the theoretical and empirical literature (presented in Chapters 2 and 3) reveals an important relationship between these forms of public funding and private firms’ innovation performance. However, this review also highlights an over-reliance on evaluations of individual innovation policy instruments in the empirical literature. By contrast, recent theoretical literature on the policy mix for innovation suggests that firms often receive a mix of innovation policy instruments. Moreover, the impact of these instruments on firm-level innovation may depend crucially on the specific mix that firms receive. Therefore, the focus of this thesis is on the innovation policy instrument mix. Bridging the identified gap in the literature between policy mix theory and empirical practice was the primary objective of this thesis.

To address this gap in the literature, this study made three significant contributions. Firstly, the present study developed a conceptual framework that distilled the policy mix concept into a usable

---

21 As outlined in Chapter 1 and detailed in Chapter 4, firms’ R&D expenditure is used as a proxy of firm-level innovation in the empirical part of this thesis.
format to facilitate impact evaluation. Drawing on policy mix theory, this framework places at its core the identification of complementary and substitutive relationships between different innovation policy instruments. Secondly, putting this framework into practice prompted the construction of three unique panel datasets. Each dataset captured the three most prominent instrument mixes available to firms in Ireland each year from 2007 to 2014. Thirdly, the empirical part of this study used econometric analysis to conduct a robust application of the policy mix for innovation concept as it applies to firms.

The theory underpinning this study prompted one overarching research question: Are different innovation policy instruments complements or substitutes? Policy mix theory suggests that complementarity between different instruments can exist in both a static and a dynamic sense. While static complementarity focuses on the combination of instruments a firm receives at a specific point in time, dynamic complementarity concentrates on the interactions between different instruments that a firm receives through time. As outlined in Chapter 3, the theoretical literature views temporal dynamics as a crucial factor in determining the impact of innovation policy instruments on firm-level innovation. However, to date the empirical literature has not investigated the dynamics of the instrument mix. Therefore, addressing the research question necessitated empirical tests for both static and dynamic complementarity.

To the best of the author’s knowledge, this research is the first to test directly for either static or dynamic complementarity between different innovation policy instruments. This novel application of the policy mix concept makes an important contribution in terms of overcoming the current impasse between theory and empirical practice in the literature, as identified by key authors such as Schmidt and Sewerin (2018), Rogge and Schleich (2018), Flanagan and Uyarra (2016) and Howlett and del Rio (2015). Furthermore, the research helps to provide policymakers with
potentially valuable insights regarding how the innovation policy instrument mix functions. These insights could increase the level of accountability in terms of public spending to support private firms’ R&D and innovation activities, as well as having the potential to aid policy improvement.

Based on the theoretical and empirical evidence compiled and analysed in Chapters 2 and 3, two hypotheses are formulated and presented in Chapter 3. The first hypothesis relates to static complementarity and substitution, while the second hypothesis concentrates on temporal dynamics in the innovation policy instrument mix. In order to answer the research question and test the hypotheses, econometric analysis (specifically a recently developed instrumental variable estimation method (Lewbel 2012; 2018)) was performed using three unique panel datasets. Each dataset was constructed by merging different sources of data, because no individual dataset captures a comprehensive set of the innovation policy instruments available to firms in Ireland from the national government. The three final panel datasets each contained 16,084 observations of 3,098 firms, from 2007-2014. As discussed in Chapter 4 and highlighted below in Section 6.3, the quality of these three datasets compares favourably to those available to previous studies and facilitates a comprehensive evaluation of the innovation policy instrument mix.

To summarise the research undertaken for this thesis, this concluding chapter brings together the main findings from each preceding chapter (Section 6.2) and discusses the contributions of the research (Section 6.3). Section 6.4 details the limitations of the research, and outlines suggestions for how future research may address them. Section 6.5 provides a final conclusion.

6.2. Summary and discussion

This section outlines the key insights from the theoretical and empirical literature that Chapters 2 and 3 reviewed, which inform this thesis. It also provides an overview of the empirical setting and
econometrics detailed in Chapter 4. Finally, the results of the econometric analysis presented in Chapter 5 are summarised and discussed.

Building on theories of innovation stemming from Schumpeter (1934, 1942), and based on contemporary academic literature (e.g. Fagerberg 2018; Roper & Hewitt-Dundas 2015) and research from entities responsible for the development of innovation policy (e.g. DBEI 2018; OECD 2018; 2017; European Commission 2017a), this study adopts a broad-based view of the literature to provide a context for the research. Following this context-setting process, the study focused on the area most relevant to this thesis: evaluating the impact of public funding on firm-level innovation.

The theoretical and empirical literature review in Chapter 2 provides clear evidence that firms’ R&D and innovation activities are crucial for national competitiveness and economic growth (Romer 1990; Pradhan et al. 2018). In this context, the chapter began with an examination of the rationale for innovation policy intervention, focusing on the two dominant branches of theory: market failure and systemic failure. The chapter highlighted the substantial debate in the academic literature regarding the most appropriate rationale for guiding innovation policy (Bleda & del Rio 2013; Godin 2017).

However, an examination of the academic literature and certain key policy documents reveals that the innovation policy frequently relies on elements of both market and systemic failure rationales (Dodgson et al. 2011; European Commission 2016; 2017b). On that basis, this chapter argues that the systemic failure rationale is more applicable at the macro-level (i.e. national and regional innovation systems), while the market failure rationale is more appropriate at the micro-level (i.e. firms). Insights from both market and systemic failure rationales are important. However, given that the units of analysis in this study are firms, the research undertaken in this thesis relies more
heavily on the market failure rationale, which is consistent with previous empirical literature. Notwithstanding this, it would be remiss not to acknowledge that the systemic failure approach can provide pertinent insights on the rationale for innovation policy intervention on a wider system-level, and the role played by firms within the innovation system.

To correct for perceived market and systemic failures, policymakers deploy a range of different innovation policy instruments targeted at stimulating different forms of firm-level innovation. Reviewing the literature concerning these instruments, Chapter 2 details the three most prominent categories of innovation policy instruments available to firms: direct innovation policy instruments, such as R&D grants (Zúñiga-Vicente et al. 2014); indirect innovation policy instruments, such as R&D tax credits (Castellacci & Lie 2015); and systemic innovation policy instruments, such as incentivised academic-industry collaborations (Smits & Kuhlmann 2004). A review of the empirical literature evaluating each instrument type reveals that in general, they have had a positive effect on firm-level innovation (European Commission 2017a). However, this review also demonstrates that the literature is characterised by an over-reliance on single policy instrument evaluations (Beck et al. 2017).

With this in mind, Chapter 3 reviews the literature relating to the policy mix for innovation. Based on evidence from both the theoretical literature (Flanagan et al. 2011; Rogge & Reichardt 2016) and empirical literature (Dumont 2017; Marino et al. 2016), the chapter argues that the impact of innovation policy instruments on firm-level innovation depends greatly on the specific mix of instruments the firm receives. Policy mix theory first entered the field of innovation policy evaluation in the early 2000s (STRATA/ETAN Expert Group 2002; Soete & Corpakis 2003), and has since gained a prominence within the literature (e.g. Edmondson et al. 2018; Schmidt & Sewerin 2018). However, while the theoretical literature has advanced, the policy mix concept has
proved difficult to apply empirically (Rogge & Schleich 2018). Some authors such as Schmidt and Sewerin (2018) and Howlett and del Rio (2015) suggest that this lack of empirical research has hindered the development of policy mix research.

Theory suggests that by concentrating on the identification of complementarity and substitution between the different innovation policy instruments, innovation policy evaluation could be more congruent with the policy mix concept (Rogge & Reichardt 2016; Flanagan et al. 2011). However, to the authors knowledge, direct testing for strict complementarity (i.e. supermodularity) and substitution (i.e. submodularity) (Mohnen & Röller 2005) between different instruments has never appeared in the empirical literature. Instead, previous studies have relied on inference. In addition, policy mix theory suggests that the temporal dynamics of an instrument mix will play an important role in determining its effectiveness. As Chapter 3 highlights, the lack of panel data available to previous studies has hindered the examination of temporal dynamics.

Overall, the previous empirical research represents the first application of the policy mix concept at the level of the firm. While offering important foundational insights into the innovation policy instrument mix, Chapter 3 demonstrates that this early literature provides little guidance on how to operationalise key aspects of the policy mix concept, such as complementarity and temporal dynamics. Thus, while providing important insights and contributions, the previous empirical research represents only a first step in evaluating the impact of the innovation policy instrument mix on firm-level innovation.

To augment the emerging debate on the policy mix for innovation, and to overcome the limitations of previously-used empirical applications of the policy mix concept, this research extends the conceptualisation of how innovation policy instruments can impact firm-level innovation. Building on the theoretical and empirical research that Chapter 3 reviews and analyses, a
conceptual framework was developed to provide a set of guiding principles for the evaluation of innovation policy instrument mix. Building on long-standing and well-studied notions of how public funding stimulates firm-level innovation, this framework takes the key insights from policy mix theory (i.e. complementarity and temporal dynamics) and converts them into a usable format for impact evaluation. As noted above, based on the theoretical and empirical evidence the research examined, Chapter 3 develops and presents two hypotheses. The first hypothesis relates to the relationship between innovation policy instruments at a point in time. In contrast, the second hypothesis focuses on the dynamic relationship between the instruments a firm receives through time, and the impact these temporal dynamics have on firm-level innovation.

However, applying the policy mix concept empirically has been a key challenge for the innovation policy evaluation literature. To overcome this challenge, Chapter 4 details the construction of three wholly novel panel datasets through a series of data merges. As described in Chapter 4, this required an extensive application process to achieve the required level of data access. Once access was granted, the researcher was required to travel to the Department of Business, Enterprise and Innovation (DBEI) and Central Statistics Office (CSO) to work with the data on dates between May 2016 and January 2018. The master dataset was the Annual Business Survey of Economic Impact (ABSEI), collected by the Department of Business, Enterprise and Innovation (DBEI). ABSEI surveys approximately 2,000 firms each year and has a large panel element. ABSEI captures each firms’ R&D expenditure, which is used as an outcome indicator for firm-level innovation in this study. In addition, ABSEI captures whether firms received an R&D tax credit, the most prominent innovation policy instrument in Ireland, in terms of both the cost of the scheme and the number of firms that avail of it each year (Department of Finance 2016). Given its importance, it was crucial that this study include the R&D tax credit.
To capture as complete a set as possible of innovation policy instruments available to firms from the national government, three administrative datasets were drawn from Ireland’s key national funding agencies: Enterprise Ireland, Industrial Development Agency (IDA) Ireland and Science Foundation Ireland (SFI). Alongside the R&D tax credit, these funding agencies represent the most important sources of innovation policy instruments for firms in Ireland (DBEI 2014a; 2018; Chief Scientific Advisor to the Government of Ireland 2016; Indecon 2017). Each of these administrative datasets was separately merged into ABSEI to create three distinct datasets, capturing the three most important combinations of innovation policy instruments that firms receive in Ireland: 1) R&D tax credit and Enterprise Ireland support; 2) R&D tax credit and IDA Ireland support; and 3) R&D tax credit and SFI linkages. Therefore, this study tested for pairwise complementarity between each of these distinct and mutually exclusive combinations of instruments (Mohnen & Röller 2005). In addition, the panel structure of the data enables this study to test for both the contemporaneous and lagged impact of innovation policy instruments on firm-level innovation.

Results from the econometric analysis presented in Chapter 5 suggest a complex relationship between R&D tax credits and R&D/innovation support from Ireland’s three national funding agencies. Enterprise Ireland support and R&D tax credits appear to be complementary. The impact of receiving both instruments at the same point in time is greater than the sum of the impact of each individual instrument. Moreover, the lag-structured models reveal that the benefit derived from receiving a concurrent combination of both Enterprise Ireland support and an R&D tax credit manifests in the same year the mix is received, and persists for two years after the mix was initially received.

In contrast to these results, receiving support from IDA Ireland or SFI in combination with an R&D tax credit has no immediate impact on firms’ R&D intensity. However, a complementary
relationship is identified in the lag-structured models. This impact materialises one year after firms receive the former mix (i.e. IDA Ireland and R&D tax credit) and two years after firms receive the latter (i.e. SFI and R&D tax credit). Using sophisticated econometric analysis to control for potential endogeneity and selection bias, these pairwise tests for complementarity demonstrate the potential benefits that the innovation policy instrument mix can have for firms.

To further explain the innovation policy instrument mix, Chapter 5 also presents the results of additional econometric analysis testing for dynamic complementarity between different instruments. Following Love et al. (2014), this analysis focuses on estimating the impact of adding something new to what the firm currently has. The results demonstrate that the transition from receiving an R&D tax credit in one year to receiving a combination of both an R&D tax credit and IDA Ireland support in the next year has a greater impact on firm R&D intensity than the transition from receiving no instrument to receiving an R&D tax credit alone. Therefore, a dynamic complementary relationship exists between R&D tax credits and IDA Ireland support, when firms receive the instruments in this sequence. It is noteworthy that dynamic complementarity is also identified between SFI support and R&D tax credits when firms received the instruments in the opposite sequence (i.e. firms transition from SFI support only in one year to a mix of SFI support and an R&D tax credit in the next year). These results support the conclusion that the different nature of the innovation policy instruments under examination leads to distinct forms of temporal dynamics, which, in turn, have differing impacts on firm-level innovation.

While there can never be a perfect innovation policy instrument mix (Flanagan et al. 2011), and policy evaluation is by no means an exact science (Lenihan & Hart 2004), there is always an opportunity for improvement. To this end, the current research points towards potential policy implications that could play a role in enhancing accountability, transparency, value for money and
policy improvement, which are important concerns in the evaluation of public funding (Lenihan 2011, OECD 2015f; Genus & Stirling 2018).

6.3. Contributions of the current research

This thesis contributes to the study of the determinants of firm-level innovation, specifically with respect to the role of innovation policy instrument mix in driving firms’ innovation outcomes. The contributions of this thesis are academic in nature, with some potential policy implications. This section examines each of these contributions in turn.

Firstly, from a theoretical perspective, the research adds to innovation theory by developing a novel conceptual framework which distils key insights from policy mix theory into a usable format for evaluating the impact of innovation policy instrument mix on firm-level innovation. Building on more traditional models for evaluating the impact of public funding for innovation, the framework this thesis develops places the identification of complementarity and substitution between different innovation policy instruments at its core. Complementary and substitutive relationships between different instruments occur in both a static sense and in a dynamic sense, which accords with policy mix theory. As such, this thesis goes some way towards bridging an identified gap in the empirical application of policy mix theory, which has been called for in the literature (e.g. Schmidt & Sewerin 2018) and was a key objective of this study.

From a methodological perspective, the research contributes to the field of innovation policy evaluation by creating three unique panel datasets through a series of data merges. These new datasets provide detailed information on a comprehensive set of innovation policy instruments that firms receive from the national government in Ireland. The panel nature of the data and its annual structure, large sample size, number of years covered, and, most importantly, the detailed
information on the prime sources of innovation policy instrument mixes in Ireland, are all improvements on data available to the vast majority of previous studies.

More commonly used datasets, such as the Community Innovation Survey (CIS), typically do not have a panel structure and consist of three-year waves. In contrast, annual data facilitate the estimation of precise lag-structured models in this thesis. In addition, as Chapter 3 discusses, datasets such as the CIS usually capture measures of whether firms received public funding for innovation that do not distinguish between the sources of funding (i.e. Enterprise Ireland, IDA Ireland or SFI), or the type of policy instrument received (e.g. R&D tax credit or R&D grant). This lack of detail limits the granular detail of econometric analysis and resulting potential policy recommendations that can emanate from innovation policy evaluations using CIS-type data. Merging different datasets to capture this form of detailed information facilitated conducting a more comprehensive analysis than was possible in previous studies.

To apply the new datasets created for this study, a sophisticated form of instrumental variable estimation was employed (Lewbel 2012; 2018) to control for the selection bias and endogeneity associated with innovation policy instruments (David et al. 2000; Czarnitzki et al. 2011). As highlighted by Love et al. (2014), most available econometric methods that specifically address these issues do not facilitate direct tests for complementarity (see also Papalia et al. (2018)). Thus, this study controls for potential endogeneity and self-selection in a more robust way than most previous studies of strict complementarity (supermodularity) and substitution (submodularity). In addition, though innovation systems can vary significantly depending on country context (Fagerberg 2017), the set of innovation policy instruments available to firms tends to be relatively homogenous across countries (Veugelers 2015; Cunningham & Link 2016). Therefore, while
Ireland is the location for the current research, the methodological approach has the potential to offer insights for innovation policy instrument evaluations in other country contexts.

A final contribution of the research comes in the form of potential policy implications. As the literature reflects, the impact of public funding on firm-level innovation is seldom evaluated from a policy mix perspective. Firm R&D expenditure plays an important role in both the Irish (Georghiou et al. 2017) and wider European innovation ecosystems (European Commission, 2017a). As such, the current research has the potential to offer helpful insights that may aid the construction of a comprehensive evidence base to inform funding-policy decisions. Therefore, the empirical findings this study presents may suggest avenues for future policy exploration in the implementation of innovation policy instruments.

While this section outlines the contribution of this thesis to the knowledge base, limitations to the research that require attention, and suggestions for how future research might address these limitations, are outlined in the next section.

6.4. Limitations and suggestions for future research

While the design of the current research has sound theoretical underpinnings and is based on robust econometric analysis, it is not without limitations. These limitations are outlined in this section, alongside some suggestions for future research.

This study uses detailed information on the innovation policy instruments firms received through time, but only one measure of firm-level innovation was available in the dataset: firms’ R&D expenditure. R&D is a key input into the innovation process, and firms’ R&D expenditure is a commonly used proxy for firm-level innovation, even in the most recent literature (e.g. Wojan et al. 2018; Wadho & Chaudhry 2018). Notwithstanding this limitation, future research would benefit
from considering a range of innovation outcome measures. In particular, outcome variables that capture firms’ actual innovation output (e.g. the introduction of new products and processes, sales from new products) and behavioural change related to innovation activity (e.g. collaboration on innovation projects, the managerial processes surrounding innovation) would be of interest in future research. Using these measures would augment the present research by demonstrating the impact of the innovation policy instrument mix on a broader spectrum of innovation outcomes.

Increasing the range of innovation outcome variables would require merging the data used in this study with another dataset that captures this information, such as the CIS (discussed above). However, in contrast to the annual data used in this study, datasets such as the CIS are recorded in waves of three years. Merging a CIS-type dataset into the data used in this thesis would entail losing the richness of the annual data. Thus, while gaining a larger range of innovation outcome measures, the precision of the analysis in this thesis (in particular the analysis of temporal dynamics) would be hindered as all data would have to be aggregated into three year waves.

In addition, the current research uses binary measures capturing every year that a firm received an R&D tax credit, R&D/innovation support from Enterprise Ireland or IDA Ireland or had a linkage with SFI. In the case of the three national funding agencies, these binary measures aggregate a range of different individual innovation policy instruments into one summary measure of support. An interesting avenue for future research would be to investigate the nature of the relationship between each individual instrument type available from these agencies and the R&D tax credit. However, in many instances very few firms receive some of the specific instruments covered by the dataset, thus raising concerns about the statistical reliability of potential findings based on an analysis of specific instrument types, as opposed to instrument sources (i.e. Enterprise Ireland, IDA Ireland and SFI).
Given that the key focus of this study was testing for complementarity, the use of binary variables capturing broader measures of support from the three national funding agencies was appropriate. However, future research trying to address a somewhat different research question could extend this study by using continuous data on the amount of funding that firms receive through each individual innovation policy instrument.

Finally, the empirical analysis is based on the ABSEI dataset, which surveys Enterprise Ireland and IDA Ireland client companies. Therefore, ABSEI is not designed to be representative of the Irish economy as a whole. Given that the key focus of this thesis was on evaluating the impact of innovation policy instruments on firm-level innovation, the data used were appropriate for this purpose. While ABSEI has important advantages over many datasets that appear in the literature, it would be beneficial to augment the research undertaken in this study with a dataset that is representative of the full Irish economy. However, it should be noted that using a more representative dataset would entail moving away from an analysis of the full population of firms that receive innovation policy instruments from the key funding agencies in Ireland. In addition, it would be instructive to replicate the empirical analysis using similar data from other countries. This would help to refine the empirical method, check how robust the results are to changes in empirical context, and facilitate cross-country comparisons (where appropriate).

6.5. Conclusion

In concluding this research, this chapter reflects on the key objectives and the corresponding research question of this study, and highlights the research findings and contributions to knowledge.
From the extensive review of the innovation-related literature, the research identified a distinct growth of interest in the policy mix for innovation concept within the field of innovation policy evaluation. However, this review also identified a dearth of evidence regarding the empirical application of the policy mix concept at firm-level. This gap led to the development of a new conceptual framework, designed to act as a set of guiding principles for applying policy mix at firm-level. Employing three new merged panel datasets provided the research with eight years of detailed information on many firms. The results of the econometric analysis confirm that in many instances, different innovation policy instruments have a complementary relationship; the impact of the whole of an innovation policy instrument mix on firm-level innovation is greater than the impact of the sum of the individual instruments that compose it. In addition, the temporal dynamics of the innovation policy instrument mix play an important role in driving impact; the innovation policy instrument(s) firms received in the past influence the effectiveness of the instruments firms receive in the current period at stimulating firm-level innovation. Therefore, supporting firms through a mix of innovation policy instruments can be an effective means of supporting firm-level innovation.
References


Department of Business, Enterprise and Innovation (DBEI). (2014) Evaluation of enterprise supports for research development and innovation, Dublin: Department of Jobs, Enterprise and Innovation.


Department of Finance (DoF). (2013) *Review of Ireland’s research and development (R&D) tax credit 2013*, Dublin: Department of Finance.


246


Science Foundation Ireland (SFI). (2010) *Centres for Science Engineering and Technology (CSET)*, Dublin: Science Foundation Ireland.


Appendices

**Appendix A** Omitted results for control variables in the dynamic complementarity and substitution regressions (Tables 19 and 20)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-Enterprise Ireland sample</th>
<th>0 lags</th>
<th>1 lag</th>
<th>2 lags</th>
<th>3 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D staff (%)</td>
<td></td>
<td>4.92***</td>
<td>5.47***</td>
<td>5.93***</td>
<td>5.93***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.14)</td>
<td>(0.17)</td>
<td>(0.20)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Export intensity (log)</td>
<td></td>
<td>0.1***</td>
<td>0.06***</td>
<td>0.05***</td>
<td>0.06***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.01)</td>
<td>(0.012)</td>
<td>(0.01)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
<td></td>
<td>0.18***</td>
<td>0.16***</td>
<td>0.14***</td>
<td>0.14***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Small</td>
<td></td>
<td>0.47***</td>
<td>0.49***</td>
<td>0.50***</td>
<td>0.54***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.12)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Medium</td>
<td></td>
<td>0.95***</td>
<td>0.97***</td>
<td>1.19***</td>
<td>1.30***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.14)</td>
<td>(0.15)</td>
<td>(0.17)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Large</td>
<td></td>
<td>1.22***</td>
<td>1.34***</td>
<td>1.70***</td>
<td>1.86***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.23)</td>
<td>(0.24)</td>
<td>(0.26)</td>
<td>(0.28)</td>
</tr>
<tr>
<td>Year dummies</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**Appendix B** Omitted results for control variables in the dynamic complementarity and substitution regressions (Tables 21 and 22)

<table>
<thead>
<tr>
<th></th>
<th>ABSEI-IDC Ireland sample</th>
<th>0 lags</th>
<th>1 lag</th>
<th>2 lags</th>
<th>3 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D staff (%)</td>
<td></td>
<td>4.86***</td>
<td>5.21***</td>
<td>5.80***</td>
<td>5.90***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.15)</td>
<td>(0.18)</td>
<td>(0.22)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>Export intensity (log)</td>
<td></td>
<td>0.10***</td>
<td>0.05***</td>
<td>0.06***</td>
<td>0.6***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.01)</td>
<td>(0.012)</td>
<td>(0.01)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
<td></td>
<td>0.17***</td>
<td>0.15***</td>
<td>0.15***</td>
<td>0.14***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Small</td>
<td></td>
<td>0.48***</td>
<td>0.54***</td>
<td>0.54***</td>
<td>0.47***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.10)</td>
<td>(0.11)</td>
<td>(0.13)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>Medium</td>
<td></td>
<td>1.01***</td>
<td>1.14***</td>
<td>1.28***</td>
<td>1.16***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.15)</td>
<td>(0.16)</td>
<td>(0.18)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>Large</td>
<td></td>
<td>1.37***</td>
<td>1.48***</td>
<td>1.72***</td>
<td>1.79***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.24)</td>
<td>(0.25)</td>
<td>(0.28)</td>
<td>(0.31)</td>
</tr>
<tr>
<td>Year dummies</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
### Appendix C  Omitted results for control variables in the dynamic complementarity and substitution regressions (Tables 23 and 24)

<table>
<thead>
<tr>
<th>Variable</th>
<th>ABSEI-Science Foundation Ireland sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 lags</td>
</tr>
<tr>
<td>R&amp;D staff (%)</td>
<td>4.87***</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
</tr>
<tr>
<td>Export intensity (log)</td>
<td>0.10***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>Training intensity (log)</td>
<td>0.17***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>Small</td>
<td>0.50***</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
</tr>
<tr>
<td>Medium</td>
<td>1.04***</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
</tr>
<tr>
<td>Large</td>
<td>1.45***</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
</tr>
</tbody>
</table>