

**THE EVOLUTION OF SUBJECT APPROACHES TO  
INNOVATION MEASUREMENT, AND IMPLICATIONS  
FOR NEW INNOVATION INDICATORS**

By

Kieran R O'Brien

BEC, BA, BIS (Hons) (University of Tasmania)

**Submitted in fulfilment of the requirements for the degree of Master of Commerce  
(by research)**

**University of Tasmania**

**March 2013**

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## **ACKNOWLEDGEMENTS**

In completing this thesis, I would like to acknowledge the wide support I have received that has enabled me to reach this milestone. Firstly, I would like to thank my advisory team, especially Professor Anthony Arundel, who has been patient and supportive throughout the process, providing critical guidance and support at key moments. I would like to thank Professor Keith Smith and Jonathan West, the other key member of my advisory group who have provided guidance throughout. I would like to thank all my colleagues and staff at the AIRC, for providing a stimulating environment conducive to learning, progress, and sharing of ideas and knowledge, and in particular my colleague Dr Ann Torugsa. Most importantly, I would like to thank the AIRC and the University of Tasmania, which have supported me throughout the process of research. I would also like to thank friends and family for putting up with me, and especially thank Anna for her kind support in the crucial final stages of research.

## **ABSTRACT**

This thesis addresses a need for further evaluation of existing and new innovation survey indicators, which now provide an important evidence base informing better policy approaches. The research focus is on indicators produced from large scale, economy-wide innovation surveys, which collect firm-level data, and move beyond traditional R&D, patent, and bibliometric approaches by providing a direct, ‘subject’ approach to measurement. Such surveys are conducted in approximately 80 countries, producing numerous indicators, though many portray counterintuitive results, and are subject to various shortcomings. Consequently, this study seeks to explore how new indicators can improve understanding of innovation.

Three indicator categories are assessed, using microdata from two iterations of a large regional innovation survey, the Tasmanian Innovation Census (TIC). Results examine three degrees of innovation novelty, and show that R&D activity and intensity provide good measures of innovation capability. Complex ‘mode’ indicators reveal the distribution of innovation characteristics at a ‘system’ level, across sectors, and for firms of different sizes, with linear, chain-link and systems theories all underpinning selected indicators. Using panel data, ‘output’ mode indicators reveal specific movement of both innovative and non-innovative firms between four innovation modes, providing a dynamic understanding of capability development and erosion over time, and suggesting that innovation capability for the most part develops cumulatively. Innovation based on diffusion is shown as most common in services. Composite indicator results provide a simple, visual picture of sectoral innovation performance, demonstrating usefulness beyond the typical macro-level of analysis. Results and discussion expose issues around theory, policy and practice with implications for related future research, including a need for further work to standardise different indicators for degrees of novelty and capability, and for research to understand the links between innovation modes and economic outcomes.

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## **GLOSSARY OF TERMS**

### ***Innovation***

An innovation is defined as ‘..the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations’ (OECD, 2005, p.46).

### ***Innovation indicators***

Innovation indicators generally consist of descriptive statistics generated from survey data, often standardised by classification variables for comparing different groups. The terms ‘indicator’ or ‘statistic’ are often used synonymously in reference to innovation indicators. The most common examples are the firm level innovation frequency or rate indicators, such as the share of innovative firms in a firm population, or the share of product innovators.

### ***Simple indicators***

An innovation indicator that is constructed generally with the use of response to a single survey question.

### ***Complex indicators***

An innovation survey indicator constructed using responses from two or more survey questions.

### ***Composite indicators***

A single summary measure, calculated using values from multiple simple or complex indicators.

### ***Subject approach***

The approach to measuring innovation at the ‘firm level’, using economy-wide, representative, innovation surveys of firms.

### ***Object approach***

The ‘object approach’ refers to the first direct approaches to measuring innovation. They focus on the actual technological innovation as the ‘object’ of measurement. This approach involves firstly identifying significant technological innovations via literature searches of technical, engineering, and trade journals or scientific publications, and secondly selecting a set of innovations to study, which is typically done by a panel of industry experts.

### ***Innovation capability***

Broadly defined as the capacity to successfully turn innovation inputs, activities and investments into innovation outputs (new products, processes, organisational or marketing methods).

### ***Innovation intensity***

The broader level of ‘innovativeness’, usually defined in reference to a combination of the level of novelty in innovations and the level of creativity or capability required for their development.

### ***Research and Development (R&D)***

Research and development, is defined as ‘creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and of the use of this stock of knowledge to devise new applications’ (OECD, 2002, p.30).

## **1.0 INTRODUCTION CHAPTER**

### **1.1 BACKGROUND**

Firm level innovation is now widely acknowledged as important for economic competitiveness and growth, for improving standards of living, social and environmental outcomes, and for meeting an ever expanding number of global challenges (OECD, 2010). Good policy development requires better economy-wide measures, as issues around innovation continue to penetrate both economic and whole of government policy agendas in advanced and developing economies (OECD, 2010). Innovation indicators now provide an important part of the evidence base informing better policy approaches. They assist policy makers by ‘telling a story’, benchmarking performance and identifying strengths and weaknesses that might warrant a response.

Since the early 1990s, large scale, economy-wide innovation surveys have collected firm level data for producing new indicators, moving beyond traditional R&D, patent, and bibliometric indicators by providing a more direct, ‘subject’ based approach to measurement. Such surveys are now carried out in approximately 80 countries (OECD, 2012), often on an annual basis. They produce a large array of indicators, which are accessible in recurrent output publications and the websites of statistical agencies responsible for conducting surveys.

### **1.2 RESEARCH RATIONALE**

Despite the wide availability of innovation survey indicators, they lack crucial information content, often portray counterintuitive patterns and results, and are subject to various shortcomings requiring further insight and improvement. These issues are evidenced in the limited uptake by policy makers and in larger measurement exercises and publications, such as the annual European Innovation Scoreboard (IUS, 2012) and the biennial OECD Science, Technology and Industry Outlook (OECD, 2012). For example, the longest running, largest cross-country survey, the European Community Innovation Survey (CIS), often depicts confusing country level results. In data for the

most recent CIS (CIS2008), results show that Portugal has a higher share of technologically innovative firms (50%) than countries such as Finland (46.8%), Sweden (44.7%), Denmark (42.5%), and the Netherlands (35%)<sup>1</sup>, despite opposite patterns observed across traditional R&D and patent indicators (Eurostat, 2010). Such results threaten the ongoing credibility of innovation survey exercises.

Much of the problem arises because widely available indicators fail to adequately differentiate between the varied levels of innovation intensity across sectors and firms, by distinguishing highly innovative from less innovative firms. Innovation surveys collect data on innovation input activities and investments (including R&D, patenting, design, knowledge acquisition, training for innovation, and collaboration), innovation outputs (new or improved products, processes, organisational or marketing methods), and impacts (sales from innovative products). Most of the resulting indicators are frequency or rate based. For example, indicators for outputs include the rate of product, process, organisational or marketing innovation, or for inputs include the rate of firms collaborating and the rate of firms undertaking R&D. This is a problem because rate based indicators reveal nothing about the diversity across innovations. New products may involve years of research and development, tens of millions of dollars in investment, and various failed prototypes before successfully making it to market. On the other hand, an innovation could simply represent the introduction of a significantly upgraded product to market, requiring no R&D, and only involving technology purchased ‘off the shelf’ (Arundel, 2007). Both types of product innovation are bundled together in the simple ‘rate of product innovators’ indicator. There is a lack of depth in available indicators, in terms of depicting innovation capability and novelty that characterise innovation intensity or the level of innovativeness. Many existing indicators fail to capture the different modes of innovation across sectors and firms,

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<sup>1</sup> Results for CIS2008 – percent of all enterprises with technological innovation (defined as firms with any implemented, ongoing or abandoned product or process innovation between 2006-2008, regardless of organisational or marketing innovation). Sourced from Eurostat (2012).



lagging theoretical sectoral and systems approaches and creating a mismatch between theory and indicators.

Much of the problem lies not in the ‘subject’ approach to measurement via firm level innovation surveys, but in under exploitation of existing survey data for indicator work. This is in turn, due largely to limitations in opportunities to access microdata. Statistical agencies, who generally administer national innovation surveys and have data access, have limited resources and little incentive to develop better indicators. While many academics have access to microdata, their focus is on econometric research rather than producing more useful indicators. This situation exposes a gap that motivates this research. Though some recent work by Arundel (2007), Bloch and Lopez-Bassols (2009) and Bloch et al. (2008) has made progress developing new indicators, many unknowns remain with regard to their usefulness and implications from a policy perspective. This need for further evaluation of new and existing indicators provides the rationale for this study, which is motivated by the central question: *How can new indicators improve understanding of innovation?*

Before outlining the methodological approach and structure of the thesis, some basic questions might first be asked. Namely, what are innovation indicators, and why are indicators produced at all? Firstly, innovation indicators generally consist of descriptive statistics generated from survey data, often standardised by classification variables for comparing different groups. As noted above the most common examples are firm level innovation frequency or rate indicators, such as the share of innovative firms in a firm population, or the share of product innovators.

An advantage of innovation indicators over econometric results, is that they can quickly and simply provide a picture of the prevalence of different activities and outputs in firm populations of interest (Arundel and Mohnen, 2003). They are more readily digestible for policy makers and the general public, and are of growing interest for policy makers because of the need to better understand innovation and a general trend towards evidence-based policy making (Pedersen, 2007; Veuglers, 2007; Finnbjornsson, 2008). Indicators have policy value because they enable benchmarking and comparison of performance on particular dimensions of innovation (Mairesse and Mohnen, 2010).

Importantly, as indicators generally have wide, representative coverage across whole economic populations (Arundel et al., 2008, Finnbjornsson, 2008), they can be used to test or validate theories about innovation, and this can influence policies that impact on societal well-being.

A second line of questioning to foreshadow this thesis includes: what should innovation indicators at the firm level measure, and why? The answers are complicated by the fact that innovation is multifaceted. However, a brief response here should set the tone for research method overview and thesis structure outline.

Indicators at the firm level need to capture factors that are relevant to innovation performance across an economy. This requires indicators that reflect significant industry variations in underlying product lines and services, technologies, markets, and challenges faced. They need also to suit the business demographic profile of modern advanced economies, many of which consist of large numbers of small or medium sized firms, as the challenges they face in achieving innovation success can be vastly different from larger firms with greater resource levels and expertise. Moreover, they need to reflect the significant diversity in innovation capability, novelty and intensity across large firm populations. Indicators should depict differences in inputs to innovation processes, including research, underpinning knowledge domains, technologies and firm strategies. They need to reflect the different types of output (for example, products or marketing methods), varied degrees of novelty in outputs (new to world or new to business), and different economic impacts from innovation (increased sales or productivity). Furthermore, they need to reflect the systemic environment that influences innovation, which consists of different interactions and knowledge flows between firms and other organisations and institutions. Most importantly, indicators need to ‘tell a story’ of relevance to policy design, monitoring and evaluation. This is a difficult challenge, if for no other reason than the heterogeneity across firm populations.

### **1.3 RESEARCH METHODOLOGY**

Since the research focus is learning how innovation indicators might improve understanding, the methodological approach of this study is based on generating and

assessing indicators, using microdata from two iterations of a large scale regional innovation survey, the Tasmanian Innovation Census (TIC). Each TIC was based on the standardised international methodology for conducting firm level or ‘subject’ based innovation surveys, defined in the OECD Oslo Manual (OECD, 2005). Consequently, the results can be generalised to any innovation survey based on the same guidelines. The author played a key role in the development and design of each TIC iteration, and has full access to TIC cross sectional and panel microdata, which was central to enabling this study.

The primary method is to use the TIC microdata resource to produce three broad categories of indicator detailed in the literature review, and to assess how they can fill gaps and deficiencies in the widely available range of simple rate based indicators. In the first category are simple indicators, generated using responses to single survey questions. The second category includes complex indicators, generated using responses to two or more survey questions, while the third features composite indices, which provide a single summary measure calculated using values from multiple simple and complex indicators.

This study uses several broad criteria to assess the capacity for different types of indicator to improve understanding of innovation:

1. The rationale for the indicator – the historical and theoretical background for its construction and use, and whether it fills a gap in existing simple indicators. For example, this includes whether the indicator supports interpretation from an innovation systems perspective, where the system represents the environment in which firms, organisations and institutions interact to produce, apply and diffuse knowledge, technology and innovation.
2. The level of information content for all respondent firms (a systems level perspective), by sector and by size.

3. The relevance of indicator results for informing policy by:
  - a. Providing a map of the patterns of innovation activities, inputs, outputs or impacts.
  - b. Providing some differentiation between different levels of innovation capability, novelty or intensity across firms or firm groupings.
  - c. Revealing changes or trends in innovation characteristics or performance over time.
  - d. Providing results that may inform policy directed at firms operating in different sectors, of different sizes, or in different regions.

## **1.4 OUTLINE OF THE THESIS**

The remaining content of this thesis is structured across six chapters. Here, the objectives, structure, and content of each is described to conclude this introduction.

### ***Chapter 2 – Literature review***

The literature review has a number of objectives that are divided across six main sections, and that progressively uncover issues around innovation indicators, in the historical context of the origins of new subject approaches to measurement. The intention is to provide the reader with a thorough understanding of how and why innovation surveys and indicators reached their current state of development, to detail the theoretical, conceptual, and empirical background behind the weaknesses that justify this research, and to consider new work that guides the approach taken. Finally, a review of the historical and theoretical background plays an important part in assessing how new indicators contribute to understanding in the results and discussion chapters. Because of the breadth of this task the literature review is broken into six sections.

The first section provides an introduction to the literature review, exploring the conceptual and definitional origins of innovation measurement, policy relevance, the

measurement challenges, and key problems that shape the literature review and research agenda.

The second section covers the pre-subject approaches to measurement, considering their theoretical and empirical basis. This section aims to provide the reader with an appreciation of how subject approaches emerged to address deficiencies in earlier approaches, and to provide an important historical backdrop for the emergence and interpretation of new indicators.

The third section details the emergence of new subject approaches, and details the evolution of the Oslo Manual, the CIS, key output types and results, and key theoretical underpinnings. The objective is to explore how new innovation survey data emerged as a resource for empirical research based on econometric methods, and for the production of innovation indicators. This provides relevant history behind the approach to presenting and interpreting indicators in later chapters.

The fourth section explores the literature critiquing innovation survey indicators as they developed, and focuses on the European Community Innovation Survey, exposing gaps that motivate this research.

The fifth section covers new work exploiting innovation survey data to produce new indicators, and to overcome limitations in many widely available simple indicators. This provides a framework for the methodological approach, and for the structure of ensuing results and summary discussions.

The final section summarises key points of the previous sections, noting gaps, issues, and objectives that justify the research question and objectives.

### ***Chapter 3 – Methodological approach***

Chapter 3 details the methodological approach to the thesis as covered above. The main approach is to generate three categories of innovation indicators: simple, complex, and composite, and to assess the capacity for each to improve understanding of innovation using several broad criteria detailed above.

#### ***Chapter 4 – Exploring indicators for novelty, capability and impacts***

This chapter is structured into three sections, and each corresponds to a different topic and set of indicators, most of which are simple. The objective of the first section is to build on the approach of Arundel (2007) and explore indicators for differing degrees of innovation novelty. The second section seeks to validate R&D as an indicator for capability, also exploring non-R&D based indicators. The third section briefly explores how weighted indicators might complement novelty indicators and reveal information about the distribution and impacts of innovation.

#### ***Chapter 5 - Exploring changes in capability and strategy with complex indicators: innovation modes***

Chapter 5 is focused on understanding how complex indicators can improve understanding of innovation. The selected mode indicators are based on recent cross-country coordinated research using CIS data, and chosen to address key gaps noted in the literature. The first section explores innovation capability using output modes. A key objective is to make a novel contribution to the indicator literature, by exploring how these modes can reveal a dynamic picture of capability using panel data. The second section explores creativity and diffusion using status modes, and the third briefly examines strategy using indicators that depict technological and non-technological modes of innovation.

#### ***Chapter 6 - Exploring sectoral capability with composite indices***

Chapter 6 aims to demonstrate how composite indices can improve understanding of strengths and weaknesses in innovation capability across sectors. The main objective is to show how this approach has use beyond macro, country level analysis.

#### ***Chapter 7 - Conclusions***

The intention of the final chapter is to summarise the content and key contributions of the thesis, to consider the implications of key results for the wider construction of indicators to inform policy, to revisit some of the main limitations of the research, and to discuss priorities for future related work.

## **2.0 INTRODUCTION TO THE LITERATURE REVIEW - THE CONCEPT OF INNOVATION AND THE RATIONALE AND CHALLENGE FOR MEASUREMENT**

While the *idea* of innovation has been a feature of language for over five hundred years (Grezl, 2007), the *phenomenon* of innovation has been ever present in human progress since the birth of civilisation (Godin, 2010; Fagerberg, 2005; Bruland and Mowery, 2005). Understanding of the concept in language has significantly changed over time. Godin (2010, p.8) notes that for over 2500 years, innovation was understood as ‘the introduction of a change in behaviours, practices and activities’, while Grezl (2007, p.51) notes early conception based on ‘the introduction of novelties, alteration of what is established by the introduction of new elements or forms, or a change made in the nature or fashion of anything’. The conceptualisation of innovation in terms of commerce and technology is a relatively recent advance, formalising in the work of the Austrian economist Joseph Schumpeter in the early 20<sup>th</sup> Century, and popularised since the 1970s (Grezl, 2007; Godin, 2010).

One theme is consistent in the vast innovation oriented literature crossing many scholarly disciplines: innovation has played a central role in the industrialisation and evolution of modern economies (Bruland and Mowery, 2005; Fagerberg, 2005; Verspagen, 2005). One needs only to think of some of the great innovations throughout history for evidence of this premise. Consider for example, the wheel and transport, the printing press and knowledge diffusion, the concept of money and development of commerce and industry, new energy sources in steam power and electricity, refrigeration and food preservation, automobiles and aeroplanes, x-rays, bio-technology, microelectronics, or telecommunications. Such innovations have transformed the world. They have crossed cultures, societies and geographies. Any discussion on great innovations of the modern age is always subject to debate and controversy, as there are so many with significant transformative effects over time (Husick, 2008). But what is meant by the term innovation? The examples above are broad and cross many conceptual and temporal boundaries.

Three key concepts need to be distinguished for any discussion on innovation: invention, innovation, and technology. Invention refers to the birth of an idea, while innovation refers to the first attempt to carry it out into practice, for example, via implementation of a new product, process or method for organising productive activities (Fagerberg, 2005). Technology is defined by the OECD as ‘a set of techniques, that are themselves defined as a set of actions and decision rules guiding their sequential application that man has learned will generally lead to predictable (and sometimes desirable) outcomes under certain specified circumstances’ (OECD, 1990, p.10).

Innovation is complex and can derive from many sources, the lone inventor, a public research laboratory, a firm or university to name just a few. Many radical innovations have their origins in public sector research institutes or investments (Smith, 2002a) (the internet for example, which emerged from public research investments in the US in the 1960s (Bruland and Mowery, 2005)). Innovation can be driven by advances in scientific knowledge on the one hand, such as new drugs emerging from advances in biomedical sciences, or by market forces on the other (Kline and Rosenberg, 1986), such as hybrid power cars or low-energy light bulbs, developed to meet environmental concerns. A prolonged and raging debate in the literature regards the market pull verses traditional science push view of innovation, though to date there lacks conclusive evidence for one view over the other (Freeman, 1979; Mowery and Rosenberg, 1997; Godin, 2010). Despite diversity in the sources of innovation, it is often the firm that constitutes the primary entity for diffusing innovations throughout the economy and society, through the production and sale of new products and services (Fagerberg, 2005; Howells, 1996), and the firm is central to research on innovation (Teece, 2010).

### 2.0.1 WHY MEASURE INNOVATION?

Innovation is now widely accepted as a central driver of long run economic growth and competitiveness (OECD, 2010), and has elevated in importance within economic policy agendas of the advanced economies (Mytelka and Smith, 2002). Yet innovation is not confined to economic policy. Central to ongoing productivity advance and welfare improvements, innovation is rapidly becoming a whole of government policy issue.



Sound measurement is essential for building understanding of innovation. In addition to informing better policy (OECD, 2010b), measuring innovation is important for building understanding from academic and business perspectives. But how does innovation benefit society and why is it of policy interest?

The positive impacts of innovation are derived through the introduction of new products and services that create new industries and markets, new sources of employment and wealth, and via improved efficiency and reduced costs in production. Innovation can also result in welfare benefits derived from advances in quality, functionality and performance of new technologies, products and processes. For examples, consider the revolutionary labour reducing changes to social and domestic life from innovations in domestic appliances such as refrigerators and washing machines, or social changes following introduction of the contraceptive pill (Smith and West, 2007). Thus innovation is increasingly seen as essential for improving not only economic but social and environmental outcomes (OECD, 2010).

This is not to say that the impacts of innovation are strictly positive. For instance, many authors attribute the recent global financial crisis to rapid innovations in complex financial products, that combined with loose regulatory institutions and regimes led to the credit crunch and meltdown in world financial markets (Park, 2009; Boz and Mendoza, 2012). Others note that the negative impacts of innovation can result in welfare loss which can have equal reach across social, environmental and economic dimensions (Courvisanos, 2012).

Governments have played and can continue to play a role when it comes to innovation (Lundvall and Borrás, 2005). Perhaps most obviously via funding and management of science, education and research infrastructures (which have sourced many of the world changing technologies and innovations throughout history (Faulkner and Senker, 1995, cited in Smith, 2002a)). For example, OECD country investment in R&D in 2008 amounted to over USD 935 billion, around half of which was publicly funded, and such investments have also been increasing in the non-OECD economies (OECD, 2010a). Additional roles for government relate to ensuring appropriation and incentive structures for firm investment in knowledge and innovation, via administering systems

of intellectual property rights, which include patenting legislation and related legal frameworks (Archibugi and Michie, 1998). Firm investments in innovation often create positive externalities, providing spillover benefits to society that are greater than private returns. This can result in firm underinvestment and justify public intervention. Recent research suggests that policy also has a role to play in terms of providing the framework conditions for systemic functioning of innovation systems, and for coordinating various system elements which fall under the control of government, including regulation regimes, institutions, research and education, and general infrastructure (BIS, 2011; Smith, 2000; 2006; 2007; Smith and West, 2007). Related policy functions include monitoring the pace of progress, and maintaining regulatory conditions that promote innovation while controlling or limiting any negative impacts.

## 2.0.2 INNOVATION STUDIES AND SCHUMPTER'S DEFINITION

So far the importance of innovation is plain to see. Measuring and understanding innovation is crucial for the ongoing development of science, technology and innovation policy, the competitiveness of modern economies, and related social and environmental outcomes. To this end, a new academic discipline of 'innovation studies' crystallised in the 1960s with the formation of the Science Policy and Research Unit at Sussex University, lead by the economist Christopher Freeman (Fagerberg, 2005; Fagerberg and Verspagen, 2009; Godin, 2010). Innovation studies draws on a diverse set of disciplines including anthropology, history, sociology, economics, business and management. The Austrian economist Joseph Schumpeter is the widely heralded father of modern innovation studies, and the field has grown exponentially following renewed interest in Schumpeterian ideas in the 1980s works of Dosi (1982), Nelson and Winter (1982) and Freeman et al. (1982) (cited in Castellacci et al., 2005).

Schumpeter defined innovation as 'new combinations' of existing knowledge and resources (Fagerberg, 2005; Fagerberg et al., 2011), providing the core definition of innovation that remains central to the field today. Schumpeter's definition identifies five main types of innovation including new products, new production methods (processes),

exploitation of new markets, new methods for organising business activities, and new sources of supply (Fagerberg, 2005; Grezl, 2007; Fagerberg et al., 2011).

### 2.0.3 THE MEASUREMENT CHALLENGE

The need for accurate measurement is a critical requirement for both understanding and promoting innovation, and Schumpeter's definition laid the foundation for modern approaches. Traditionally, indicators such as counts of research and development personnel or expenditure, scientific patents, or scientific publications have dominated empirical studies, though such measures capture only parts of the innovation process. As the field of innovation studies has developed, new forms of measurement have emerged. The concept of innovation has been operationalised in a standard international framework for the measurement of innovation, the OECD Oslo Manual, which was first published in 1992 (OECD, 1992), and defines innovation as:

...the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations (OECD, 2005, p.46).

This has coincided with the development of new, direct, approaches to measuring innovation, at the innovation level (an object approach), and from the level of the firm introducing or diffusing the innovation (the subject approach).

The need for economy-wide measures of innovation led to the widespread uptake of the subject approach, which manifested in firm level innovation surveys based on the Oslo Manual. The results provide an important new source of economic data for both econometric research, and the production of comparable indicators for cross-country benchmarking of innovation performance. However, the latter objective has come to provide the main justification for ongoing surveys (Mairesse and Mohnen, 2010), as innovation indicators provide an important part of the expanding 'evidence base' for informing policy (Finnbjornsson, 2008; Pedersen, 2007; Veuglers, 2007), and also for testing theories across wide and representative firm populations (Arundel et al., 2008;

Finnbjornsson, 2008). Consequently, many governments of the world invest in conducting large-scale innovation surveys, which are now carried out in approximately 80 countries (OECD, 2012). Shortcomings in the existing range of indicators require further insight. In addition, many indicators have yet to be refined or utilised to their full potential. These themes provide the central point of focus for this thesis. The research interest is innovation surveys using a firm level, ‘subject’ approach. Of primary concern is how survey indicators can be better exploited to improve understanding of innovation, and have improved policy relevance.

In the following literature review, the intention is to provide the reader with a deep understanding of the current state of innovation measurement. The historical and theoretical background plays a part in assessing the contribution of new indicators to improved understanding. This story consists of five sections that progressively uncover the research rationale. In the first, traditional measurement approaches and theories on economic growth are briefly overviewed, providing an important context for the following discussion. The second part considers the evolution of subject approaches. Discussion tracks three key streams of underlying innovation theory corresponding to development of the OECD Oslo Manual (OECD, 2005) and new indicators. Attention is directed to the evolution of the European Community Innovation Survey (CIS), the largest ongoing, cross-country innovation survey. Part three covers progressive critique of surveys and indicator weaknesses, before covering new indicator work in part four. Finally, the fifth section summarises the literature and exposes the main research question driving the empirical component of this study.

## **2.1 OVERVIEW OF THE HISTORY AND DEVELOPMENT OF PRE-SUBJECT APPROACHES TO INNOVATION MEASUREMENT: Traditional and Object Approaches and Theoretical Background**

### **2.1.1 CONCEPTUAL AND THEORETICAL ORIGINS OF INNOVATION MEASUREMENT IN TRADITIONAL THEORIES ON ECONOMIC GROWTH**

The origins of new approaches to measuring innovation can be found in traditional theories developed to explain economic growth, and specifically the impact of

technological change on growth. Such theories of growth provide important context and impetus for the emergence of innovation surveys and differing theoretical accounts of innovation, and a basis for explaining the emergence of new innovation indicators. For this reason they are the subject of a brief discussion here prior to exploring the early or ‘traditional’ approaches to measuring innovation.

In the late 19<sup>th</sup> and early 20<sup>th</sup> century, neoclassical economic approaches were dominant in shaping efforts to understand links between technology and economic growth. Within the growth accounting approach, the enduring production function was the main tool used to model and explain increases in economic output, as an econometric function of increases in capital and labour inputs. Innovation formed part of a ‘technical change’ residual in the production function, and work in this tradition showed that the amount of growth driven by technical change (and not explained by capital and labour increases) in the post second world war period was very large (Solow, 1957; Abramovitz, 1956; Verspagen, 2005; Fagerberg et al., 2010). This was significant for the development of modern attempts to measure innovation, as it stimulated a body of work aimed at measuring and quantifying the components of technical change, particularly knowledge and innovation (Verspagen, 2005; Mytelka and Smith, 2002).

New growth or endogenous growth theories that followed, treated technical change as endogenous (Romer, 1994). As the source of new knowledge, the research sector became an important inclusion for such approaches and new sources of R&D data were used to represent a knowledge stock in econometric models of the production function (Robertson, 2009). Subsequent empirical work in this tradition by Griliches (1979; 1980a; 1980b; 1986; cited in Hall et al., 2010) focused on measuring the relation between R&D and productivity at the firm, sector and country level. This indicated that industry and economy-wide output increases attributable to R&D inputs were significant, with spillover returns from R&D investment found to be larger than private returns (Fagerberg et al., 2010; Verspagen, 2005). This work created an interest in R&D data and indicators that came to dominate traditional approaches to measuring innovation.

Dissatisfaction with neoclassical approaches also saw neo-Schumpeterian or evolutionary theories emerge in the 1980s and 1990s, found in the writings of Nelson and Winter (1982), Dosi (1982), and Freeman et al. (1982) (cited in Castellacci et al. (2005)). In contrast to the neoclassical tradition, in which growth is subject to forces of equilibrium, and innovation is omitted as an explanatory factor, such theories see innovation in the novelty and variety of goods produced as a key driver of growth (Verspagen, 2005). Under evolutionary theory the nature of new technologies and innovations is characterised by uncertainty and unpredictability. Growth occurs via ongoing ‘creative destruction’, as new and improved technologies, products and processes emerge and are adopted and diffused based on forces of market selection, replacing old with new; and akin to evolution through ongoing mutation and natural selection in Darwin’s theory of evolution (Verspagen, 2005; Hospers, 2005). As Mytelka and Smith (2001; 2002; 2003) have argued, modern innovation studies is borne out of the evolutionary tradition, and so too, following this argument, are the new approaches to measuring innovation that provide the subject of enquiry in this thesis. Thus within the broad tradition of theoretical and empirical work relating to understanding economic growth, innovation crystallised as an essential ingredient, and for this reason measuring innovation became widely acknowledged as central to understanding and promoting economic growth.

## 2.1.2 HISTORY OF THE MEASUREMENT OF INNOVATION – INNOVATION THEORIES AND MEASURES

Historically, key efforts to measure innovation can be categorised into three temporal tranches: traditional approaches (consisting primarily of bibliometrics, patents and research and development statistics), direct object-based approaches, and direct subject-based approaches. This thesis is concerned with indicators based on a subject approach, though a discussion of the former two categories provides the historical context from which these evolved, and important background for the evaluation of new indicators in later parts of the thesis.

Successive measurement efforts have been influenced by concomitant developments in theoretical approaches to understanding innovation. Three major theoretical approaches dominate in the field of innovation studies: the ‘linear’ model of innovation, the ‘chain-link’ model of innovation, and ‘systems’ theories. Despite various theoretical permutations relating to aspects of innovation and its relationship to productivity, growth and industrial development, these three key streams of theory are predominant in the measurement literature, and consequently provide the main theoretical focus for this thesis. The following sections explore development of the three main tranches of innovation measurement, and correspondent theoretical underpinnings.

### 2.1.3 TRADITIONAL MEASURES OF INNOVATION, RESULTS AND THEORETICAL UNDERPINNINGS

Traditional approaches to measuring innovation draw on three main sources: bibliometrics, patenting data, and data on Research & Development (R&D). For each category, this section briefly reviews the origins and nature of related measures. This provides an important part of the discussion on how and why new innovation surveys emerged, how they complement traditional approaches, and their value in progressing understanding of the innovation process. This discussion is important for appreciating the contributions and limitations of innovation survey indicators, and any bias towards particular types of indicator.

Beyond the tradition of economic growth theories, contemporary statistical definitions and approaches to measuring innovation have origins in a long history of science and technology measurement and, in particular, the development of statistics on R&D, which for a long time provided the principal source of data for innovation studies. There is a common theme in the literature that extensive use of R&D as a proxy measure for innovation has influenced theoretical conceptions of innovation over time, and the bias towards R&D indicators in scholarly and policy domains (Godin, 2000a; Arundel, 2007). For this reason, and because R&D is also central to new measurement approaches, R&D indicators are here considered in more detail than bibliometrics and patents.

### ***2.1.3.1 R&D data and indicators***

Documented interest in statistical measurement relating to the role and impact of science and research in economic growth dates back to the mid-nineteenth century in the work of the British scientist Francis Galton, originally borne out of a discipline of eugenics and a general concern that there were not enough ‘men of science’ in Great Britain to continue civilisation’s progress through technology advance, industrialisation, and growth (Godin, 2006). Galton began a tradition of counting the number of scientists per capita, and developed a system for ranking scientists by the magnitude of contributions to scientific knowledge and societal advance. Larger country based repertories of scientific activities and personnel materialised in the 1930s in the US, Canada and Great Britain for the purpose of mapping industrial R&D activities and developing science policy (Godin, 2001; 2006; 2006a; 2004). The key motivation behind such efforts was to develop knowledge of existing scientific and technological capabilities and resources firstly, for mobilisation in case of military conflict, and secondly, to further understanding of the impact of science and research on economic growth and prosperity (Godin, 2001; 2005). It was from these endeavours that contemporary efforts to measure science and research via collection of R&D statistics emerged, and in the 1960’s work to internationally coordinate the measurement of R&D began under the auspices of the OECD (Godin, 2008), culminating in the OECD ‘Frascati Manual’.

Developed in 1962, the Frascati Manual provided an agreed conceptual framework for standardised statistical measurement of R&D. It was widely introduced by member countries in 1963 and is currently in its sixth edition. Widespread use of R&D as an innovation indicator in research, policy and analysis owes much to the long historical time series of available cross-country data, with a good level of international comparability and consistency due to the agreed Frascati framework (Steward, 2008).

The measurement concepts and definitions of R&D were subject to a long, widespread and ongoing debate leading to formalisation in the Frascati Manual (Godin, 2001; 2006a). The main conceptual approach of the manual is to define activities that are



counted as R&D, and those that are not, and to collect data on the human and financial resources devoted to R&D activities (Smith, 2005; OECD, 2002).

R&D is defined as ‘creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and of the use of this stock of knowledge to devise new applications’ (OECD, 2002, p.30). Thus R&D under this definition essentially involves the production of new knowledge, and the application of existing knowledge in new ways. These activities are defined in terms of three main categories: basic research (which has also been historically referred to as *pure research* or *fundamental research*), applied research, and experimental development:

*Basic research* is defined as ‘experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view’. Thus it is most often undertaken in universities.

*Applied research*, is ‘original investigation undertaken in order to acquire new knowledge..directed primarily towards a specific practical aim or objective’, Thus it is often undertaken in industrial research laboratories.

*Experimental development*, is ‘systematic work, drawing on existing knowledge gained from research and/or practical experience, which is directed to producing new materials, products or devices, to installing new processes, systems or services, or to improving substantially those already produced or installed’ (OECD, 2002, p.30).

The key criteria used to define R&D relates to the degree of novelty in resolving scientific or technological problems, such that someone with access to all knowledge in the field of enquiry could not answer the specific problem given access to that existing knowledge, or using that knowledge in pre-determined ways (OECD, 2002; Smith, 2005). Thus R&D involves generating new knowledge required to solve a problem, or use of existing knowledge in entirely new ways.

R&D activity can occur in business, government, higher education institutions or private non-profit organisations. Entities within these sectors constitute the statistical units in R&D surveys, which comprise the main method of measurement. R&D activities are also classified according to research field, application area, and socio-economic objective.

Common use of R&D as an innovation indicator has centred on the expenditure allocated to R&D by sector, and the total of all sector expenditure at the country level as a share of economic output – which is described as a country's R&D 'intensity'. In the same way, R&D intensity at the firm level is calculated as firm R&D expenditure expressed as a share of turnover, and at the industry level as aggregate industry R&D expenditure as a share of industry output.

Business R&D typically accounts for over half of the total R&D expenditure in many developed economies, and is often the focus of scholarly work and policy efforts. Key approaches to analysis involve comparing R&D intensities at the firm, industry and country level as a proxy for innovation performance.

A wide body of academic research studies the relationship between R&D and productivity, largely influenced by neoclassical growth theories. Key studies have importantly established a positive association between R&D expenditure, productivity and output, and provided empirical evidence of R&D knowledge spillovers – where the impact of R&D investment on output at the economy level, is greater than aggregate industry investment levels (Hall et al. (2010) provide a good discussion). Thus R&D constitutes an indicator of innovation input activity which can lead to the production of new products and processes, or the refinement or improvement of existing products and processes.

Despite the important ongoing contribution of R&D statistics to understanding of science, technology and innovation, they are also subject to various limitations. The most relevant to this study concerns a long running debate as to the difficulties in distinguishing between R&D and non-R&D activities for survey respondents (Guellec and Pattison, 2001; Arundel, 2007; Arundel et al., 1998; Sandven, 1998; Smith, 2005;

Archibugi and Simonette, 1998). It is argued that this problem stems from the Frascati definition that focuses on ‘systematic’ investigation, and so R&D data will subsequently include activity in larger firms with large scale, formal R&D departments, though miss activity in smaller and medium sized firms that tend to conduct R&D only on an occasional basis (Archibugi and Pianta, 1996; Symeonidis, 1996; Guellec and Pattison, 2001; Smith, 2005; 1998; Godin, 2000). This is evidenced in disparities between R&D counts coming from official R&D surveys, innovation surveys, and from datasets of government agencies administering R&D tax credit claims (Pattison, 2009; Mairesse and Mohnen, 2007; Godin, 2002).

R&D as an indicator has been subject to misinterpretation and misuse when comparing country level performance based on R&D intensity (aggregate R&D expenditure as a share of GDP). Larger countries often have more developed R&D capabilities and greater aggregate expenditure. Countries also vary greatly in their industrial structures, and between and within industries R&D intensity varies greatly. Though for some time these issues have been known and various papers have used methods of adjustment to account for size and structural differences (Sandven, 1998; Sandven and Smith, 1998; Arundel and O’Brien, 2009), standard R&D intensity indicators continue to dominate innovation policy discourse for many advanced economies (Arundel, 2007).

It is important to make the point here that use of R&D data and indicators is also tied in with a key theoretical notion – the so called ‘linear model’ of innovation. In particular, the history of debate regarding conceptual and definitional differences between basic and applied research and development influenced permeation of the linear theory (Godin, 2000; 2005a). Rhetoric in discussions regarding the causal and sequential nature of relationships between different stages of research flowed into cross disciplinary views of the innovation process (Godin, 2001), and manifested in the linear theoretical conception of innovation (Godin, 2005a), which is discussed further at the end of this section. This point also relates to another shortcoming in R&D based innovation indicators: they only provide an input measure, and do not reveal any result, output or outcome, and as such provide an intermediate rather than direct measure.

A final point beginning to emerge from the latter part of this discussion warrants mention concerning the relationship between science and innovation indicators, theory, and policy. This is complex and circular, as each has influenced the development of one another in an iterative process of progressive development and evolution. Theories influence measurement approaches, policies reinforce the focus on particular indicators, and dominant indicators influence theoretical developments and policy rhetoric. This theme is revisited in later parts of the thesis.

### ***2.1.3.2 Patent based indicators and measures***

A second major ‘traditional’ source of innovation measurement consists of statistics on patents. Patent statistics are a by-product of the patent process, generated from an administrative process rather than direct survey based research. Patenting has a long history stretching back to the thirteenth century (Granstrand, 2005). Patenting systems, processes and policies have differed across countries historically, although efforts to harmonise systems have been increasing. The two key sources of patent data currently are the United States Patent and Trademark Office (USTPO) and the European Patent Organisation (EPO). In general, within the process of applying for a patent, a series of detailed technical information about the patent is collected and recorded, including information on the particular technological field.

Iversen (1998, p.56) and Smith (2005, p.159) provide succinct overviews of the nature of patent data and its advantages as an innovation indicator, synthesised in the following points:

- There is a centuries long record of patent data to draw upon, enabling analysis of inventive activity over time in relation to economic change.
- Patent data is recorded using a detailed standard patent classification that has been relatively stable over time.
- Patents are granted for inventions with commercial potential (innovations).
- Patent data is systematically collected as part of the application process.

- The patent system relates inventions to particular technologies and to citations in scientific and technical literature.
- Patent data is highly accessible.

Patent data has key applications in terms of analysis of innovation and a number of related areas. In particular, patents are of use for mapping inter-sectoral technology and knowledge flows (based on patent related information on technology fields and scientific citations), for analysing the links between inventive and innovative activity, between technological and economic activity, and for analysing inventive activity, R&D (creative activity) and knowledge spillovers<sup>2</sup>.

Indicators generated from patent data are often used to complement new innovation survey indicators, and many innovation surveys, which are discussed further on, also ask firms questions on their patenting activity. The limits of patent data for measuring innovation activity are well known, and are one reason for the development of new measurement approaches. Patents do not represent a direct measure of innovation, rather they directly represent invention. A patent does not necessarily result in the market introduction of new products or processes, or yield significant economic value if it does, while companies can undertake patenting activity for strategic reasons (for example, to prevent innovations from competitors) (Steward, 2008; Iversen, 1998; Smith, 2005).

### ***2.1.3.3 Bibliometrics***

Bibliometrics provides a third traditional approach to measuring innovation. Bibliometrics refers to the systematic measurement of scientific publications and citations, and involves tracking the development and diffusion of new scientific knowledge originating in scholarly scientific publications. Such publications constitute

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<sup>2</sup> The OECD Patent Statistics Manual (OECD, 2009a) (first published in 1994) provides standardised guidelines for the compilation and analysis of patent data.

the statistical unit for bibliometric studies. Although the origins of bibliometrics are often associated with the introduction of the Scientific Citation Index (SCI) in 1963 by Eugene Garfield, the approach historically evolved in the broader tradition of scientometrics - efforts to analyse and measure science – as did traditional R&D based indicators (Godin, 2006b; Kaloudis, 1998).

Essentially, bibliometric methods involve measuring the quality and quantity of new scientific knowledge, via counts of peer reviewed publications and counts of citations. Thus bibliometrics do not directly measure innovation by standard definitions or in a statistical sense, but rather measure the production and diffusion of new knowledge. In this regard, bibliometric data can be used to analyse part of the innovation process i.e. the origins and sources of new knowledge and technology sourcing innovation. Though bibliometrics have often been relied on to measure innovation, at best they provide proxy indicators which capture knowledge inputs relevant to innovation processes, and the production and diffusion of new knowledge (particularly scientific knowledge).

#### 2.1.4 THE LINEAR MODEL OF INNOVATION

The linear model of innovation is the main theory underpinning the historical development and widespread use of traditional innovation indicators. It is often argued that its influence remains in terms of the focus on R&D indicators and policies, and the theory is considered here as it provides part of the theoretical background for interpretation of indicators in this thesis. In general the linear model explains innovation as a sequential process beginning with new scientific knowledge and followed by invention, production and diffusion of the new product or production methods. The typical format begins with scientific discovery or the production of new knowledge, followed by application to new uses in products or processes, and diffusion throughout an economy.

The status of the theory has been the subject of much debate in the literature. Godin (2005a, p.4) notes that the ‘precise source of the linear model remains nebulous, having never been documented’, while Edgerton (2004; cited in Godin, 2005a; Balconi et al., 2008) proclaims that the linear model ‘did not exist’. The emergence of the theory is

often linked to the release of V. Bush's *Science, the Endless Frontier* in 1945, a report commissioned for the President of the United States to provide a blueprint for science policy in the US (Smith, 1998; 2002; Godin, 2005a). However, the role of this report in influencing the linear model has also been refuted by various scholars (Godin, 2005a). Recent work by Godin (2009) attributes the first systematic version of the model to a 1928 research paper titled 'the research cycle' by Maurice Holland, who was then a director of the US National Research Council.

According to Godin (2005a) the linear model is a construction of industrialists, policy makers, researchers and academics. Godin provides a taxonomy of the model that shows variations in terminology and sequences over twenty years or so from the 1960s. Despite minor variations across the taxonomy, the most typical version defines innovation in terms of the following sequence of discrete activities:

Basic research → applied research → development → production → diffusion.

The model gained traction in the context of justifying basic research funding requests from the scientific community, though it was also embedded through the widespread use of R&D indicators, which were in turn facilitated by the availability of standardised R&D data from the 1960s. However, widespread use of the whole family of traditional approaches (including patent and bibliometric indicators) inadvertently promoted a linear notion of innovation by focusing on scientific inputs – thus the argument that indicators themselves contributed to the longevity of a linear theory of innovation, by reinforcing a sequential notion of the innovation process beginning with science (Bloch, 2007; Godin, 2000; Arundel, 2007; Smith, 2005).

So the linear model underpinned much use, interpretation and analysis of traditional indicators, and these in turn influenced the prevalence of the linear model. Understood in the context of a linear and sequential process, traditional indicators could be interpreted as steps that would necessarily result in innovations: higher R&D was conducive to more innovations, more patents implied more innovations, and more publications meant increases in the stock of scientific knowledge that under a linear model would result in more innovations. The key problem with this approach, is that

innovation in reality does not always take the shape of a sequential, chronological chain of events. For evidence of this, scholars simply point to examples of modern innovations that were produced without any R&D, such as the bicycle (Haukka, 2005). Innovations do not depend on, or even necessarily involve any R&D, and conversely, R&D activity does not necessarily result in an innovation.

Critique of the linear model is commonplace in the recent literature (Gittelman and Kogut, 2001; Ruttan, 2001; Pavitt, 2005), and it was Kline and Rosenberg's work in the 1980s 'Positive Sum Strategy' that marked a shift in thinking away from linear approaches (Kline and Rosenberg, 1986). Kline and Rosenberg's seminal work presented the chain-link model for explaining the innovation process, which represented the first major theoretical alternative to linear approaches. This is covered in later discussion.

## 2.1.5 KEY RESULTS FROM TRADITIONAL MEASURES

Despite limitations of traditional innovation indicators, the range of empirical studies reliant on their analysis have cemented a number of relevant historical learnings with respect to understanding innovation, and are considered here prior to discussing the emergence of new approaches. These contributions are best summarised by Smith (2006, p.9-10) and the OECD (1992, p.14-15), including the following stylised facts:

- Technical change is the most important factor in economic growth.
- At a country level, innovation as measured by R&D and patents is associated with higher levels of national output and income.
- At a country level, innovation as measured by R&D and patents is associated with higher shares of world trade and exports.
- At the firm level, R&D is associated with higher productivity levels.
- Rates of return on investment in R&D are high, and public or social returns are often higher than private returns due to knowledge spillovers.



- The fastest growing industries in terms of trade shares are technology intensive (as measured by R&D and patents).

## 2.1.6 THE EMERGENCE OF DIRECT MEASURES OF INNOVATION - OBJECT APPROACHES

This section overviews the emergence of direct approaches to measuring innovation. This is an important precursor to exploring the development and contribution of subject approaches, that provide the focus for this thesis.

Direct approaches to measuring innovation emerged in the 1970s and 1980s, as growing recognition of the importance of innovation for economic policy led to increasing demand for better indicators. This was particularly the case in the United States in the 1970s, where following a global recession there was renewed urgency in increasing productivity levels as a means of restoring economic growth rates (Smith, 1998; Mytelka and Smith, 2002). In this environment, science, innovation and technology policy elevated in importance within the economic policy agenda due to in part to the expanding empirical evidence linking technical change to higher levels of productivity and growth (Smith, 1998; 2002, Mytelka and Smith, 2002). These conditions provided an important driver for the development of new direct approaches to measuring innovation.

The literature identifies the 1967 Steacie Report by the US Department of Commerce (UNU-INTECH, 2004; Godin, 2002) as an instrumental policy document influencing the shift towards more direct measurement of innovation. The Steacie Report defined innovation in terms of design engineering, tooling and engineering, manufacturing, and marketing categories in addition to R&D, and importantly found that R&D accounted for only 5 to 10 percent of innovation costs (UNU-INTECH, 2004). This exposed a limitation of R&D as an innovation indicator, and revealed a need for alternatives.

The first direct approaches to measuring innovation were of the so called ‘object’ variety – they focus on the actual technological innovation as the object of measurement. This approach involves firstly identifying significant technological

innovations via literature searches of technical, engineering, and trade journals or scientific publications, and secondly selecting a set of innovations to study, which is typically done by a panel of industry experts. From the sampled innovations, the firms responsible for their production are then surveyed via interviews or survey questionnaires, and the data collated in innovation databases for analysis (Godin, 2002).

An important milestone in the evolution of direct approaches in Europe originated in the OECD *Gaps in Technology* report published in 1968, and a follow up report in 1971, which, by using an object approach to study 140 innovations dating back to 1945, showed that a much larger share of significant innovations were commercialised in the US compared with Europe and the rest of the world (Godin, 2003; UNU-INTECH, 2004). This provided an important stimulus for debate in Europe that inevitably created interest in establishing better measures to track, monitor and improve comparative innovation performance.

Two pioneering studies using an ‘object approach’ were the large-scale survey of around 8000 innovations implemented by small businesses in the US during the year 1982, and analysed in Acs and Audretsch’s (1990) seminal study, and the Science Policy and Research Unit’s (SPRU) study at the University of Sussex in the UK (Archibugi and Pianta, 1996; Smith, 1998; 2005), which involved around 4300 UK innovations spanning from 1945 to 1983, analysed in seminal papers by Pavitt (1984; 1989) and Robson et al. (1988).

Object based surveys of innovation offer some clear advantages over traditional approaches and have generated some important and enduring results. Archibugi and Pianta (1996) note advantages in the capacity to review changing innovations over time, analyse the role of science and technology in successful innovations, and study the economic value of innovations. Innovation data from object based studies facilitates analyses of firm characteristics, and the location and origins of important innovations. Such data also enables analysis of innovations in relation to traditional economic data sources, such as production or employment data. Within the innovation studies literature, Keith Pavitt is one of the most influential scholars for pioneering an object approach. Pavitt’s seminal 1984 paper, based on analysis of the SPRU database (Pavitt,

1984), presents a comprehensive taxonomy of technology and innovation that has retained relevance and influence despite the emergence of new measurement approaches.

Pavitt's work develops a classification based on the different modes, sources and activities of innovation, and moves beyond the traditional classifications based on R&D activity and expenditure. This paper, and a later study by Robson et al. (1989) reveal two major findings: firstly that the nature of innovation and inputs to innovation differ substantially across industry, and secondly, the importance of inter-sectoral flows of technology and innovation, represented in Pavitt's *taxonomy of innovation* (Pavitt, 1984; Robson et al., 1989; Smith, 2005). Pavitt's taxonomy groups firms into four main clusters based on technological innovations (Pavitt, 1984; Robson et al., 1989; Smith, 2005):

#### ***Supplier based firms***

These are firms in traditional industries such as textiles and furniture manufacturing. Most technological innovation is acquired and embodied in equipment and machinery, so links with suppliers are important. Much innovation within these sectors relates to tacit knowledge (learning by doing or using) based improvements in processes, that influence innovations upstream with equipment suppliers.

#### ***Specialised suppliers***

These are firms in sectors that produce capital goods and equipment. They interact closely with customers downstream, which are a key source of innovations (e.g. mechanical engineering departments in customer organisations), though R&D and technological knowledge also influence innovations.

#### ***Science based industries***

These are industries that emerge from new developments in scientific knowledge, such as biotechnology and pharmaceuticals, or microelectronics, chemicals and aerospace. These industries have close links with universities, and high level in-house R&D capabilities that source much codified knowledge and innovation.

### *Scale intensive industries*

Industries involved in mass production, such as the automobile industry. Firms in these industries have large R&D departments that source much process innovation, while innovations also come from suppliers of components and intermediate input goods.

Despite making important contributions, object based approaches suffer a significant limitation in terms of bias of the sampling approach and method. In general the selection process means that only highly innovative firms are studied, often at the expense of incremental innovations, and product innovations over process innovations (which are not as frequently reported in trade journals). This is a problem because theory and research suggests that it is via incremental innovations and diffusion of innovations throughout the economy that economic value is realised (often via ongoing and continual phases of incremental change, adaption and improvement) (Verspagen, 2005). Smith (1998; 2002) argues that these limitations present a key constraint to policy use and understanding, because mainstream economic theory and policy applies to economy-wide firm populations, while object approaches are limited to sub-populations of innovative firms.

This critique also extends to traditional measurement approaches. Patenting is an innovation activity, thus patent data only applies to firms already pursuing inventive innovation strategies that involve the appropriation of innovations through intellectual property protection. R&D statistics are compiled for firms that are known to be undertaking R&D – thus already innovating based on creative R&D strategies.

Measurement efforts and empirical evidence to this point in time are limited by restriction to specific samples of firms that are innovative in particular ways, and neglect firms that are innovative via other methods (for example, by adopting or adapting innovations), and non-innovative firms. Thus a need for broader economy-wide understanding led to the emergence of new ‘subject’ (firm level) approaches to measurement, while the sectoral diversity of innovation characteristics evidenced in object studies suggested that cross industry, economy-wide studies were possible and justified (Smith, 1998; 2000a).

## **2.2 SUBJECT APPROACHES TO INNOVATION MEASUREMENT AND THEORETICAL UNDERPINNINGS**

Early innovation surveys using the subject approach emerged in the 1980s, and were initially conducted in a relatively disparate and uncoordinated way in countries including Italy, the US, Canada, Germany and the Scandinavian countries (Arundel and O'Brien, 2009; Smith, 2005; 1998; UNU-INTECH, 2004). Results of these studies indicated that it was possible to generate valid and reliable innovation data based on a firm level approach (Smith, 1998), while at around the same time in Europe, interest in developing understanding of innovation was gathering momentum in response to the growing concern with the technology gap between Europe and the US (Smith, 1998; Mytelka and Smith, 2002; 2003).

As was the case with the internationalisation of R&D measurement, the OECD took on the role of coordinating a standardised approach to the collection of innovation statistics. This was influenced by a large regional study of innovation activities in the Scandinavian countries that resulted in an early conceptual framework designed to systematically measure innovation and produce new indicators. The first manual was drafted by Mikael Akerblom and Keith Smith, respectively of the Finland Central Statistical Office and Innovation Studies and Technology Policy Group in Oslo.

Following a series of workshops and conferences on new innovation indicators in the two years from 1989, a standardised conceptual framework and methodology for the collection of innovation statistics was released in 1992; this was the first OECD Oslo Manual, which was to provide the guidelines for subsequent innovation surveys carried out in many countries.

The arrival of the first Oslo Manual also heralded the formalisation of the second major theoretical approach to the understanding of innovation – the so called chain-link model. Developed by Kline and Rosenberg in 1986, the chain-link model underpins the first Oslo Manual and subsequent innovation surveys and indicators based on the manual, which are the focus of this thesis. Consequently, the chain-link theory is

discussed prior to exploring the evolution of the Oslo framework and corresponding innovation surveys taking a subject approach.

### 2.2.1 THE CHAIN LINK MODEL

The ‘chain-link’ model presented the first major alternative to the linear theory of innovation. Strongly aligned with thinking in Nelson and Winter’s evolutionary growth theory (Nelson and Winter, 1982), the first incarnation of the model appeared in a Stanford university report by Dr Stephen Kline in 1985 (Mahdjoubi, 1997). The refined version, that was to diffuse and become a widely accepted theory of innovation, was first presented in 1986 by Kline and Rosenberg in their influential article ‘An overview of innovation’ (Kline & Rosenberg, 1986). The theory essentially rests on rejection of innovation as a linear process, insofar as innovation that is conceptualised as a set of chronological or sequential and discrete steps, and this is consistent with evolutionary theory’s rejection of the neoclassical static or steady state and equilibrium driven views of growth.

One key advance in the chain-link approach is that it dispels notions of innovation and diffusion as distinct phenomena. Thus, by explanation, innovation and diffusion are interlinked and often indistinguishable. As innovation diffuses throughout an economy, further innovations are made. Incremental improvements and adaptations are implemented as new technologies disseminate throughout new economic and geographical environments; diffusion is also innovation (Mytelka and Smith, 2002). This implies a need to measure and produce indicators for diffusion based modes of innovation.

This notion is particularly relevant to the elevated role of design under the new chain-link theory, and also relates to product and process life cycle theories in the sense that during periods of instability when new products, processes and markets develop, technical specifications, functions and designs are developed and improved on, until a dominant design shapes market path and growth phases (Teece, 1986). Innovation occurs continuously during phases of diffusion, and the implication is that indicators need to capture this.



to be undertaken in a problem solving capacity only where required at various stages in a process of getting an innovation to market. The second implication of this relates to the view of knowledge, which does not necessarily originate from an R&D process, but that can be generated from understanding of market needs, or tacitly throughout iterative phases of design, testing, distributing and marketing noted above. Knowledge generated from these processes can feed back into R&D efforts. Thus an emphasis on interactive learning processes and knowledge flows is a key point of difference in the chain-link model that has shaped current conceptions of knowledge – knowledge is interactive and systemic, it can flow from science and research (a science-push view) or from market and innovation processes back to science and research (a demand-pull view). This advance is relevant for both the production and interpretation of innovation indicators, which need to capture design activities, market elements and interactive knowledge flows.

In addition, it is more often the case than not, that research does not feature in the innovation process. Consequently, there is a much greater emphasis on non-R&D activities within the chain-link view of the innovation process, and the need for measurement to capture these. Such activities derive largely from Frascati Manual definitions of what is *not* defined as R&D (such as design, acquisition of machinery and equipment, acquisition of know-how in licences and patents, design, marketing research) (OECD, 2002). Arundel and Smith (forthcoming) suggest that because the Frascati Manual viewed these *non-R&D* innovation activities as supplementary to R&D, a lasting ambiguity was created in the definition of innovation; that the chain-link approach could equally be interpreted as applying to R&D or non-R&D performing firms. As the chain-link view in turn influenced the definitional framework for subject approaches prescribed in the OECD Oslo Manual (OECD, 1992), this point is important to the development and interpretation of related definitions and indicators covered in the ensuing discussion.

In the chain-link approach, the innovation process is design centric. The primary determinants of an innovation process relate to the market opportunities that present to a firm and its available stock of knowledge and technological capabilities, and innovation indicators need to reflect both. The whole process as defined above is an iterative and



continuous one, and a certain level of uncertainty is present at each stage. Phases of design shape the cycles of creative destruction and improvement, and relate to product and process life cycles.

A final point to emphasise about the chain-link model regards its influence on the view of knowledge as interactive, systemic, and subject to ongoing cumulative improvement and expansion via feedback loops within various stages of the innovation process. This notion has been cemented in academia and policy circles since the chain-link model, and was instrumental in the theoretical evolution towards understanding innovation as a systemic phenomenon. This theoretical development is explored further following discussion of the OECD conceptual framework for survey measurement, and the correspondent development of innovation surveys.

## 2.2.2 THE CO-EVOLUTION OF THE OSLO MANUAL CONCEPTUAL FRAMEWORK AND THE EUROPEAN COMMUNITY INNOVATION SURVEY

This next section reviews the evolution of subject approaches to innovation measurement. The discussion focuses on the structure and content of the OECD standard conceptual framework for innovation measurement. It considers changes to two revisions of the Oslo Manual, corresponding developments in early innovation surveys, and the concomitant evolution of a new theoretical approach to understanding innovation as a systemic phenomenon. This importantly provides the background for the following section's review of the nature and format of survey results and outputs, and the value of innovation indicators. This is followed by a section exploring limitations and developments of early survey based approaches and indicators, which provides part of the research rationale, before considering recent work using new survey data. This thesis is concerned with the history and evolution of new forms of innovation measurement, and primarily in terms of innovation surveys and indicators. As the European Community Innovation Survey (CIS) is the largest, most developed, ongoing cross-country survey, this provides the focus for discussion.

### ***2.2.2.1 Objectives and advances of the Oslo Manual***

The first Oslo Manual emerged from a widespread need to understand innovation and technological development beyond the limited picture afforded by traditional patent and R&D statistics, and a particular need for new indicators with consistency and cross-country comparability for research and policy development in Europe (Mairesse and Mohnen, 2010). There was also a need for firm level data with the capacity to be linked and analysed alongside conventional sources of economic data on employment and output for studies of economic growth (Arundel and Smith, forthcoming; Smith, 2000a; Archibugi and Pianta, 1996).

There are some notable features of the first Oslo Manual with regard to the content of early innovation surveys which are characteristic of the state of theory and measurement at the time of its release. Firstly, the Oslo Manual represented a theoretical shift away from a strictly linear view of innovation, as the chain-link model of innovation influenced its construction. The manual describes the innovation process as the interaction between market, scientific and technological opportunities, firm capabilities, and firm strategies. Moreover, the manual defines three main options available to firms that intend to innovate (STEP, 2000; OECD, 1992):

- Strategic – including decisions about market opportunities.
- R&D – including decisions about undertaking basic or applied R&D, or purchasing R&D.
- Non-R&D – Other activities involved in innovation, including organisational marketing activities, purchasing of embodied technology in equipment, or disembodied technology in know-how such as licences, patents, skills, consultancies.

Though the 1992 manual specifically details Kline and Rosenberg's chain-link theory, it does not prescribe it as a 'definitive' model, rather presents it as a best fit for capturing the dynamic complexity of the innovation process as it was understood at the time (OECD, 1992).

In terms of the methodological approach, the first Oslo Manual was designed to provide guidelines for surveys of the business enterprise sector in the manufacturing industry, and did not include other industry sectors such as services. Nor did the manual provide any provision for measurement outside of the business enterprise sector (i.e. the public research, university and government sectors). Although the first manual describes the object approach, it only provides guidelines for innovation survey measurement using a subject approach, and is limited in scope to the measurement of technological innovation in the manufacturing sector, defined as follows:

Technological innovations comprise new products and processes and significant technological changes of products and processes. An innovation has been implemented if it has been introduced on the market (product innovation) or used within a production process (process innovation). Innovations therefore involve a series of scientific, technological, organisational, financial and commercial activities. (OECD 1992, p.27).

The manual for the first time dealt systematically with some key definitional issues regarding innovation, in particular the definition of ‘new’ or ‘novel’ in a way that was meaningful and commensurable across different firms and sectors of the economy (Smith, 2005). ‘Product innovations’ were classified as either *major innovations*, representing significantly *new* products, or *incremental innovations*, representing significant *improvements* to products.

The distinction between ‘new or significantly improved’ and simple ‘product differentiation’ is explained as changes in performance characteristics and functional attributes for the former, in contrast to the latter which applies to minor technical or aesthetic modifications that ‘do not significantly affect the performance, properties, cost or use of materials and components in a product’ (OECD 1992, p.30). The minimum threshold for classification as ‘new’ is that a product needs to be at least new to the firm to be defined as innovation.

However, Arundel and Smith, (forthcoming) also note that definitions in the first Oslo Manual did not dispel ambiguity between R&D and non-R&D activities created in the

Frascati Manual (OECD, 2002), continuing the view of innovation as a supplementary activity to R&D, which influenced enduring use and interpretation of R&D and innovation survey indicators for some time.

#### ***2.2.2.2 Topics for measurement and new measures: inputs and outputs***

The 1992 Oslo Manual flags a number of core issues for survey based investigation, including corporate strategies, the role of diffusion, sources of, and obstacles to innovation, innovation inputs and outputs, and the role of public policy in innovation activities. Each issue informs specific recommendations on aspects of the innovation process to measure via sets of recommended survey questions. Overall, the main objectives of survey measurement prescribed in the first Oslo Manual – and assumed in many early innovation surveys – are to distinguish between innovative and non-innovative firms; identify characteristics of innovative firms, innovative activities and outcomes; and to improve understanding of how and why firms innovate and the effects of innovation (OECD, 1992; UNU-INTECH, 2004; Salazar and Holbrook, 2004; Arundel, 2007; Mairesse and Mohnen, 2010).

The provision of new innovation input and output measures in the Oslo Manual represented a key departure from traditional indicators and a significant evolution in conventional measurement (Smith, 1998; OECD, 1992). The output indicator is premised on a need to understand the effects of innovation at the firm level, and as Smith (1992; 1998; 2005) notes, the basis for the indicator resides in the assumption that most firms are aware of the level of change in product mixes. Thus innovation output is firstly measured as the reported introduction of new and significantly improved products (and processes) during the survey reference period (and firms can be asked to report the number of product innovations), and secondly by the reported share of total sales deriving from different categories of innovative products. The resulting output indicators provide a firm level measure of the rate of technological innovation and change, and the economic significance for the firm. Smith (1998) notes that these indicators were previously tested in a 1987 Italian innovation survey and provided acceptably reliable results.

In terms of the prescribed measure of innovation inputs, this is based firstly on firm estimates of total expenditure on all innovation activities, and secondly on estimates of the percentage distribution of total expenditure between a discrete number of categories of activity. The intention of this approach was to determine levels and patterns in the distribution of investment in innovation that could be linked to output and other innovation characteristics of firms. The rationale for the input question originated in the 1967 Steacie report by the US Department of Commerce (cited in UNU-INTECH, 2004), which showed that R&D expenditures only accounted for a small share of total innovation expenditures (5 to 10%), and the specific categories of innovation activity detailed closely match those in Kline and Rosenberg (1986, cited in Smith, 2005) and also those non-R&D 'related scientific activities' defined in the Frascati Manual (OECD, 2002).

#### ***2.2.2.3 The European Community Innovation Survey (CIS)***

Following the release of the Oslo Manual in 1992, the European Commission coordinated a major pilot study through the European statistical agency Eurostat. The study covered a sample of approximately 40,000 firms across thirteen European countries, and constituted the first incarnation of the European Community Innovation Survey (CIS) (UNU-INTECH, 2004; Smith, 2005; 1998; Archibugi and Pianta, 1996). The CIS represented the first large scale, cross-country, firm level innovation survey harmonized in accord with the Oslo framework.

To date the CIS is the largest innovation survey of its kind, conducted bi-annually, currently in its eighth iteration and consisting of around 196,000 responding firms in the most recent survey (Arundel and Smith, forthcoming). As the most developed survey, with the widest scope and longest history, the CIS is the leader in the field of innovation surveys, thus provides the main model on which to base discussion of subject approaches, and the focus for discussion in this thesis.

The CIS1 covered innovation activities in the 3 year survey reference period 1990-1992. The content of the CIS1 was closely aligned with the Oslo Manual, with the survey including questions on the following topics:

- General information on the enterprise structure (whether part of an enterprise group, the industry of main commercial activity).
- Innovation status – whether the firm had introduced any technologically changed products and processes over the reference period.
- Sources of information for innovation activities (internal or external sources).
- Objectives of innovation (such as extending product range, creating new markets, lowering costs).
- Acquisition and transfer of technology (purchase of R&D, knowledge and licences, consultancies, hiring of skilled employees).
- R&D activity (nature of R&D – product or process, internal or external, expenditure on R&D, R&D cooperation).
- Factors hampering innovation (cost, risk, economics).
- Costs of innovation (expenditure on particular activities).
- Impact of innovation activities (on share of turnover from products based on different stages of the product life cycle, and shares of turnover deriving from incremental verses significantly changed products).
- Appropriation methods (e.g. use of patents etc.).
- Technology transfer (inward and outward).

Though a key objective of the first CIS was to generate internationally consistent and comparable innovation data across the participant countries, the reality was that the first country based results were not directly comparable due to differences in approach taken by some countries (EIMS, 1995). The main differences were in survey content and definitions (due to some countries adjusting questions), survey frames, harmonisation of sampling methods and varying levels of non response which were much higher for some countries (EIMS, 1995).

Despite the limitations of the first CIS it generated a number of positive results. The resultant data was still relatively robust and spurred a number of early empirical studies analysing patterns of innovation, productivity and competitiveness in participant countries (EIMS, 1995). As the CIS1 functioned as a pilot study, results also fed into an improved design for the second iteration undertaken in 1996, which covered the reference period 1994 to 1996 and included 15 of the 25 EU member States as well as Norway, Romania, and the Russian Federation. Many of the coordination issues were improved on for CIS2 and CIS3, with a harmonised survey methodology carried out under gentleman's agreement between the European commission and participant countries, and the number of firms in the sample increased to 64,000 (Eurostat, 2010).

#### ***2.2.2.4 Changes to the Oslo Manual and Community Innovation Surveys over time***

Following the wave of research utilising data from CIS1 and CIS2, and reviews of the CIS such as those by Arundel et al. (1998) and more formal Eurostat reviews (EIMS, 1995), revisions were made to the Oslo Manual, and the second edition was released in 1997. The major change to the 1997 edition involved an expanded survey scope to include service sectors. This was largely driven by increasing interest in the role of services in innovation and growth. In the advanced western economies the share of services in total value added, output and employment had demonstrated dramatic increases in the preceding decade (in contrast to correspondent decreases in the manufacturing sectors as production shifted to developing economies), which had stimulated increasing interest in the role of knowledge intensive services sectors, and spurred the concept of knowledge-based economy (OECD, 1996; cited in OECD, 1997).

The second Oslo Manual recommends expanding survey sector coverage to include construction, utilities, and marketed services sectors, and definitions and concepts within the manual are updated accordingly, while there is additional detail on theory and related survey topics. A notable content change in the 1997 manual includes reference to the 'systems' view of innovation and more specifically the National Systems of Innovation (NSI) model in discussion of the economics of innovation (OECD, 1997, p.17). The systems view of innovation also features in the amended conceptual

framework section, which includes a map of the innovation policy terrain with an implicit assumption of a national innovation system (OECD, 1997, p.19; STEP, 2000, p.16), defining the following four core elements:

- Framework conditions – “the general conditions and institutions which set the range of opportunities for innovation”.
- Transfer factors – “Human, social and cultural factors influencing information transmission to firms and learning by them”.
- Innovation dynamo – “Dynamic factors shaping innovation in firms”.
- Science and engineering base – “Science and technology institutions underpinning the innovation dynamo”.

This marked change in the underpinning theoretical approach to defining and measuring innovation is reflective of wider advances in theoretical thinking, though had no real impact on remaining manual content with regards suggested questions. The systems approach is discussed further towards the end of this section.

The third CIS was run in 2000, and covered the survey reference period 1998-2000, including further expansion in sector coverage and including all 25 EU member states as well as Iceland, Norway, Turkey and Romania. There were some key methodological differences in the CIS3, including a lower target population cut off at 10 employees (compared to 20 employees in CIS2), a changed definition of innovation that removed the term ‘technological’ in survey question wording (due to inclusion of service sectors), and greater number of questions (Eurostat, 2012). The CIS3 also featured a greater level of cross-country standardisation in the survey methodology and questionnaire format due to statistical agencies or ministries taking responsibility for the survey administration (Tsipouri, 2007).

Another key development with CIS3 was that Eurostat collected and aggregated country microdata in accordance to the European Commission Regulation 831/2002 (Eurostat, 2010), with the aim of providing survey microdata access to analysts, policy makers and scholars for research and analysis. Though many previous studies had established



positive relationships between R&D, patenting activity, and growth in output and trade (at firm, industry and country level), there was still a significant gap in the understanding of precisely how innovation impacted on growth (Smith, 2005), and a key advantage offered by firm level data was the potential for directly studying the nature and mechanics of relationships between firm level innovation strategies, investments, activities and growth.

Despite an increasing trend towards greater harmonisation that culminated in the 2002 legislative mandate, some methodological differences in sector coverage, reference period length and sample coverage between participant countries in the CIS remained. The fourth CIS was undertaken in 2004 (and 2005 in some countries), covering the period 2002-2004. For the first time the survey was conducted under European Commission Regulation No 1450/2004, implementing Decision No 1608/2003/EC of the European Parliament and of the Council and providing the Commission regulation on innovation statistics, making the standardisation of collection compulsory. Thus the level of methodological standardisation was much better than for previous iterations. The CIS4 questionnaire was much shorter than CIS3, and included short pilot questions on organisational and marketing innovations.

The third and most recent version of the Oslo Manual was released in 2005 following CIS4. The major change in the 2005 Oslo Manual involves a widening of the definition of innovation to include organisational and marketing innovations, and the recommendation to incorporate related questions in the scope of future surveys. The manual is much longer and more detailed in all sections than previous editions. The theoretical approach to defining the conceptual measurement framework had also evolved. The manual 'represents an integration of insights from various firm-based theories of innovation with those of approaches that view innovation as a system', (OECD, 2005, p.33) and specifically defined four elements in the framework:

- Innovation in the firm.
- Linkages with other firms and public research institutions.
- The institutional framework in which firms operate.

- The role of demand.

Other notable differences to previous versions relate to the inclusion of theoretical references to regional and sectoral dimensions of the innovation process, as well as a greater emphasis on the role of knowledge, interactive learning, linkages and diffusion, reflecting wider developments in the field and heralding the permeation of a systems approach to thinking and measurement, which is discussed further in the following section.

### 2.2.3 THE EVOLUTION OF INNOVATION SURVEYS IN OTHER COUNTRIES INCLUDING AUSTRALIA

Over this period following the first CIS in 1992, through to the fourth CIS in 2004 and subsequent release of the third Oslo Manual, a number of other countries were active in conducting innovation surveys. The most thorough account is provided in the report by UNU-INTECH (2004). Covering the history of innovation survey development in both emerging and developed economies from the 1990s, and variations in methodology, survey content and frequency over the period, the report notes that 51 countries undertook innovation surveys over this period, which consisted of 30 OECD or developed countries and 21 non-OECD or developing countries. Of those, 33 countries conducted follow up surveys; 23 OECD and 10 non-OECD countries (UNU-INTECH, 2004).

Canada was a leading country in the development and implementation of innovation surveys over the same period, implementing the first innovation survey of manufacturing firms in 1993, an innovation survey of the communications, financial services, and technical business services industries in 1996, and a 1999 innovation survey that included the construction and related industries, and selected natural resource industries (Schaan and Nemes, 2002). Over this time the USA and Japan were not active in undertaking surveys based on the Oslo framework, and Godin (2002) argues that this was due to their dominance and leadership in innovation over an extended period, noted in the OECD ‘technology gap’ reports, which meant the need for new types of survey data was less pressing than for policy makers elsewhere.

Following pilots in 1993, in Australia the first innovation surveys drawing on the Oslo framework were covered the 1993-94 period. Separate surveys were conducted for manufacturing and non-manufacturing industries, and a survey of 5800 firms in the industrial sector was undertaken for 1996-7 (UNU-INTECH, 2004; Guellec and Pattison, 2001). The first integrated, economy-wide innovation survey was run in 2003. There have been four subsequent iterations, once in 2005, and again in 2006-7, 2008-9, and 2010-11. Despite close alignment of Australian surveys with the Oslo framework, a number of methodological and content differences exist compared with the CIS.

The systems view of innovation had a clear influence on the conceptual frameworks prescribed in the 1997 and 2005 iterations of the Oslo Manual, though its influence on the range of survey questions and output is not as obvious from the discussion so far. As noted at the beginning of section 2.1, for the purpose of this thesis, the ‘innovation systems’ model is considered the third major theoretical approach underlying historical developments in innovation measurement, thus before further consideration of the outputs, results and contributions of innovation surveys and indicators, the origins, content and advantages of this theoretical approach warrant clarification.

#### 2.2.4 INNOVATION SYSTEMS THEORY

The discussion above noted the influence of a systems view of innovation on new forms of measurement through the revised conceptual framework in the 1997 Oslo Manual, and a more significant presence in the 2005 version. This reflected a broader trend by scholars and policy makers towards adoption of the third major theoretical approach to understanding innovation - the innovation systems approach – which materialised in the late 1980s and begun to widely diffuse in academic and policy circles from the early 1990s. Because of its central role in shaping conceptual measurement frameworks, the systems approach underpins the development and interpretation of many new innovation survey indicators, so is discussed here to provide the theoretical background for the ensuing chapters.

Systems thinking was gaining popularity with various innovation scholars during the 1980s (Mytelka and Smith, 2003; Smith, 2000), and though Lundvall et al. (2002) credit

Lundvall (1985) with introducing the ‘innovation system’ concept, the literature generally acknowledges Christopher Freeman’s work (Freeman, 1987) as first establishing a national ‘innovation systems’ concept and approach (Godinho et al., 2004; Edquist, 2005). In publications based on his study of the Japanese system, Freeman (1987) introduced the concept of a ‘national system of innovation’, which was described as the “network of institutions in the public and private sectors whose activities and interactions initiate, import and diffuse new technologies” (Freeman, 1987, cited in Edquist, 2005, p.183). However both Edquist (2005), and Mytelka and Smith (2003) note two key books in the early 1990s that signalled the broader arrival of systems theory as *National Systems of Innovation: towards a Theory of Interactive Learning* (Lundvall, 1992) and *National Innovation Systems: A Comparative analysis* (Nelson, 1993).

Various authors note the rapid rate of adoption and diffusion of the systems approach throughout the academic and international policy community (Edquist, 2005, Mytelka and Smith, 2003; Edquist and McKelvey, 2000, cited in Manley, 2002). The approach featured in the context of innovation policy discussions in the 1992 OECD report *Technology and the Economy: the Key Relationships*, and Mytelka and Smith (2003) emphasise its diffusion and culmination via subsequent OECD reports covering productivity, learning and employment including *National Innovation Systems* (OECD, 1997a) and *Managing Innovation Systems* (OECD, 1999).

Systems theory is premised on the idea that factors outside the individual strategies of the firm affect a firm’s innovation decisions, capacity and performances (Smith, 2000; Mytelka and Smith, 2003). Systems thinking germinated in empirical work indicating that most innovating firms collaborated, often with suppliers or customers, and that much technological innovation occurred as a result of interactive learning via firm user-producer-customer interactions and collaboration (Smith, 2000). As understanding of the innovation process came to incorporate interactive knowledge generation and non-R&D based inputs, the systems approach evolved to encompass the set of innovation based interactions that were wider than simply firm to firm. Systems consist of networks of firms, but also much broader sets of organisations and institutions. In terms

of indicators, this development suggests that collaboration, interaction and knowledge diffusion should be captured.

The concept of innovation as a systemic phenomenon rests on the idea that innovation – the introduction of new goods, services, production processes, organisational and marketing methods – occurs not in isolation, but in the context of a collection of organisations and institutions, which are usually specific at least in some respect to the boundaries defined at a country level - thus the common reference to a ‘national innovation system’. It is these organisations and institutions that constitute the environment in which the firm operates *and impact on firm level innovation* by providing the ‘framework conditions’ described in the most recent two editions of the Oslo Manual (OECD, 1997; 2005). Different countries have very different economic structures, legal systems, tax and trade policies, and cultural and political environments – some key elements comprising the system environment, and which provide the conditions that influence a firm’s capacity to innovate. Indicators need to reflect these differences.

Thus the systems approach represents an evolution in theory from the chain-link model, insofar as it extends the context for interactive learning from the direct firm level set of interactions within the innovation process to the wider environment in which the firm innovates (Mytelka and Smith, 2003). This implies that the interactive and cumulative nature of knowledge is not confined to flows and feedback loops within various phases of the innovation process defined in the chain-link framework, but involves two way knowledge flows between the firm and the relevant elements or actors in the system environment in which the firm operates, so has direct implications for innovation measurement.

An *innovation system* thus represents the environment in which firms, organisations and institutions interact to produce, apply and diffuse knowledge, technology and innovation. Thus the systems model is commonly conceptualised and defined as a set of components (firms, organisations, institutions), and their interactions. Much of the literature discusses differences in definitions, and system elements, and there still lacks consensus in terms of specific details in this regard (Edquist, 2005). The key point to

draw from these discussions is that selected system elements can depend on the needs of analysis or discussion. Though this is vague in terms of measurement, which requires more precise guidelines to produce consistent, reliable and valid indicators, there are direct implications for how new innovation surveys might capture characteristics of an innovation system.

There is a need to measure knowledge flows between actors in a system, and a need to understand how firms innovate in terms of the interactions with various elements in the system. Many attempts to measure and compare entire innovation systems have begun to emerge more recently (Godinho et al., 2004). It is not the task of this thesis to review these efforts, moreover to understand some implications for developing or interpreting new survey indicators. In respect to the trend towards systems thinking this concerns how innovation survey indicators can contribute to a systemic understanding of innovation. The practical implication is that indicators should be presented at a ‘system’ level, whatever that may be.

Though there is some debate in the literature regarding whether the innovations systems approach constitutes a specific theory (Edquist, 2005), it is the view of this dissertation that the approach provides the third major theoretical paradigm underlying developments in innovation measurement. The dominance of the systems approach in academic and policy thinking is plainly evident from a brief overview of the literature; and for improving understanding through new indicators, the dominant underlying approach is the systems view of innovation.

## 2.2.5 KEY RESULTS FROM NEW APPROACHES TO MEASURING INNOVATION

The previous sections considered how new innovation surveys using a ‘subject approach’ evolved from theories of economic growth, and gaps in traditional science and technology based indicators. So far the discussion has covered historical development of the standard OECD conceptual framework for new measures, and broad changes in correspondent survey methodologies, content, and underpinning theoretical approaches, though has yet to explore the specific nature and format of results and

outputs. In what tangible formats do new surveys manifest and how have they contributed to understanding innovation?

Addressing these questions plays an important part of establishing the current state of innovation indicators, and uncovering the problems and issues that provide the rationale for this study. This task is approached here by considering two key avenues for exploiting innovation survey data to improve understanding: generating innovation indicators and conducting econometric analysis. This thesis is concerned with the former. However both aspects of measurement are central to the contributions of subject approaches to date, and typically feature in different types of output publication. The results of econometric studies inform the development and selection of indicators, so here we consider both approaches before exploring the main output publications and some key contributions to knowledge on innovation.

#### ***2.2.5.1 Innovation surveys, indicators and econometric studies***

As the CIS was adopted by a greater number of countries, it became more formalised, with national statistical agencies assuming responsibility for survey coordination in many cases. This necessarily meant greater restrictions to microdata, which is required for statistical analysis. Thus although the CIS was originally designed to produce a new data resource for econometric analyses, the main objective for conducting large-scale surveys has shifted to the production of innovation indicators (Mairesse and Mohnen, 2010).

Innovation indicators generally consist of descriptive statistics generated from survey data, often standardised by classification variables for comparing different groups. The terms ‘indicator’ or ‘statistic’ are often used synonymously in reference to innovation indicators. The most common examples are the firm level innovation frequency or rate indicators, such as the share of innovative firms in a firm population, or the share of product innovators. Other indicators aggregate or weight results by economic variables such as employment (Arundel and Mohnen, 2003). Innovation survey indicators can be classed in three broad categories: simple, complex, and composite indicators.

Simple indicators are calculated using responses to single survey questions. An example indicator is the number of employees that received training for implementing innovations. Complex indicators combine responses to two or more survey questions. An example is the number of product innovators with collaboration and R&D activity. Thirdly, composite indicators or indices are those single measures that combine results from multiple individual indicators into one summary measure. Common examples using economic data include stock indices or a consumer price index. Using innovation survey data the most common example is the summary innovation index featured in the European scoreboard publications (though these also draw on indicators from other sources).

An advantage of innovation indicators is they can quickly depict a picture of the prevalence of different activities and outputs in firm populations of interest (Arundel and Mohnen, 2003). Indicators are of growing interest for policy makers because of the need to better understand innovation and a general trend towards evidence-based policy making (Pedersen, 2007; Veuglers, 2007; Finnbjornsson, 2008). Indicators have policy value because they enable benchmarking and comparisons of performance on particular dimensions of innovation (Mairesse and Mohnen, 2010). The quality of innovation indicators is largely determined by the quality of contributing questions on innovation surveys. These have evolved over time with the Oslo Manual, the CIS, progressive survey results and user feedback, and are the topic of further discussion in the following sections.

Econometric analyses involve a set of more sophisticated analytical techniques that can reveal the nature of relationships between different variables on innovation surveys. Econometric methods offer two major advantages, they control for possible confounding factors that may lead to incorrect interpretation of indicators and observed patterns of innovation, and can simplify analysis when multiple variables are involved (Arundel and Mohnen, 2003). By establishing correlations and causal relationships (if there is panel data), econometric methods are the main method for progressing empirical understanding of innovation determinants and effects. Econometric analyses are dependent on the nature of the underlying survey data and quality of indicators, and the results are more geared toward scholarly audiences.



These two key approaches to exploiting innovation survey data generally feature in different categories of the output literature. This literature incorporates key contributions of subject approaches to knowledge on innovation, and is discussed here to provide important background for this study, by providing an understanding of where gaps lie that new indicators can help to fill, but also key stylised facts that help to inform indicator development.

#### ***2.2.5.2 Key categories of literature featuring analyses of innovation survey data and indicators***

Smith (2005, p.167) overviews three main categories of literature, featuring results, indicators and analyses deriving from the European Community Innovation Surveys (CIS) up to the release of the third Oslo Manual that focus the discussion here: Descriptive overviews of results at a national level, analytical research sponsored by the European Commission (EC), and empirical scholarly studies. The former two predominantly feature indicators, while the latter category typically focuses on econometric methods.

For the first category, there are the main reports generated by the official statistical agencies responsible for running surveys. In general these produce sets of simple indicators at a national level that correspond to the key topics prescribed in the Oslo Manual and noted in Section 2.2.2.2. This includes reports such as the annual *Science, Technology and Innovation in Europe* publication series by Eurostat (Eurostat, 2011) featuring CIS data from the 2005 edition onwards (Eurostat, 2005), in Canada the survey of innovation related publications from Statistics Canada (Statistics Canada, 2002; Uhrbach, 2009), and in Australia the *Innovation in Australian Business* publications from the Australian Bureau of Statistics (ABS, 1995; 1998; 1998a; 2003; 2005). These publications provide the primary source of output data from innovation surveys. The main approach of these types of report is to present innovation indicators by industry, firm size, and at the economy-wide level, and to make cross-country comparisons for indicator values. Frequency or rate based indicators, presented by industry, size groups, or all firms are the predominant type featured.

A popular example indicator is the rate of technological (product or process) innovation, frequently used as benchmark indicator. This is commonly defined as the share of firms in a subpopulation that reported either product *or* process innovations over the survey reference period. This measure assumes that on average, for firms pursuing an innovation based competitive strategy, the rate of product or process development, replacement or improvement is commensurate with the survey reference period, so that those firms not introducing any of these changes in the survey period are defined as non-technologically innovative. The length of the reference period for the CIS and many innovation surveys is typically 3 years, which derives from the original Oslo Manual and was prescribed in line with typical manufacturing product commercialisation and process implementation cycles. Consequently, the reference period is central to the definition of innovation. As most other indicators are rate based, for example, the frequency of non-technological (organisational and marketing) innovation, this aspect of the methodology for innovation surveys plays a key part in determining their meaning and comparability. For example, a shorter survey reference period will reduce the frequency of innovation and indicator values, because of the time taken to develop and implement innovations. Other methodological factors that can impact on indicator comparability include survey industry coverage and scope (size of firms), as well as survey questionnaire content and response categories, and statistical processes (sampling, editing, data imputation) (Arundel and O'Brien, 2009).

The primary benchmark indicator in many statistical publications is the rate of innovation, expressed as the percentage share of firms implementing any type of innovation in a given population. This indicator is subject to various limitations that have been discussed in the early measurement related literature. For example, Guellec and Pattison (2001) note that definitions of an 'innovative firm' vary (often due to differing survey reference periods), and related indicators face substantial limitations. For example, firms are sometimes defined as innovative if they reported one of either *technological* innovation or *non-technological* innovation, in other instances if they simply reported other types of innovation activities over the reference period (R&D, patenting, etc.), and in others if they reported one of either technological innovation, non-technological innovation or innovative activities (Guellec and Pattison, 2001). In

addition, firms with abandoned, planned or unfinished innovations and activities are often counted as innovative. Disparities in survey reference periods need to be considered when interpreting differences in the shares of innovative firms across countries (for example, the Australian innovation survey has a one year reference period compared to three for the CIS).

Most of the indicators produced in statistical publications are rate based indicators. For example, indicators for outputs (the rate of product, process, organisational or marketing innovation), and for particular types of input activities, including collaboration and creative and inventive activities (R&D, patenting, design and knowledge acquisition, training for innovation). These rate indicators only represent a binary indicator of the number or share of firms that innovated. This is because innovation surveys generally ask not about *particular* firm innovations, but *any* firm innovations over the reference period, and these are qualified mostly by questions in a yes/no format (the focus is on the innovating ‘subject’ – the firm). Thus data and indicators derived from innovation surveys can be said to represent various innovations and activities across the firm for those firms with multiple innovation projects (Godin, 2002).

This is an important point, because it raises a serious limitation with many indicators that provides much of the rationale for this study. Because such indicators refer to any innovations, they bundle high intensity and low intensity innovations together. There is no differentiation between intensity. For example, a new product may involve years of research and development, tens of millions of dollars in investment, and various failed prototypes before successfully making it to market. On the other hand, an innovation could simply represent the introduction of a significantly upgraded product to market, requiring no R&D, and simply involving technology purchased ‘off the shelf’ (Arundel, 2007). This matter is revisited in later chapters. An important point to note here is that simple, rate based indicators are predominant in statistical publications, and their limitations are substantial.

In the second category of literature, international policy organisations have produced research reports that compare innovation indicators across countries and assess relative

innovation performance in order to inform policy. The European Commission (EC) is responsible for funding a number of analytical research projects that utilise the CIS data to produce more sophisticated results for European countries. A major example of this is through the Pro-Inno Europe initiative of the EC Enterprise and Industry Directorate, and specifically through the Inno-metrics program that has since 2001 produced the annual European Innovation Scoreboard (EIS) publication using CIS data, and the Regional Innovation Scoreboard since 2006<sup>3</sup>. CIS data is used in the construction of country level composite indicators for innovation and technological capabilities such as the EIS Summary Innovation Index, which is used to monitor policy progress (though most EIS indicators are not CIS based). Though indices are useful for reducing multiple indicators to a single measure for comparing relative performances, they entail various implicit limitations, namely due to data availability, methodological and quality differences in the underlying survey data, and subjectivities with weightings of constituent indicators (Archibugi, 2009; Mairesse and Mohnen, 2010). The OECD has also produced various research reports that utilise both CIS data and data from the innovation surveys of other member countries to produce indicators that compare countries, including the bi-ennial ‘Science and Technology and Innovation Scoreboard’ (since 1999) and ‘Science, Technology, and Innovation Outlook’ (since 2002) publications, though in general, assessments in these publications are heavy on traditional indicators (R&D and patents etc.) and light on new survey indicators (Arundel and O’Brien, 2009).

Table 2.1 shows some of the most common or ‘core’ example indicators that feature in some of the statistical publications, websites of statistical agencies, and research reports above. Indicators are grouped by the particular measurement dimensions (for example, inputs, outputs).

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<sup>3</sup> See IUS (2012) for the latest European report, and Hollanders et al. (2009) for the latest regional report.

**Table 2.1 Key published indicators and sources**

Publication Source	Key indicators
Eurostat Website <sup>4</sup>	<p><b>Type of innovation</b></p> <ul style="list-style-type: none"> <li>• Frequency/proportion of firms with implemented, ongoing, or abandoned technological (product or process) innovation</li> <li>• Frequency/proportion of firms with</li> <li>• New to the firm only product innovation</li> <li>• New to the market product innovation</li> <li>• Novel process innovation</li> <li>• Organisational innovation</li> <li>• Marketing innovation</li> <li>• Organisational and/or Marketing innovation</li> </ul> <p><b>Innovation inputs</b></p> <ul style="list-style-type: none"> <li>• Frequency/proportion of firms</li> <li>• Engaged in intramural R&amp;D</li> <li>• Engaged in extramural R&amp;D</li> <li>• Engaged in acquisition of machinery, equipment and software</li> <li>• Engaged in training</li> <li>• Engaged in other preparations</li> <li>• Engaged in innovation activities</li> <li>• Engaged in any cooperation</li> <li>• Engaged in co-operation with <ul style="list-style-type: none"> <li>○ Other enterprises within enterprise group</li> <li>○ Suppliers of equipment, materials, components or software</li> <li>○ Clients or customers</li> <li>○ Competitors or other enterprises of the same sector</li> <li>○ Consultants, commercial labs, or private R&amp;D institutes</li> <li>○ Universities or other higher education institutions</li> <li>○ Government or public research institutes</li> </ul> </li> </ul>
European Innovation Scoreboard (IUS, 2012)	<p><b>Type of innovation</b></p> <ul style="list-style-type: none"> <li>• Proportion of all SMEs with product or process innovations developed in house</li> <li>• Proportion of SMEs with product or process innovation</li> <li>• Proportion of SMEs introducing Organisational and/or Marketing innovation</li> </ul> <p><b>Innovation inputs</b></p> <ul style="list-style-type: none"> <li>• Proportion of SMEs reporting any co-operation activities</li> <li>• Non R&amp;D innovation expenditures</li> </ul> <p><b>Impacts</b></p> <ul style="list-style-type: none"> <li>• Sales from new to market and new to firm product innovations (as a share of turnover)</li> </ul>
Eurostat Science, Technology and Innovation report (Eurostat, 2012)	<p><b>Type of innovation</b></p> <ul style="list-style-type: none"> <li>• Proportion of all firms with any innovation activity (any implemented, ongoing or abandoned product, process, organisational or marketing innovation)</li> <li>• Proportion of enterprises with any implemented, ongoing or abandoned Technological (product and/or process) innovation</li> <li>• Proportion of enterprises with any non-technological (Organisational and/or Marketing) innovation</li> <li>• Proportion of enterprises with any implemented, ongoing or abandoned Technological <i>only</i> innovation</li> <li>• Proportion of enterprises with non-technological (Organisational and/or Marketing) only innovation</li> <li>• Proportion of enterprises with technological and non-technological innovation</li> <li>• Proportion of organisational innovators with a particular type of innovation (three indicators for three types – new business practice, new methods for organising work responsibilities or decision making, new methods of organising external relations)</li> </ul>

<sup>4</sup> <http://epp.eurostat.ec.europa.eu/portal/page/portal/eurostat/home/> (Accessed August 2012)

	<b>Objectives</b> <ul style="list-style-type: none"> <li>Proportion of technological innovators with highly important objectives (nine separate indicators for nine objectives)</li> </ul>
<b>OECD STI Outlook</b> (OECD, 2010)	<b>Type of innovation</b> <ul style="list-style-type: none"> <li>Proportion of all firms with new to market product innovations</li> <li>Proportion of all firms with non-technological (organisational and/or marketing) innovation</li> <li>Proportion of all firms with technological (product and/or process) innovation <i>only</i></li> <li>Proportion of all firms with non-technological (organisational and/or marketing) innovation <i>only</i></li> <li>Proportion of all firms with technological <i>and</i> non-technological innovation</li> </ul> <b>Innovation inputs</b> <ul style="list-style-type: none"> <li>Proportion of all firms collaborating internationally on innovation</li> </ul>

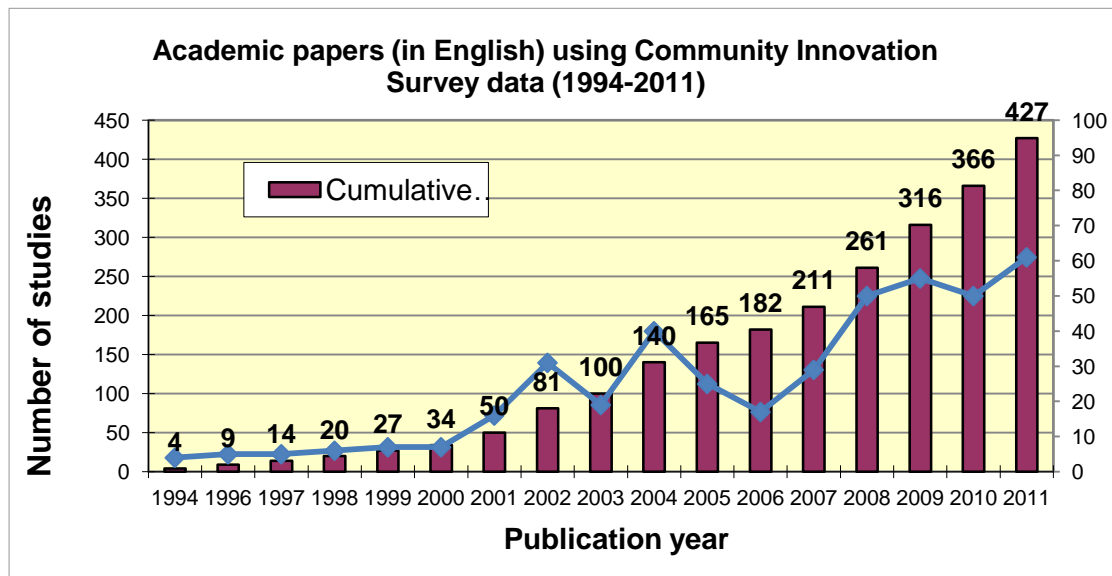
Table 2.1 does not provide an exhaustive list of indicators featured in the relevant sources, but covers the majority in most instances. What is apparent is that the majority of indicators are simple, rate based indicators. The main point here is that these types of indicators are predominant in statistical publications, and they are subject to notable limitations. This matter is revisited in later chapters.

### ***2.2.5.3 Empirical research based on econometric methods***

Scholarly research publications featuring econometric and statistical analyses of innovation survey data and indicators form a large part of the measurement literature, and perhaps the fastest growing category since the introduction of innovation surveys (Smith, 2005; Arundel, 2007). Here, we give brief consideration to this category of literature, because it is the results from this empirical research that influence the development and validation of innovation indicators, as well as theoretical developments that are important for indicator development.

Figure 2.2 shows to 2011, the increasing number of economic papers using CIS data, based on a database from the UNU-MERIT institute. As the CIS has evolved the rate number of studies has been increasing at a higher rate.

**Figure 2.2 Economic papers using EU CIS data**

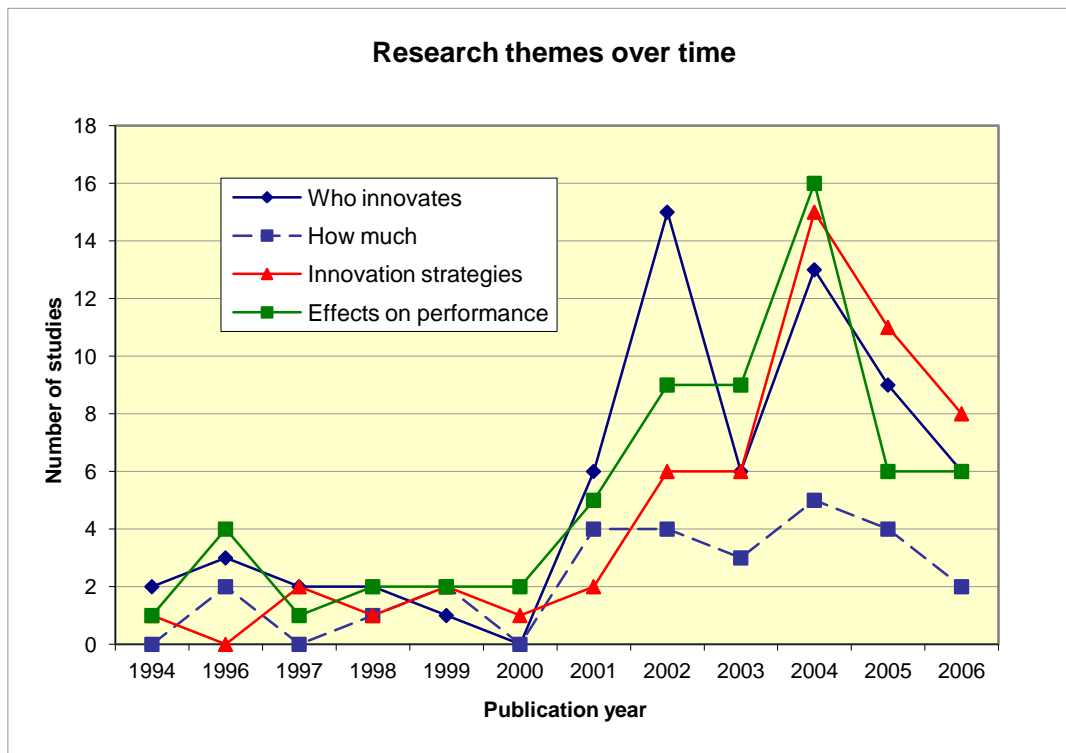


Source: UNU-MERIT

Figure 2.3 shows papers using CIS1 to CIS4 data, classified into four general theme areas. As further data has become available and the number of studies increased, the main research focus has shifted from understanding who innovates, to the effects of innovation on performance, and to innovation strategies.

An in depth review of this substantial volume of empirical literature is not within the scope of this dissertation. Rather, an overview of some of the main related works and findings under each research theme provides a summary of their contribution. This is important as these key findings and resulting stylised facts shape the production and interpretation of many survey indicators, and provide information on what types of indicators are important.

**Figure 2.3 Research themes over time – CIS1-4**



Source: UNU-MERIT

#### *Who innovates/determinants*

In terms of who innovates and how much, studies on the determinants of variety in innovation have focused on the influence of industry sectors, firm size and structures, and location. Such studies have confirmed a positive relationship between firm size and the rate intensity of innovation (Cohen, 1995; Evangelista and Mastrostefano, 2006; Arundel and Mohnen, 2003) though not between size and innovation output in sales from innovative products (Mairesse and Mohnen, 2010). Though econometric studies using CIS data have importantly demonstrated diversity in innovation activities and performance across countries, and within and across industries and firm populations (Evangelista et al., 1998; Mohnen, Mairesse, and Dagenais, 2006; Castelacci, 2003), large unexplained residuals in many of the resulting innovation models also exposed gaps in understanding of specific innovation processes. The results from these studies



suggest that indicators need to be produced at the sector level, and for different firm size ranges.

#### *Innovation strategies (and effect on performance)*

Such findings led to a shifting research focus towards understanding the dynamics of different firm innovation strategies. This typically involved identifying patterns in the mix of innovation input activities (often categorized as R&D and non-R&D based), collaboration methods, innovation outputs in terms of new processes, products and related product sales, and organisational and marketing oriented innovations. Though the positive correlation between R&D activities and innovation output is an important and recurring finding in the earlier empirical literature (Mairesse and Mohnen, 2010; Brouwer and Kleinecht, 1996; Crepon et al., 1998), studies finding significant levels of innovation output unexplained by R&D (Mairesse and Mohnen, 2010) turned attention increasingly to the impact of non-R&D based factors (see for a more recent example Arundel, Bordoy and Kanerva, 2008). Such studies highlight the need for innovation indicators to capture different types of innovation strategy, including both R&D and non-R&D activities and modes of innovating.

A large share of the empirical literature is devoted to exploring the impact of collaboration on innovation, with sectoral structure and technology systems, appropriability levels and spillovers shown to impact on types of collaboration (Cassiman and Veugelers, 2002; Leiponen, 2002), suggesting a need for collaboration indicators to reflect sector and size variables.

#### *Effects of innovation*

Many studies on the effects of innovation attempt to measure the impact of innovation on productivity or sales (Pianta and Vaona, 2006), typically analysing variation in sales ratio's from novel products, or in overall sales and employment as output measures (Mairesse and Mohnen 2010, provide a good discussion). The CDM model by Crepon, Duguet, and Mairesse (1998) provides the most well known and widely used framework for estimating the impact of innovation on productivity. The CDM model uses a three stage approach for analysis: first, innovation activities are modeled against investment

intensities, secondly, investments are modeled against innovation outputs (in innovative sales and patents), and thirdly, innovative outputs are modeled against labor productivity (in terms of sales per employee) (Mairesse and Mohnen, 2007; 2008; 2010; BIS, 2011). The CDM approach has shown that innovation is positively associated with productivity increases (which is not limited to R&D), and has produced robust results across firms, countries, and within industries (Criscuolo, 2009; Mairesse and Mohnen, 2007; 2008; 2010; BIS, 2011). This work has implications for indicator development, as it suggests that innovation activities and investments are important topics.

The burgeoning number and range of outputs and research using new innovation survey data have made many key contributions to understanding innovation processes at the firm level, and surveys offer key advantages over traditional indicators and data sources in their coverage of whole economic populations within sectors, regions and nations (Guellec & Pattison, 2001), and in their potential for international comparability, consistency, and integration with other traditional sources of economic data (e.g. value added, R&D data) (Smith 1998; 2005; Archibugi and Pianta, 1996). At the core of these contributions, are survey indicators, which feature both in statistical publications and as underlying variables in econometric approaches.

The empirical contributions of the many studies and output publications using new approaches to measuring innovation have manifested in a series of stylised facts about innovation, as well as influencing embodied co-evolutions in theoretical approaches. In a number of key publications Smith, (2002; 2002a; 2005; 2006), Mytelka and Smith (2001; 2002; 2003) as well as Guellec and Pattison (2001), Smith and West (2005; 2007), and Archibugi and Pianta (1996), comprehensively detail key stylised facts, many of which new innovation surveys have played a role in confirming. Summaries offered by these authors are synthesized in the points presented below, and form an important part of the discussion regarding the broader contribution of innovation survey based approaches to understanding, to recent theoretical developments, and to the development and interpretation of innovation indicators:

- The rate of innovation is influenced by firm size.

- Innovation impacts on profitability, competitiveness and firm growth.
- Innovation is sectoral, and pervasive across the economy.
- Collaboration is central to innovation processes, and characteristic of its systemic nature.
- Innovation involves interaction with science.
- Innovation strategies are heterogeneous, and involve investments with risk and uncertainty that shape technological capabilities.
- Innovation is a regionally impacted phenomenon.
- Innovation impacts on quantity and quality of employment.

The points above illuminate two distinctive theoretical developments that have co-evolved with innovation surveys. Firstly, the sectoral specificity of innovation processes highlights the need for sector specific approaches to understanding innovation, which has manifested in a Sectoral Innovation Systems (SIS) outgrowth of systems theory. Similarly, the burgeoning empirical evidence regarding regional differences and variations in innovation activity and performance led to the evolution of a Regional Innovation Systems (RIS) approach. Because these developments underpin advances in measuring and understanding innovation, each are now explored further prior to considering the weaknesses of new survey approaches and indicators, and recent work developing new indicators. The SIS approach is more relevant to the indicator focus in this study, so is considered in comparatively more detail.

#### 2.2.6 SECTORAL INNOVATION SYSTEMS

The sectoral innovation systems approach has grown to represent an outgrowth of systems theory, with origins in the rich body of theoretical and empirical literature concerning the dynamics of innovation processes, growth and change within and across particular firms and industry sectors. Key concepts embodied in the SIS approach have

become central to contemporary empirical innovation studies, so are particularly relevant to the discussion regarding new indicators.

Authors such as Dolata (2009) and Malerba (2005) identify origins of the SIS approach in evolutionary theory and the early works of Dosi (1982) and Nelson and Winter (1977), while Malerba (2002; 2005; 2005a) emphasises genesis in Schumpeter's seminal works (*Business cycles* and *Capitalism, socialism and democracy*), in the industrial economics literature, and in a body of studies concerning sectoral technological development, firm and market structural change and growth. Works in these traditions emphasise the role of knowledge and learning processes, appropriability, market structures and demand, and technological regimes, opportunities, and trajectories in sectoral transformation and growth. These concepts provide the building blocks of the SIS approach and have shaped recent attempts to understand sectoral innovation patterns.

Despite some definitional variations in the innovation literature, sectoral innovation systems are generally described in terms of the system of creation, production and sale of a set of related products, and a set of common system elements that include knowledge, technology and learning processes, both firm and non-firm agents or actors, market and non-market interactions, institutions, and demand (Malerba 1999; 2002; 2003; 2005; 2005a).

Malerba (1999, p 4) offers the following definition:

A sectoral system of innovation and production is composed by the set of heterogeneous agents carrying out market and non-market interactions for the generation, adoption and use of (new and established) technologies and for the creation, production and use of (new and established) products that pertain to a sector ("sectoral products").

Additionally, Malerba (2002a) defines sectoral systems in terms of three main components:

- Knowledge and technology

- Actors and networks
- institutions

In order to understand processes of innovation, growth, and transformation in any sector over time, the SIS approach advocates an analysis of the constituent system elements, their interaction and co-evolution. System changes and innovations may be driven by different system elements, and these elements may vary significantly across sectors.

This approach focuses on the role of knowledge and technology underpinning particular product groups, and as with evolutionary theory and broader system theory, knowledge is defined as tacit or codified, though also discussed in terms of equivalent knowledge domains – mainly *scientific or technological* (often codified), and *applied or product-market based* (often tacit – learning by doing or via customer and market feedbacks) (Malerba, 2005). SIS approaches build on the chain-link model and broader systems model in their exposition of knowledge and learning processes, by focusing on sectoral and technological dimensions to learning via an extended set of actors and interactions.

In the SIS literature, knowledge is conceived in terms of ‘accessibility’ – ease of acquisition, and of ‘cumulativeness’ – the extent to which acquisition or development of knowledge depends on existence of prior knowledge (Malerba, 2002; 2005; 2005a). These characteristics affect learning processes for innovation – determining whether knowledge is gained via search (R&D) processes or applied processes (interaction with the market). The knowledge domain, accessibility, and level of cumulativeness determine levels of appropriability and rates and paths of innovation. Collectively these dimensions of knowledge constitute what Nelson and Winter (1982) termed the ‘technological regime’ of a sector, which also determines the organisation of innovation processes and the structure of firms and sectors in terms of organisation and change. As Malerba (2002) notes, sectors where the underlying knowledge domain is mostly scientific and technological with a high level of cumulativeness and low accessibility (requiring well developed capabilities to develop and exploit) are often characterised by high levels of industrial concentration and few large firms. Sectors with high accessibility and low cumulativeness are often characterised by lower appropriability,

high levels of turbulence or churn with many new entrants, as firms can readily imitate innovations (Malerba, 2002; 2003; Klevorick et al., 1995).

Malerba (2002; 2005) likens these two modes of technological regime to Schumpeter's cyclical concepts of 'creative destruction' and 'creative accumulation'. Sectoral change often involves shifting between the two modes as new knowledge leads to introduction of new technologies and products, that through evolutionary processes of selection eventually mature, stabilise and shape industry dynamics and structures (e.g. large incumbent firms either successfully integrate new technologies or are replaced by new entrants). These ideas are evident in Teece's (1986) earlier discussion around firm strategy and appropriability, and the shift between product and process innovation as industry structures stabilise around a 'dominant design'. The obvious implication for innovation indicators is that they must take into account differences across sectors, and capture sectoral changes over time.

Thus the technology regime embodies a second concept that is central to the SIS approach - the level of 'technological opportunity' available to a sector. Technological opportunity reflects the knowledge 'search space' available for solving innovation related problems, as well as the potential return on investment for investing in knowledge (Malerba, 2003; 2005). Thus R&D activity provides a key measure of technological opportunity – high levels of R&D reflect high levels of search activity, which are indicative of the opportunities identified by firms seeking to profit from investing in new knowledge generation. Technology regimes and opportunities shape sectoral technological trajectories – development along the lines of particular sets of technological knowledge and related investments, and which can also lead to technological 'lock-in' when firms invest in and are committed to particular technologies that become superseded and inhibit new development paths; for example, with analogue film replaced by digital storage technologies for cameras, or digital versatile disks and CD-ROM technologies superseding magnetic tape technologies for audio and video. This point is important to this study, as it shapes the interpretation of innovation indicators based on R&D, which reflects firm capabilities for exploring the 'search space'.

As well as concepts related to the *technology regime*, key building blocks of the SIS approach include actors, interactions, institutions and demand. Malerba (2002; 2005) argues that a key advantage of the SIS approach over the industrial economics tradition is the wider focus on non-firm actors and non-market interactions, which provides a means of better understanding differences in sectoral innovation performance across countries (as institutions and non market actors differ across national systems), and a greater capacity for mapping and understanding dynamic changes and transformation of sectors over time. On a practical level this means collaboration measures should capture all types of actor.

The SIS approach is significant for this study as an underlying theoretical approach for new indicators. The main implication is that the sources, inputs, outputs and processes of innovation differ substantially by sector. Firms compete based on product lines incorporating similar knowledge and technology inputs into production processes. Consequently, innovation indicators should be produced at the sector level.

One critique of the SIS approach is the lack of information on the interplay between other types of systems, in particular between sectoral, national and regional systems, and this point draws attention toward the third major extension of systems theory with relevance to innovation measurement: regional innovation systems.

#### 2.2.7 REGIONAL INNOVATION SYSTEMS

The Regional Innovation Systems (RIS) approach to understanding innovation is the third extension of the systems thinking that first appeared in the early 1990s. Several drivers of expanding interest in the RIS approach include increasing competitive pressures faced by regions due to globalisation, interest in successful industrial districts and clusters (such as Silicon Valley, Hollywood, and biotechnology clusters in San Francisco), increasing empirical evidence suggesting the influence of regional factors in the production and diffusion of knowledge, learning and innovation capabilities (STEP, 2000), and perceived inadequacies in existing regional studies in accounting for variations in regional economic and innovation performance (Uyarra, 2009; Doloreux and Parto, 2004; Sharpe, 2007; Asheim & Gertler, 2005).

For the RIS approach, innovation and economic performance cannot be understood from the firm level alone, but in the context of the institutions, agents and interactions within a region. Local systems of governance and administration, and research, training and education institutions are all agents in a RIS that make up the specific regional conditions, and influence production and diffusion of knowledge and innovation.

The RIS concept is premised on the cumulative nature and types of knowledge (tacit or codified), the evidence suggesting an increasingly pivotal role of tacit knowledge in supporting innovation (Pavitt, 2002), and the importance of spatial proximity for the efficient transfer and flow of tacit knowledge. It is via face to face contacts that tacit knowledge is most effectively passed on, often through informal networks comprising of trust based relationships, which importantly affect regional innovation performance (Asheim and Gertler, 2005; Doloreux and Pardo, 2004; Maskell and Malberg, 1999). This describes a ‘sticky’ nature of tacit knowledge – it is not easily transferable or mobile (in a codified structure), is regionally clustered and essential for much innovation and regional growth (Asheim and Gertler, 2005).

The main implication in terms of measurement and the development of innovation indicators, is a need to take into account regional factors where possible (OECD, 2011; STEP, 2000), and the ‘sticky’ or tacit knowledge flows that shape capability development within regions. However, despite popularity of the RIS approach, it contains a number of deficiencies and its use as a theoretical or empirical framework is subject to considerable ongoing debate (Uyarra, 2009; Asheim and Gertler, 2005).

There is a lack of definitional clarity with respect to what elements are included in an RIS and the boundaries that define an RIS. There is no consistent definition of ‘region’ that applies within the approach, and it has been applied to sub-national regions, including small urban districts, cities and states, as well as at the country level (Uyarra, 2009; Doloreux and Pardo, 2004). This creates problems for empirical analysis. Though studies such as those of Evangelista et al. (2002) and STEP (2000) have come some way in developing consistent methodologies for analysis of RIS, there lacks a definitive method for identifying an RIS, or distinguishing between what is, and what is not, an RIS.



Although this study uses data from an innovation survey administered in a regional economy, no comparison with data from other regions or sources is attempted. Incorporating an RIS approach would require establishing a level of regional specificity in terms of innovation. As noted above, the difficulties in establishing such conceptual boundaries are one pitfall of the RIS approach. Such a task is outside of the scope of the main objectives of this thesis. The focus here is on better understanding survey indicators irrespective of regional specificities, so the main strands of innovation theory discussed prior to the RIS approach are most appropriate. Consequently, the RIS approach has less direct relevance for this study.

## **2.3 WEAKNESSES IN NEW SUBJECT APPROACHES TO INNOVATION MEASUREMENT**

The discussion so far has highlighted the evolutionary nature of subject approaches and their advantages for measurement, their significant contributions to understanding, and developments in theoretical approaches including sectoral and regional extensions of the systemic approach. This next section considers disadvantages and shortcomings of ‘subject’ based innovation measurement. The focus is on the CIS, its methods and related indicators. Arundel and Smith (forthcoming) note that the history of the CIS naturally divides into two periods: pre and post CIS4. The first is characterised by change, as conceptual frameworks, methods, and CIS questionnaire content evolved, while the second is more stable as the core CIS content settled. Much of the discussion here features critique up to CIS4, because this is the focus in the relevant available literature. Though there are more recent developments, which are covered throughout this section and in the next, the discussion here is important as it provides knowledge on how key indicators have been developed and improved over time, and the context for remaining issues that provide the rationale for this research.

In the years following the early Community Innovation Surveys and leading up to the third edition of the Oslo Manual, a number of authors identified deficiencies in survey based approaches and indicators. Such critique has stemmed from empirical analyses of survey indicators and ongoing evaluation processes of statistical agencies, from

advances in theoretical thinking and research in related cross disciplinary fields, and from the need to evolve to reflect and capture wider global economic change.

New innovation surveys were developed to provide better information on the nature of innovation processes for empirical analysis by researchers (in particular on innovation activities and outputs), and to provide indicators for benchmarking, monitoring and evaluating cross-country innovation performance to inform policy (Salazar and Holbrook, 2004; Arundel, 2007; Mairesse and Mohnen, 2007; 2010). Thus many early criticisms of the CIS relate to the inconsistency and incomparability of data across countries, due to differences in methodology and survey questionnaire content (Archibugi and Pianta, 1996; Arundel et al., 1998). Specifically, much critique focused on technical deficiencies related to survey design, such as poorly designed questions and response categories and scales, excessive questionnaire length, and variation in questions across countries (STEP, 2000; Arundel et al., 1998). Disparities in question and firm response rates also had an impact on the early CIS results, with some country samples biased towards innovating firms (due to low response from non-innovators), which inflated rates of innovation in official figures (STEP, 2000).

Looking beyond the CIS, comparability becomes more problematic, as despite general alignment with the Oslo Manual guidelines, the methodology and content for innovation surveys in countries such as Australia and Canada differs once again. Nevertheless, comparability is a problem for all statistics, and consistency has been improving over the years for innovation data. Many of the above criticisms of the CIS have been addressed with ongoing improvements to questionnaires and methodology (Arundel and Smith, forthcoming).

As the Oslo Manual evolved and CIS content changed, some criticised the time series value in the data, as questions changed over time or were replaced. For example, the ‘objectives of innovation’ questions in CIS2 were replaced by questions on ‘impacts of innovation’ in CIS3 (Mairesse and Mohnen, 2008), though were later returned for CIS2008. Though post CIS4, the CIS questionnaire content has stabilised, with a set of repeating, core questions, there is still some ongoing change as improvements are made and content added.

In comparison to object approaches, subject approaches in general capture less detailed qualitative information on the character of innovations. Many published survey indicators lack richness in terms of depicting the varying spectrum of innovation intensity across firms. This is partly due to the nature of the survey instrument, which is predominantly based around binary or categorical question response categories, but mostly limitations in indicator definitions and the prevalent types of indicators.

From early on, the share or rate of innovative firms was widely promoted as a benchmark indicator to compare countries and industries, drawing some notable criticism in the literature. Because repeated survey results showed increasing firm propensity to innovate with increasing firm size, and varying rates of innovation by sector (Smith, 1998), rate indicators were criticised for neglecting variations in industrial structure when comparing countries, or variations in firm populations (by firm size) at the industry level<sup>5</sup> (Guellec and Pattison, 2001). Guellec and Pattison (2001) give the example of a country with a higher share of firms innovating just once over the reference period, which appears more innovative than a country with a lower share of firms innovating multiple times, and on an ongoing basis.

In addition, rate indicators reveal nothing about the quality or intensity of innovation occurring in firms, simply the share of firms that are innovating. Early on, Archibugi and Pianta (1996) criticised the definition of a technologically innovative firm<sup>6</sup> and resulting indicator for lacking information on the technological nature of innovations (for example, the technological or knowledge domain of the innovation), and the lack of detail in this indicator drew general criticism of the early CIS (STEP, 2000). Innovation rate indicators were criticised for failing to differentiate between creative innovators and adopters or diffusers (STEP, 2000), and as not useful at all by authors using early CIS

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<sup>5</sup> For example, a country with a larger number of high tech firms will have a higher share of innovating firms than a country that is resource based.

<sup>6</sup> Defined in the Oslo manuals and CIS as a firm that has implemented a new or significantly improved product or process over the survey period.

data (Mohnen and Dagenais, 2002). There were similar criticisms of rate indicators for activities (which do not indicate the quality or extent of activities) (STEP, 2000). Though these indicators do have use for measuring baseline activity and continue to feature widely in survey output publications, similar criticisms are evident in more recent literature (Arundel, 2006; 2007; Arundel and O'Brien, 2009).

### 2.3.1 INNOVATION NOVELTY, INPUT AND OUTPUT INDICATORS

Product novelty indicators from early CIS questionnaires based on the share of firms with 'new to market' innovations have been criticised due to survey questions not taking into account variations in the nature or location of markets (Mortensen, 2008; Bordt, 2008). Viotti and Gusmao (2007) note the counterintuitive example of Italy compared to Germany. The former shows the highest share of 'new to market' innovators though the lowest share of innovators, while Germany shows a comparatively higher share of innovators, though lower share of 'new to market' innovators. A firm servicing only a small domestic market might have new to market innovations, and may simply be introducing products that exist elsewhere into the local setting. In contrast, another firm might introduce novel products onto international markets, which implies a higher level of novelty (and assumed creative capability) due to a wider competition base. Both appear to have the same level of innovativeness on this indicator, which may explain strange comparative country rankings based on results for sales shares indicators (Arundel, 2007). Though from the 2010, CIS questions have been updated to reflect market characteristics<sup>7</sup>, indicators to reflect these changes are not yet available, and such results have more broadly threatened the credibility of new innovation surveys.

Kleinecht et al. (2002) discuss the weak nature of survey measures of innovation inputs or investments, which are based on interval level survey questions asking for

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<sup>7</sup> In CIS2010, firms are asked whether any of their product innovations are a first in their country, Europe, or the world.

expenditure on various innovation activities (acquisition of capital, training for innovation, design etc.). Expenditure and related indicators have been criticised due to historically low question response rates (Mortensen, 2008), and the fact that responses are based on very subjective estimates, as categories for innovation expenditure do not align neatly with standardised accounting concepts for expenditure items reported by businesses. Canibano et al. (2000) discuss the issue of misalignment between innovation expenditure categories and accounting categories, though conclude that despite such limitations, input measures provide a useful basis for reviewing trends in the mix of inputs and important explanatory variables for analysis against different innovation outcomes. There is evidence that the quality of CIS innovation expenditure data is improving based on increasing question response rates over time (Eurostat, 2010, Arundel, 2007; Arundel et al., 2010), and there is a strong need for some estimate of the levels and variation in firm investments in innovations other than R&D, as repeated studies have shown that non-R&D innovation expenditures account for a large share of total innovation expenditures. For example, Evangelista et al. (1998) using CIS1 data showed that for 13 European countries, R&D on average accounted for 20% of total innovation expenditures, while in Australia, in 2003 R&D accounted for 31% of total innovation expenditures (ABS, 2003). However, the quality of data from innovation survey questions on expenditures remains lower than for other questions. Data on investments in R&D from specific R&D surveys (based on the Frascati Manual) still provide the best quality survey indicators on innovation investments, which should complement innovation survey indicators.

Output measures based on sales attributable to product innovations by level of novelty (new to firm or new to market) have also been criticised due to reliance on subjective firm judgements of sales shares, which result in noisier output data compared with some R&D data (Mairesse and Mohnen, 2007). They have also produced counterintuitive country results, with low shares in innovative countries like Denmark, and higher shares in countries such as Italy (Arundel et al., 2010). Part of this is due to the issues with product novelty questions (Arundel et al., 2010). Despite low levels of comparability, innovation sales data are generally seen as of reasonable quality for econometric analyses, though may need interpretation as categorical rather than continuous outputs

due to the subjectivity of firm sales share estimates (Mohnen and Dagenais, 2002; Kleinecht et al., 2002; Mairesse and Mohnen, 2010; Arundel, 2007). An additional problem with output indicators relates to the fact that firms can have multiple product innovations. This means that part of new to market innovation sales for example, could include sales from products with improvements that are new to the market (incremental innovations), as well as sales from products that are entirely new, and include elements of radical new technologies. This is a key limitation in innovation survey output indicators, and related to the subject approach and survey questions that apply to ‘any’ innovations. Separate questions on specific innovation types (e.g. radical or incremental) could help to avoid this problem. However, quantitative survey data on output are still regarded as less reliable for developing indicators.

### 2.3.2 WEAKNESSES IN SECTOR COVERAGE – SERVICES AND LOW-TECH INDUSTRIES

Many early criticisms of initial CIS iterations related to a perceived bias towards technological product innovation in manufacturing (Mortensen, 2008), at the expense of accurately capturing innovation characteristics in services sectors (Bloch, 2007), and low technology sectors (Cox et al., 2002, Frenz and Ietto-Gillies: 2009; Laestadius, 2008). For example, in early CIS questionnaires there were no questions on the impacts of process innovations (such as through reduced costs or greater efficiencies), which are more important for services and low-tech sectors than for medium and high tech manufacturing (Mortensen, 2008). This was a remnant of the original Oslo Manual and first CIS, which were designed to capture innovation in manufacturing only.

Contrary to traditional views, increasing evidence of widespread innovation in services has revealed many distinctive characteristics of service innovation with implications for measurement. Firstly, organisational innovations are important for effectively implementing process innovations, product and process innovations are often indistinguishable and can occur simultaneously, and intensive client interactions are characteristic of much innovative activity (customisation) (Bloch, 2005; 2007; Salazar and Holbrook, 2004). Innovation and knowledge in services is typically embodied in

routines, procedures, and organisational methods rather than in R&D, while dramatic advances in ICT have improved access to knowledge, accelerating diffusion and opening up new channels for knowledge flows and linkages (Salazar and Holbrook, 2004). In the advanced service based economies, knowledge is more complex, specialised, and distributed, and organisational methods and human capital resources determine the capacity to access, acquire, absorb and apply the knowledge which is essential for successful innovation (Bloch, 2005). These factors, and the increasing economic importance of the service sectors in advanced economies, led to the shift in focus and scope of the second Oslo Manual (OECD, 1997) and CIS to include services.

From the CIS3 on, questions were asked on the effects of process innovations, while from the CIS4, separate questions were used to ask about goods and service innovation. Despite these early changes, many authors criticised the adequacy of standard CIS questions in capturing the specificities of service innovation (Tether, 2001; Bloch, 2007, Salazar and Holbrook, 2004). Much of the expanding literature on services innovation showed the correlation between organisational type innovations and services innovation (Salazar and Holbrook, 2004), and the importance of marketing innovations for services. Both types were limited in detail in CIS questionnaires until CIS2006. However, since then, there are expanded questions on the development and effects of these types of innovation.

Another major criticism of innovation surveys centred on the omission of questions on the human capital aspects of the innovation process, especially as these are seen as crucial to services innovation (Tomlinson, 2000). While literature emphasising the importance of both tacit and codified knowledge for successful innovation has grown (Mairesse and Mohnen, 2007), many have argued that innovation survey questions have not kept pace in capturing the human capital related dimensions of effective organisational innovations, such as investment in training, knowledge management systems, ICT technologies etc.. Apart from asking about the share of graduates qualified in science and engineering or related disciplines in the firm's workforce, and whether investment is allocated to training for innovation, there is little focus on this topic in the CIS, and many separate studies have begun to emerge to fill the gap (Tomlinson, 2000).

Each line of criticism above relates to a broader limitation of innovation surveys, in terms of capacity to capture all important aspects of innovation for all firms and all sectors. The subject measurement approach is limited by the survey instrument, and such practical considerations as maintaining consistency of content for creating time series data, for maintaining the length and complexity of the questionnaire to minimise respondent burden and ensure sufficient response rates and data quality. These limitations must be borne in mind when considering issues with correspondent survey indicators.

### 2.3.3 CRITICISM BASED ON THEORY

A number of authors have criticised survey measurement for falling behind theoretical conceptions of innovation, specifically in terms of failing to provide good measures of the characteristics and functioning of innovation systems, and in particular for sectoral and regional systems (Bloch, 2007; Salazar and Holbrook, 2004). While innovation surveys capture inbound diffusion by asking about ‘new to firm’ innovations, Bloch (2007) highlights the lack of outbound diffusion measures, while others have identified the need for better measures of knowledge linkages. It is argued that survey approaches need to better reflect the systems view that primarily sees innovation as a function of linkages and knowledge flows between networks of actors in the system (Tomlinson, 2000; Bloch, 2005).

Tomlinson (2000) argues that it no longer makes sense to speak of a single business source of innovation in the modern global economy, rather innovations come to being through complex networks of businesses and institutions contributing in some way to the production of new innovations. Tomlinson (2000) cites the example of the ICT industry, in which single product innovations develop through extensive collaborations between hardware, software and telecommunications sectors as well as the science and university system, arguing that in such an environment it makes no sense to analyse innovation based on single business entities. Similar critique has stemmed from research on supplier-producer and demand or user driven innovations (Freeman and Soete, 2009; Bloch, 2005), which indicates an increasingly important role for both users



and market needs in developing and generating knowledge and innovations (Von Hippel, 2005). Examples include scientists who modify existing equipment or develop new equipment, consumers of intermediary or capital goods making innovative improvements to such goods that are subsequently adopted by producers, or new methods of market research (Bloch, 2005).

#### 2.3.4 CRITICISM BASED ON POLICY RELEVANCE

Finally, surveys have been criticised for lacking policy relevance (Viotti and Gusmao, 2007; Colecchia et al., 2007). Arundel (2007) demonstrates this point via the lack of references to CIS indicators in a study featuring interviews with 67 members of the policy community across 19 countries, and by the noted dominance of traditional innovation indicators in policy rhetoric, related program targets, and academic studies, which also indicates an enduring influence of the linear model despite proclamations of its demise (Salazar and Holbrook, 2004; Arundel, 2007). Perhaps the best demonstration of this critique is via reference to the primary mandate of innovation surveys – to provide a mechanism to benchmark and compare inter-country innovation performance. This is hindered by the lack of comparability of data due to remaining cross-country methodological differences, but also due to inadequacies of the main innovation rate indicators based on the proportion of innovative firms. Arundel's (2007) study notes that less than 5% of European program expenditures on innovation were non-R&D based. Thus with policy directed at high R&D intensity firms and surveys geared towards non-R&D types of innovation, Arundel (2007) argues that the lack of policy interest comes as no surprise. Prevalent rate based indicators fail to distinguish between different levels of 'innovativeness' for firms with both non-R&D and R&D modes of innovation, and better indicators could inform a wider understanding of innovation and discourse to inform policy.

The uptake of innovation survey indicators for policy related measurement exercises has some way to go. For example, in the 2011 European Innovation Scoreboard exercise, of 26 featured indicators used for calculating indices, only 6 are sourced from innovation surveys. Incidentally, 4 of these are rate based indicators. The OECD STI Outlook for

2010 (OECD, 2010) provides comparison of 13 innovation indicators for Australia with the OECD average, only 3 of which are sourced from innovation surveys and all are rate based indicators (rate of firms collaborating, rate of firms with new to market product innovation, rate of firms with non-technological innovation). Arundel et al. (2008) note that the cross sectional nature of many CIS based studies has limited many analyses, and that study of causal relationships provide analyses of greater policy relevance. This requires panel data, which is limited in availability, and impacted by methodological factors such as low sampling fractions and changes in methods and content over time.

What factors are important to the policy relevance of indicators? And what is meant by policy relevance? These questions are considered here to provide an appreciation of the need for new indicators, and the gaps that motivate this study. It must be made clear that it is not the intention to explore particular policy issues or policies, but rather to consider how innovation survey indicators might provide better information content to support policy, given the limited penetration so far in this respect.

As discussed in section 2.2.5, and noted in the literature (Arundel et al., 2008; Arundel and Mohnen, 2003; Smith, 1998, 2005; Archibugi and Pianta, 1996), a key advantage of innovation survey indicators is offered by wide coverage across large populations of firms, and for providing a descriptive, economy-wide picture of the distribution and patterns of innovation. In an early discussion on the policy relevance of survey indicators, Pianta and Sirilli (1998) note the need for balance between two approaches to policy, supporting larger, high technology based firms that are highly innovative, or assisting smaller firms to become more innovative. The challenges that different types of firms face in terms of innovating can be vastly different. For example, larger firms can often focus on incremental innovations that maintain their advantage in particular product markets, though face an ‘innovator’s dilemma’ when disruptive technologies emerge (Christensen, 1997). In contrast smaller firms could be highly innovative in dynamic sectors such as information and communications technologies. Innovation survey indicators will be inadequate for capturing all innovations of course, such as those outside of the business sector (such as in public sectors organisations) or in micro-businesses excluded from most surveys, however they can produce indicators that can

better reflect the diversity in innovation activities, and outputs across different types of firms.

Thus to tell a story of relevance to policy, indicators need to be able to capture the different patterns and modes of innovation across firms in different industries and of different sizes. They need to reflect differences in innovation performance across the economy, the different inputs to innovation processes, including technology, research, knowledge, and capabilities, and different innovation outputs, such as new products, or new marketing methods. They need to reflect varied degrees of novelty in outputs (e.g. new to world or new to business), and the systemic environment, consisting of different interactions and knowledge flows between firms and other organisations and institutions.

Indicators need to reflect these elements in order to ‘tell a story’ that is relevant to the design, monitoring and evaluation of policies (Finnbjornsson, 2008). Arundel and Hollanders (2008), in their discussion of innovation scoreboards (which draw on numerous innovation indicators), note that indicators have policy relevance by acting as ‘early-warning’ systems for potential problems at an economy-wide level, for tracking changes in strengths and weaknesses, and for helping to motivate reactions across government and businesses that may result in improved innovation capabilities. Veuglers (2007, p.35) discussion highlights the role that indicators play in assessing ‘innovative capacity’, defined as ‘the ability of systems not only to produce new ideas but also to commercialise a flow of innovative technologies in the longer term’. Much of the focus in the repeated series of European Innovation Scoreboard reports (EIS, 2001; 2003; 2004; 2005; 2006; 2008; 2009; IUS, 2012), which are designed to inform European innovation policy, is on tracking national strengths and weaknesses across different dimensions of innovation, in order to build a picture of innovation capability, and how it develops and changes over time. Thus drawing on relevant parts of the literature, ‘innovation capability’ can be defined as the ability to successfully turn innovation inputs (activities and investments such as R&D and non-R&D activities) into innovation outputs (new products, processes, marketing or organisational methods) (Smith et al., 2012).

It should be noted here that the author has worked with local, state, and federal policy agencies in Australia in relation to production and interpretation of innovation indicators, and this experience partly shapes assumptions behind the concept of ‘policy relevance’. Synthesising this experience, discussions in the literature above and in previous sections, it can be noted here then, that by policy relevance, indicators should meet any or all of the following objectives:

1. They reveal strengths or weaknesses in innovation performance or characteristics.
2. They provide a map of the patterns of innovation activities, inputs, outputs or impacts.
3. They provide some differentiation between different levels of innovation intensity, novelty or capability across firms or firm groupings.
4. They reveal changes or trends in innovation characteristics or performance over time.
5. They provide results that may inform policy directed at firms operating in different sectors, of different sizes, or in different regions.

#### 2.3.5 SECTION SUMMARY

Concluding this section, in terms of the latest changes incorporated in the third Oslo Manual, there has been much progress and improvement in the related CIS and other innovation surveys and indicators over time. Critique in the literature tracks CIS methods and indicators as they developed and evolved, firstly in terms of methodological issues associated with inconsistency in approaches and comparability of indicators, and secondly in terms of definitions and quality of specific indicators (such as rate indicators and those for innovation expenditure and sales). Over time, the quality of many indicators has improved due to ongoing coordinated work to improve the quality of innovation questionnaires and indicators. A CIS task force consisting of 10 National Statistical Offices (NSOs) is responsible for developing changes to the CIS

questionnaire to be signed off by participant countries (Arundel and Smith, forthcoming). Since the CIS4, a comprehensive report covering reasons for any questionnaire content changes, indicator quality issues, and surveys of policy, academic and business users of CIS data informs task force decisions on progressive development of the CIS. These reports feature detailed discussions on the quality of particular indicators. For example, Arundel et al. (2010) provide evaluations of question and indicator quality based on survey question non response rates, variations across sector and size variables, and perceived relevance to users.

Despite these ongoing improvements, some of the substantial indicator limitations discussed in this section remain, notably the issues around prevalent rate based indicators, and this is evidenced in their limited uptake by policy makers and in broader measurement exercises mentioned above. Some critical gaps remain in terms of indicators mapping different innovation novelty, capability and intensity levels, and strengths and weaknesses across these dimensions are of key interest for policy. Nonetheless, authors such as Colecchia (2007) and Freeman and Soete (2009) argue that new survey approaches have made significant contributions to understanding, are progressively developing with potential for further improvement, and have a vital role to play in further building on understanding into the future. These points are also apparent from the discussion thus far on the history, rationale and results of new subject approaches and survey indicators.

A key outcome of the 2006 blue sky conference is the general theme that many limitations are based on specific indicators, not on the subject approach to measuring innovation. Authors such as Mairesse and Mohnen (2010), Perani (2008), Arundel (2007), and Arundel et al. (2008) note that in order to develop new indicators that address some of the deficiencies discussed above, there is a need for a greater level of access to innovation survey microdata, and for linkages with other sources of business microdata. Data from new innovation surveys is not limited to producing the indicators discussed in this chapter (such as rate based indicators or the share of innovative firms or of innovative sales), these are just those produced by statistical agencies and available in reports and on relevant websites. Surveys have produced rich datasets that are yet to be fully exploited in terms of developing better indicators (Bloch, 2005;

Arundel, 2007; Arundel et al., 2008; Colecchia 2007). As well as improving survey content and methodology, improvements in access to survey microdata will facilitate better use of existing data in terms of developing and evaluating new indicators. These themes are central drivers for this study. In the next section we explore some of the latest related work that partly guides the method and approach taken for this thesis.

## **2.4 NEW DEVELOPMENTS IN SUBJECT APPROACHES TO INNOVATION MEASUREMENT**

Section 2.3 discussed the weaknesses and limitations of new innovation surveys using a subject approach. This section reviews some of the latest work on new and improved indicators that begin to overcome such limitations.

As discussed thus far, a critical limitation of many survey based approaches relates to the lack of information provided on the varying levels of innovation intensity across firms, which is an issue firstly because research has shown that the inputs, methods and outputs of innovation vary significantly across firms, sectors and countries, and secondly because the policy interest is often in high intensity and high technology (R&D) innovation (Arundel, 2007). Many key indicators output from the CIS show strange and often counterintuitive results, and there is a need for measures that better reflect varying firm innovation intensities or innovativeness.

Arguably beginning with Pavitt's seminal taxonomy of innovation modes (Pavitt, 1984), a history of empirical literature confirms a varying spectrum or continuum of inventiveness, creativity and intensity with respect to innovation inputs and activities, outputs and impacts on the firm across various sectors. On one end of the scale, firms can innovate by simply purchasing new technologies and innovations embodied in the form of machinery and equipment in order to improve production processes. Moving up the intensity spectrum, firms can modify and adapt technologies to their own specific requirements for innovation, and further still, firms may continuously engage in R&D projects in order to research and develop new technologies to implement in entirely new products sold onto global markets. This is a simplification of the range of innovation modes or methods that might occur, and the literature features various classification

schemes designed to similarly categorise innovation modes into common taxonomies for analysis (for example, Tether (2001), using CIS2 data, Arundel et al. (2007), using CIS3 data). As an example, Arundel and O'Brien (2009, p.54) overview five broad methods of innovating from the literature:

- Technology adoption
  - The technology is simply bought in from external sources and use by the innovating firm.
- Modifications or incremental changes
  - This can involve changes and improvements made to existing technologies, products and processes that result in innovations.
- Imitation including reverse engineering
  - Activities to replicate and implement products and processes existing on the market.
- Combining existing knowledge in new ways
- Research and experimental development

The lack of depth in many rate based survey indicators in terms of capturing intensity levels is the cause of much of the critique discussed in section 2.3. Arundel and O'Brien (2009) note that such issues lie not necessarily with the Oslo Manual definitions of innovation or the subject approach to innovation measurement, but in the types of indicators that are produced, arguing that new indicators need to be generated from existing survey data that reflect different modes of innovating, both in terms of innovation methods (how firms innovate) and outputs (the level of novelty, location of markets serviced, and nature of demand) (Arundel and O'Brien, 2009; Arundel et al., 2008; Colecchia, 2007).

Following the Blue Sky 2 Conference in 2006, work has progressed advancing new and improved survey indicators. For the following discussion, indicators generated using a

subject approach are classified into three broad categories detailed in section 2.2.5.1: simple or basic indicators, composite indicators and complex indicators. As discussed earlier, an ‘indicator’ generally refers to a statistic with some meaningful context (for example, the number of innovators expressed as a share of all firms).

Simple indicators are those generated using firm level responses to single questions on an innovation survey. For example, the share of product innovators, the share of process innovators, or the share of firms with collaboration activity. Most of the available indicators discussed to this point fall into this category. Composite indicators are single indices produced using responses to multiple questions, and are generated much in the same way as any other economic indice measure, condensing many different types of survey indicator into a single summary measure. Complex indicators are generated from combining firm responses to two or more survey questions to represent a particular aspect of innovation. Much of the recent scholarly work developing improved indicators draws on complex measures to develop innovation mode schemes, and these provide the main focus of this discussion.

#### 2.4.1 COMPOSITE INDICATORS

Composite indicators have most commonly been used to inform policy by creating a single measure of innovation that can be used to summarise and compare performance across countries. These types of indicator feature predominantly in the European Innovation Scoreboard and Regional Innovation Scoreboard reports mentioned in section 2.2.5.2. Other well known composite indices include the European Commission’s Summary Innovation Index and Global Summary Innovation Index, or the World Bank’s Knowledge Index (Archibugi et al., 2009). These indicators are widely used in such reports as they provide simple summary measures that can provide a picture of relative global innovation capabilities, and are attractive for policy makers. However, such index measures are subject to various limitations related to the quality and methodology of constituent data and weighting methods (Grupp and Schubert, 2010; Archibugi et al., 2009; Schibany and Streicher, 2008), which need to be taken into account and can constrain their usefulness. They are primarily concerned with



cross-country comparisons, and are not the subject of further discussion here, but are explained further in chapter 6.

#### 2.4.2 COMPLEX MEASURES AND INNOVATION MODES

The latest measurement work using innovation survey data centres on building indicators for firm level innovative capability that reflect the varying methods and outputs across the innovation continuum, via construction of ‘innovation modes’ based on complex indicators. Complex indicators generally classify firms based on answers to two or more innovation survey questions rather than a single question. Firms are classified using ‘innovation modes’ – classes of categories based on complex indicators, where a ‘mode’ scheme corresponds to particular aspect of innovation (Bloch and Lopez-Bassols, 2009; Arundel and Hollanders, 2005).

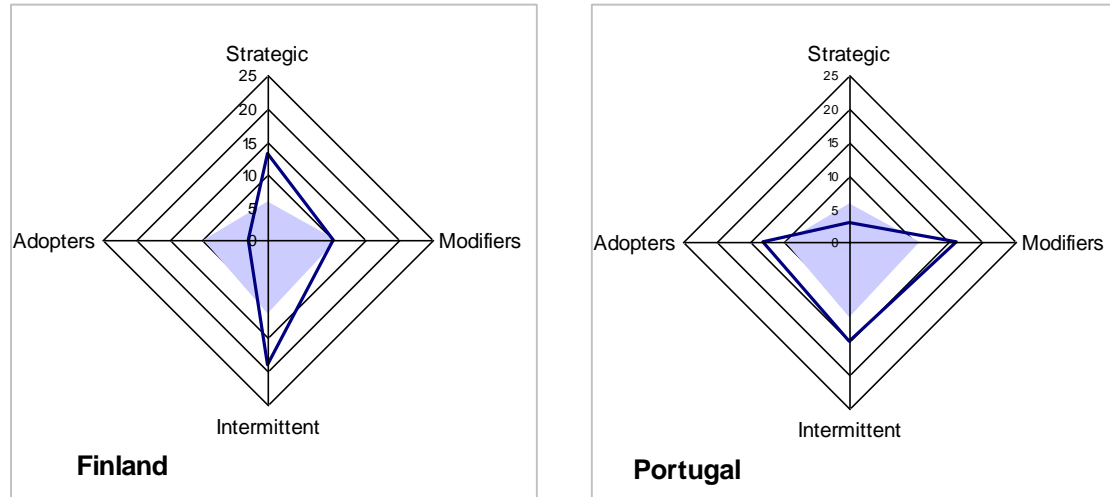
With innovation ‘modes’ firms are assigned to one of a number of exclusive modal categories based on their answers to a series of questions. Modes can be constructed to capture various dimensions of innovation, including input, output and collaborative activities. Modes enable analysis of the distribution of firms by innovation intensity levels across an economy, and within industry sectors or size classes, which addresses the need to distinguish between highly innovative and less innovative firms.

The first modes were produced by Tether (2001), Hollenstein (2003) and Arundel and Hollanders (2005), and increasingly feature in the recent literature (NESTA, 2008; OECD, 2009; Arundel and O’Brien, 2009; Polder et al., 2009; Frenz and Lambert, 2009; Fitjar and Rodriguez, 2011). Comparing Portugal and Finland using CIS3 data, Arundel and Hollanders (2005) demonstrate how modes can overcome key limitations in simple indicators. They note that 46% of firms are innovative in the former compared to 45% in the latter, a questionable result given the superior innovation performance of Finland across a number of other traditional indicators including R&D expenditures and patenting activity (Arundel and Hollanders, 2005).

Using the same data, Figure 2.4 shows Arundel and Hollander’s (2005) innovation modes. These modes classify firms into four categories of increasing innovation

intensity based on methods of innovating: adopters, modifiers, intermittent innovators and strategic innovators. These categories better depict the variation in innovation capabilities between countries. Strategic and intermittent innovators are the categories of highest innovation intensity based on novelty and inventiveness, with the level of R&D activity (continuous or intermittent) differentiating the two respective categories. In contrast, ‘adopters’ represent the lowest level of intensity, for firms simply buying in technology to produce innovations, while modifiers undertake some creative and inventive activities to modify technology for innovation. Thus Figure 2.4 shows the clustering of different innovative firm populations. In Finland, a larger share of firms are clustered in the top two intensity categories (the vertical axis), while Portugal has higher shares across the lower two intensity categories (the horizontal axis). The shaded sections represent the average distributions for all European firms, while the sum of shares on each axis adds to the total share of innovative firms.

**Figure 2.4 Innovation modes for Finland and Portugal**



Source: Arundel and Hollanders (2005). Each of the four axes sum to the total percent of innovative firms.

By dissecting firm populations using different modes of innovating, innovation mode indicators in Figure 4.2 have addressed a key problem with the rate based, share of

innovative firms indicator (which was raised in section 2.2.5.2), showing comparative country level innovation profiles that make more intuitive sense. Innovation modes provide a new way of extracting meaningful information from survey data that better depicts the variation in innovation intensity across firm populations. However, an open question remains regarding the full explanation of confusing country level results for simple rate based indicators. These might be due to narrow definitions (which include any product *or* process innovation regardless of the significance or intensity). Though there may be other explanations, such as remaining differences in international comparability. These can stem from differences in survey methodologies (despite standardisation via the Oslo Manual) including sampling methods, questionnaire format or designs, or data collection methods. Other factors at play might include cultural differences that impact on the interpretation of innovation, political regimes that influence the types and levels of firm response, or simple translation issues occurring for standardised questions and concepts. Though methodological issues are considered in this thesis, investigating these broader factors potentially impacting on comparability is not within the scope of the research objectives. However, the reader should bear in mind such issues as the following chapters unfold. Attention here is directed at unpacking and explaining innovation with new indicators from the existing data, with a focus on innovation modes.

Using varied combinations of survey questions, modes can be constructed to represent innovation inputs – such as methods for how firms innovate – and outputs (including destination markets and the combinations of product and process innovations etc.), or other dimensions depending on the needs of analysis. They can also be used for econometric investigations using survey data, though due to endogeneity issues with output modes, only input modes can be used as independent variables (Arundel and O’Brien, 2009).

A number of studies have emerged that use different mode schemes to classify and analyse variations in innovation and firm performance. Focusing on the services sectors, Hollenstein (2003) uses factor and cluster analysis techniques on data from the Swiss CIS to identify five modal categories based on technological and non-technological innovation, finding that firms undertaking both types tend to show a higher

performance. Two more recent studies, though using different modal schemes, show similar results with higher performance in firms with ‘mixed’ modes. Jensen et al. (2007), using data from a Danish innovation survey, identify Scientific, Technological and Innovation (STI), and Doing, Using and Interacting (DUI) modal categories, based on innovation and knowledge characteristics. They find that firms undertaking both forms of innovation perform better. Battisti and Stoneman (2010) use data for UK firms in the CIS4 to create mixed modes of technological and organisational type innovations, showing complementarity between modes and better performance for firms undertaking both types.

In addition to these studies, there is a broad literature related to development of different taxonomies for innovative modes across firms, sectors and economies. This literature can be seen as an ongoing evolution of Pavitt’s seminal work (Pavitt, 1984), and involves numerous different studies since, drawing on many different data sources and using various methods of analysis. These often include, but are not limited to, cluster and factor analysis methods, and feature varied units of analysis (De Jong and Marsili, 2006). De Jong and Marsili (2006) provide a comprehensive overview of this literature. One issue with this large body of work is the sheer diversity of methods, approaches and results. These and other mode studies above tend to be narrow in focus in terms of countries and sectors included. They generally do not produce indicators that can be reproduced across countries or sectors. Two major projects in Europe recently further work on innovation modes using the CIS data, and consistent methodologies across multiple countries: the Nordic Innovation Indicators (NIND) project, and the OECD Microdata project, and this thesis draws on much of this work.

Through the NIND project, Bloch et al. (2008) develop and review a number of different mode schemes for different dimensions of innovation including outputs (based on novelty in products and markets serviced), inventiveness and diffusion, and collaboration, intended to demonstrate the potential policy relevance of new possible indicators drawing on existing data. They explore seven different mode schemes designed to improve on existing simple indicators; by capturing different dimensions of the innovation process, addressing limitations of simple indicators and better aligning with new theoretical developments.

Table 2.2 presents the proposed mode schemes, the correspondent modal categories, and the uses and benefits.

**Table 2.2 Innovation modes schemes: NIND Project**

Modal schemes	Modal categories	Uses and benefits
Output based technological modes	<p>New to market international innovators</p> <p>Have the highest degree of novelty. They have introduced novel products, operate on international markets, and have undertaken in-house R&amp;D.</p> <p>New to market domestic innovators</p> <p>They have developed novel product innovations, though do not operate on international markets, and have undertaken some level of creative in-house development.</p> <p>In-house modifiers</p> <p>These firms have introduced new to enterprise innovations though not new to market, and have some level of in-house development activity.</p> <p>Adopters</p> <p>These firms have had any product or process innovations developed externally, with no in-house development activities.</p>	<p>Categorise firms into four exclusive categories of increasing intensity based on creativity and inventiveness of outputs.</p> <p>Can be used to categorise firms across industry, size class and country.</p>
Diffusion and inventive activity	<p><i>Inventive collaborative innovators</i></p> <p>Firms that applied for a patent and conducted R&amp;D</p> <p><i>Inventive non-collaborative innovators</i></p> <p>Firms that applied for a patent</p> <p><i>Informal collaborative innovators</i></p> <p><i>Informal non-collaborative innovators</i></p>	<p>Designed to measure the Linkages and knowledge flows between firms and actors in the innovation system based on R&amp;D activity and collaboration partners.</p>
Dual innovators	<p><i>Services only innovation</i></p> <p><i>Goods only innovation</i></p> <p><i>Dual innovators</i> – goods and services innovation</p>	<p>Designed to capture the dual modes of innovation, especially considering the trend to services innovation in manufacturing.</p>

Modal schemes	Modal categories	Uses and benefits
Technological and non-technological	<p><i>Integrated innovators</i></p> <p>These firms have implemented new to market innovations, operate on international markets, have in-house development activities, and also have organisational innovations</p> <p><i>Technological innovators</i></p> <p>These firms have introduced new to market innovations, operate on international markets, have in-house development activities, though no organisational innovations.</p> <p><i>Modifiers</i></p> <p>Same as above</p> <p><i>Technological adopters</i></p> <p>Same as above</p> <p><i>Soft innovators</i></p> <p>These are firms that have implemented a marketing or organisational innovation, though no product or process innovations.</p>	These modes are designed to measure differences in innovation strategies that combine both technological and organisational and marketing innovations. They allow measurement of the effects of different types of strategies and modes on firm level outcomes.
Subtypes of technological and non-technological innovation	<p><i>Product and process and marketing/organisational innovation</i></p> <p><i>Product and/or process only</i></p> <p><i>Product and marketing/organisational</i></p> <p><i>Process and marketing/organisational</i></p> <p><i>Marketing and/or Organisational only</i></p>	Designed to measure more precisely the different combinations of strategy and their determinants and effects.
Degree of interaction with external sources	<p><i>Cooperation</i></p> <p>Firms that cite clients or competitors as important information sources and are engaged in active collaboration with them</p> <p><i>Arms length</i></p> <p>Firms that cite clients or competitors as important information sources but are not engaged in active cooperation with them</p>	Designed to better measure the intensity of collaboration activities, their determinants and effects.
Innovation drivers	<p><i>Market driven</i></p> <p>Firms with product innovation and market</p>	Based on Pavitt's taxonomy and designed to capture 5 major sources or modes of innovation

Modal schemes	Modal categories	Uses and benefits
	cooperation activity (with clients or competitors) <i>Technology driven</i> Firms with R&D or acquired R&D and cooperation with public research institutes or commercial R&D labs <i>Both market and technology driven</i> <i>Supplier driven innovation</i> Firms that cooperate with suppliers and are not technology or market driven <i>Internally driven innovation</i> Firms that do not have cooperation with any external entities, any cooperation is internal sources only (other enterprises within their enterprise group).	strategy.

Source: Bloch et al. (2008).

In addition to innovation modes, Bloch et al. (2008) explore a number of alternative improvements to new survey indicators. Firstly, they demonstrate simple indicators adjusted to account for industry and firm size differences. This technique overcomes the criticisms of Guellec and Pattison (2001) from section 2.3, improving indicator comparability across countries and regions. For example, a country might show a high level of innovation based on a comparatively higher share of firms in innovative industries, or a low share of innovation due to a comparatively high share of firms in industries with low innovation. Bloch et al. (2008) calculate industry adjusted figures for three types of simple indicators, which shows the greatest impact on the share of turnover from innovative products. As innovation propensity is shown to increase with firm size, this process can also be used to adjust for size variations across region and country populations.

A second technique recommended by Bloch et al. (2008) is employment weighting for rate indicators. For employment weighting, rather than the share of innovative firms, the share of employees working for innovative firms is calculated. This provides an

indication of the impact of innovations on the workforce and economy, and is recommended by Arundel and O'Brien (2009) in their analysis of innovation indicators for Australia. Weighted indicators can also be produced for different types of innovation, for example, for product innovators, process innovators, new to market or new to firm innovators, and offer another way to ameliorate the effects of firm size distributions on indicators and improve comparability, building a better picture of the impacts and reach of innovation. Bloch et al. (2008) and Arundel and O'Brien (2009) both show that the share of employees working for innovative businesses is much higher than the share of innovative businesses.

The 2009 OECD microdata project incorporates much of the above work in the NIND project, and is designed to overcome access limitations to innovation survey micro data, through international coordination of analytical work across 20 countries. The objective is to use consistent methods and techniques for data processing and analysis (including for industry and firm size classifications) to maximise consistency, comparability and quality of results.

Within the project, Bloch and Lopez-Bassols (2009) develop four main sets of innovation modes covering innovation outputs, innovation status, and innovation types. Their 'output' modes are similar to those of Bloch et al. (2008) in Table 2.2, though they add a fifth modal category, which effectively splits the modifier category into international or domestic modifiers (based on whether firms export or not). Their innovation status modes are the same as the diffusion and inventive activity modes of Bloch et al. (2008) and classify firms based on inventive or creative activities (indicated by in-house R&D or patent application) and diffusion (indicated by collaboration or external involvement in developing innovations), and include four modal categories:

- Informal non-collaborative

Do not have inventive in-house activities, nor do they actively access external knowledge.



- Informal collaborative

Do not carry out creative in-house activities but actively access external knowledge.

- Formal non-collaborative

Carry out creative in-house activities, but do not actively access external knowledge.

- Formal collaborative

Both carry out in-house creative activities and rely on diffusion in their innovation activities.

Bloch and Lopez-Bassols (2009) analysis presents modes across countries and broad industry sectors (manufacturing and services), showing Canada, Denmark, Finland, Luxembourg and Sweden as leading countries based on output modes (from a selection of sixteen countries). In an extension to the NIND work, they use employment weighting with innovation output modes, which changes country rankings and increases shares of innovative activity, particularly for firms operating on international markets. On innovation status modes they show that the majority of manufacturing firms with collaboration also engage in in-house innovation, while collaboration alone is more important in services. Bloch and Lopez-Bassols (2009) also use the ‘dual innovator’ modes from the NIND project, as well as a set of technological verses non-technological modes<sup>8</sup>.

Within the OECD project, Frenz and Lambert (2009) use factor analysis to identify three prevalent modes of innovating across nine countries: new to market product

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<sup>8</sup> These include four categories: product and/or process innovator only, product and/or process innovator and organisational/marketing innovator, organisational and/or marketing innovator only, and non-innovator.

innovators, wider innovators (primarily non-technological innovators), and process modernisers. They find that some modes appear to increase productivity (measured as log sales per employee), though find no consistent effects across countries, indicating different country environments and potentially varied responses to similar policy instruments (OECD, 2009).

The OECD report (OECD, 2009) concludes with a number of observations made regarding general improvements to surveys, some of which correspond to observations discussed earlier. Firstly, the report identifies a need to better understand non-innovators, who are often skipped out of most survey questions. Secondly, the 'obstacles to innovation' questions are criticised for measuring only respondent perceptions. Thirdly, better measures of effects on firm performance are recommended, specifically a measure for the impact of process innovations which has not featured in the CIS to date. Finally, the need for more information on linkages, collaboration, sources of information, the role of users, and non-technological innovation is recognised.

#### 2.4.3 SECTION SUMMARY

In concluding this discussion on recent survey measurement related literature, there are a number of points to be made before summarising the broader literature review and exposing the research question for this thesis. Firstly, there are three major requirements noted in the literature here with regard to improving innovation indicators using existing surveys: improved access to microdata for researchers and policy makers, further analysis of innovation survey panel and time series data, and further linking of innovation survey data with alternative economic data sources (such as other types of business or employment surveys) (Mairesse and Mohnen, 2007; 2008; 2010; Arundel, 2007; Colecchia, 2007; Arundel et al., 2008). This thesis partly addresses the first two points.

Finally, despite the recent efforts at developing improved indicators discussed above, and the different types of indicators discussed, simple indicators remain the most widely available type, predominantly due to restricted access to microdata. As Arundel and

Smith (forthcoming) note, for the CIS, the 90 published indicators available through Eurostat are all simple indicators. Though these do have some use for benchmarking, they still produce counterintuitive results and are subject to many limitations discussed through this literature review. It is these limitations, the issues of access, and the need for new improved indicators that drive this research thesis, which draws on the latest coordinated work discussed here in shaping the approach. In conclusion to this literature review, the following section provides a summary of the previous chapters to this point, and the issues identified that provide the motivation for this study.

## **2.5 IDENTIFIED GAPS FROM THE LITERATURE AND RESEARCH RATIONALE**

This background literature review explored the theoretical underpinnings and historical evolution of new ‘subject’ approaches to measuring innovation, which manifested in large-scale innovation surveys conducted over the past 20 years across many developed and developing countries. The discussion focused on the evolution of the community innovation survey, the main results, outputs, and indicators produced. Originally, innovation surveys were designed to produce microdata for econometric analyses, and to generate comparable indicators for cross-country benchmarking and monitoring of innovation performance. Though scholarly studies featuring econometric analyses continue to provide important empirical results, the latter objective now provides the main justification for large-scale surveys such as the CIS (Mairesse and Mohnen, 2010), and simple innovation indicators represent the most widely available set of new direct measures to inform policy. Yet these have significant weaknesses. Despite recent work on developing new indicators, they are yet to be adopted or consistently produced, and there are still many unknowns in terms of their usefulness for improving understanding of innovation.

In summary, this literature overview has revealed theoretical and practical weaknesses in the current range of innovation survey indicators that provide rationale for this thesis, and the impetus for the central research question. Specific gaps identified that justify this research include the following points.

Firstly, existing indicators do not adequately differentiate between the varied levels of innovation intensity across sectors and firms, by distinguishing highly innovative (for example, those who invest considerable amounts of resources into the research, development, design, marketing and distribution of new to world products and processes) from less innovative firms (for example, those that may simply purchase new tools or machinery to make improvements to existing products or processes). This threatens the credibility and viability of ongoing surveys and limits their contribution to understanding. One reason for this is that the widely published range of indicators do not differentiate between levels of innovation capability and novelty, that determine intensity, which is a result of the historical trajectory and institutional evolution of conceptual and measurement approaches. Similarly, ambiguity in the theoretical interpretation and evolution of R&D and innovation concepts has influenced a prevailing view of the two as supplementary (Arundel and Smith, forthcoming), leading to bias towards R&D indicators, while the literature suggests a need for better understanding of non-R&D based innovation. Consequently, existing indicators fail to capture diversity in the different modes of innovation across sectors and firms, lagging theoretical sectoral and systems approaches and creating a mismatch between theory and indicators.

Secondly, it is widely acknowledged that innovation survey data is underexploited (OECD, 2009; Arundel and Smith, forthcoming; Arundel et al., 2008; Colecchia, 2007). The indicator problem is not necessarily a problem with the subject approach to measurement, or the survey data produced (Arundel and O'Brien, 2009), but in the types of indicators generated from the data. Little is known about the dynamics of non-innovative firms, for example (OECD, 2009). Resolution of these issues via development of new indicators of innovation is inhibited by restricted access to survey microdata, and in particular panel data. Statistical agencies generally administer innovation surveys, and determine access to the data, and have little resource or incentive to develop better indicators. While many academics have access to microdata, their focus is on econometric research rather than producing more useful indicators. There is an unmet need for work to explore how new indicators might improve the understanding of innovation.

These gaps expose the rationale and research question for this thesis:

*How can new indicators improve understanding of innovation?*

‘New indicators’ in this context refers to the simple, complex and composite innovation indicators generated with data from firm level, ‘subject’ based surveys. Indicators provide the most accessible source of information and understanding for many policy makers, innovation analysts, researchers, and businesses. It is important that indicators are relevant, valid, robust and reliable, and this research process contributes to the broader goal of improving indicators, and in so doing, the broader task of innovation measurement.

A number of sub-questions provide key objectives that guide this research:

1. How can new complex indicators reveal information about the character and distribution of innovation capabilities across firms?
2. How can complex indicators differentiate between less and more innovative firms?
3. How can new indicators improve understanding of innovation strengths and weaknesses within an economy and across sectors?
4. How can new innovation indicators improve understanding of capability development for non-innovative firms?

### **3.0 METHODOLOGICAL APPROACH**

This chapter outlines the methodological approach taken for the empirical component of this thesis. To address the research question, this study uses microdata from two iterations of a large scale regional innovation survey, the Tasmanian Innovation Census (TIC). Since the objective of the research is to understand how indicators might improve understanding, the methodological approach is based on generation and assessment of three main categories of indicator. Because each TIC was based on a methodology defined in the OECD Oslo Manual (OECD, 2005), the results can be generalised to innovation surveys based on the same guidelines. The author played a key role in the development and design of each iteration of the TIC, and has full access to TIC cross sectional and panel microdata, which was central to enabling this study. The first part of this chapter describes the TIC method and datasets, while the second part details the approach to answering the research question.

#### **3.1 METHODOLOGICAL APPROACH FOR THE MAIN DATASET – THE TASMANIAN INNOVATION CENSUS**

The Tasmanian Innovation Census (TIC) study represents the first large-scale, regional study of innovation in Australia. The TIC involves a firm level innovation questionnaire, administered via Computer Assisted Telephone Interviews (CATI), with some follow up questionnaires completed by mail. The scope covers all businesses with five or more Full Time Equivalent (FTE) employees in the regional economy and state of Tasmania. Tasmania has a population of approximately 500,000, with a per capita Gross State Product of \$48,743 as at June 2011<sup>9</sup>. The private sector economy is characterised by a relatively large agriculture, forestry and fishing sector, and a mostly low-technology manufacturing base, concentrated in food and beverage product manufacturing, primary metal and metal product manufacturing, transport and

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<sup>9</sup> Measured in current prices. Source: ABS Cat 5220.0, Australian National Accounts: State Accounts, 2010-11, Table 1. Gross State Product, Chain volume measures and current prices.

equipment and machinery manufacturing, and wood product and pulp and paper manufacturing.

The TIC covers all industries in the private sector economy. As responses are sought from all in-scope businesses across all industry sectors in the target population, the study represents a census, so does not involve sample selection.

There have now been two iterations of the TIC. The first was conducted in 2007, with a target population of 2807 eligible private sector firms with 5 or more FTE employees. Of these, 1591 firms completed the questionnaire, giving a response rate of 56.7%. The main observation period for the 2007 census is the three-year calendar period 2004 to 2006. Financial data on turnover and export shares were obtained for the financial year ended on or before 30 June 2006, while employee count data is for December 2006.

The second TIC study was undertaken in late 2010 and covers activities in the period 2007/8 to 2009/10. The 2010 TIC target population consisted of 2266 eligible private sector firms (with 5 or more FTEs)<sup>10</sup>. Of these, 1401 firms completed the questionnaire, giving a response rate of 61.8%. The main observation period for the 2010 census is the three-year period 2007/8 to 2009/10, with financial data referring to the financial year ended on or before 30 June 2010, and employee count data for June 2010.

For both the 2007 and 2010 TICs, a follow-up survey of a sample of non-respondents was undertaken to test for non response bias. The 2007 non response survey achieved a 100% response rate while the 2010 survey the response rate was lower at 44%. For each TIC, a non response survey analysis found no statistically significant differences in the proportion of innovators (product or process) among the non-respondents compared to the respondents. The results of this analysis indicate that the census results are unbiased. Unweighted results for data from the census studies are consequently assumed to provide unbiased representations of the overall target population (as there is no

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<sup>10</sup> The decrease compared to 2007 is due to natural attrition of businesses, as well as improvements in quality of the population frame, that resulted in fewer duplicate records for example.

statistical evidence of differences in the non response population) and are sufficient for generating representative indicators. Consequently, confidence intervals are not required for given indicators. However, because of the lower response rate in the 2010 TIC non response survey, the possibility that some differences in the 2010 non-respondents may impact on indicator results cannot be entirely discounted. This limitation should be considered when interpreting results.

The 2010 TIC generated a first wave of panel data which includes firms responding to both the 2007 and 2010 questionnaires. Of the 1401 respondent firms in the 2010 TIC, 820 or 58.5% also responded in 2007. These firms constitute the 2007-2010 TIC panel. Indicators generated for results and discussion chapters are produced using both 2010 cross sectional data, and 2007-2010 panel data. Table 3.0 below details the distribution of respondents by sector and size for each dataset.

**Table 3.0 Respondent characteristics by industry and firm size**

<i>Industry</i>	<i>N</i>	<i>2010 Cross sectional Firm Size (%)</i>				<i>N</i>	<i>2010 panel Firm Size (%)</i>			
		<i>5-19</i>	<i>20-99</i>	<i>100+</i>	<i>Total</i>		<i>5-19</i>	<i>20-99</i>	<i>100+</i>	<i>Total</i>
Natural resources	95	56.8	31.6	11.6	<b>6.8</b>	70	57.1	35.7	7.1	<b>8.5</b>
Manufacturing	291	62.4	30.3	7.2	<b>20.7</b>	181	59.1	32.6	8.3	<b>22.1</b>
Infrastructure	197	51.3	38.1	10.7	<b>14.1</b>	105	54.3	37.1	8.6	<b>12.8</b>
Retail, wholesales, accommodation & food services	363	71.1	24.5	4.4	<b>25.9</b>	201	68.7	28.4	3.0	<b>24.5</b>
Knowledge intensive business services	305	67.5	27.5	4.9	<b>21.8</b>	178	70.8	25.3	3.9	<b>21.7</b>
Other services	150	70.0	26.0	4.0	<b>10.7</b>	85	69.4	23.5	7.1	<b>10.4</b>
<b>Total</b>	<b>1401</b>	<b>64.6</b>	<b>28.9</b>	<b>6.4</b>	<b>100.0</b>	<b>820</b>	<b>64.3</b>	<b>29.9</b>	<b>5.9</b>	<b>100.0</b>

*Note: 'Natural resources' includes agriculture, forestry, fishing and mining sectors 'Infrastructure' includes electricity, gas, water and waste services, construction, and transport, postal and warehousing sectors; 'Knowledge intensive business services' includes information, media and telecommunications, professional, scientific and technical services, financial and insurance services, rental, hiring and real estate services, administrative and support services; 'Other services' includes public administration and safety, education and training, health care and social assistance, and arts and recreation services.*



Table 3.0 shows that the respondents largely consist of smaller firms. Over 90% of firms have less than 100 FTE employees, in both the 2010 cross-section and panel. For example, as shown by the totals to the left side of Table 3.0, 64.6% of all respondent firms in 2010 have 5-19 employees, and 28.9% have 20-99 employees, adding to 93.5%. The distribution of firms in the panel closely resembles the 2010 cross-section, suggesting a good level of representation. In both datasets, the services sectors (defined as all sectors apart from natural resources and manufacturing) account for most firms. For example, in 2010 cross sectional data, firms in service sectors account for 72.5% of all firms, and 69.4% in the panel. The mix in both size and sector distributions shows a similar pattern to many advanced economies. Presentation of indicators for both TIC cross sections was not necessary for addressing the research question. Because the cross sectional data for 2007 TIC was not used to generate all indicators, similar industry and size response data is not presented here<sup>11</sup>.

Each TIC questionnaire features much of the same core content as the CIS, in particular for topics on innovation type (product/process/organisational/marketing), novelty, input activities and expenditures, collaboration, and outputs (sales from innovative products). Specific content differences of relevance are discussed throughout results and discussion chapters. The core question topics and question formats are detailed in Table 3.1<sup>12</sup>.

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<sup>11</sup> For some mode indicators results (in chapter 5), results are presented for 2007 TIC snapshot data, however, these are only presented for all 1591 respondents and not disaggregated further. Panel data is used to review changes in indicators over time as it provides a more reliable picture of change. This is because of variations in the different firms responding to each TIC, due to natural firm attrition, firm deaths, births, mergers, changes etc.

<sup>12</sup> This list is not exhaustive, and core components of the respective questionnaires are included in Annex A.

**Table 3.1 Questionnaire content**

<i>Questionnaire content</i>	<i>Measurement level</i>
Main business activity	Text (manually coded)
Business part of an enterprise group	Nominal (yes/no)
Location of head office	Nominal (yes/no)
Sales of goods or services by markets location	Interval (%)
Product (good or services) innovation	Nominal (yes/no)
Product novelty	Nominal (yes/no)
New to business only	
New to market	
Share of turnover from innovative products	Interval (%)
New to market, New to firm, unchanged	
Process innovation	Nominal (yes/no)
Process novelty	Nominal (yes/no)
New to industry in Tasmania, Mainland	
Australia, Overseas	
Innovation activity and expenditure	Nominal (yes/no), and Interval (\$) or (%) for expenditure
Acquisition of machinery, equipment and software	
In-house R&D	
External R&D	
Acquisition of external knowledge	
Training for innovative activities	
Design	
Market introduction of innovations	
Collaboration activity by partner type and location (local, national, overseas)	Nominal (yes/no)
Other businesses within your business group	
Suppliers of equipment, materials, services, or software	
Clients or customers	
Other businesses in your sector, including competitors	
Consultants, commercial labs, or R&D institutes	
Universities or other higher education institutions	
Public research institutes such as CSIRO or Cooperative Research Centres	
Non-technological innovation in:	Nominal (yes/no)
Corporate strategy	
Business practices	
Organising work responsibilities and	
Decision making	Interval (\$)
Marketing concepts or strategies	Interval (number)
Business turnover	
Number of FTE employees	

When compared to the 2007 TIC, two main changes to core questionnaire content in 2010 impact on comparability for the panel data results and consequently, influence the structure and content of panel data indicators. Firstly, the 2010 question on process innovation was expanded to include a broader definition of process innovation provided in the third Oslo Manual (OECD, 2005), and secondly, there was a change to the

question on innovations *not* implemented, which impacted on the questionnaire filters for subsequent innovation input questions. Details are provided in Table 3.2.

**Table 3.2 Questionnaire content changes between the 2007 and 2010 TIC**

<i>Question</i>	<i>2010 Format</i>	<i>2007 Format</i>
Process innovation	During the three calendar years 2004 to 2006, did your enterprise introduce any new or improved processes for <ol style="list-style-type: none"> <li>1. Producing or supplying your goods and services</li> <li>2. Back office systems such as operations for purchasing, accounting, computing, or maintenance</li> </ol>	During the three calendar years 2004 to 2006, did your enterprise introduce any new or improved processes for producing or supplying goods or services?
Innovations that were not implemented in the survey reference period	In the past three financial years to June 2010, did your business have any activities to develop new or improved goods, services, or processes, which were not yet completed or abandoned?	Does your business plan to introduce a new good, service or process within the next three calendar years 2007, 2008 or 2009?

For process innovation, a narrow (2007) definition is used for any comparison of indicators in results and discussion chapters. This is to maintain a consistent definition of process innovation for panel data. In addition, the second part of the process innovation question in 2010 (on back office systems) determines whether firms are asked follow up questions about innovation input activities and expenditures (R&D, purchase of external knowledge or R&D, design, purchase of equipment etc.) and collaboration activities. Because these are filter questions, the content differences impact on comparability. For example, more firms could have ‘planned’ to innovate compared to those with abandoned or incomplete innovations. This potentially leads to underestimated activity for collaboration indicators in 2010. Conversely, the share of firms with abandoned innovations could be greater than those with planned innovations. The questions are essentially asking different things, so the counts for collaboration and activity indicators could differ. These are both indicators that feature in the results. As a result, only firms with implemented innovations are compared.

### **3.2 THE APPROACH FOR PRESENTING RESULTS AND DISCUSSION**

This research thesis is concerned with how new indicators can improve understanding of innovation. Consequently, the primary method involves utilising the TIC microdata resource to produce indicators covering three broad categories, to assess how they fill gaps and deficiencies in the widely available range of simple indicators, and whether they display policy relevance.

As well as meeting these objectives, there are a number of possible factors that can determine the quality and usefulness of indicators for contributing to understanding. These can depend on the purpose or needs for analysis. Reviewing the 2010 CIS, Arundel et al. (2010), note three key dimensions that underpin the quality of an innovation indicator: i.) quality of the questionnaire source data, measured by survey question response rates ii.) variation across key dimensions of interest, including firm size and sector, and iii.) usefulness for practitioners, in terms of capacity to inform policy, academic research, and to a lesser extent business usage. For innovation indicator evaluation, Graversen and Siune (2008) note factors of relevance, accuracy, timeliness, accessibility, comparability and coherence.

In considering how indicators are assessed in this study, two related questions can be asked: what should indicators measure and why? The answers can be found in the literature review, and these guide the approach for assessing the validity of indicators here. Firstly the literature clearly shows that innovation survey indicators need to capture factors that are relevant to innovation performance across an economy. In particular, they must tell a story of relevance to policy, as clear failings in available indicators are evidenced in their limited use by policy makers, and also in wider measurement exercises (Arundel, 2007; Arundel and O'Brien, 2009).

In this sense, indicators must be able to reflect specificities of the relevant innovation system, and reflect widely accepted systems views of innovation as discussed in section 2.2.4. Secondly, indicators must reflect the sectoral diversity of innovation processes and outputs, and capture industry variations in underlying product lines and services, technologies, markets, and challenges that are evidenced in a wide body of empirical

literature, and in sectoral systems approaches covered in section 2.2.6. Thirdly, indicators should reflect the heterogeneity across firms. Section 2.2.5.3 discussed empirical research showing that the rate of innovation varies by firm size, so indicators should also be able to reflect differences in relevant business size demographics.

Indicators must also satisfy some practical requirements if they are to inform better understanding. They must be of a sufficient quality, which can be measured by item non response rates as suggested by Arundel et al. (2010). They must also have some basis or rationale in the related empirical, theoretical or historical literature; the latter in terms of the development of conceptual frameworks and survey indicators covered in Section 2.2.2. A key objective of this study is to explore the usefulness of different indicators for measuring the characteristics and patterns of innovation activity, to highlight indicator weaknesses, potential improvements, amendments or additions, and to consider how indicators might contribute to a better understanding of innovation from policy, practical, and academic perspectives.

In summary, these elements are synthesised into a broad criteria-based framework that guides the validation and assessment of how well particular indicators improve our understanding of innovation. Before detailing the framework, two novel elements in the methodological approach warrant explanation. Firstly, this study uses panel data to assess how complex indicators can reveal a dynamic picture of innovation characteristics over time. Secondly, complex indicators using panel data are used to track the development of innovation capability in non-innovative firms over time.

Thus the following elements or criteria constitute the framework for the results and discussion chapters. Not every criteria is considered for each chapter, as they depend on the nature of indicators presented.

1. The rationale and background for the indicator (historical and theoretical)
  - a. This concerns the historical and theoretical background for indicator construction and use, and whether it fills a gap in existing simple indicators. A factor in understanding how an indicator can contribute to understanding concerns the background rationale behind development and use, which is

covered in the literature review. This can include aspects of the theoretical, empirical and conceptual background. Past research has led to the development and refinement of most indicators, and this is important for assessing their contribution to understanding of a particular aspect of innovation, and for assessing whether the indicator achieves what it was designed to.

## 2. How the indicator is constructed

- a. This includes the constituent source question/s and data elements, and the corresponding levels of quality, measured by item non response rates. Low question response rates signal poor understanding of the question, poor question design, and poor quality in resulting indicators.
- b. This also relates to how the indicator differs from existing available indicators in terms of method of construction, and to the implications of any differences.

## 3. The level of observable and significant variation in performance across sector and/or size classification variables, and the information content for all respondent firms

- a. Theoretical and empirical research has shown that the sources, inputs, processes and outputs of innovation vary by sector and size (Veuglers, 2007; Malerba, 1999; 2002; 2003; 2005). These are often levels at which relevant policies seek to leverage outcomes, for example, through specific industry policies or programs that seek to support small or medium sized businesses. A key factor in determining whether an indicator has value for understanding and informing policy, is observed and significant variations across these classification variables. For example, if a 90% of all firms in every sector and size group are process innovators, the share of process innovators is not a useful indicator for revealing information which improves understanding or is of relevance to policy. Results for most indicators are presented by sector and size. Some indicators are presented using employment weighting. This provides further information about the size distribution of particular

characteristics and their potential impacts. The information content in indicator results for all firms combined is also important for determining usefulness in contributing to understanding at a 'systems' level.

#### 4. Relevance for results from a policy perspective

As the discussion so far has revealed, the primary reason for developing indicators is to 'tell a story', to provide information that contributes to understanding and is useful for policy makers. As discussed in section 2.3.4, it can be noted here then, that by policy relevance, indicators should meet any or all of the following objectives:

- a. They reveal strengths or weaknesses in innovation performance or characteristics.
- b. They provide a map of the patterns of innovation activities, inputs, outputs or impacts.
- c. They provide some differentiation between different levels of innovation intensity, novelty or capability across firms or firm groupings.
- d. They reveal changes or trends in innovation characteristics or performance over time.
- e. They provide results that may inform policy directed at firms operating in different sectors, of different sizes, or in different regions.

Results and discussion sections are combined, and are structured into three main chapters that correspond to particular areas of weakness that are identified in widely published simple indicators. The first (chapter 4), explores indicators for novelty, capability, and impacts in three sections which focus mostly on simple indicators. In chapter 5, a selection of complex indicators, or mode schemes, provide the main focus, again structured in three sections. The selected modes are based on previous research by Arundel (2007), and by Bloch and Lopez-Bassols (2009), and Bloch et al. (2008) which featured in the 2009 OECD microdata project and earlier NIND project discussed in

section 2.4.2. These projects represent some of the first coordinated efforts to produce new, harmonised survey-based indicators across countries.

One problem with new indicator work noted in the literature is the diversity of ad-hoc approaches, and a lack of consistency and comparability in methods and approaches (Veuglers, 2007). By using a similar approach to the OECD and NIND project work where possible, this research hopes to avoid exacerbating the problem. Instead it aims to build on this recent coordinated work by further investigating the value in some of the proposed indicators by using comparable TIC data. Three different mode schemes are selected for review. Though there are many possible modes, the few featured were selected because they address key gaps in basic rate indicators, including a need for better indicators for capability, intensity, and for innovation types and strategies.

Chapter 6 explores variations in sectoral capability using composite indices. These are the primary method used for compiling and analysing innovation indicators for cross-country innovation performance in the ongoing European Scoreboard measurement exercises. The intention here is to assess how composite indicators might promote better understanding innovation within an economy.

Broad assessments of different indicator categories against the framework above show how new indicators can tell a story of relevance to policy, and depict characteristics of innovation not evident in the range of simple available indicators discussed in section 2.2.5.2. Each chapter section concludes with a summary discussion, that evaluates the potential for indicators to contribute to understanding of innovation. This can include: evaluations of the theoretical rationale for the indicator construction and interpretation; potential uses; implications and applications for indicators (predominantly from a policy perspective); any limitations in construction or use – including practical issues for wider adoption; and areas for future research.

The intention is not to explore particular policy issues or innovation policies. This type of investigation or discussion is beyond the scope of this thesis. However, one of the main factors shaping the assessment and discussion of indicators is their potential policy relevance. In this regard, the author has worked with local, state, and federal policy



agencies in relation to production and interpretation of innovation indicators. This experience partly shapes assumptions behind the concept of ‘policy relevance’, and this concept also draws on discussions in the literature covered in section 2.3.4, for example, by Arundel et al. (2010), Arundel et al. (2008) Arundel and Hollanders (2008), and the various policy related discussions in the European Innovation Scoreboard documents (EIS, 2001; 2003; 2004; 2005; 2006; 2008; 2009; IUS, 2012), as well as OECD reports (OECD, 2010; 2010b).

This approach generally dictates descriptive methods of review for the three main groups of indicators noted above. They include bivariate and multivariate cross tabulations, and non-parametric statistical tests (chi-square) for differences in observed indicator values by sector and size variables. In section 4.2.4, reported R&D activity and intensity are evaluated as capability indicators using a binary logistic regression method. Although these are well established traditional indicators, the issues around differences in figures reported on R&D or innovation surveys are well known in the literature and are one reason for work to validate such indicators. The underlying objective here is to analyse the correlation between reported R&D, R&D intensity, and the likelihood of implementing novel innovations (either product, or process). There are two outcome variables: implementation of novel product innovation (yes/no), and implementation of novel process innovation (yes/no). Since the outcome variables are dichotomous (binary), a binary logistic regression model is employed. This method is also suitable because independent variables contain a mix of categorical/binary and continuous variables.

The first model includes R&D activity as an independent variable (yes/no). The second model includes R&D intensity as an independent variable, which can have three values (R&D intensity = 0, R&D intensity  $\leq 1\%$ , R&D intensity  $\geq 1\%$ ). In each model, dummy variables are included to measure the impact of industry, and a continuous variable is included to measure firm size (a continuous variable for natural-log of firm no of employees).

The defined model is specified as:

$$\text{Probability}(Y=1) = P(Y=1) = (e^{\alpha + \beta_1 X_1 + \dots + \beta_2 X_2 + \dots + \beta_k X_k}) / (1 + e^{\alpha + \beta_1 X_1 + \dots + \beta_2 X_2 + \dots + \beta_k X_k})$$

Where  $Y$  is the probability that a firm implemented a novel innovation,  $\beta$  is the regression coefficient of the predictor variables,  $\alpha$  is the constant,  $e$  is the base of natural logarithms (Menard, 2010).

The TIC question item non response rates are one factor that signals the quality of respective indicators produced and this was noted in the framework above. Because almost all indicators are sourced from nominal data they are, generally, of notably high quality. Many item non response rates are less than 2%. Arundel et al. (2007) note the need for item non response rates of less than 5% for nominal (yes/no) questions, less than 10% for ordinal questions, and less than 25% for interval level questions. As mentioned above, there is no evidence of bias in the TIC non-respondents. Owing to the sound data quality, imputation was deemed unnecessary for the purpose of calculating and assessing indicators in this thesis, as there is an assumed negligible impact on the patterns observed and the interpretation of results<sup>13</sup>. Although for this thesis, item non response rates are used as a key measure of indicator quality (as under criteria two in the framework on previous pages), there are other elements that can influence data quality that this measure may not capture, that should be considered by the reader when interpreting results. Misinterpretation or misunderstanding of survey questions is one source of poor quality data, and this might not be completely reflected in item non response rates (for example, by respondents that provided inaccurate answers). This can occur as a result of poorly designed questions, or questions that have not been subjected to sufficient cognitive testing with typical survey respondents. The TIC questions are mostly based on those in the CIS which have been subject to cognitive testing (and are based on guidelines in the Oslo Manual), and for each TIC a number of test interviews were conducted during the questionnaire design phase to remove ambiguities in

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<sup>13</sup> It might have a small, proportional increase in some indicators, though a negligible impact on patterns observed and indicator assessment.

question wording and maximise data quality. However, the possibility remains that errors of interpretation are present in data, and the reader should bear this in mind when considering results.

In the following chapters, the above framework guides the evaluation of indicators and the results and summary discussions, with policy relevance a central consideration for interpreting results.

## **4.0 EXPLORING INDICATORS FOR NOVELTY, CAPABILITY AND IMPACTS**

The intention of this chapter is to address the research question by exploring how innovation survey indicators can improve understanding of innovation novelty, capability, and impacts. The chapter considers the conceptual basis and rationale for product and process novelty indicators, and for links between R&D and innovation novelty. This provides background to discussion around R&D indicators as a measure of capability, while non-R&D based indicators are considered in light of the historical ambiguity around R&D and innovation concepts. Finally, the need for better impact measures is addressed by reviewing employment weighted indicators. Consequently this chapter makes the first step in addressing gaps described in the literature review, exploring how existing survey data can be better exploited to improve understanding of innovation. This provides the platform for an exploration of complex indicators and composite indices in the following chapters. This chapter is broken up into three sections for each indicator topic, with each concluded with a summary discussion.

### **4.1 INNOVATION NOVELTY**

The literature reveals a need for indicators that differentiate between degrees of innovation novelty. The emphasis on novelty stems from early Schumpeterian approaches and later evolutionary economic theories that view novelty as a driver of economic growth, as new products replace old, creating new sales and economic activities, new industries and sources of employment (Verspagen, 2005; Hospers, 2005). One of the key contributions of the original Oslo Manual was to classify degrees of novelty as they applied to product and process innovations, differentiating between new for the industry world-wide, new to industry in a particular country, and new only to the firm (OECD, 1992). By the 2005 Oslo Manual (OECD, 2005), the three levels of novelty were defined as new to the firm, new to the market, and new to the world. Despite these definitions, CIS surveys did not include novelty questions for process innovations until CIS2008, though product novelty questions had been present from the beginning. In addition, many available simple indicators produce confusing results, and

fail to exploit the data to represent different degrees of novelty (Arundel, 2007). Here we consider how data might be better utilised in this respect, by reviewing novelty indicators using TIC data. As described in the methodology in chapter 3, a broad criteria-based framework guides the presentation of results presented. A key part of this involves presenting results by sector, as any observed patterns across industries partly indicate the usefulness of indicators, and in particular from a policy relevance perspective.

#### 4.1.1 PRODUCT NOVELTY – BACKGROUND AND INDICATOR CONSTRUCTION

Firstly, indicators for product novelty are considered. Most innovation survey questionnaires differentiate between products that are new to the market, or new to the firm only. The resulting indicators are the number or percentage of firms with any new to market product innovations over the observation period (the innovation ‘producers’), and the number or frequency of firms with any new to firm only product innovations (the innovation ‘adopters’, who draw on technology and innovation produced elsewhere). Because markets have not been defined in many survey questionnaires, these indicators have produced counterintuitive results that have drawn critique in the literature, discussed in section 2.3.1, and one explanation is the varying size and sophistication of markets that different firms can serve (Mortensen, 2008; Bordt, 2008; Arundel, 2007; Viotti and Gusmao, 2007). As Arundel (2007) shows, a way around this is to combine responses on product innovation with responses on the geographical markets served. Here we further consider this approach, using TIC 2010 cross sectional data.

There are two TIC questions covering product novelty and market locations that source the indicators here:

### ***Product novelty***

These are identical to those on the CIS, and asked of all firms that reported implementing any goods or service innovations in the 2010 TIC reference period (2007/8 to 2009/10):

*Q6a. Were any of your new or significantly improved goods or services new to your market?(yes/no)*

### ***Market destination***

This question was asked of all firms.

*Q3. Can you estimate the percentage of your business's total income in the 2009/10 financial year from the sale of goods or services in*

- a. Tasmania* \_\_\_\_\_%
- b. Australia* \_\_\_\_\_%
- c. Outside of Australia* \_\_\_\_\_%

The quality of data for these questions is considered high (Arundel et al., 2007), with an item non response rate of 1.8% for Question 6a, and 3.4% for Question 3.

## **4.1.2 RESULTS FOR PRODUCT NOVELTY**

Three indicators were constructed that combine responses to market and novelty questions, featured in columns B to D in Table 4.10 below. These are designed to capture different degrees of innovation novelty that reflect the competitive market environment, and are compared to the widely available indicator for the percent of new to market product innovators in column A (which is based only on responses to Question 6a). This approach is based on the work of Arundel (2007), though a key difference is the inclusion of novelty indicators for national markets and domestic markets (in addition to international markets). Consequently, the indicators represent

three degrees of novelty, from high, in column B (novelty and trading on international markets), to low in column D (novelty and trading on local markets only). For example, if a firm reports new to market product innovations in Question 6a *and* sales to overseas markets in Question 3c, they are defined as a high novelty innovator, and included in column B below. Firms that report new to market product innovations *and* sales to national markets (but not overseas markets) are defined as a medium novelty innovator and included in column C.

**Table 4.10 Novel product innovation, 2010 TIC**

Industry	Percent of firms with new to market product innovation	Percent of firms with new to market product innovation and sales to overseas markets	Percent of firms with new to market product innovation and sales to national markets	Percent of firms with new to market product innovation and sales to Tasmanian markets
	A	B (High)	C (Medium)	D (Low)
Manufacturing, <i>N</i> =291	41.2%	14.8%	15.5%	11.0%
Knowledge intensive business services, <i>N</i> =305	34.4%	6.9%	14.8%	12.8%
Other services, <i>N</i> =150	30.0%	3.3%	6.7%	20.0%
Retail, wholesales, accommodation & food services, <i>N</i> =363	29.2%	2.2%	6.9%	20.1%
Natural resources, <i>N</i> =95	24.2%	8.4%	7.4%	8.4%
Infrastructure, <i>N</i> =197	23.9%	4.6%	5.1%	14.2%
<b>All sectors, <i>N</i>=1401</b>	<b>31.8%</b>	<b>6.7%</b>	<b>10.1%</b>	<b>15.0%</b>
	<i>Pearson Chi-Square results, df =5 Share of firms with new to market product innovation: <math>\chi^2=22.5</math>, <math>p&lt;.001</math></i>	<i>Pearson Chi-Square results, df =5 Share of firms with new to market product innovation and sales to overseas markets: <math>\chi^2=46.7</math>, <math>p&lt;.001</math></i>	<i>Pearson Chi-Square results, df =5 Share of firms with new to market product innovation and sales to national markets: <math>\chi^2=28.7</math>, <math>p&lt;.001</math></i>	<i>Pearson Chi-Square results, df =5 Share of firms with new to market product innovation and sales to local markets only: <math>\chi^2=18.5</math>, <math>p&lt;.01</math></i>
<b>Indicators</b>		<b>Construction</b>		
• (A) Share of firms with new to market product innovation		(Count of: if $Q6a=1$ / number of responding firms)		
• (B) Share of firms with new to market product innovation and sales to overseas markets		(Count of: If $Q6a=1$ and $Q3c>0$ / number of responding firms)		
• (C) Share of firms with new to market product innovation and sales to national markets		(Count of: If $Q6a=1$ and $Q3c=0$ and $Q3b>0$ / number of responding firms)		
• (D) Share of firms with new to market product innovation and sales to local markets		(Count of: If $Q6a=1$ and $Q3c=0$ and $Q3b=0$ and $Q3a >0$ / number of responding firms)		

Firms are ascribed to their highest level of novelty. For example, a firm with high novelty (in column B), could also report sales to national or Tasmanian markets, but not the other way around. Thus the values for each indicator in column B to D sum to the percent of new to market product innovators in column A<sup>14</sup>.

In column B of Table 4.10, adding the overseas market dimension shows a different picture compared to the percent of new to market product innovators in column A. Although manufacturing is still ranked the highest on the combined indicator in column B, the ranking of natural resources elevates from fifth to second, and infrastructure from sixth to fourth, while the rank of service sectors is lower. In column C, the ranking for novelty on national markets only is similar to that for those operating on overseas markets in column B, though service sectors perform relatively better and infrastructure worse.

For novelty on local markets only, shown in column D, novelty rates are understandably much higher, as the market is much smaller with less competition. Rankings are notably different, with retail, wholesale, accommodation and food services and other services showing relatively higher performance, while manufacturing and natural resources are lower ranked. This emphasises the role of service sectors in diffusing innovations produced elsewhere, for example, using information technology to implement new business processes or offer new online services. Observed differences in the share of firms across sectors are significant for each indicator.

The results demonstrate how three degrees of novelty can be represented by combining responses from two survey questions. If there is policy interest in identifying the highest intensity innovation, then the column B indicator should be used. If there is a need to distinguish degrees of product novelty, all three indicators together are useful (B to D). The results emphasise the importance of sectoral differences in novelty levels, which should be useful for benchmarking sector performance, and informative for sector

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<sup>14</sup> There are some minor discrepancies due to rounding.



related policy development and monitoring. For example, each indicator could provide different benchmark measures depending on the region for which policy applies.

However, there are also limitations in these indicators that warrant consideration. An underlying assumption links responses from product novelty questions to questions on geographical markets, as the two question modules are completely separate on the TIC questionnaire. For example, one possibility is that a firm has new to market product innovations for local markets only, despite also operating on international markets. This issue arises in previous studies on the quality of CIS data (Arundel et al., 2006; Bordt, 2007), and since the 2010 CIS, has been resolved in the CIS questionnaire by adding the following question (after questions on product innovation):

Were any of your product innovations during the three years 2008 to 2010?

- A first in [your country]
- A first in Europe
- A world first<sup>15</sup>

Secondly, the high novelty indicator is biased towards exporting firms. This needs to be taken into account when interpreting sector results from a policy perspective. For example, it may not make sense to use the high novelty indicator as a benchmark for some service sectors (such as retail, wholesale, accommodation and food services).

A final issue worth considering is whether firms understand or interpret the questions on product novelty correctly. One way of checking this is by cross-referencing responses to questions on product innovations to questions on novelty in product innovations. For example, in the TIC 2010, the question on product innovation is as follows:

*Q4. In the past three financial years to June 2010, did your business introduce any:*

*a. New or significantly improved goods? (yes/no)*

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<sup>15</sup> Question as it appears on the CIS2010 Questionnaire.

*b. New or significantly improved services? (yes/no)*

Both the CIS and TIC use the same questions in this regard, whereby all firms that answer ‘yes’ to either goods or services innovation are defined as product innovators, and asked questions on product novelty. In the TIC 2010, these are structured in two questions as follows:

*Q6a. Were any of your new or significantly improved goods or services new to your market? That is, your business introduced them onto your market before your competitors? (yes/no)*

*Q6b. Were any of your new or significantly improved goods or services only new to your business? That is, they were already offered by a competitor in your market? (yes/no)*

The product innovations should at a minimum be new to the firm, so if a firm answers ‘yes’ to the first product innovation question (Q4), and ‘no’ to both product novelty questions (Q6a and Q6b), then this shows a misunderstanding of novelty concepts/questions. Table 4.11 shows the share of product innovators that answered ‘no’ to both product novelty questions, by sector and firm size to see if there are any patterns in errors. Consequently, this represents an error rate for product novelty questions.

**Table 4.11 Error rate for ‘new to business’ product innovation by sector and size, 2010 TIC**

<i><b>Industry</b></i>	<i><b>Firm size</b></i>		
Natural resources	11.6%	Less than 20 FTE	10.2%
Manufacturing	6.8%	20 to 49 FTE	7.1%
Infrastructure	11.7%	50 to 199 FTE	11.7%
Retail, wholesales, accommodation & food services	12.2%	200 + FTE	11.5%
Knowledge intensive business services	7.5%		
Other services	12.4%		
<b>All sectors</b>	<b>9.8%</b>		

Table 4.11 shows that 9.8% of all product innovators have misunderstood novelty questions. There are no particular patterns in error by sector or size. However, the results do suggest a higher rate of error than revealed by item non response rates for novelty questions (which are 1.6% for the question on new to firm product novelty, and 1.8% for new to market product novelty). This suggests a need for better explanations on the degrees of novelty to improve question performance. However, as a product innovation must at least be new to the firm, then an alternative solution is to simply impute a ‘yes’ for the new to the firm question for these firms.

#### 4.1.3 PROCESS NOVELTY – INDICATOR CONSTRUCTION

Degrees of novelty can also be differentiated for process innovation indicators. In the TIC, two questions were asked to ascertain whether a firm had process innovations:

*Q8. In the past three financial years to June 2010, did your business introduce any new or significantly improved processes for:*

- a. Producing or supplying your goods and services (yes/no)*
- b. Back office systems such as operations for purchasing, accounting, computing, or maintenance (yes/no)*

A firm answering ‘yes’ to either Question 8a or 8b was defined as a process innovator. Process innovators were then asked follow up questions to determine the level of novelty:

*Q10. To the best of your knowledge, were any of your new or significantly improved processes new to your industry in:*

- a. Tasmania (yes/no)*
- b. Australia (yes/no)*
- c. The World (yes/no)*

The item non response rates for the process novelty questions (Q10-10c) were 6.7%, 8.8%, and 12.1% respectively. Though these rates are relatively high for binary (yes/no) questions, data are considered to be of sufficient quality for the purpose of presenting indicators here.

#### 4.1.4 RESULTS FOR PROCESS NOVELTY

The results from these novelty questions can be useful from a number of perspectives. They can provide a picture of the relative rate of novelty *within* sectors, which includes the indicators in columns A to C in Table 4.12 below. Indicators can also provide a picture of the distribution of all reported novel innovations *across* sectors, giving an economy-wide perspective, as demonstrated by indicators in columns D to E below.

**Table 4.12 Process novelty by sector, 2010 TIC**

Industry	Percent of new to world process innovators A (High)	Percent of new to Australia only process innovators B (Medium)	Percent of new to Tasmania only process innovators C (Low)	Industry share of new to world process innovators N=77 D (High)	Industry share of Australia only process innovators N=159 E (Medium)	Industry share of firms N=1401 F
Natural resources, N=95	12.6%	6.3%	29.5%	15.6%	11.8%	6.8%
Manufacturing, N=291	9.6%	3.8%	25.1%	36.4%	21.6%	20.8%
Knowledge intensive business services, N=305	4.6%	4.3%	26.2%	18.2%	25.5%	21.8%
Infrastructure, N=197	4.6%	3.6%	18.3%	11.7%	13.7%	14.1%
Other services, N=150	4.0%	4.0%	16.7%	7.8%	11.8%	10.7%
Retail, wholesales, accommodation & food services, N=363	2.2%	2.2%	14.0%	10.4%	15.7%	25.9%
<b>All sectors, N=1401</b>	<b>5.5%</b>	<b>3.6%</b>	<b>20.9%</b>	<b>100.0%</b>	<b>100.0%</b>	<b>100.0%</b>
<i>Pearson Chi-Square results (A), df=5</i>			<i>Pearson Chi-Square results (B), df=5</i>			<i>Pearson Chi-Square results (C), df=5</i>
<i>New to world process innovators:</i>			<i>New to Australia process innovators:</i>			<i>New to Tasmania process innovators:</i>
$\chi^2=49.6, p<.001$			$\chi^2=4.5, ns$			$\chi^2=25.3, p<.001$
Indicators			Construction			
Share of new to world process innovators			Sum of Q10c / Total number of firms (N)			
Share of new to Australia only process innovators			(If Q10c = 'no') - Sum of Q10b = 'yes' / Total number of firms (N)			
Share of new to Tasmania only process innovators			(If Q10c and Q10b = 'no') - Sum of Q10a = 'yes' / Total number of firms (N)			
Industry share of new to Australia only process innovators			Sector sum of Q10b = 'yes' / Total number of firms answering 'yes' to Q10b (all firms)			
Industry share of new to world only process innovators			Sector sum of Q10b = 'yes' / Total number of firms answering 'yes' to Q10b (all firms)			

The indicators in column A to C show the percent of firms that report a certain level of process novelty within each sector, and for all firms. For example, column A shows that for all 1401 respondent firms combined, 5.5% reported new to world process innovations, while 12.6% of 95 respondent firms in natural resources report this type of innovation. Column B shows that for all respondent firms, 3.6% reported process innovations that were new to Australia (and not new to world), while in column C, 20.9% of respondents reported process innovations that were new to Tasmania only.

The three levels of novelty can be considered high (new to world in column A), medium (new to country in column B) and low (new to Tasmania in column C). A firm is defined by the highest novelty category. For example, a new to world process innovator can also report new to Australia process innovation, but not the other way around. In this respect, natural resources is the most innovative sector on high process novelty, followed by manufacturing. For medium novelty process innovations (new to Australia), natural resources and knowledge intensive business services (KIBS) show above average performance and higher rankings, though sector differences are not significant, suggesting similar rates of inbound diffusion across sectors, in terms of process innovation originating in other countries. Rankings for the low novelty measure are mostly the same as for the highest level. Medium and low novelty process indicators represent innovation diffusion, where process technologies are imported, while high novelty indicators represent creative innovation. Sector differences are significant for low and high novelty indicators, suggesting that these indicators should be produced by industry.

Novel process indicators can also be viewed from a different perspective, in order to build an economy-wide picture of the distribution of novel process innovation, as shown in the indicators in columns D to F of Table 4.12. The indicators in Column D show the industry distribution of all firms that report new to world process innovation. For example, a total of 77 respondent firms reported new to world process innovations, and column D shows that the greatest share of these firms (36.4%) were in manufacturing. In the same way, column E shows the distribution of all firms that reported novel process innovation in Australia (and not new to world). For example, column E shows that of the 159 respondent firms reporting new to Australia process innovation, the

greatest share were clustered in knowledge intensive business services (25.5%). These percentage values reflect the size of the sector in terms of the number of firms. So Column F presents the distribution of all responding firms by sector to give perspective to Column D and E indicators. For example, Column F shows that of all 1401 respondent firms, the greatest share (25.9%) were in retail, wholesale, accommodation and food services. The value in both column D and E indicators lies in comparison with the distribution of firms across sectors in column F.

Where the industry share of process innovators in column D or E is proportionately higher than the industry share of firms in column F, this indicates a clustering of novelty and high performance. In this respect, new to world process innovations are disproportionately clustered in natural resources and manufacturing, sectors in which the Tasmanian economy specialises. At the medium novelty level, natural resources shows the highest performance, followed by knowledge intensive business services and other services, a result that again emphasises the services sectors as important for diffusing externally produced innovations. These results could have policy relevance from two perspectives. Firstly, high rates of process novelty can identify areas of high performance. Secondly, low rates of process novelty can provide an indicator of weakness, in which there may be a role for policy support (for example, policies to promote technology acquisition).

The results show that it is possible to produce better indicators for process novelty using existing survey data, though differences in the TIC and CIS questions deserve some consideration. While the TIC distinguishes between process innovations that are new to industry at three levels of geography (as does the Australian innovation survey), the CIS has only included a process novelty question from CIS2008, which asks the following:

*Were any of your process innovations introduced between 2006 and 2008 new to your market?*

This question could be improved by adopting the same format as the TIC and Australian innovation survey, which would allow indicators for the three degrees of novelty demonstrated above, and fill a key gap noted in the literature review. In addition, the wording of ‘new to market’ for the CIS question could be confusing, as it implies the

selling of process innovations, which may not be the case in many valid instances of firms implementing process innovations by technology adoption. Although this question format is preferable, further work should be done to investigate respondent interpretations, and improve the item non response rates.

#### 4.1.5 SUMMARY DISCUSSION

This section addressed the research question by exploring how indicators drawing on existing survey data can improve understanding of the different degrees of novelty in product and process innovations, contributing to the measurement literature by further evaluating possible indicators, suggesting potential areas for improvement, and addressing a real need for better measures of innovation intensity.

Combining market location and product novelty question data allowed differentiation of low, medium, and high novelty product innovators. Significant differences by sector suggest a need for indicators to be produced at this level. The results show that service sectors generally have a higher share of firms on medium and low novelty indicators, while manufacturing and natural resources sectors performed better on high novelty indicators. However, the high novelty indicator is biased towards tradable sectors, which needs to be taken into account when producing and interpreting results from a policy perspective. For example, policies to improve capabilities to absorb new technologies might improve innovation novelty and performance in the-non traded sectors.

To improve the data and indicators in the TIC and similar questionnaires based on the Oslo Manual, a question should ask whether product innovations were new to markets by geographical location (e.g. state, country, world). To improve the logic and data quality, these questions could be linked to product novelty questions. Taking the CIS for example, the question quality could be improved if all three options for market novelty are only asked only of those firms that reported ‘new to market’ products. The follow up question could be amended as follows:

*Were any of your new to market product innovations during the three years 2008 to 2010?*

- *A first on markets in [your country]*
- *A first on markets in Europe*
- *A first on world markets<sup>16</sup>*

The logic of the question as structured on the current CIS questionnaire is not completely sound, as the question is asked of both firms that report new to firm only and new to market products. For example, how could a firm with new to firm only product innovation have new to world innovations? Products that are only new to the firm could be a first on markets in Europe or the country. So the question format above could be asked also of new to firm only product innovators as a follow up, in the following structure:

*Were any of your new to firm product innovations during the three years 2008 to 2010?*

- *A first on markets in [your country]*
- *A first on markets in Europe*

This structure, although increasing the questionnaire space consumed and burden slightly, should substantially improve the question logic and the quality of the response data and resultant novelty indicators. As these questions and indicators are so crucial in the context of developing better indicators, these changes should be seriously considered by statistical agencies.

Additionally, depending on the data collection method, a question filter could ensure that firms are only asked about product novelty for markets they operate on, as reported in the market location questions. For example, a firm with sales only within their country, would only be asked the first follow up question. This would lower respondent burden and reduce error, but would be suitable only for surveys administered using CATI or internet questionnaires, as these can utilise more complex question skip/filter

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<sup>16</sup> Question as it appears on the CIS2010 Questionnaire.



routines. It is harder for respondents to follow complex skip routines on a mailed, paper questionnaire. However, data quality processes should also take these issues into account.

Similarly, indicators for novel process innovation show low, medium and high novelty, based on whether process innovations are new to industry at the local, national, or world level. These indicators were shown to have use for identifying industry clusters of capability, by comparing the absolute firm distribution of novel process activity with the distribution of firms across industries. Results for process innovation showed varied sector performance by novelty levels, and that again services has a higher share of firms on low and medium novelty indicators. This again highlights the importance of services for diffusing innovations, via implementation of technologies, products and services that are new domestically, though produced elsewhere. An example is the implementation of ICT technologies that improve productivity.

From a theoretical perspective, evolutionary economics underlies the focus on indicators presented, viewing novelty as a source of economic growth. Chain-link and systems approaches are also relevant for the interpretation of novelty based indicators, as varying degrees of novelty differentiate between the creation or diffusion of novelty, both of which are argued to have positive economic impacts (Kline and Rosenberg, 1986; Mytelka and Smith, 2002). From this viewpoint, the more innovation novelty the better, and novelty indicators have policy relevance for identifying areas of strength and weakness within an economy, and for benchmarking performance against other economies where comparable indicators are available. This should be possible in the future, as the CIS has evolved to include questions on both product and process novelty (since CIS2008). However, results also revealed some indicator limitations. Potential improvements could facilitate better comparability, and should be considered prior to concluding this discussion.

Firstly, concerns remain regarding respondent understanding of novelty concepts as defined in innovation surveys. The TIC data suggests that approximately 10% of respondents do not understand the definitions relating to product novelty, which increases to around 12% given question non response rates. Question non response rates

for process novelty questions, though considered acceptable, are also a little higher than for other questions seeking nominal data (yes/no questions). Data item imputation is one method for addressing these errors. However, this result implies that even though questions on product/process novelty are part of the core content on the CIS and many other innovation surveys, their quality should not be taken for granted. On a practical level, the question on process novelty on the CIS should be changed to ask about new to ‘industry’ for country, Europe, and outside Europe, as use of the term ‘market’ could confuse respondents implementing process innovations based on technology adoption. In addition, product novelty questions should be better linked to questions on novelty by markets to reduce potential errors.

In summary, this chapter answered the research question by showing how indicators based on widely available data can differentiate three levels of novelty, and that small changes to CIS questions could provide similar indicators for process innovation. Further research on respondent perceptions or interpretations of novelty concepts and definitions (for example, by cross-referencing response data to related questions on product novelty) might help to improve data quality. This is important given that novelty indicators presented here can make a valuable contribution to understanding innovation intensity across sectors, firms and at an economy-wide level, which is of interest from both academic and policy perspectives. In the next section we examine links between inputs and innovation novelty.

## **4.2 R&D INDICATORS AS A MEASURE OF CAPABILITY, AND NON-R&D INDICATORS LINKING INNOVATION INPUTS AND OUTPUTS**

### **4.2.1 BACKGROUND**

This section examines innovation survey indicators linking R&D and non-R&D modes of innovation to novel outputs, seeking to validate R&D indicators as measures of innovation capability.

Linear theory views R&D as the primary source of novel innovations, and much of the literature suggests that firms undertaking more sophisticated R&D projects are likely to

be innovating with a higher degree of novelty in their products and processes (Bloch, 2007; Godin, 2000; Freeman and Soete, 1997; cited in Armbruster et al., 2007). Despite the advent and diffusion of chain-link and systems approaches, and evidence showing that much innovation does not involve R&D (Arundel, 2007; EIS, 2005), an academic and policy bias towards R&D indicators remains (Arundel, 2007). This is often attributed to enduring influence of the linear model (Arundel et al., 2008; Arundel, 2007), though according to Arundel and Smith (forthcoming), part of the reason relates to confusion between R&D and innovation concepts, which stems from ambiguity in original definitions of R&D and non-R&D activities provided in the Frascati Manual (OECD, 2002), which was carried through to the chain-link approach and definitions in the Oslo Manual.

Innovation surveys offer the possibility of exploring both R&D and non-R&D indicators and methods of innovating (Arundel et al., 2008a). Though R&D is classed as a traditional indicator in section 2.1.3, questions on R&D activity and expenditure are also part of the core set of questions on most innovation surveys. However, various authors have highlighted problems for survey respondents in distinguishing between R&D and non-R&D activities (Gullec and Pattison, 2001; Arundel 2007; Arundel et al., 1998; Sandven, 1998; Smith, 2005; Archibugi and Pianta, 1996). Others note the discrepancy between R&D figures and indicators sourced from R&D surveys, compared to those sourced from innovation surveys (Godin, 2002; Pattison, 2009; Mairesse and Mohnen, 2007). Given these background conceptual, theoretical and practical issues, this section queries the usefulness of innovation survey indicators for R&D and non-R&D modes of innovation, and how they might contribute to a better understanding of innovation.

The section has three related objectives. The first is to explore what indicators combining responses to R&D and novelty questions reveal about innovation inputs and outputs, based on R&D and non-R&D modes or strategies. The second objective is assess whether R&D as reported on innovation surveys provides a good measure of innovation capability, as this interpretation underpins the development of new complex indicators featured in the following chapters, and the focus in much empirical work. Assessment of R&D as a capability measure is undertaken using a binary logistic

regression to model the relationship between reported R&D and innovation novelty. The third objective is to explore indicators for non-R&D modes of innovation.

#### 4.2.2 INDICATOR CONSTRUCTION

Firstly, indicators are calculated to depict a descriptive picture of the link between R&D activities and novelty, for firms with either implemented, ongoing or abandoned technological (product or process) innovations in 2010<sup>17</sup>, labelled here as ‘innovation active’ firms for simplicity. Firms are defined as innovation active if they answered yes to any one of the following TIC questions:

*Q4. In the past three financial years to June 2010, did your business introduce any*

*a. New or significantly improved goods? (yes/no)*

*b. New or significantly improved services? (yes/no)*

*Q8. In the past three financial years to June 2010, did your business introduce any new or significantly improved processes for:*

*a. Producing or supplying your goods and services (yes/no)*

*b. Back office systems such as operations for purchasing, accounting, computing, or maintenance (yes/no)*

Three separate indicators are calculated. These show the percent of innovation active firms with:

##### 1. Novel product (new to market) innovation

This includes firms who answered ‘yes’ to:

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<sup>17</sup> Firms with ‘ongoing or abandoned’ innovations are also included because the TIC 2010 questionnaire asked those firms whether they undertook R&D (as it could have been for products or processes to be implemented in the future). ‘Technological innovation’ here refers to product or process innovation only, as R&D questions refer only to these types of innovation.

*Q6a. Were any of your new or significantly improved goods or services new to your market? (yes/no)*

2. Novel process (new to industry),

This includes firms who answered ‘yes’ to any of the following:

*Q10. To the best of your knowledge, were any of your new or significantly improved processes new to your industry in:*

- a. Tasmania (yes/no)*
- b. Australia (yes/no)*
- c. The World (yes/no)*

3. Novel product *and* process innovations.

There are two categories for R&D status that provide the denominator for calculating percentage indicators. These are based on two R&D related questions on the TIC questionnaire, which are the same as those featured in the CIS. The first ‘yes/no’ question asks firms whether they conducted any R&D in the TIC observation period (2007/8 to 2009/10):

*Q12b. In the past three financial years to June 2010, did your business conduct, on an occasional or regular basis, research and development in-house? (yes/no)*

Firms answering ‘yes’, are asked to estimate their expenditure on R&D activity in the most recent financial year (2009/10):

*Q12b1. What was your expenditure on in-house R&D in the 2009/2010 financial year only? (\$)*

The three novelty indicators are presented for innovation active firms that reported any R&D (compared to those that did not), and a subset of R&D performing firms by R&D intensity (measured as the firm level R&D expenditure to turnover ratio). High intensity R&D performers report expenditure in 2009/10 that is greater than 1% of 2009/10 turnover. For low intensity firms, expenditure is less than or equal to 1% of turnover. The indicators draw on seven survey questions, six of which have item non response

rates of less than 2%, while the novel process indicator has a non response rate of 8.2%. Thus the underlying data is of sound quality.

#### 4.2.3 RESULTS – R&D AND NOVELTY

The three novelty indicators are presented in Table 4.20 below. As an example, column A shows that for innovation active firms reporting R&D activity, 53.7% were novel product innovators, compared to 32.3% of those not reporting R&D. All three indicators in Table 4.20 suggest that R&D activity has a strong impact on the incidence of novel innovation. For firms reporting any R&D activity (between 2007/8 to 2009/10), there is a higher rate for each innovation novelty indicator compared to firms reporting no R&D activity. Similarly, there is a higher rate for each innovation novelty indicator for firms with high intensity R&D compared to firms with low intensity R&D.

**Table 4.20 Distribution of firms by innovation novelty and R&D status, 2010 TIC**

<b>R&amp;D status</b>	<b>Percent of novel product innovators A</b>	<b>Percent of novel process innovators B</b>	<b>Percent of firms with novel product <i>and</i> novel process innovation C</b>
Firms engaged in R&D	53.7%	40.8%	26.4%
Firms with high intensity R&D	66.3%	52.7%	39.7%
Firms with low intensity R&D	48.3%	35.1%	19.7%
Firms without R&D	32.3%	20.7%	9.7%
Firms engaged in R&D, N = 603	Firms with high intensive R&D, N= 184		
Firms without R&D, N = 372	Firms with low intensive R&D N = 325		

*Note: the number of firms with high or low intensive R&D does not sum to the share of firms reporting R&D. This is because many firms reporting R&D activity reported no R&D expenditure in 2009/10.*

Extending on these results, indicators are developed for aggregated innovation sales shares by R&D status. These indicators are calculated from survey questions asking for

the percentage share of total 2009/10 sales generated from new to firm or new to market products<sup>18</sup>:

*Q.7 What percentage of your sales income in the last financial year was from new or significantly improved goods or services that were:*

*a. New to your business (%)*

*b. New to your market (%)*

*c1. Unchanged (%)*

The percentage responses to these questions were combined with reported 2009/10 turnover figures to derive a dollar value. This was then aggregated for the two firm groups based on R&D status, to explore whether R&D activity is correlated with increased sales from novel products. The item non response rates for these indicators are approximately 10%. Though they are higher than for other questions, they are considered acceptable given the interval level data sourcing indicators<sup>19</sup>. Results are shown in Table 4.21.

**Table 4.21 Innovation sales by R&D status, 2010 TIC**

<b>R&amp;D status</b>	<b>Share of sales from new to business products A</b>	<b>Share of sales from new to market products B</b>
Firms engaged in R&D	5.1%	8.3%
Firms with high intensity R&D	6.8%	16.5%
Firms with low intensity R&D	5.4%	6.6%
Firms without R&D	6.2%	4.9%

<sup>18</sup> These questions are the same as those asked on the CIS.

<sup>19</sup> Only firms that provided responses to source questions are included in calculations.

In column A, the share of sales from new to business products is notably higher for firms with intensive R&D than for firms without intensive R&D. This may indicate an absorptive capacity effect, whereby firms with higher capability are also better at incorporating external knowledge, technology and innovation in new to business innovations. Firms that do not report R&D show a higher aggregate sales share from new to business products compared to firms that do report R&D. This result implies that new to business products sold embody R&D conducted elsewhere, so this higher sales share for firms that do not conduct R&D can be interpreted as representing spillover effects from diffused innovations produced externally.

Results in column B show that for firms reporting R&D activity, aggregate sales from new to market products account for 8.3% of total sales, nearly double that of firms that report no R&D activity (4.9%). For firms with high R&D intensity, aggregate sales from new to market products are more than double the share compared to firms with low R&D intensity<sup>20</sup>. This suggests that R&D provides a good measure of innovation capability, in terms of the capacity to turn innovation inputs into innovation outputs.

#### 4.2.4 VALIDATING R&D AS A MEASURE OF INNOVATION CAPABILITY – REGRESSION ANALYSIS

As expected, the two sets of descriptive indicators above suggest a clear positive relationship between R&D activities, intensity, and the likelihood of firms implementing novel innovations. In particular, firms with intensive R&D are more likely to implement novel products and processes than firms with non-intensive R&D. However, these indicators do not control for factors such as firm size and industry, which are noted determinants of R&D in the literature (Smith, 2005; Arundel and O'Brien, 2009; Arundel et al., 2008). We can use regression analysis to take these factors into account and test whether the relationship is statistically significant.

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<sup>20</sup> The share of sales by R&D intensity do not sum to the share of sales by R&D activity status, as a number of firms reported R&D activity, but no expenditure.



This type of analysis serves two main functions here. Firstly, to validate R&D indicators based on innovation surveys as a measure of innovative capability. The aim is to use regression results to provide further support for reported R&D as a capability measure, by confirming the observed relationship above with further assessment of the influence of R&D status on novel outputs (novel products, processes etc.). This is important, because of a need for measures of capability noted in the literature review, and because capability indicators form the basis for complex indicators in the following chapter. Secondly, this analysis informs a concluding discussion around how and why indicators for R&D and non-R&D modes of innovation might contribute to the measurement literature and a better understanding of innovation.

To analyse the significance of different factors for innovation novelty in a multivariate framework, logit regression models are estimated for R&D and non-R&D, and for high intensive R&D and low intensive R&D. Two regressions are run because the R&D question on innovation surveys is broken into two parts (for activity and expenditure as described above), and each generates a different innovation capability indicator of interest<sup>21</sup>. For example, a firm can report R&D activity over the three year observation period on an innovation survey, though report no expenditure, because firms are only asked about expenditure for the most recent one year period, and firms may have spent their R&D budget in prior years<sup>22</sup>.

The dependent variables in these models are the introduction of new to market products and new to industry processes by firms. Independent variables for industry and firm size are included. Sector dummies measure the effect of industry, with retail, wholesale, accommodation and food services the reference category. Firm size is measured by the number of employees (a continuous variable based on natural logarithm of the number

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<sup>21</sup> This format for R&D questions is the same for both the TIC and CIS.

<sup>22</sup> In the 2010 TIC, 54 firms reporting R&D activity reported zero expenditure.

of employees). Each regression is run on the 2010 cross sectional snapshot<sup>23</sup>, and the sample consists of 970 technological (product or process) innovators.

Table 4.22 presents the results of logit regressions that examine the effect of any reported R&D activity (over the three years to 2009/10) on the probability of novelty in products or processes. The results confirm that innovative firms undertaking R&D are more likely to introduce novel products and novel processes than those that do not undertake R&D.

**Table 4.22 Logit regression results 2010 TIC, any R&D activity and novelty**

	<i>Product Novelty</i>		<i>Process Novelty</i>	
	<i>B</i>	<i>S.E.</i>	<i>B</i>	<i>S.E.</i>
Constant	-0.780**	0.238	-2.244***	0.268
<b>R&amp;D engagement</b>	0.948***	0.142	0.905***	0.154
Firm size	0.052	0.067	0.213**	0.069
<i>Sector<sup>a</sup></i>				
-Natural resources	-0.658*	0.303	1.506***	0.313
-Manufacturing	-0.027	0.196	0.575**	0.211
-Infrastructure	-0.442	0.238	0.318	0.255
-Knowledge intensive business services	0.004	0.194	0.726**	0.212
-Other services	-0.210	0.244	0.083	0.275
N (observations)	970		970	
2 Log likelihood	1279.550		1176.251	
Model chi-square ( <i>df</i> )	57.321 (7)		92.538 (7)	
Pseudo R <sup>2</sup>	0.077		0.125	

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$

<sup>a</sup>Retail, wholesale, accommodation and food services sector is used as the reference category. Only technologically innovative firms were included in the analysis.

Source: TIC data, calculations by the author with the assistance of Dr A Torugsa.

<sup>23</sup> Binary logistic regression is the chosen model, as this method is suitable for binary outcome variables, and for when independent variables contain a mix of categorical/binary (industry dummies) and continuous variables (firm size based on employment).

Firm size and sector also have an influence on novelty. Larger firms have a greater chance than smaller firms of implementing novel processes. Firms in the natural resources sector are less likely to introduce novel products compared to the reference category of retail, wholesale, accommodation and food services. Firms in natural resources, manufacturing and KIBS sectors are more likely to introduce novel processes than those in retail, wholesale, accommodation and food services.

Similar results are found for logit regressions that examine the effect of R&D *intensity* on the probability of novelty in products or processes. The reference category for R&D is no reported R&D activity. The results are shown in Table 4.23, and reveal that firms engaging in low or high intensive R&D are significantly more likely to introduce novel products than those firms with no R&D.

**Table 4.23 Logit regression results 2010 TIC, intensive R&D and novelty**

	<i>Product Novelty</i>		<i>Process Novelty</i>	
	<i>B</i>	<i>S.E.</i>	<i>B</i>	<i>S.E.</i>
Constant	-0.827**	0.251	-2.357***	0.287
<b>Low intensive R&amp;D (&lt;1%)</b>	0.713***	0.162	0.659***	0.176
<b>High intensive R&amp;D (&gt;1%)</b>	1.550***	0.202	1.345***	0.203
Firm size	0.090	0.073	0.278***	0.077
<i>Sector<sup>a</sup></i>				
-Natural resources	-0.786*	0.337	1.550***	0.350
-Manufacturing	-0.156	0.209	0.516*	0.227
-Infrastructure	-0.448	0.254	0.116	0.278
-Knowledge intensive business services	-0.104	0.208	0.610**	0.227
-Other services	-0.260	0.261	0.049	0.294
N (observations)	970		970	
2 Log likelihood	1135.690		1036.407	
Model chi-square ( <i>df</i> )	73.669 (8)		105.339 (8)	
Pseudo R <sup>2</sup>	0.108		0.155	

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$

<sup>a</sup>Retail, wholesale, accommodation and food services sector is used as the reference category.

Only technologically innovative firms were included in the analysis.

Source: TIC data, calculations by the author with the assistance of Dr A Torugsa.

Firms in natural resources are less likely to introduce novel products (compared to retail, wholesale, accommodation and food services firms). The results also show that firms with low or high intensive R&D are significantly more likely to implement novel processes than those without R&D, while sector and size also influence process novelty. Firms in natural resources, manufacturing and KIBS are more likely to implement novel processes (than firms in retail, wholesale, accommodation and food services). Larger firms are significantly more likely than smaller firms to implement novel processes, which is consistent with the results in Table 4.22. One explanation is that larger firms have greater resources available to continually monitor, develop, modify and implement novel processes or process improvements.

The results for each regression confirm that when controlling for sector and size, novelty in innovation is positively correlated with R&D activity and intensive R&D activity. These results justify using R&D activity or intensity as indicators for innovative capability or creativity, because R&D activity is significantly correlated with the likelihood of introducing novel innovations. However, a possibility is that for some firms undertaking R&D activities, novel innovations are unrelated to that activity. For example, a firm could undertake R&D that does not lead to the introduction of novel products, but introduce novel products using other methods. We have no way of knowing whether this is occurring from results so far. This is one reason for the bias towards R&D indicators, as ‘hidden’ non-R&D innovation is often obscured by R&D activities (Arundel and O’Brien. 2009).

Partly for this reason, innovation that does not involve R&D still represents a large unknown in the literature, and despite results that clearly link R&D with novel innovation outcomes, emerging innovation research suggests that much innovation, including novel product and process innovation, is achieved without undertaking any R&D. There is a need to develop indicators that demonstrate non-R&D modes of innovation, improve understanding of non-R&D based innovation, and the links to novel outcomes. This is an important part of countering the bias towards R&D indicators, and the idea that R&D and innovation are always paired, and provides the rationale for a brief exploration of non-R&D based indicators here.

#### 4.2.5. SIMPLE INDICATORS FOR NON-R&D BASED INNOVATION

The notion of non-R&D based innovation is gradually becoming more widespread (EIS, 2008), with non-R&D based indicators at the country level featured in recent OECD publications (OECD, 2009; 2010). This section aims to consider how indicators can improve understanding around non-R&D modes of innovation. This contributes to the limited but growing literature around this type of innovation, by further investigating non-R&D indicators using TIC data.

Table 4.24 presents simple indicators that show the percentage of technologically innovative firms with no R&D activity (Based on answers to Question 12b described above). Technologically innovative firms here are those firms that implemented product or process innovations over the survey period (answered ‘yes’ to either Q4 or Q8 on the 2010 TIC, as detailed above).

Table 4.24 shows results by sector for 2010 TIC cross sectional data. For example, column A shows that of those technologically innovative firms in natural resources (implemented either a product or process innovation between 2007/8 and 2009/10), 27% reported no R&D activity.

**Table 4.24 Innovation without R&D by sector, 2010 TIC**

<b>Innovation activity</b>	Percent of technologically innovative firms (N=970) with no R&D 2010 <b>A</b>
Natural resources	27.0%
Manufacturing	23.0%
Infrastructure	41.8%
Retail, wholesales, accommodation & food services	48.7%
Knowledge intensive business services	45.9%
Other services	42.9%
<b>All sectors</b>	<b>39.1%</b>

*Pearson Chi-Square results,  $df=5$ ,*

*Sector and share of non-R&D innovators, 2010:  $N=970$ ,  $X^2=52.5$ ,  $p<.001$*

There are statistically significant differences across sectors, which provide a case for presenting sector level results. There is a higher rate of non-R&D innovators in services and infrastructure. This result is consistent with the literature with respect to innovation in services and low-tech sectors. The general view is that prevalent modes of innovation in these sectors are not reliant on direct inputs of science and research (Mortensen, 2008; Miles, 2005; EIS, 2008).

Many technologically innovative firms without R&D also generate novel innovations. This notion is important for dispelling bias towards R&D indicators, promoting a broader perspective for understanding innovation processes, and for informing policy. Table 4.20 confirmed this, showing that 32.3% of all innovation active firms were also novel product innovators with no R&D, 20.7% were novel process innovators and 9.7% were both.

Table 4.25 presents a second set of indicators, showing the share of technologically innovative firms that implement *novel* innovations without undertaking R&D. Results are presented by sector (this excludes those with only planned, unfinished or abandoned activities which are included in Table 4.20 figures).

**Table 4.25 Novel Innovation without R&D – as a share of technological innovators**

Industry	2010 TIC		
	Percent of technologically innovative firms, with no R&D and novel product innovation A	Percent of technologically innovative firms, with no R&D and novel process innovation B	Percent of technologically innovative firms, with no R&D and novel product <i>and</i> process innovation C
Retail, wholesales, accommodation & food services	19.3%	7.5%	5.3%
Knowledge intensive business services	14.4%	11.3%	3.2%
Other services	14.3%	4.8%	2.9%
Infrastructure	11.5%	9.8%	5.7%
Manufacturing	5.2%	4.8%	2.2%
Natural resources	4.8%	11.1%	3.2%
<b>All sectors</b>	<b>12.4%</b>	<b>7.9%</b>	<b>3.7%</b>

*Pearson Chi-Square results, df =5,*

*Sector and share of non-R&D novel product innovators: N=970 ,  $X^2=25.6$ ,  $p<.001$*

*Sector and share of non-R&D novel process innovators: N=575 ,  $X^2=11.5$ ,  $p<.05$*

*Sector and share of non-R&D novel process innovators: N=575 ,  $X^2=4.9$ , ns*

There is a notable share of novel product or process innovators with no R&D. Though results in the previous section show a significant correlation between R&D and the introduction of novel products and processes, these results demonstrate that R&D is not always essential for producing novel innovations.

There is a clear sectoral trend in Table 4.25, with statistically significant differences by sector for indicators in column A and B. For each indicator, a notably higher rate of firms are observed in service sectors. One exception is for natural resources, which shows the second highest rate of novel process innovators without R&D in 2010. A key point here is that these indicators reveal different modes of innovating across sectors. Novel product and process innovation without R&D occurs mostly in services. This supports a sectoral view of innovation, and suggests that indicators should always be produced by industry. It also suggests a need to capture further information about different modes of innovation by sector. If firms are not undertaking R&D, what are the main activities that lead to novel innovations, and can indicators capture these? These

questions are partly addressed with complex innovation indicators explored in section 5.1.

The results in Table 4.25 also raise the question as to whether observed novel innovations are based on non-R&D strategies, or whether they simply involve R&D inputs not observed due to a time lag effect between R&D projects and implementation of innovations. We can check this by reviewing similar indicators using panel data. The panel data allows the construction of indicators that show the percent of different type of innovative firms in the 2010 TIC that reported no R&D activity in either the 2010 TIC or 2007 TIC. Results are shown in Table 4.26.

**Table 4.26 Non-R&D indicators for 2007-2010 panel data**

	Percent of technologically innovative firms with no R&D in 2007 or 2010 TICs	Percent of technologically innovative firms with no R&D in 2007 or 2010 TICs and novel product innovation	Percent of technologically innovative firms, with no R&D in 2007 or 2010 TICs and novel process innovation
Other services	21.1%	**	**
Infrastructure	18.6%	**	**
Knowledge intensive business services	14.4%	3.8%	4.5%
Retail, wholesales, accommodation & food services	12.8%	3.2%	8.0%
Manufacturing	9.3%	1.3%	2.0%
Natural resources	7.8%	2.0%	2.0%
<b>All sectors</b>	<b>13.2%</b>	<b>3.0%</b>	<b>5.4%</b>

*\*\* removed due to low firm counts*

*Pearson Chi-Square results,  $df=5$ ,*

*Sector and share of non-R&D innovators:  $N=575$ ,  $X^2=8.1$ , *ns**

*Sector and share of non-R&D novel product innovators:  $N=575$ ,  $X^2=10.4$ , *ns**

*Sector and share of non-R&D novel process innovators:  $N=575$ ,  $X^2=5.2$ , *ns**

*For all technologically innovative panel firms in 2010 with no R&D in 2007 or 2010,  $N=76$ .*

Firstly, indicators in Table 4.26 show that every sector has technologically innovative firms in 2010 that did not report any R&D in either TIC period (between 2004 and 2006



for the 2007 TIC, and 2007/8 and 2009/10 for the 2010 TIC). Other services has the highest share of non-R&D innovators, followed by infrastructure and KIBS. Secondly, for all sectors combined, there are non-R&D innovators in 2010 with both novel products (3% of all technological innovators) and novel processes (5.4%). There is a small possibility that some firms had R&D activities in the first half of 2007 – which was not covered in the respective TIC reference periods (the 2010 reference period covers from the second half of 2007 to 2009/10). Nevertheless, these figures strongly suggest that observed rates of novel innovation are not simply due to a lag time in the effects of R&D. This is an important result, because it demonstrates how indicators can reveal novel innovations occurring without any R&D inputs, supporting a market-pull perspective, negating the linear view of R&D and addressing a bias towards R&D indicators. Sector differences observed in Table 4.25 suggest that innovation modes and outputs differ by industry, with non-R&D modes more common in services. This emphasises a need for new indicators to better account for differences in how firms innovate.

#### 4.2.6 SUMMARY DISCUSSION.

This section set out to address the research question by exploring how survey indicators can contribute to understanding links between R&D and non-R&D modes of innovation. As the literature review revealed, a bias towards use of R&D indicators in academic and policy domains alike is the product of a long history of widely available, internationally comparable R&D data, dating back to the inception of the first Frascati Manual in 1963 (Steward, 2008; Arundel and Smith, forthcoming), and there is a need for new indicators to capture innovation without R&D. The aim of this section was twofold. Firstly, to contribute to the measurement literature by re-visiting the links between R&D and novelty as reported on innovation surveys, and in so doing, validating the use of R&D indicators based on innovation surveys as measure of innovation capability, which underpins the development of various new complex measures explored in the following chapter. Secondly, the section contributes to a better understanding of non-R&D based modes of innovation, which is seen as an increasingly important area for research in the literature.

Descriptive indicators showed a clear link between R&D activity and the incidence of novelty in innovations, also suggesting an impact on innovation sales, and regression analysis confirmed a significant correlation between the intensity of R&D activity and the likelihood of novel innovations. These results support the use of reported R&D activity and intensity as measures of innovation capability. However, indicators for non-R&D based innovation also make an important contribution, demonstrating that a significant share of firms implement novel innovations without any R&D inputs, and that this mode of innovation is more common in services sectors.

From a theoretical perspective, the linear approach underpins the use of R&D as an innovation indicator, and the positive influence of R&D on novelty can certainly be explained from this science-push viewpoint. However, non-R&D indicators highlight the inadequacy of the linear view for explaining all innovation activity, with a percentage of technological innovators in every sector introducing novel innovations without R&D inputs. These indicators emphasise the need for a flexible theoretical approach to understanding and explaining innovation.

Indicators presented in this section are of high quality, all with relatively low item non response rates, however possible limitations impacting on the analyses should be considered before concluding. As R&D is a technical concept, some firms have difficulty in distinguishing between R&D and non-R&D activities. This is a recurring issue in the literature, and highlighted by differences between R&D statistics based on R&D surveys compared to innovation surveys, and from administrative sources. This issue may also be present in the R&D indicators presented in this section, as R&D rates for the TIC were higher than might be expected, suggesting that some firms misunderstood the question, and included non-R&D activities in responses. If anything, this suggests that non-R&D innovation might be higher than indicated here.

Another issue concerns the structure of the R&D question on innovation surveys such as the TIC and CIS. Firms are asked firstly whether they conducted any R&D in a three year observation period, and if yes, they are asked for R&D expenditure in a one year period. This introduces a possibility for intensity measures to underestimate R&D activity in some instances, as a firm might have spent the R&D budget prior to the one

year period. Thus simple R&D frequency indicators might overestimate R&D activity due to respondent misinterpretation, while intensity measures may not capture all activity. These issues are not considered to impact on the key results, though should be considered in the interpretation of R&D based indicators generated from innovation survey data.

A final limitation worth discussion regards the possibility of selection issues from potential respondent errors in the data, and how these might impact on analyses presented. While R&D may or may not lead to novel innovations, from the opposite perspective, truly novel innovations – that is new to world – must arguably contain some component of R&D. Although the novelty indicators presented in these sections did not distinguish between levels of novelty, section 4.1 showed that a small percentage of respondent firms (5.5%) reported new to world process innovations, or new to market product innovations while operating on overseas markets (6.7%). If firms reporting this type of innovation report no R&D, then either there is reporting error in novelty questions (overstated novelty), or under-reporting of R&D activity. The possibility of these types of error would also impact on the analyses of correlations between R&D activity and the likelihood of novel innovation. However, only 1% of respondent firms fall into this category. Therefore these errors are not assumed to impact on the results presented in this section or the key themes that emerged. Nevertheless, this issue is important to highlight, and future work on non-R&D indicators should take into account the impact of respondent errors. Further research on respondent interpretation of standardised innovation concepts and ongoing improvements to questionnaire design should reduce this as a source of potential error in future analyses.

In summary, this chapter answered the research question by showing indicators that demonstrate how both science push and market pull views can explain different modes of innovation, that R&D activity provides a good measure of innovation capability, and that the modes of innovation differ by sector, implicating a need for better information on innovation modes. The next section briefly considers some innovation impact indicators, prior to exploring complex indicators.

### **4.3 INDICATORS FOR INNOVATION IMPACTS**

A recurring theme in the measurement related literature is a need for better indicators on innovation impacts. The range of readily available published indicators has good coverage of input activities and innovation outcomes, though there are few available impacts measures. Various econometric studies explore the link between innovation characteristics and impacts in terms of innovation sales shares or productivity improvements (based on sales per employee over time), involving multi-staged regression analyses, and there is a need for better simple impact indicators. This final section briefly considers how weighting of indicators using employment data might improve understanding of the impact and distribution of innovations.

#### **4.3.1 EMPLOYMENT WEIGHTED PRODUCT AND PROCESS INDICATORS**

Employment weighting of selected innovation indicators is considered as a means of measuring impacts. As covered in section 2.4.2 on new indicators, authors such as Bloch and Lopez-Bassols (2009) recommend employment weighting for measuring impacts using common innovation indicators. Here the relevance of employment weighting is considered for novelty indicators, by sector. Employment weighting uses data on the reported number of employees, to describe the number of total employees working for firms with a given characteristic, which in this case includes innovation characteristics. Employment data is of very high quality, with negligible question non response rates (0.3%).

Table 4.30 presents three innovation indicators, using firm frequencies and employment weights for comparison: The share of technologically innovative firms, the share of novel product innovators, and the share of novel process innovators (all based on definitions and methods of construction explained in the previous section). Weighting can provide a picture of the relative impact or reach of respective innovation types, and of the distribution in activities across firms by size.

**Table 4.30 Employment weighted indicators by sector, 2010 TIC**

	Percent of technologically innovative firms 2010	Percent of employees that work for technologically innovative firms 2010	Percent of novel product innovators 2010	Percent of employees that work for novel product innovators 2010	Percent of novel process innovators 2010	Percent of employees that work for novel process innovators 2010
	<b>A</b>	<b>B</b>	<b>C</b>	<b>D</b>	<b>E</b>	<b>F</b>
Natural resources, N=95	66.3%	79.3%	24.2%	39.9%	42.1%	58.2%
Manufacturing, N=291	79.0%	88.2%	41.2%	37.8%	34.0%	46.6%
Infrastructure, N=197	61.9%	81.9%	23.9%	41.5%	23.9%	33.0%
Retail, wholesales, accommodation & food services, N=363	62.8%	75.1%	29.2%	51.4%	16.0%	31.6%
Knowledge intensive business services, N=305	72.8%	79.6%	34.4%	35.9%	31.5%	32.9%
Other services, N=150	70.0%	70.0%	30.0%	26.3%	20.0%	27.2%
<b>All sectors</b>	<b>69.2%</b>	<b>80.1%</b>	<b>31.8%</b>	<b>40.3%</b>	<b>26.4%</b>	<b>37.6%</b>

The firm level indicator is calculated based on the frequency of firms with a given characteristic, while employment weighting shows the share of total employees that work for firms with a given characteristic. For all sectors combined, employment weighting increases the rates of innovation on each indicator. Column A shows that for all respondent firms (N=1401), 69.2% are technologically innovative, while the weighted indicator in column B shows that 80.1% are employed by technologically innovative firms. Similarly, in column C there are 31.8% of firms with novel product innovation, though these account for 40.3% of all employment, shown in column D. A larger effect is observed for novel process innovation: 26.4% of firms report this type of innovation in column E, while they account for 39.8% of all employment in column F. This implies that innovative activities have a wider impact across the labour force than suggested by frequency based indicators, and are more common in larger firms.

These impacts could be either positive or negative. For example, process innovations that reduce the need for labour inputs might negatively affect employment levels, or require higher skill levels and workforce training, while new product innovations with high levels of success might increase production and stimulate demand for skilled

employees. The relationship between innovation, skills and employment, however, is subject to ambiguity and debate in the literature in this regard (Pianta, 2005; Tether et al., 2005).

Nevertheless, weighted indicators may be of particular use for understanding shifting skill requirements, as high performance on weighted innovation indicators can direct attention to sectors where the rate of technological change might yield wider impacts on employment. For example, natural resources has the highest weighted share of novel process innovation (58.2%). This suggests that firms with novel process innovation tend to be larger, and technological change impacting on processes in natural resources might have a wider impact on employees in this sector than such changes in other services.

#### 4.3.2 SUMMARY DISCUSSION

This section sought to address the research question by briefly considering how indicators based on existing survey data might improve understanding of innovation impacts. This was approached using employment weighting for selected novelty indicators, drawing on recent measurement related literature (Bloch et al., 2008; Bloch and Lopez-Bassols, 2009).

Employment weighting increased the share of innovation for each innovation indicator, and results provide an indication of the size distribution of activities across firm populations. This may have policy relevance in terms of indicating potential impact and reach of innovation on the labour force, with implications for skills needs based on technological change. These indicators could be useful for informing policies directed at firms of a particular size range for instance.

In summary, this brief section answered the research question by showing how weighted indicators can provide an indication of the distribution of impacts within different firm populations, and these are used to complement complex indicators presented in the following chapter.

## **5.0 EXPLORING CAPABILITY AND STRATEGY MOVEMENT WITH COMPLEX INDICATORS: INNOVATION MODES**

In section 2.4.5 of the literature review, discussion on new developments in (survey based) innovation measurement revealed that much recent research is focused on new ‘complex’ or ‘innovation mode’ indicators that combine responses to multiple survey questions, in order to better depict varied innovation modes and intensities. The objective of this chapter is to address the research question by exploring how results for three mode indicator types can reveal differences in firm level innovation capability, intensity and strategy. These modes were selected based on relevance to the research question, the available innovation dataset, and to maintain some consistency with the work of Bloch et al. (2008) and Bloch and Lopez-Bassols (2009)<sup>24</sup>, contributing to this limited literature by building on recent indicator work.

Each of the modes is explored by producing results using TIC cross sectional data for 2010, and TIC 2007-2010 panel data, which provide respective static and dynamic pictures. The results and discussions around each mode are presented in three separate sections, with each structured using the approach outlined in the methodology chapter.

### **5.1 INNOVATION OUTPUT MODES**

#### **5.1.1 BACKGROUND**

This section presents the first set of complex indicators: innovation ‘output’ modes. Output modes featured here are based on those from Bloch et al. (2008), with origins in earlier work by Arundel (2007) and Arundel and Hollanders (2005). Output modes classify firms into four discrete categories: technology adopters, technology modifiers, novel domestic innovators, and novel exporting innovators. Firms are classified into one of the four categories on the basis of innovation novelty, measured by questions on

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<sup>24</sup>The same method of construction is employed where TIC questions allow.

novelty in product or process innovations (new to market or new to industry respectively), market sophistication or competitiveness, measured by questions on export markets, and in-house capability, measured by questions on R&D and non-R&D activities. These modes consequently combine simple indicators for innovation outputs, inputs, and market conditions. The major advantage of output modes over individual simple indicators, is they enable firms to be classified via escalating levels of innovation capability or intensity, as the four categories are incrementally ordered from low through to high intensity. In this discussion, the terms ‘intensity’ and ‘capability’ are used interchangeably with regard to innovation performance based on output modes.

An assumption underlying output modes, drawn from the theoretical and empirical measurement literature (Huang et al., 2010; Arundel and O’Brien, 2009; Pavitt, 1984; Robson et al., 1989; Smith, 2005; Bloch et al., 2008; Bloch and Lopez-Bassols, 2009), is that a linear progression in innovation intensity or capability exists and is captured through the four mode categories. This assumes some underlying, unobserved level of innovation capability, that is measured by the output modes. Each of the mode categories is detailed below in Table 5.10, including details on the method of construction based on relevant TIC questions.

### 5.1.2 INDICATOR CONSTRUCTION

The output mode categories in Table 5.10 are ranked in order from top to bottom, from the highest level of innovation intensity (novel exporting innovators), to the weakest level of innovation intensity (technology adopters).



**Table 5.10 Output mode indicators**

<i><b>Innovation output modes</b></i>	<i><b>Method of firm classification-includes firms that:</b></i>
<b>Novel exporting innovators</b> These firms have in-house capabilities (R&D), new to market product innovations or new to industry process innovations and export to overseas markets	<ul style="list-style-type: none"> <li>• If Introduced a novel process (in 2010 – Q10a or Q10b or Q10c =1, for 2007 – Q29=1) or a new to market product (in 2010 – Q6a=1, in 2007 – Q13=1), AND</li> <li>• Had export sales to overseas markets (in 2010 – Q3c&gt;0, in 2007 – Q9&gt;0), AND</li> <li>• Conducted in-house R&amp;D (in 2010 – Q12b=1, in 2007 – Q31=1)</li> </ul>
<b>Novel domestic innovators</b> These firms have in-house capabilities (R&D,) new to market product innovations or new to industry process innovations and sales to domestic markets only (Tasmanian or mainland markets)	<ul style="list-style-type: none"> <li>• Were not novel exporting innovators, AND</li> <li>• Introduced a novel process (in 2010 – Q10a or Q10b or Q10c =1, for 2007 – Q29=1) or a new to market product (in 2010 – Q6a=1, in 2007 – Q13=1), AND</li> <li>• Conducted in-house R&amp;D</li> </ul>
<b>Technology modifiers</b> Mostly non-novel innovators ( <i>only</i> new to enterprise, or significantly improved product or process innovations) with acquired research, acquired external knowledge or design activities	<ul style="list-style-type: none"> <li>• Were not novel exporting innovators, AND</li> <li>• Were not novel domestic innovators, AND</li> <li>• Introduced a product or process innovation (in 2010 – Q4a or Q4b=1, in 2007 – Q5 or Q6 = 1), AND</li> <li>• Purchased external R&amp;D (in 2010 – Q12c=1, in 2007 – Q55=1) OR Purchased external knowledge (in 2010 – Q12d=1, in 2007 – Q61=1) OR conducted design activities (in 2010 – Q12f=1, in 2007 – Q67=1)</li> </ul>
<b>Technology adopters</b> Product or process innovators based on adoption, often through machinery and equipment acquired for innovations.	<ul style="list-style-type: none"> <li>• Were not novel exporting innovators, AND</li> <li>• Were not novel domestic innovators, AND</li> <li>• Were not technology modifiers, AND</li> <li>• Introduced a product or process innovation (in 2010 – Q4a or Q4b=1, in 2007 – Q5 or Q6 = 1)</li> </ul>

At the lowest level (technology adopters), firms mostly innovate by adopting innovations or technologies developed by other firms, for example, those embodied in capital equipment, machinery, or software (Smith, 2005), or by implementing products that are only new to the business, and were developed elsewhere. An example in this category could be a construction firm that simply improves its processes by purchasing new drills, or a services firm that improves service by offering home delivery for the first time.

At the second level (technology modifiers), firms report undertaking some in-house activities to modify technologies, products, processes or machinery developed elsewhere. The inherent assumption is an additional level of capability required by these

activities compared to simple adoption by purchasing and using machinery or equipment. Non-R&D in-house capabilities are represented by reported design activities, purchase of external knowledge, or extramural R&D.

The highest categories of innovation intensity are divided into two groups on the basis of whether or not the firm exports to overseas or domestic markets. The highest intensity category (novel exporting innovators), are those firms operating on overseas export markets. As with the product novelty indicators in section 4.1, since the firm is exposed to global competition, the innovation intensity level is assumed to be greater than that of domestic-only innovations (Bloch et al., 2008; Mortensen, 2008; Bordt, 2008). The second highest intensity category is novel domestic exporters. If a product innovation is only new to a domestic market, the implication is innovation based on diffusion of technology developed elsewhere (Arundel and Smith, forthcoming). The output mode indicator consequently addresses a key weakness of simple product novelty indicators (Viotti and Gusmao; 2007; Mortensen, 2008; Bordt, 2008), by incorporating the different degrees of novelty. However, this differentiation is subject to two limitations discussed in section 4.1: the first is due to unlinked market and product novelty questions, and the second due to a bias towards exporting firms.

The modes are mutually exclusive, with firms placed in the highest intensity category that applies. The mode categories above differ from those of Bloch and Lopez-Bassols (2009), by including one category of technology modifier (described in Table 5.10) rather than two<sup>25</sup>, so include four mode categories in total. Another key difference is that in-house development here is measured by R&D activity (yes/no), whereas a separate survey question determines in-house development in existing mode schemes<sup>26</sup>.

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<sup>25</sup> Bloch and Lopez-Bassols distinguish between international modifiers – those with new to business only product/process innovations that operate on international markets, from domestic modifiers – those that only operate on domestic markets. Differences in TIC and CIS questionnaires are one reason for the different categories, and four categories were viewed as preferable for results here.

<sup>26</sup> The CIS asks questions on the origin of product and process innovations, which are used to construct the Bloch and Lopez-Bassols output indicators – the 2007 TIC did not include these questions.

This is mainly due to differences between constituent TIC and CIS survey questions, though the four category mode scheme is also chosen to allow comparable modes for TIC panel data, and to maintain a consistent approach to mode calculation.

A key advantage of this set of output modes is the ordered intensity categories. Firstly, this allows the mapping of innovation intensity across different groups, which overcomes a major deficiency in the widely available set of simple indicators. Secondly, it allows monitoring of shifting capabilities.

An important consideration for the use and interpretation of any output mode indicators concerns the quality of constituent indicators used. This is measured by item non response rates for questions used in mode construction. Each output mode category in Table 5.10 is constructed using three to five survey questions, and in total, ten different survey questions are used. For seven of ten questions, the item non response rate was less than 2%. Three source questions on novel process innovations, asking whether process innovations were new to the local, national or world industry, had comparatively higher non response rates, (6.7%, 8.8%, and 12.1% respectively), however, these questions combine into a single novel process indicator, with an effective item non response rate of 8.2%<sup>27</sup>. Item non response rates for employment are less than 0.5%, so adding employment weights does not affect the quality of output modes. Thus the quality of source indicators for output modes is generally high (all but one with item non response rates of less than 2%), and item non response rates have a negligible effect for the purpose of presenting results here.

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<sup>27</sup> This is because a firm is defined as a novel process innovator if there is any process novelty (new to local, national or international industry), so this rate includes only those that could not answer either two or three of the constituent questions. The reason for use of a broad process novelty indicator rather than only including 'new to world' in the highest category, is due to changes in the process novelty questions between the 2007 and 2010 TICs. The 2007 TIC did not distinguish levels of novelty, so the broad definition was selected to ensure consistency and comparability of the measures presented here.

Importantly, to enable the comparison in panel data results, output mode indicators are only presented for technological innovators. A consistent definition of technological innovators is used for each TIC, which includes any firm that implemented a new or significantly improved product (good or service) or process in the TIC observation period<sup>28</sup>.

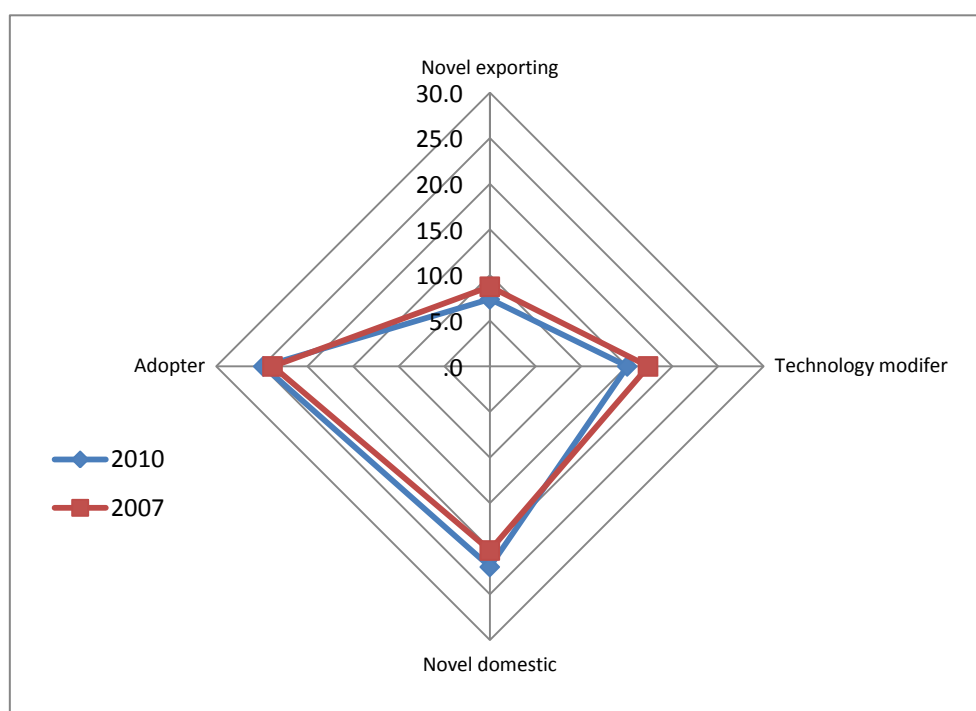
### 5.1.3 ECONOMY-WIDE OUTPUT MODES

As a first step, output modes are presented at an economy-wide level – here for all responding firms in the TIC data – providing a macro picture of the distribution of innovation intensity or capability. Figure 5.10 presents the distribution of all technologically innovative firms across output modes, for the 2010 and 2007 TIC cross sectional data snapshots. In each snapshot, the four points on the radar chart sum to the share of technologically innovative firms among respondents. The percentage shares of responding firms in each mode category are listed in the corresponding table, as well as employment weighted values. For example, in 2010, 69.2% of firms are technologically innovative, while these firms account for 80.1% of total employment across all firms. The table below Figure 5.10 shows the distribution of technological innovators across all mode categories. For example, 22% of all 1401 responding firms are novel domestic innovators. These modes exclude the non-innovators, which make up the remaining 30.8% of firms. Equivalent figures are shown for 2007 cross sectional data, with 70.1% of firms that are technologically innovative, accounting for 79.8% of total employment.

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<sup>28</sup> Changes in questionnaire wording and skip routines between the 2007 and 2010 TIC mean that only those firms with implemented technological innovations can be compared over time. Depending on the survey definitions and application of output modes, firms without implemented innovations might be included in mode calculations, for example firms with abandoned or ongoing innovation. In addition, a narrow definition of process innovation is used for consistency, which includes innovations in ‘production or supply of goods or services’.

**Figure 5.10 Output modes – all firm distribution, 2007 and 2010 TIC**



Output mode	2010 N=1401 %	2010 Employment Weighted %	2007 N=1591 %	2007 Employment Weighted %
Novel exporting	7.4	14.6	8.7	19.0
Novel domestic	22.0	18.8	20.2	17.6
Technology modifier	15.1	28.2	17.3	21.4
Adopter	24.8	18.6	23.8	21.8
<b>Technologically innovative</b>	<b>69.2</b>	<b>80.1</b>	<b>70.1</b>	<b>79.8</b>
<b>Non-innovative</b>	<b>30.8</b>	<b>19.9</b>	<b>29.9</b>	<b>20.2</b>

*Note: some disparity in totals due to rounding.*

In 2010, the majority of technologically innovative firms are either the lowest ranked adopters, or second ranked novel domestic innovators. Technology modifiers account for 15.1% of respondent firms, and only 7.4% of all respondents are the most highly innovative novel exporters. On average, Tasmania has a low share of high intensity innovators, and high share of technology adopters.

In Figure 5.10, firm level indicators show a remarkably similar distribution across output modes in each time period. This suggests a lack of significant change in the aggregate distribution of firm level capability over time. If a policy goal is to improve capability, this result might be a cause for concern. However, as capabilities take time to develop, a longer time period may be required before such results sound a ‘warning signal’ for policy makers.

The comparative distribution of employment weighted modes suggests the economic impact of high intensity innovation is greater than indicated by firm level results. In 2010, the share of employment weighted novel exporters (14.6%) is nearly double the firm share (7.4%), while also higher for technology modifiers, though lower for adopters and novel domestic innovators. A similar pattern is observed for 2007 data. These results suggest that at a broad level, high intensity innovation has a disproportionately greater economic impact than the firm share of activity, as do innovations in technology modification, while novel domestic and adoption modes of innovation have lower impacts. Given the need for impact and output measures, weighted modes might be relevant for policy makers. For example, an increasing trend in the share of high intensity novel innovators might assist in identifying and targeting future skills needs. Conversely, low shares on a particular capability mode could signal areas in which skills are lacking.

Similar output modes presented by Bloch et al. (2008), although not directly comparable, show an opposite pattern for Scandinavian countries, with high shares of novel exporters (20% or more of innovative firms) and low shares of adopters (10% or less), a pattern broadly observed for many advanced countries in output modes used by Bloch and Lopez-Bassols (2009). In the former example, the proportion of firms in each mode is expressed as a share of innovators only, and in the latter, as a share of all firms, as in Figure 5.10. The latter is preferable, as it provides the distribution of capability relative to the whole firm population, contextualising indicators against the broader rate of innovation. For example, there might be a much lower share of innovators in Scandinavian countries compared to other countries, with a greater proportion of novel exporting innovators. This could make the share of novel exporters seem very high,

even though they might account for a much smaller share of the whole firm population compared to other countries.

Though these different figures obviously reflect significant differences in the size and structure of relevant economies as well as differences in output mode calculations or formats, they do suggest that economy-wide level mode distributions can be useful for benchmarking capability, if the same methods are used and relevant adjustment factors applied. Output mode indicators can consequently promote understanding from an innovation systems perspective when produced at economy-wide levels of aggregation (such as country level).

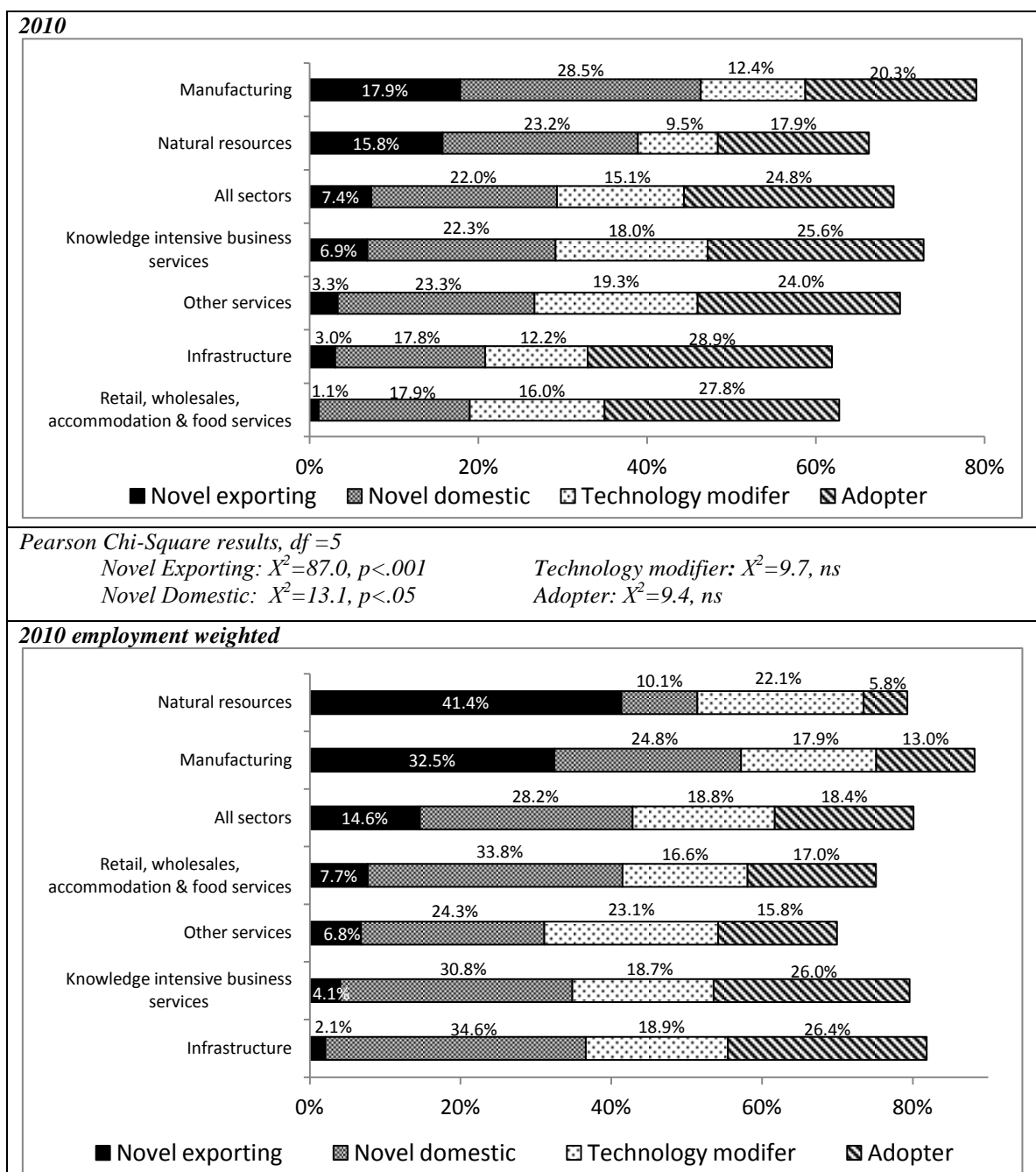
#### 5.1.4 INNOVATION OUTPUT MODES BY SECTOR – 2010 CROSS SECTIONAL DATA

Because of the great diversity in sectoral innovation systems, it is essential that new output mode indicators are produced by meaningful industry categories. Both theoretical and empirical literature reveals that innovation is both pervasive across sectors and underpinned by different technological regimes that shape sectoral opportunities, innovation modes and industry structures (Pavitt, 1984; Robson et al., 1988). The types of goods and services produced and markets served vary by sector. Consequently the skills, technology, knowledge and innovation capability inputs and activities all vary significantly across industries, and it is important for indicators to capture sector differences.

Bloch and Lopez-Bassols (2009) and Bloch et al. (2008) showed differences in output modes for manufacturing and services sectors for selected countries, for both firm based and employment weighted indicators. Here results are presented in the same way, though disaggregated by more detailed sector and size categories.

Figure 5.11 presents results for both the firm level and employment weighted distribution of firms across output modes by sector, for 2010 cross sectional snapshot data. Sectors are ranked by the share of novel exporting innovators in each period (the highest category for innovation intensity).

**Figure 5.11 Output modes – by sector, 2010 TIC<sup>29</sup>**



<sup>29</sup> In each chart in Figure 5.11, the sum of the four categories represents the total share of innovative firms. Thus the remainder represents the share of non-innovative firms. For example, manufacturing has the highest share of innovative firms and the lowest share of non-innovative firms.



For firm level results, differences between the share of novel exporters and novel domestic innovators by sector are statistically significant. There are observable (though not significant) differences in the share of adopters and modifiers across sectors. These variations support the case for producing sector level indicators.

Manufacturing has the highest share of novel exporters, followed by natural resources, and knowledge intensive business services. If the share of firms in this highest intensity mode category is interpreted as a measure of sectoral innovation capability, then these three sectors are the most innovative. Similarly, if the share of firms in the second highest intensity category is interpreted as a relative measure, then manufacturing, natural resources, and other services are the most innovative in domestic markets. From a policy perspective, these measures could be useful if a goal is to identify areas of strength, comparative advantage and growth potential.

Indicators in Figure 5.11 reveal that two lower intensity innovation modes are prevalent in services sectors. Technology modification is more important for firms in other services, knowledge intensive business services, and retail, wholesale, accommodation and food services. The largest share of adopters are in infrastructure, and retail, wholesale, accommodation and food services.

Output mode indicators produced by Bloch et al. (2008) and Bloch and Lopez-Bassols (2009) generally suggested a similar pattern at the country level, with lower shares of novel exporting innovators in services compared to manufacturing. This result is noteworthy from a policy relevance perspective. For example, one implication is that policies aimed at improving high intensity innovation (such as R&D subsidies) might be misdirected for service sectors, where modification and adoption appear to be prevalent modes of innovation. This highlights one reason for producing indicators at the sector level: innovation policies often target or apply to particular industries. If a policy goal is to increase sector capability over time, then changing shares of firms in each mode category have potential use for providing a measure of progress.

Figure 5.11 also presents employment weighted output modes by sector for 2010 cross sectional data, showing the share of sector employees that work for firms innovating via

a particular mode category. Weighting changes the ranking of sectors based on intensity, and accentuates the economic impact of high intensity innovation. The pattern observed for all firms combined repeats across all sectors apart from infrastructure. In natural resources, novel exporters account for 15.8% of all firms, though 41.4% of all employment, and 17.9% of firms in manufacturing though 32.5% of employment. A similar pattern is observed for novel domestic innovators in infrastructure and retail, which account for 17.8% and 17.9% of firms respectively, though 34.6% and 33.8% of total sector employment.

Weighted output modes by sector could have particular policy relevance for understanding differences in the economic impact of technological change and innovation on the labour force. For example, if the rate of novel exporting innovators increases in manufacturing, and these account for a disproportionately large share of employment, then this indicator might provide a picture of the wider impact (whether positive or negative) on demand for skilled employees or workforce training needs. However, employment weighted sector results might be impacted by concentrations of large firms.

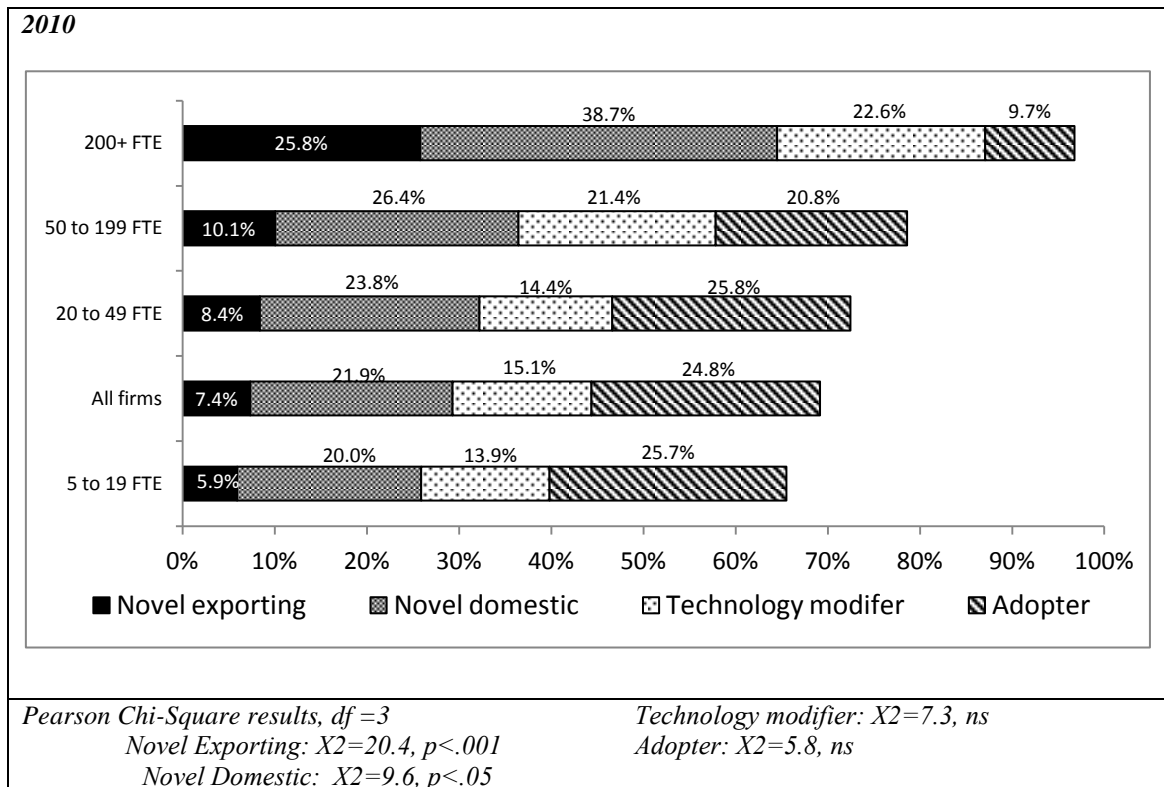
Size impacts on the resource levels and innovation strategies that firms pursue, and policies often impact on firms differently depending on their size (for example, grants with turnover or employment cut offs or SME based policies). This provides one reason for presenting output modes by firm size. Another is to review how capability is distributed across firms of different sizes, and in particularly smaller firms.

#### 5.1.5 OUTPUT MODES BY FIRM SIZE

Figure 5.12 shows the distribution of respondent firms across output modes by size class. As might be expected, larger firms (with 200 or more employees) have a comparatively higher share of novel exporting innovators (25.8%), compared to smaller firms with 5 to 9 employees (5.9%). Statistically significant differences are observed between size class and the share of novel exporters and novel domestic innovators. For the three highest intensity modal categories, the share of firms increases monotonically with size, while in the lowest intensity category of adopters (firms innovating by simply

adopting technology or purchasing equipment), the opposite pattern is observed. Bloch et al. (2008) observe a similar pattern for output modes at the country level for Scandinavian countries, with general increases by size in the share of firms in the highest two intensity categories and decreases in the share of adopters with increasing firm size. Overall, the results suggest that output mode indicators by size class are useful if there is interest in monitoring or increasing capabilities for firms of a particular size range. As policies are often geared towards smaller firms, output indicators by size could assist with the task of monitoring policy effectiveness.

**Figure 5.12 Output modes – by firm size, 2010 TIC<sup>30</sup>**



<sup>30</sup> In Figure 5.12, the sum of the four categories represents the total share of innovative firms. Thus the remainder represents the share of firms that are non-innovative.

### 5.1.6 INNOVATION OUTPUT MODES – PANEL DATA

Though various econometric studies draw on innovation panel data, to the author's knowledge, there is little or no coordinated work using panel data to generate innovation mode indicators. This represents a key gap in the literature, making the contribution of this section unique, moving beyond the often static picture provided with cross sectional indicators, and building on the work of Bloch and Lopez-Bassols (2009) and Bloch et al. (2008). The intention is to address the research question by exploring how panel indicators might be used to reveal a dynamic picture of innovation output capability across sectors. Chain-link and systems theories view innovation in terms of interactive knowledge and cumulative learning processes, suggesting that capability builds incrementally. Panel based mode indicators can potentially improve understanding of how capability develops. If a role of policy is to accelerate capability development, then these indicators may be of great value.

Using TIC 2007-2010 panel data, output modes are presented in Table 5.11. A 'long' format of the panel dataset was created<sup>31</sup>, including panel year as a grouping variable. This allows us to test the significance of any change in the share of firms in each modal category over time (using chi-square tests).

Table 5.11 shows the changing distribution of technologically innovative<sup>32</sup> panel firms by output modes for 2006 and 2009/10. The share of technologically innovating firms is expressed as a percentage of all responding firms. Consequently, the mode figures represent an economy or sector-wide measure of innovation for panel firms. The results in Table 5.11 are useful in two respects. Firstly, they reveal trends over time for all

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<sup>31</sup> This is where the panel data is viewed vertically, with mode variables for 2007 stacked on top of mode variables for 2010. This allows non-parametric (chi-square) tests for significant movements in the frequencies of firms in each modal category over time.

<sup>32</sup> These are firms that implemented a new or significantly improved product (good or service) or process in 2004-6 or 2007/8-2009/10.

firms, providing an aggregate measure of innovation capability change, and secondly, they reveal trends at the sector level.

Table 5.11 shows that overall trends are the same as for cross sectional data in Figure 5.10. In 2010 the wider distribution in capability based on output modes has remained broadly similar over time, with technology adopters making up the largest share of panel firms, followed by novel domestic innovators, technology modifiers, and novel exporters. This result again suggests that mode indicators are suitable for providing an economy-wide output capability ‘map’.

**Table 5.11 Innovation output modes – 2007-2010 panel data**

	Natural resources	Manufacturing	Infrastructure	Retail, wholesales, accommodation & food services	Knowledge intensive business services	Other services	All Tas
<i>Total (N)</i>	<i>70</i>	<i>181</i>	<i>105</i>	<i>201</i>	<i>178</i>	<i>85</i>	<i>820</i>
<i><b>Novel exporting innovators</b></i>							
2007	15.7%	18.8%	4.8%	1.5%	12.9%	3.5%	<b>9.6%</b>
2010	15.7%	17.7%	2.9%	0.5%	6.2%	3.5%	<b>7.4%</b>
$X^2$	0.0	0.1	0.5	1.0	4.7*	0.0	<b>2.5</b>
<i><b>Novel domestic innovators</b></i>							
2007	15.7%	26.5%	20.0%	14.4%	24.2%	23.5%	<b>21.0%</b>
2010	25.7%	29.8%	17.1%	19.4%	22.5%	18.8%	<b>22.6%</b>
$X^2$	2.1	0.5	0.3	1.8	0.1	0.6	<b>0.6</b>
<i><b>Technology modifiers</b></i>							
2007	22.9%	16.0%	14.3%	11.9%	23.6%	16.5%	<b>17.1%</b>
2010	11.4%	14.4%	8.6%	15.4%	21.3%	21.2%	<b>15.9%</b>
$X^2$	3.2	0.2	1.7	1.0	0.3	0.6	<b>0.4</b>
<i><b>Technology adopters</b></i>							
2007	21.4%	19.3%	27.6%	25.9%	17.4%	28.2%	<b>22.7%</b>
2010	20.0%	21.5%	27.6%	26.9%	24.2%	23.5%	<b>24.3%</b>
$X^2$	0.0	0.3	0.0	0.1	2.5	0.5	<b>1.9</b>

$X^2$ =Chi-square values with 1 degree of freedom. \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$

Source: TIC 2007-2010 Panel data, author calculations with the assistance of Dr A Torugsa.

The figures in Table 5.11 depict a mixed change in aggregate level capability (though no changes show statistical significance). The share of highest intensity novel exporters has decreased slightly over time, while the share of novel domestic innovators, the second highest intensity category, has increased slightly.

At lower capability levels, the share of technology modifiers has decreased, while the share of adopters has increased slightly. The interpretation of trends depends on the analytical or policy needs. For example, if an economy is strong in sectors where process modification is the main mode of innovation, then increasing the share of modifiers might be a valid goal for achieving aggregate productivity improvements. An increase in the share of adopters could be interpreted positively or negatively, depending on whether the increase is due to non-innovative firms becoming innovative, or innovative firms shifting to a lower intensity mode (e.g. from modification to adoption). An advantage of panel data is the capacity to map these specific firm movements, which is further explored in the following tables.

If the goal of policy is to improve innovation output capability, then aggregate level output modes using panel data can provide benchmark measures to inform policy efforts. Similarly, sectoral results can assist in benchmarking industry performance. They could help identify areas where sectoral capability might be assisted with intervention, reveal areas of high performance where policy efforts might have minimal effect, or strengths which policies could help build on. Alternatively, if there is a role for policy, by depicting the varied modes of innovation, sectoral mode results could help to understand what types of policy might be appropriate (for example, policies to improve the supply of engineers in modifier based industries where process innovation is dominant, or links with universities where science based research is needed to improve or develop new products).

In Table 5.11, individual sectors generally follow the wider trend (for all firms), and it is the observed sectoral deviations that are potentially more informative. For example, infrastructure, KIBS and other services all show a decrease in the share of firms in the second highest intensity category, indicating decreasing innovation performance domestically. Against the trend for all firms, the share of technology modifiers has

increased in retail, wholesale and accommodation and food services and other services, and the share of technology adopters has decreased in other services. Again, the interpretation of these results depends on needs of the analysis or particular policy goals. By identifying areas of weakening or improving capability, these sectoral trends could be useful for informing sectoral policy efforts, or conversely identifying or monitoring where policy efforts may be failing or succeeding. This depends on whether a goal is to shift upwards in capability modes. For example, in non-tradable sectors the goal might be simply to increase the share of novel domestic innovators. The results in Table 5.11 are limited to the sample of 820 panel firms, though results do provide a picture of trends for survivor firms. One possibility is to weight panel responses against the wider respondent or target population to build a broader picture of trends. This is not attempted here, the main point is to highlight possible ways these indicators might improve understanding of capabilities.

#### 5.1.7 SHIFTS IN INNOVATION CAPABILITIES BASED ON OUTPUT MODES – PANEL DATA

Though output modes presented in Table 5.11 could be useful for informing policy by benchmarking and monitoring sectoral innovation performance, a weakness is they only indicate broad trends in capability for the panel. They do not reveal specific directional shifts in and out of, or between specific categories (for example, from adopter to modifier, or adopter to modifier or novel exporter), or the interplay between innovative and non-innovative firms in given distributions. For example, when a non-innovative firm becomes innovative, what mode do they shift to? Conversely, what is the share of firms in each mode that become non-innovative over time? We would expect incremental improvements in capability, based on theoretical notions of cumulative knowledge and interactive learning (Edquist, 2005; Teece, 1986; Huang, et al., 2010).

These questions can be partly answered by presenting two additional tables of mode indicators. Table 5.12 includes all firms in the panel, and tracks the directional movement of firms from their 2007 output mode status, to a particular status in 2010. Table 5.12 shows the distribution of firms across 2010 output mode categories, for firms

in each output mode category in 2007. Expected frequencies are calculated based on marginal row and columns totals, and shown for reference. The expected frequencies assume no relationship between innovative status in 2007 and 2010. In addition, for firms in each output mode in 2007, the percentage in each 2010 output mode is shown below the observed frequency. For example, of those 186 firms that were adopters in 2007, 30.1% were again adopters in 2010, while 18.8% became modifiers.

**Table 5.12 Specific movement in capabilities over time**

Innovation output mode status 2007	Non- technologically innovative 2010		Technology adopter 2010		Technology modifier 2010		Novel domestic innovator 2010		Novel exporting innovator 2010		Percent Inn
	<i>Obs</i>	<i>Exp</i>	<i>Obs</i>	<i>Exp</i>	<i>Obs</i>	<i>Exp</i>	<i>Obs</i>	<i>Exp</i>	<i>Obs</i>	<i>Exp</i>	
Adopter, N=186 22.7%	51 27.4%	55.6	56 30.1%	45.1	35 18.8%	29.5	38 20.4%	42.0	6 3.2%	13.8	72.6%
Technology Modifier, N=140 17.1%	41 29.3%	41.8	33 23.6%	34.0	31 22.1%	22.2	29 20.7%	31.6	6 4.3%	10.4	70.7%
Novel domestic innovator, N=172 21%	39 22.7%	51.4	32 18.6%	41.7	23 13.4%	27.3	71 41.3%	38.8	7 4.1%	12.8	77.3%
Novel exporting innovator, N=79 9.6%	7 8.9%	23.6	6 7.6%	19.2	11 13.9%	12.5	18 22.8%	17.8	37 46.8%	5.9	91.1%
Non technologically innovative, N=243 29.6%	107 44.0%	72.6	72 29.6%	59.0	30 12.3%	38.5	29 11.9%	54.8	5 2.1%	18.1	56.0%
Total N=820	245 29.9%		199 24.3%		130 15.9%		185 22.6%		61 7.4%		

$$X^2 = 278.14, df = 16, p < .0001, \text{Cramer's } V = 0.2912$$

The percentage share of each group that are technological innovators again in 2010 is shown in the far right column (the remainder became non-innovative, shown in the far left column). The chi-square test shows significance, with a Correlation of 0.29, which is considered moderately high. This provides a basis for interpreting and discussing the results in terms of capability movements.



The results in Table 5.12 are useful from two perspectives. Firstly, in terms of tracking positive movements in capability, represented by upward shifts through modal categories, and secondly, for monitoring backwards movement or decreases in capability, represented by downward shifts in modal categories.

Based on the theoretical and empirical literature, we might expect to see mostly incremental improvements in capability, evidenced by firm movement up one contiguous mode category over time, for example, from adopter to modifier status. This is observed for the most part. However, there are some deviations. For those technological innovators that are adopters in 2007 (the lowest capability innovators), by 2010, a slightly greater share have become novel domestic innovators (the second highest intensity level) than technology modifiers (the third highest, and contiguous intensity level). They have ‘jumped’ a modal category, moving up in capability at a faster rate than expected. In addition, a small share (3.2%), have reached the highest intensity category. For those firms that are non-technologically innovative in 2007, 2.1% became novel exporters, with larger shares in the second and third intensity categories.

What determines the ability to ‘leap’ categories, or more rapidly develop capabilities is of great interest from a scholarly and policy perspective. Various factors could explain such movements, such as firm mergers that increase capability, or hiring of new staff for example. A limitation is these indicators do not reveal determinants, rather, they reveal patterns which may direct further analysis and research depending on policy or analytical needs.

For those firms that are technology modifiers in 2007, a fifth have improved capabilities by one modal category, becoming novel domestic innovators in 2010, while a much smaller share have become novel exporters (4.3%). For novel domestic innovators in 2007, 4.1% have reached the highest category of novel exporter by 2010. Expected values are higher than observed values for higher level categories, which can be explained by the negative trends in higher capability over time shown in Table 5.11.

It appears that firms with lower level capabilities are more likely to improve performance over time. For firms that are adopters in 2007, over 40% have improved capabilities in 2010. For technology modifiers, 25% have improved capabilities, while 4.1% of novel domestic innovators have improved capabilities. This tends to confirm a view of innovation and technological capabilities as cumulative. The more innovative a firm becomes, the higher the level of cumulativeness of technological knowledge, the lower the level of accessibility due to time and difficulty required to develop higher capabilities. This explains the lower transition rates for more innovative categories. These results highlight one potentially important implication for policy. They suggest that support for capability development might be best targeted only to a point, after which the likelihood of improving decreases. This notion is consistent with literature on cycles of technological innovation and diffusion (Teece, 1986). However, there are some important considerations that might impact on these explanations.

Firstly, a key assumption behind this interpretation is that each modal category is discretely ordered by capability. Secondly, as these figures include all firms, this assumes that in all sectors, shifting up modes is desirable and achievable. The highest intensity modes are biased towards tradable sectors, so this must be taken into account (although this bias does not apply to remaining categories). Despite such issues, the results demonstrate the value in panel indicators for tracking capability improvements.

Taking a different perspective, the results in Table 5.12 reveal decreases in capability. If the goal of policy is to prevent erosion of important innovation capabilities, then identifying declining capability may have more relevance for policy than improvements. For example, it is often argued that the ‘Dutch disease’ is a significant problem for Australia, as the resources boom and high currency value erodes manufacturing capability, which moves offshore. Given the cumulative nature of capability and the inevitable demise of the boom, there are very negative consequences for long term competitiveness because of the time taken to rebuild any lost capability. In this respect, some important points can be drawn from Table 5.12.

Firstly, a measure of decaying capability is the share of innovative firms in 2007 that become non-innovative in 2010. For adopters and modifiers this is highest at just under

30%, while around a fifth of novel domestic innovators become non-innovative in 2010 and 8.9% of novel exporters.

The rates of capability decrease are seen to vary by output capability in 2007. Firstly, for 23.6% of modifiers, capability decreased (they became adopters), while there are declines for 32% of novel domestic innovators, and 44.3% of novel exporters. For the latter group, firms were more likely to decrease in capability by one modal step, indicated by monotonically decreasing shares for this group. These figures are informative in two respects. Firstly, they suggest that highly innovative firms are less likely to sharply decrease innovation performance than weakly innovative firms, indicated by a relatively higher rate of decrease beyond one modal category for the latter group. Secondly, they can provide an indicator for the rate of capability decline, which may be of value for policy. If the interest is in understanding these trends at the industry level, then these indicators should be presented by sector. The main point here is to demonstrate how these indicators have potential value for improving understanding.

In a final exploration of change in capability using output modes, Table 5.13 focuses on the group of firms from the second last row of Table 5.12. These are panel firms that transition from a non-innovative to innovative status, and Table 5.13 reveals their movement across output modes in 2010, by sector. If a policy interest is to expand innovation performance across the economy by targeting improved performance in low performing firms, then these indicators are of particular interest. They also promote understanding of how firms become innovative and build capability.

**Table 5.13 Transition of 2007 non-innovators to 2010 innovative status by output modes**

Sector	N	Technology adopters	Technology modifiers	Novel domestic innovators	Novel exporting innovators	Total innovative	Total non-innovative
Natural resources	17	35.3%	5.9%	17.6%	11.8%	70.6%	29.4%
Manufacturing	35	37.1%	11.4%	22.9%	5.7%	77.1%	22.9%
Infrastructure	35	25.7%	8.6%	5.7%	0.0%	40.0%	60.0%
Retail, wholesales, accommodation & food services	93	26.9%	12.9%	12.9%	0.0%	52.7%	47.3%
Knowledge intensive business services	39	30.8%	12.8%	7.7%	2.6%	53.9%	46.2%
Other services	24	29.2%	20.8%	4.2%	0.0%	54.3%	45.8%
<b>All Tas</b>	<b>243</b>	<b>29.6%</b>	<b>12.3%</b>	<b>11.9%</b>	<b>2.1%</b>	<b>56.0%</b>	<b>44.0%</b>

The results for all firms provide evidence of cumulative change in capabilities over time, with the share of firms in each mode category decreasing monotonically by escalating intensity, a trend repeated across most individual sectors. However, there are sector deviations in manufacturing and natural resources, with greater than average increases in the shift of non-innovative firms to novel exporting (the highest intensity) and novel domestic (second highest intensity) categories. In manufacturing, the transition rate to novel domestic innovation status is almost double the average. In natural resources, the transition rate to the highest intensity category of novel exporters is five times the average, while the transition rate to a novel domestic innovation status is almost double the average. Other services shows a relatively faster than average shift to technology modification in 2010.

Thus comparing sector transition rates to the average for all firms is one way of identifying sectors with a faster rate of innovation capability increase, which may reflect the more competitive and innovative nature of particular sectors. Conversely, results could be used to identify sectors with slower than average rates. Both results have use from a policy perspective. A key question for policy is whether to focus support on accelerating development for weaker or stronger sectors.

### 5.1.8 SUMMARY DISCUSSION

This section set out to address the research question by exploring how output mode indicators can contribute to a better understanding of innovation. Results were presented using cross sectional data, by sector and size, and giving employment weighted figures as a measure of impact. Panel data was used to explore how output modes could contribute to understanding the dynamics of innovation capability across industries. In pursuing this task, a broad framework for indicator assessment guided the presentation and interpretation of results. This focused on the general rationale behind the indicator use, the quality and method of construction, how results were positioned against recent related literature, the observable trends by sector and size, and the interpretation of results in terms of potential relevance for policy. Before considering some of the limitations of results and their ultimate contribution to answering the research question, it is important to revisit the theoretical basis for these indicators, in terms of their use and interpretation. This informs the concluding points.

As noted at the beginning of the chapter, innovation output modes combine separate measures for innovation input, output, and markets into a single measure designed to represent discrete and ordered categories of innovation capability or intensity. The theoretical rationale for output mode indicators lies in the broad theoretical and empirical measurement related literature covered in chapter 2, including the weaknesses identified in the predominant range of simple indicators. Consequently, all three of the major strands of innovation theory are present in this mode measure via the constituent simple indicators. For example, the use of R&D as a measure of in-house capability is influenced by the linear theory of innovation. The use of non-R&D activities such as design, purchase of external knowledge or extramural R&D is influenced by a chain-link approach, while inclusion of a market environment measure can be interpreted from a systems perspective. The use of discrete and ordered categories of capability draws on the various empirical literature that integrates these theoretical viewpoints, including, but not limited to, the work of Teece (1986), Pavitt (1984), Malerba (2002; 2005; 2005a), Tether (2001), Hollenstein (2003), Arundel and Hollanders (2005), Arundel (2007), Bloch et al. (2008), and Bloch and Lopez-Bassols (2009). Of particular

relevance to the use, interpretation and contribution of output mode measures is the notion of cumulativeness of technological knowledge and innovation capability, present in more recent systems approaches for understanding innovation (Malerba, 2002; 2005; 2005a; Smith, 2000; 2002), which are underpinned by broader theories of evolutionary economics, and the role of learning in innovation (Smith and Arundel, forthcoming).

Thus some results can be interpreted against this theoretical background, in addition to the practical objective of indicator assessment from a quality and policy relevance perspective. Firstly, output mode results using cross sectional data at an economy-wide level reflect a systems view of innovation, whereby the aggregate distribution of capabilities is shaped by the relevant systemic conditions. Secondly, detailed cross sectional results reflect a sectoral view of innovation, based on significant differences in observed modes of innovation across industries.

Thirdly, presenting a dynamic view of output mode indicators with panel data shows generally cumulative shifts in innovation capability levels over time. These results can be explained through notions of cumulative technological knowledge and capability build up, emphasising the role of knowledge and learning in innovation processes, and the importance of knowledge ‘cumulativeness’ and ‘access’ in understanding innovation. Thus these results partly reflect a sectoral systems view of innovation, where the underlying knowledge base and technological domain must inform efforts to understand innovation and economic growth.

Some of the results show unexpected ‘leaps’ in capability, which also challenge the assumption of ‘cumulativeness’, suggesting a need for theoretical approaches to better explain how capabilities can be rapidly developed. However, this result may also relate to limitations in output mode measures. Thus consideration of the limitations in results presented here must inform the concluding comments with respect to the research question.

Some of the limitations relate to practical issues involved with the construction of output modes, based on constituent indicators. Firstly, the main measure of high level in-house capability is provided by whether a firm reported R&D activity. Although this

was established as a sound capability indicator in section 4.2, in comparison, the output modes used by Bloch et al. (2008) and Bloch and Lopez-Bassols (2009) use questions on the source of product and process innovations to measure in-house capability. These questions ask whether product or process innovations were developed by modifying products or processes originally developed by other organisations, in collaboration with other businesses, or mainly by the responding business. The rationale for the addition of these questions to the CIS was that there are many in-house capabilities (capacity to pilot test, market, refine and implement) that do not involve R&D. Subsequently, this method provides a broader definition of capability that is not limited to R&D.

In the output modes presented in this section, non-R&D in-house capability is measured differently by the undertaking of design, purchase of external knowledge, or the introduction of new products or processes (without undertaking R&D). The reason for this different method of calculation was practical. The 2007 TIC questionnaire did not include the questions on the source of innovation, and a consistent definition was required to produce identical indicators over time, which is the main rationale for the approach taken. The impact of this difference should not be significant in terms of the results (for example, the majority of those firms that undertook R&D also answered ‘yes’ to the questions on in-house development of products processes in the 2010 TIC), but is important to note, as it means the output modes here are not directly comparable to those in the recent literature.

Secondly, the measure of ‘novel process innovation’ used in the calculation of output mode indicators does not distinguish between the level of novelty (for example, new to country or new to world), but simply ‘new to industry’, which could be new locally, nationally or internationally. The reason for this was again differences in the 2007 and 2010 TIC questionnaires, as in 2007 firms were only asked whether process innovations were ‘new to industry’, and in order to have comparable measures over time, which was a priority, the same definitions were required. Ideally, future output modes would include a high intensity process innovation in the highest intensity modal category. For the CIS, this would also require changes to current process innovation questions recommended in section 4.1. These practical issues are not considered to significantly impact on the research objectives or results, though should be considered in their

interpretation, and do raise some key points with respect to the use of complex indicators for improving the measurement of innovation.

Firstly, if these indicators are to be adopted, then they must be produced in a way that is not only consistent with the theoretical and empirical literature, but that is practical and consistent in implementation. If comparable indicators are to be calculated, then they should focus on the 'core' set of repeating innovation survey questions over time. They should be calculated in a way that uses consistent definitions, and takes into account questionnaire skip routines and individual quality levels of constituent questions. This in itself presents a challenge and limitation in progressing the use of these new indicators. A final practical limitation involves any errors that may be present in constituent indicators that may not be reflected in item non response rates (for example, errors in respondent interpretation of survey questions and definitions). This possible limitation is hard to avoid. It may be ameliorated by ongoing improvements to questionnaire design through cognitive testing, though this highlights a need for further research on respondent interpretations of questionnaire concepts (such as novelty as discussed in section 4.1), and the impact on indicators.

Finally, some of the limitations in these indicators relate to the potential policy relevance of results. For example, the highest intensity output mode category is biased to firms in the tradable sectors. As firms that do not export overseas will never be classified into this category, it makes no sense to have the highest category as a target for some sectors. This reiterates the need to produce results at the sector level, which was supported by the results in this section. Secondly, the indicators do not reveal whether it is more or less profitable to innovate in a particular mode. This assumption is based on the theoretical background discussion in chapter 2. For example, modification may be the most profitable form of innovation for certain industry sectors, and shifting modes may not be a desirable policy outcome. These factors need to be taken into account in assessing the policy relevance of these indicators and in designing new types of measure for benchmarking and monitoring policy. As Autant-Bernard et al. (2010) note, there is scant evidence on the impact of particular modes of innovation on performance (for example, in terms of increased sales or productivity improvements). Consequently before performance targets for output mode indicators are set, there is a



need for more research on the impact of modes on performance, and on whether it is indeed desirable or achievable to increase innovation in a particular mode in all industries.

In summary, this chapter has presented results for innovation output modes that provide clear answers to the research question. Firstly, results have shown that new output mode indicators can improve understanding of innovation by providing discrete categories of capability or intensity that allow mapping and benchmarking of innovation performance. These can improve understanding of the distribution of capability at the economy-wide level, and the distribution of capabilities across sectors and firms of different sizes (indicating the impact of different innovation modes with employment weighted indicators). These are all levels at which innovation policies may apply. Secondly, the results have shown that new innovation indicators can improve understanding of the dynamics in capability development over time. These results are informative from both a scholarly perspective and policy perspective, though the limitations above must inform their interpretation and wider adoption.

## **5.2 INNOVATION STATUS MODES**

This section explores a second set of complex innovation indicators: ‘innovation status’ modes. These modes are based on the work of Bloch and Lopez-Bassols (2009), Bloch et al. (2008), and Arundel (2007), and are designed to measure two important innovation inputs: creativity or inventiveness, and diffusion. The intention of this chapter is to address the research question by exploring how these status modes might improve understanding of innovation, and particularly from a policy perspective. The chapter builds on existing work by considering status modes in more depth by sector and size, and assessing how panel data might improve their usefulness and policy relevance.

### **5.2.1 BACKGROUND**

Although historically, ‘diffusion’ and ‘production’ of knowledge, technology and innovation have been treated as conceptually distinct (Rogers, 1962), since the

emergence of the chain-link view, innovation and diffusion concepts have often been viewed as interlinked (see section 2.2.1). This is because as innovations are adopted or imitated, they are often improved upon, creating further innovations that can feed back to the producer (also because the minimum criteria for an innovation that be ‘new to the firm’ (OECD, 2005)). This raises a key challenge for innovation indicators: to reflect the difference between innovations produced by the firm, and innovations based on diffusion. Diffusion is defined as the ‘spread of innovations’ (OECD, 2005, p.78), so in this sense innovation based on diffusion occurs via sharing, adopting, or actively building on externally produced technologies, knowledge, or innovations. This can occur both formally (through active collaboration on innovation projects) and informally (through adoption via equipment purchases, attending conferences, accessing open information sources etc.). Both producing and capturing the value of innovation, and promoting rapid diffusion are recognised as important sources of competitiveness, growth, and prosperity, and understanding the distribution and dynamics between diffusion verses production based innovations in an economy is important from a scholarly and policy perspective.

Bloch and Lopez-Bassols (2009) highlight discussions with policy makers, in which creative and informal activities were identified as of interest for policy, while Arundel (2007) notes policy interest in collaboration indicators based on interviews with members of the European policy community in 17 countries. Various simple indicators are designed to separately measure the elements of creativity and diffusion. Status modes are an attempt to combine some of these in order to improve understanding of their distribution across firm populations.

### 5.2.2 INDICATOR CONSTRUCTION

Innovation status modes classify firms into four categories based on the mix of in-house creativity or diffusion in their innovations: creative collaborators, creative non-collaborators, informal collaborative innovators, and informal non-collaborators. Each

of the status mode categories is explained in the table below, including details on the method of construction based on responses to TIC survey questions<sup>33</sup>.

**Table 5.20 Innovation status mode definitions and method of construction**

<i><b>Innovation status mode</b></i>	<i><b>Method of construction</b></i>
	Includes technological (product or process) innovators (In 2007 – answered ‘yes’ to Q11 or Q12 or Q8a, in 2010 – answered ‘yes’ to Q4a or Q4b or Q8a) that:
<b>Creative collaborators</b> both carry out high-level in-house creative activities (R&D) and collaborate in their innovation activities.	Conducted R&D (in 2010 – answered ‘yes’ to Q12b, In 2007 – answered ‘yes’ to Q31), AND Collaborated on innovation projects (in 2010 – answered ‘yes’ to Q13, in 2007, answered ‘yes’ to Q18)
<b>Creative non-collaborators</b> perform research and development, but do not actively collaborate to access external knowledge.	Conducted R&D and did not collaborate
<b>Informal collaborative innovators</b> do not perform research, but they collaborate on innovation.	Collaborated on innovation projects, but did not conduct R&D
<b>Informal non-collaborators</b> neither perform research nor actively collaborate to develop innovations.	Did not Conduct R&D or collaborate on R&D projects

Within the status mode categories, the level of in-house creativity is measured by the conduct of research and development, (which can also be interpreted as a measure of capability, as with the previous set of output modes). The level of diffusion is measured by participation in active collaboration on innovation projects. The TIC definition of collaboration is consistent with the Oslo Manual (OECD, 2005) and CIS: ‘collaboration between the responding business and other organisations to develop new or significantly improved goods, services, or processes. This excludes pure contracting out, and both collaboration partners do not need to benefit commercially, or share risks’<sup>34</sup>.

<sup>33</sup> Relevant questions are based on the OSLO manual definitions and feature in the CIS.

<sup>34</sup> Definition provided on the TIC, included in Annex A.

Collaboration provides a measure of diffusion because it involves interaction with external organisations, typically motivated by access to external knowledge, technology, complementary assets and expertise not possessed by a firm in isolation (Mowery et al., 1998; Grant and Baden Fuller, 1995; Teece, 1986). Knowledge, technology, innovation and capability diffuse via collaboration activities. Diffusion of these phenomena via collaboration in turn can promote further innovation as firms improve on the ideas, technologies, products and processes developed by partner organisations (Arundel and Hollanders, 2006).

Within the four status mode categories there is an implicit assumption of increasing capability from the bottom modal category in Table 5.20 to the top category. At the lowest category (informal non-collaborators), firms introduce product or process innovations, though do not collaborate or conduct R&D. Innovation is therefore based on adoption of externally produced knowledge, technology or innovations.

In the second lowest category (informal collaborative innovators), firms collaborate with other actors on the development of product or process innovations, but do not conduct formal research or development. Innovation is based on active diffusion of knowledge and technology between the firm and partner organisations.

In the second highest capability category (creative non-collaborators), firms innovate and conduct formal research and development related to their product or process innovations. And in the highest capability category (creative collaborators), firms both conduct formal research and collaborate for the development of innovations.

This method of status mode calculation differs from that of Bloch et al. (2008), Bloch and Lopez-Bassols (2009), and Arundel (2007) in two ways. Firstly, in their work, a firm is classified as creative if they undertook R&D *or* applied for a patent. Secondly, diffusion is measured by collaboration activity *and* responses to questions on the source of product or process innovations. If a firm reported collaboration *or* that product or process innovations were developed with or solely by others, they are classified as collaborative. The reason for the different method of calculation chosen here is small differences in the 2007 and 2010 TIC questionnaire content. The priority was to

maintain consistency in the indicators in order to allow panel data calculations (and neither TIC asked about patenting activity, while the 2007 TIC did not ask questions on who developed innovations).

The quality of innovation status modes is high based on non response rates for constituent questions. There are five separate TIC questions used for calculating modes. The non response rate for each question is below 1%. These had a negligible impact on the calculation of indicators here.

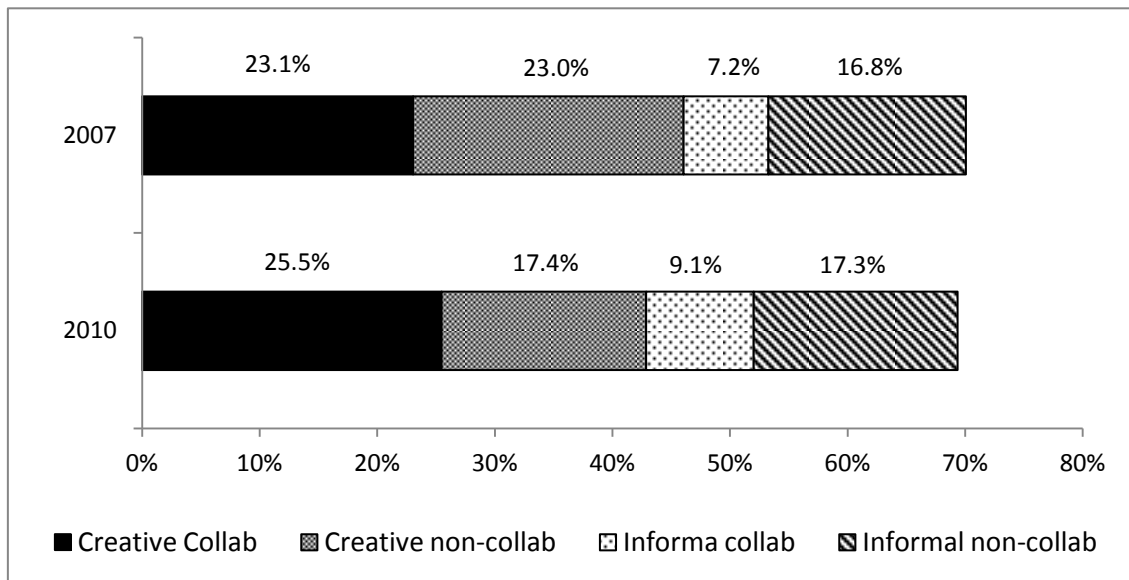
In Table 5.20 the term ‘informal’ is used to define innovation without high-level in-house creative abilities, as indicated by conduct of research and development. Thus informal can be interpreted to denote a non-creative mode of innovation input.

### 5.2.3 ECONOMY-WIDE INNOVATION STATUS MODES

The first step in evaluating the status mode indicators is to present them for all respondent firms using cross sectional data. Figure 5.20 reveals the distribution of technologically innovative firms by status modes for the 2010 and 2007 TIC snapshots, expressed as a share of all responding firms (providing a picture of both innovation modes and the level of innovation). For example, the share of firms in each category in 2010, sums to the share of technologically innovative firms in 2010. Alternatively, modes can be presented as a distribution for innovators only as Bloch et al. (2008) have done, though this format might be less useful for economy-wide comparisons, because innovation rates vary across economies.

Status modes at an economy-wide level are potentially useful from two points of view. Firstly, they can depict the aggregate mix of creative and collaborative innovation, which may provide a useful benchmark if figures are available for relevant comparison economies. Secondly, they can be used to track change over time.

**Figure 5.20 Status modes – all firm distribution, 2007 and 2010 TIC**



2010, *N* = 1401. 2007, *N*=1591.

Figure 5.20 shows how the share of all firms that are creative collaborators has increased slightly in 2009/10 (to 25.5%) compared to 2007 (23.1%), suggesting some upward shift in creative capability over time, while the share of creative non-collaborators has decreased. The share of informal collaborators has increased. The lower share of firms overall in 2010 reflects a slightly lower share of technologically innovative firms compared to 2007.

These comparisons over time could be useful if a goal is to increase a particular status mode of innovation. The share of creative collaborators might provide a target for measuring improved performance over time, as a greater level of creative collaborative activity may lead to acceleration of innovation and diffusion of skills and knowledge between organisations, with assumed positive macro economic impacts from increases in novelty and knowledge spillovers. Conversely, decreases in performance on particular mode categories might provide useful information on where policy might be best directed (for example, by stimulating creativity through R&D incentives, or developing programs to promote collaboration). However, at an economy-wide level, these indicators could also be misleading, as they might simply reflect industrial

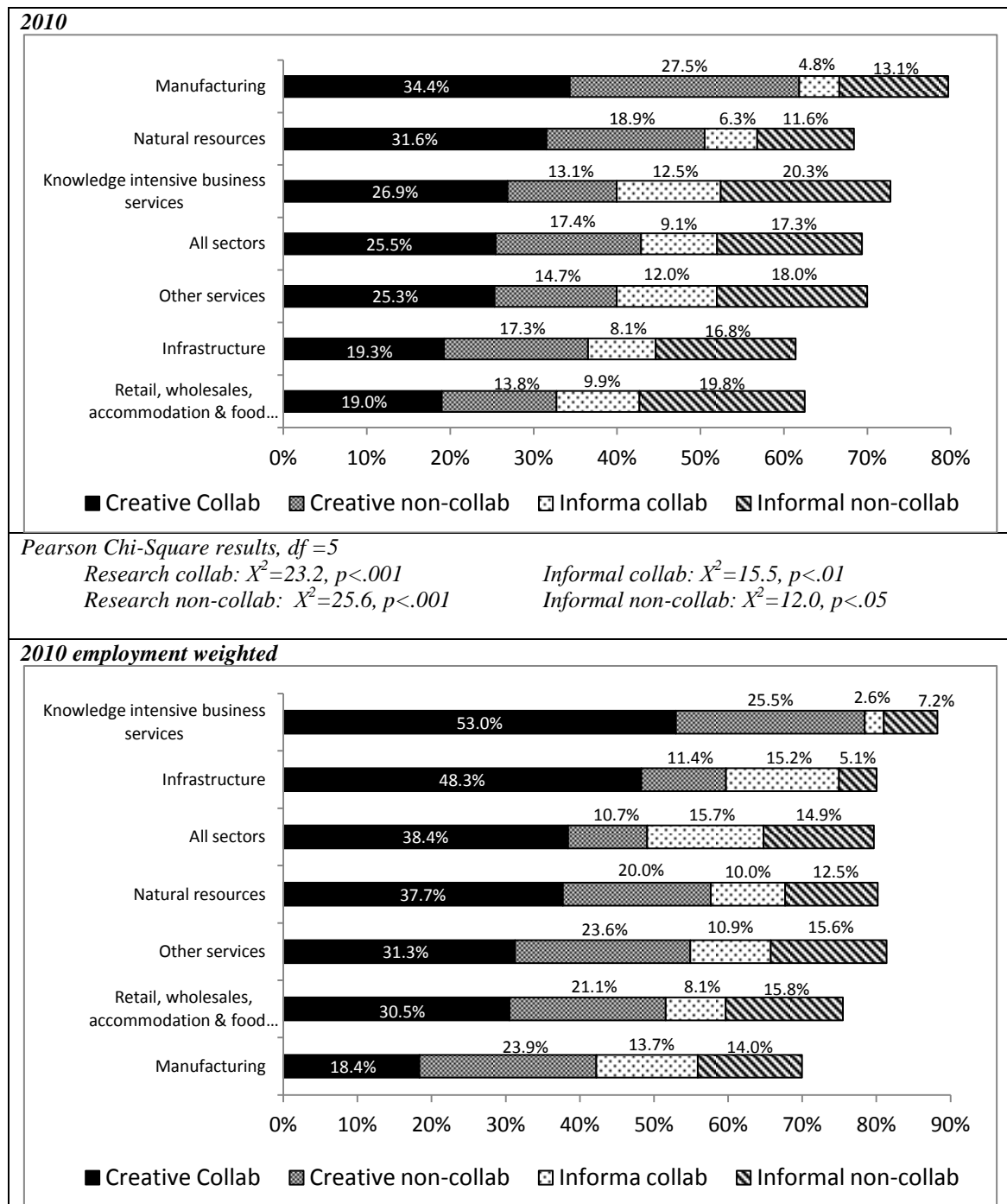
specialisation, which justifies the need for sector level results. Unless relevant policy applies at an economy-wide level, at this level of aggregation status mode indicators might be less informative.

#### 5.2.4 INNOVATION STATUS MODES BY SECTOR

Figure 5.21 presents the distribution of firms across status modes by sector for 2010 cross sectional data, also showing employment weighted figures as a measure of impact. There are statistically significant sector differences in the share of firms across each mode category apart from informal non-collaborators, which supports the case for presenting these indicators by sector.

Manufacturing has the highest share of creative collaborators followed by natural resources. These two sectors also have the highest share of creative non-collaborators. Conversely, service sectors have comparatively higher shares of informal innovators: knowledge intensive business services has the highest share of informal non-collaborators, followed by retail, wholesale, accommodation and food services, while other services has the highest share of informal collaborators. Bloch and Lopez-Bassols (2009) note a similar pattern in status modes presented for selected OECD countries. They disaggregated sector results into services and manufacturing categories, showing a generally higher share of creative collaborators in manufacturing and higher shares of informal collaboration in service sectors. The results suggest that informal rather than creative based innovation is more important for services. This implies that policies to encourage collaboration and knowledge and technology flows might be of more benefit for services.

**Figure 5.21 2010 status modes – by sector, N=1401**



The employment weighted status modes by sector demonstrate how weighted performance might have potential implications for skills related policies. The



differences between firm level and employment weighted figures provide an indication of the broader impact of particular modes in this regard.

For all firms, weighted shares of creative collaborators and informal collaborators are notably higher than firm shares. On a sector level, there are greater differences observed for infrastructure and knowledge intensive business services, with weighted shares double firm shares. These results might provide a useful indicator of demand for human capital to support creative capability in these sectors, for example, the need for employees trained in engineering and science disciplines. They could also suggest that in these sectors innovation might be accelerated via collaboration. However a limitation is that weighted indicators do not reveal the share of employees involved in firm innovation activities.

At the sector level, the disparity between weighted and firm shares for informal collaborators is driven by manufacturing. Again this could be interpreted as an indicator for demand; for skills that support collaborative modes of innovation in this sector (for example, business skills to seek out, sell, initiate and manage collaborative relationships). Alternatively, the results could suggest a link between collaboration activities and employment levels in manufacturing. Though testing for such relationships requires econometric analyses of microdata, these indicators can importantly reveal patterns to inform further investigation.

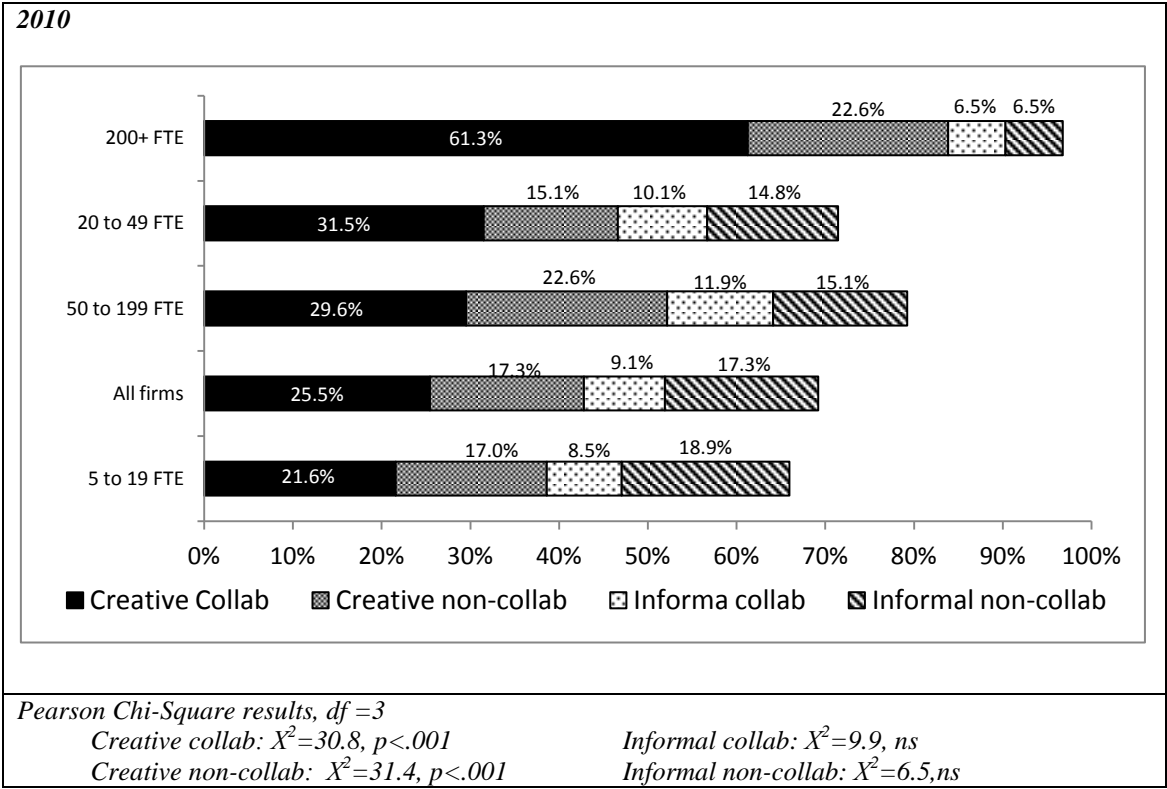
The propensity and capability to innovate is known to be influenced by firm size, and results for status modes might also be impacted by the size distribution of firms. Presenting status modes by size class is one way of exploring how size relates to innovative status.

#### 5.2.5 INNOVATION STATUS MODES BY SIZE

Figure 5.22 presents status modes by firm size category for cross sectional data. There are statistically significant differences between size class and the share of firms with creative innovation modes, though only observed differences between size and informal mode categories. The results suggest that capacity for creative modes of innovation is

greater for firms of the largest size group. This result likely reflects quality differences in the nature of activities and creative innovations by firm size (for example, with larger firms implementing many more incremental upgrades or improvements across multiple product lines). If support policies to increase creative based innovation are directed at small firms or SMEs, then producing these indicators by size could provide useful benchmark or target measures. The results also suggest that support policies for creative modes of innovation (for example, R&D subsidies) might favour larger firms. They suggest less value in producing informal modes by size class.

**Figure 5.22 Status modes by size, 2010 TIC, N=1401**



### 5.2.6 INNOVATION STATUS MODES – PANEL DATA

This section draws on panel data to explore status modes in a novel way, by reviewing their potential use for depicting change in the distribution of creative and collaborative

innovation modes over time. In this sense, the panel results may be of use for monitoring innovation input activities within sectors.

The direction of firm movement is reviewed for two groups here, persistent innovators (those firms that were technologically innovative in both the 2007 and 2010 TIC), and firms that were non-innovative in 2007 then became innovative by 2010. The latter makes an important addition to the literature by providing information on how capabilities may be built up over time for non-innovative firms. The former tracks movement in the innovative firm population. Both should be of interest for policy. Table 5.21 presents the results for persistent innovators, showing the share in each mode in each TIC period.

**Table 5.21 Shifts in creativity and diffusion based on status modes, persistent technological innovators, 2007-2010 panel**

Innovators in both panels	N	Creative collaborators innovators		Creative non-collaborators		Informal collaborative innovators		Informal non-collaborators	
		2007	2010	2007	2010	2007	2010	2007	2010
Natural resources	39	48.7%	51.3%	30.8%	25.6%	7.7%	10.3%	12.8%	12.8%
Manufacturing	124	36.3%	41.9%	42.7%	34.7%	4.0%	7.3%	16.9%	15.3%
Infrastructure	45	33.3%	28.9%	28.9%	33.3%	8.9%	17.8%	28.9%	20.0%
Retail, wholesales, accommodation & food services	76	26.3%	32.9%	35.5%	18.4%	18.4%	17.1%	19.7%	27.6%
Knowledge intensive business services	111	46.8%	41.4%	26.1%	16.2%	6.3%	13.5%	20.7%	27.0%
Other services	44	34.1%	31.8%	25.0%	20.5%	9.1%	15.9%	31.8%	29.5%
<b>All Tas</b>	<b>439</b>	<b>37.8%</b>	<b>38.7%</b>	<b>33.0%</b>	<b>24.8%</b>	<b>8.4%</b>	<b>12.8%</b>	<b>20.7%</b>	<b>22.1%</b>

The potential usefulness for the indicators in Table 5.21 lies in their depiction of broader trends, and the differences across sectors. For innovative firms, the share of creative non-collaborators has notably decreased. This could be as result of creative firms shifting to a ‘creative collaborative’ status, as they initiate collaboration arrangements, or it could be due to creative firms ceasing R&D activities, and shifting

to an ‘informal collaborative’ status. The aggregate figures suggest the latter explanation, as the share of informal collaborators has increased while the share of creative collaborators has remained steady.

However, the broader trends might not be very informative or meaningful, given the varied trends across sectors, and sector trends are likely to be most useful from a policy perspective. For example, one interpretation of the drop in aggregate level, creative non-collaborators might be a need to improve on this metric via policies promoting R&D activity. However, at a sector level, in manufacturing, which is the locus of most R&D activity in the economy, the decrease in the share of creative non-collaborators is offset by an increase in the share of creative collaborators. This pattern is the same for the retail, wholesale, accommodation and food services sector. Conversely in knowledge intensive business services, the share creative innovators has dropped, and been offset by increases in informal modes of innovation. So promotion of R&D activity may be warranted for KIBS though perhaps not for the former two sectors, which have improved performance on this metric. Thus the aggregate indicator might be misleading if used to inform policies that impact on all sectors.

This illuminates a problem with status modes – there does not appear to be an ordered progression between modal categories, which makes it difficult to interpret whether observed trends or changes are either positive or negative outcomes. As with the output modes however, this is to some extent due to a lack of information on specific directions in movement. This can be partly addressed by reviewing the shift of firms from a non-innovative status in 2007 to different status modes in 2010, shown in Table 5.22.

**Table 5.22 Shifts in creativity and diffusion based on status modes, non-innovators in 2007**

Non-innovators in 2007	N	Informal non-collaborators		Informal collaborative innovators		Creative non-collaborators		Creative collaborators innovators	
		2007	2010	2007	2010	2007	2010	2007	2010
Natural resources	16	0.0%	31.3%	0.0%	6.3%	0.0%	25.0%	0.0%	25.0%
Manufacturing	32	0.0%	28.1%	0.0%	9.4%	0.0%	28.1%	0.0%	18.8%
Infrastructure	31	0.0%	19.4%	0.0%	6.5%	0.0%	12.9%	0.0%	3.2%
Retail, wholesales, accommodation & food services	82	0.0%	19.5%	0.0%	7.3%	0.0%	14.6%	0.0%	19.5%
Knowledge intensive business services	31	0.0%	29.0%	0.0%	25.8%	0.0%	6.5%	0.0%	6.5%
Other services	20	0.0%	30.0%	0.0%	15.0%	0.0%	15.0%	0.0%	10.0%
<b>All Tas</b>	<b>212</b>	<b>0.0%</b>	<b>24.1%</b>	<b>0.0%</b>	<b>10.8%</b>	<b>0.0%</b>	<b>16.0%</b>	<b>0.0%</b>	<b>14.6%</b>

In Table 5.22, for all 2007 non-innovators combined, the results show that the greatest share became informal non-collaborators by 2010, which might be expected as this mode category is implicitly ascribed the lowest level of intensity or innovativeness<sup>35</sup>. The share of firms does not decrease evenly across the remaining categories (ordered in increasing intensity from left to right). There are also mixed results across sectors. In general natural resources and manufacturing sectors show a greater shift to creative modes, while KIBS and other services show relatively greater shifts towards informal status modes (which is consistent with firm level 2010 ‘snapshot’ patterns in Figure 5.21). Apart from these broader patterns, specific trends are difficult to identify from the mixed results in Table 5.22, especially in terms any notion of incremental improvement in capability or ‘innovativeness’ that might be expected based on the innovation literature. This suggests that if the goal is to understand improvements in innovation creativity or diffusion over time, then these status modes are not an effective measure. This also suggests that part of the problem is that the modal categories do not capture an ordered, increasing scale of intensity. As with output modes, even an approximated

<sup>35</sup> All figures for 2007 are ‘0%’ because this table includes only firms that were non-innovative in 2007.

order of increasing intensity allows mode indicators to fulfil a key function in measuring improvement or decline in innovation capabilities or performance over time, which is of great value in identifying relative strengths and weaknesses to inform understanding and policy.

Another part of the problem lies in the constituent indicators used. They are limited in terms of measuring intensity levels, and a broader approach should be employed in order to improve understanding of creativity and diffusion over time. Firstly, R&D alone might not be the best measure of creativity. As explained above, Bloch et al. (2008), and Bloch and Lopez-Bassols (2009) also include patenting activity, which is preferable, though still limited. Ideally there would be an incrementally ordered level of creativity (e.g. low, high), and the results in section 4.2 suggest that R&D intensity categories could achieve this. Secondly, diffusion is measured by *any* type of collaboration activity. This might be too broad a measure to accurately capture diffusion. Diffusion through collaboration can be with various types of partners and in various locations, and there are many additional channels and activities that represent innovation diffusion. Diffusion can be through purchase of machinery, equipment and software (embedded innovations), purchase of knowledge via patents or licenses for example, via purchase of research, or via open sources (OECD, 2005). Different diffusion methods might also involve different capabilities, that may allow ranking in discrete ordered categories of intensity, in the same way as with output modes. It is not the intention to cover all alternatives or develop these categories here. Rather, we can present an alternative picture of the shift of non-innovative firms to different modes of innovation based on diffusion, to begin to understand how these activities might be structured or ranked to better capture differing innovation intensity.

To illustrate, Table 5.23 shows, for those firms that were non-innovative in 2007, movement in 2010 across four possible modes of diffusion, and two measures for creativity.

**Table 5.23 Distribution of 2007 non-innovative firms by diffusion and creativity, 2010**

<b>Innovation transition measure</b>		<b>Percent of Non-innovators in 2007 (N=243)</b>
<b>Diffusion</b>	• Acquired advanced machinery, equipment, computer hardware or software for technological innovation	51.9
	• Purchased R&D from other businesses, universities or research institutes	10.3
	• Purchased or licensed patents and non-patented inventions, know-how, or other types of knowledge from other businesses or organisations	6.2
	• Introduced new to business products	21.0
<b>Creativity</b>	• Conducted R&D, with expenditure less than or equal to 1% of turnover	21.8
	• Conducted R&D, with expenditure greater than 1% of turnover	3.7

Of those non-innovative firms in 2007, just over half innovated and purchased machinery or equipment in 2010. There are notably lower shares that purchased R&D (10.3%), or purchased other types of knowledge (6.2%), while 21% introduced product innovations that were new to the business, which represents product innovation by diffusion of technologies or innovations developed elsewhere. We might assume that the purchase of research or external knowledge involves a higher level of capability than simply purchasing machinery or equipment, based on the theoretical and empirical literature suggesting that capability, knowledge and technology develops cumulatively. This assumption finds some support in the lower transition rate observed for these activities. It is unclear how new to firm product innovations could be used in a ranking, but they nevertheless provide an indicator for diffusion.

There are two points to be made here. Firstly, status modes for innovation diffusion need to incorporate ordered modal categories, in order to improve understanding of the different dimensions of innovation diffusion, and for maximising their capacity to inform policy. Secondly, these results suggest that it is possible to achieve this via

diffusion measures that include ordinal ranked categories. Some practical limitations for these improvements are discussed in the summary to this chapter.

Similarly, the level of creativity can be ranked, and Table 5.23 provides an example, by categorising firms as either low creative innovators (R&D less than or equal to 1% of turnover), or high level creative innovators (R&D >1%). It is a fair assumption that firms investing more heavily in R&D can be considered more creative than those that invest less (and this assumption provides the basis of the standard technology intensity classification). The disparity between the two measures in Table 5.23 tends to support this assumption, as the lower share of high level creative innovators suggests that it is less likely for firms to rapidly develop high levels of creativity from a non-innovative status. Similarly, a creativity measure could differentiate between continuous and intermittent R&D performers, which is possible with CIS data though not for the TIC<sup>36</sup>.

#### 5.2.7 SUMMARY DISCUSSION

This section addressed the research question by evaluating the potential for innovation ‘status modes’ to improve understanding of innovation. The status modes selected were based on recent work by Bloch et al. (2008) and Bloch and Lopez-Bassols (2009), and are designed to capture variations in creativity or inventiveness, and diffusion in firm level innovations. Status modes were presented at an economy-wide level, by sector and firm size and using employment weights as an impact measure, with their potential use for informing policy considered at each level. The high quality level of constituent indicators, and observed variations in indicators produced suggest that modes should be presented by sector and size, and are useful for developing a simple picture of the distribution of capability and diffusion based innovations. Results using cross sectional data showed that diffusion based modes are generally more common in services, while creative modes more so in manufacturing and natural resources, and larger firms. Status modes were also presented using panel data to evaluate their potential for presenting a

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<sup>36</sup> The TIC does not include questions on the continuous or intermittent nature of R&D.



dynamic and policy relevant picture of creative and diffusion based modes. However, during this process a number of indicator weaknesses were exposed. Before discussing the significance of these limitations and the implications for measurement and understanding, it pays to again revisit the theoretical rationale for producing and explaining results for innovation status modes.

With roots in evolutionary economic theory, a long running theme in the innovation literature since the proliferation of the chain-link approach, is the notion that innovation and diffusion are difficult to distinguish, and that much of the economic impact from an innovation is yielded in the process of diffusion throughout an economy (Kline and Rosenberg, 1986; Mytelka and Smith, 2002). As innovations diffuse they also develop and evolve, as firms improve on initial designs, functionality, efficiency, materials and performance characteristics, and integrate new technologies that become accessible and affordable (OECD, 2005; Teece, 1986). Innovation can consequently have a cascading effect beyond production, with important benefits for productivity, competitiveness, increased sales and economic growth. At the firm level, innovations that are produced elsewhere and adopted by the firm might have equal or additional economic value than those produced in-house.

Both the creation and diffusion of innovations are important for growth. Again, all three major branches of innovation theory covered in the literature review underpin status modes. The linear view influences R&D as a measure of creativity, while the chain-link approach is evident in the focus on diffusion. The complex interaction between the two can be interpreted from a systems approach, as interactive learning between firms and other actors via collaboration explains innovation development, new knowledge generation and diffusion (Mytelka and Smith, 2002). Though still many unknowns remain regarding the relationship between creativity and diffusion dimensions and their impact on performance. The Oslo Manual (OECD, 2005) consequently notes a need to understand the weight of production and diffusion based innovations in an economy. This explains the rationale behind the development of status modes. However, a major limitation in the modes presented in this section and by other authors relates to the lack of depth based on the number of constituent indicators, and the inability to differentiate between differing degrees of creativity or diffusion.

This limitation became apparent when reviewing status modes for panel data. Despite demonstrated use in presenting a static picture across sectors and firms using cross sectional data, panel indicators were not adequate for understanding shifts in creative capability or diffusion levels over time. The main reasons for the identified deficiency relate to the constituent indicators, and the lack of discrete and ordered modal categories that can be easily interpreted from a policy perspective. While Bloch and Lopez-Bassols (2009) and Arundel (2007) note that discussions with policy makers were a reason for developing status modes – due to policy interest in creative and collaborative activities – the true value in these measures could be derived from a greater capacity to identify weakness and strength in the two input dimensions, and in monitoring improvements or declines in performance over time. This requires added depth to modal categories. In addition, there is a need to better understand the link between innovation modes and innovation performance.

In a final table, this section demonstrated movements in panel firms from a non-innovative status to different categories of diffusion and creativity, suggesting that improvement could be made to status modes by including additional attributes in constituent modal categories to allow rankings. Specifically, diffusion needs to be measured in a more sophisticated way, drawing on the available questionnaire data, as does the level of creativity. This might be done by using responses to innovation activity questions (that incidentally provide some of the capability measures in innovation output mode categories), and by differentiating between low and high intensity R&D performers, which in section 4.2 were demonstrated to be sound capability measures. However, doing so also presents complications by increasing the potential number of modal categories. For example, creating a high-low category for both diffusion and creativity would create five extra status mode categories, with nine in total, which would overly complicate the presentation and interpretation of results. An alternative would be only to include ‘high’ creativity and ‘high’ diffusion’ categories and maintain the existing four category structure. This would make sense if the policy or benchmarking goal is to improve performance. On the other hand, there could be separate mode schemes created for diffusion and creativity. The cross sectional results suggest measures of diffusion would be more appropriate for services, in which

diffusion is a more common mode of innovating, while creativity modes are better suited to manufacturing and natural resources. A limitation in the results is they provide no indication of the link between different modes and performance. Resolving issues around intensity categories would be best served by further econometric research to clarify the relationship between differing levels of creativity and diffusion, and firm level performance based on output indicators (such as sales growth or productivity improvements).

The results also highlight some practical issues that inform any wider adoption and use of status mode indicators. Firstly, there must be consistent definitions used if these indicators are to be presented at different time points. This requires using survey questions that are likely to remain stable over time – ‘core’ innovation questions, and careful attention to differences in questionnaire skip routines that might impact on definitions or comparability. These factors can directly influence the indicator results produced. Given the challenges involved in comparability gaps for innovation surveys across countries, even within the CIS, these suggested improvements might seem unlikely. However using the TIC data, we have shown that even without comparison data, innovation modes can be used to monitor trends and performance within an economy, which can be useful for policy.

In summary, this section has provided answers to the research question. Firstly, by demonstrating that status modes using cross sectional data can provide a basic but potentially useful picture of the balance between creativity and diffusion based innovations when disaggregated by sector and size, though this is limited in scope at broader levels of aggregation. Secondly, by demonstrating how improvements to modal categories to develop a discrete, ordered set of mode categories could greatly improve the value in these indicators for understanding change in creativity and diffusion levels and their policy relevance, especially using panel data.

### **5.3 TECHNOLOGICAL MODES**

This section explores a final set of complex indicators in technological modes, which are identical to those presented by Bloch and Lopez-Bassols (2009) and similar to those

of Bloch et al. (2008). Compared to the previous output and status modes, technological modes differ in approach. They aim to measure innovation modes based on different types of innovation, representing differences in innovation strategy or outputs, rather than capabilities or input characteristics. The intention of this final section is to address the research question by evaluating how these technological modes can improve understanding of innovation, by exploring results in more detail by sector and size, and using panel data.

### 5.3.1 BACKGROUND

The literature review revealed that the original Oslo Manual and early innovation surveys were designed to measure technological innovation in manufacturing sectors. Over time, this led to growing criticism in the adequacy of subject based approaches, as in the decades leading up to the release of the Oslo Manual and beyond, the services sectors had grown to represent the majority of industry growth in the advanced economies. From the CIS2 onwards, surveys evolved to capture services activity, and the major change in the third Oslo Manual was to recommend inclusion of organisational and marketing innovations, the predominant forms of service sector innovation. However, despite these developments, an ongoing problem relates to broadly defined innovation rate indicators, such as the share of innovative firms, and the lack of differentiation by innovation type. For example, a firm is defined as innovative that has introduced either a product, process, organisational or marketing innovation (OECD, 2005). Though available simple indicators capture each type of innovation individually, for example, the share of product innovators or share of marketing innovators, there is an ongoing need to understand the interplay between each type, and the underlying strategies, determinants, and effects. This provides the main rationale behind the development and use of technological modes, which are designed to capture differences in strategies based on the four major types of innovation covered under the Oslo Manual definition.

### 5.3.2 INDICATOR CONSTRUCTION

Technological modes classify firms into four categories based on the combination of different types: technological only innovators, non-technological only innovators, both technological *and* non-technological innovators, and non-innovators. Each of the four categories, and the method of calculation is described below in Table 5.30.

**Table 5.30 Technological mode definitions and method of construction**

<i>Technological innovation mode</i>	<i>Method of construction</i>
<b>Technological innovators:</b> product or process innovators only (with no organisational or marketing innovations)	Technological (product or process) innovators (in 2010 – answered ‘yes’ to Q4a or Q4b or Q4c or Q8a, in 2007 – answered ‘yes’ to Q11 or Q12 or Q8a), and NO non-technological innovation.
<b>Non-Technological innovators:</b> organisational or marketing innovators only (with no product or process innovation).	NOT a Technological innovator, AND implemented non-technological innovation (In 2010 - answered ‘yes’ to Q15a or Q15b or Q15c or Q15d, in 2007 – answered ‘yes’ to Q91 or Q92 or Q93 or Q94)
<b>Technological and non-technological innovators:</b> firms reporting both product or process and organisational or marketing innovations.	Implemented both a Technological AND non-technological innovation
<b>Non-innovators</b> Firms that were non-innovative (no technological or non-technological innovation)	No innovation

The four mode categories in Table 5.30 can be seen as representing three main types of innovation strategy. The first is focused on innovation via technological innovation only, defined as implementation of new or improved products (goods or services) or processes only. The second strategy involves innovation based on non-technological types of innovation only, via implementation of new organisational methods or marketing methods. While the third strategy is based on mixed methods, which include both technological and non-technological innovators.

An organisational innovation is defined in alignment with the Oslo Manual definitions, and includes any of the following:

- Implementation of a new or significantly changed corporate strategy
- Implementation of new or significantly changed business practices such as supply chain management, knowledge management, or quality systems
- Implementation of new or significantly changed methods of organising work responsibilities and decision making, such as cross-functional teams or outsourcing activities

A marketing innovation includes implementation of any new or significantly improved marketing concepts or strategies to increase market share or target new markets.

These TIC definitions are the same as those used in the CIS4, which sourced data for technological modes presented by Bloch and Lopez-Bassols (2009). Since the CIS4, questions on marketing and organisational innovations have expanded and enable more detailed classifications of each type by subcategories. However, modes in this section are limited by the definitions above. They do not include any qualitative information on the nature of innovation by type. The quality of the constituent indicators used in calculating technological modes is high. There are eight questions used in calculating technological modes, with question non response rates for each question of less than 1%.

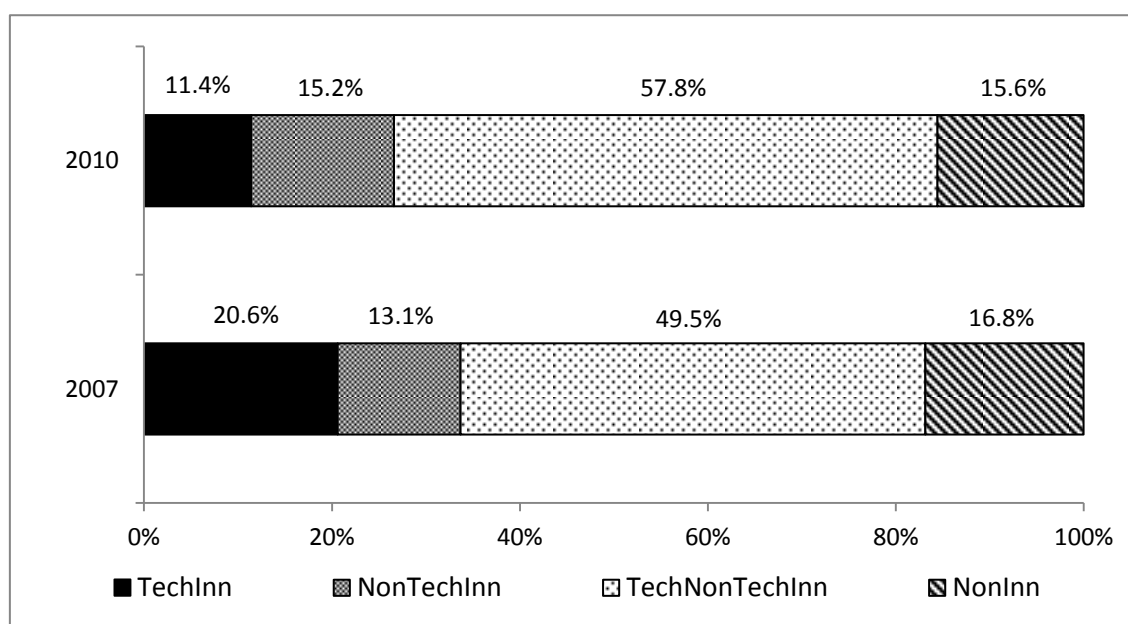
### 5.3.3 ECONOMY-WIDE TECHNOLOGICAL MODES

Again, the first step for considering the usefulness of technological modes is presenting the distribution of firms at an economy-wide level, which has potential relevance for representing the aggregate distribution of technological modes and providing benchmark measures.

Figure 5.30 shows the distribution of all respondent firms across technological modes for 2010 and 2007 cross sectional data. Because the modes include both innovative and non-innovative firms, all respondent firms are included in figures. For example, in 2010 the share of technological innovators has decreased to 11.4% of all responding firms, compared to 20.6% in 2007. This is offset by an increase in the share of firms with mixed modes of innovation, and an increase in the share of firms with non-

technological innovation only. The broad patterns are similar to those observed by Bloch and Lopez-Bassols (2009) using data for a number of OECD countries, insofar as the majority of innovative firms are mixed mode innovators.

**Figure 5.30 Innovation technology modes – all firms, 2010 TIC**



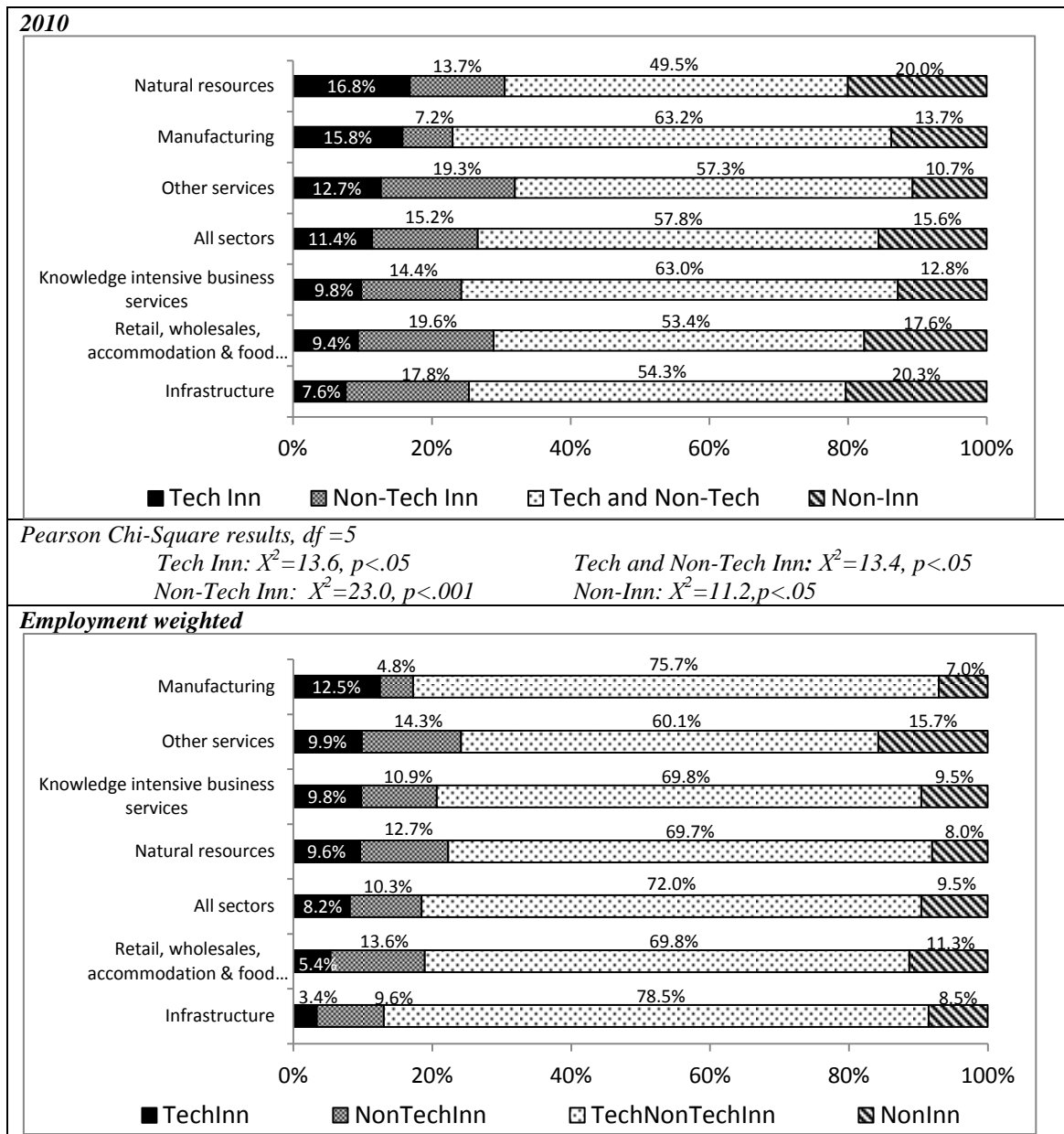
*Note: In 2010, N=1401, for 2007, N=1591.*

These results may be of use for benchmarking against other economy-wide data. For example, a broad benchmark measure might be the share of mixed mode innovators in relation to a comparison economy. The results are also useful in the sense that they demonstrate the importance of measuring non-technological innovation. The observed high incidence of non-technological innovation supports the inclusion of questions on these types of innovation on innovation surveys, which has been the subject of ongoing debate as surveys have developed (Arundel et al., 2007). As with the output and status mode indicators, part of evaluating the usefulness of technological modes involves reviewing the results by sector.

### 5.3.4 TECHNOLOGICAL MODES BY SECTOR

Figure 5.31 presents the distribution of firms across technological modes by sector, using both firm and employment weighted figures. Sectors are ordered by the share of technological innovators.

**Figure 5.31 Technological modes by sector, 2010 TIC**





Differences in the share of firms in each mode category by sector are statistically significant. This emphasises sectoral diversity in innovation strategies, and suggests that if technological modes are adopted by policy makers, they should be presented at sector level. In 2010, the highest share of technological innovators is in natural resources, followed by manufacturing and other services. Manufacturing has the highest share of firms with mixed modes, followed by KIBS and other services. In general, service sectors show higher shares of firms with non-technological only innovation. The results also highlight the importance of non-technological innovations in natural resources and manufacturing, sectors traditionally viewed in terms of technological product and process innovation.

Employment weighted modes have potential value for indicating the economic impact of particular types of innovation, when comparing firm shares to weighted values. In this respect, there is one notable trend. For all firms combined and for every sector, the employment weighted share of mixed mode innovators is much higher than the firm share. This suggests that success in mixed mode strategies may have a relatively greater impact on the labour force over single mode strategies. However this result may simply reflect firm size distributions, and results are presented by size class in Figure 5.32.

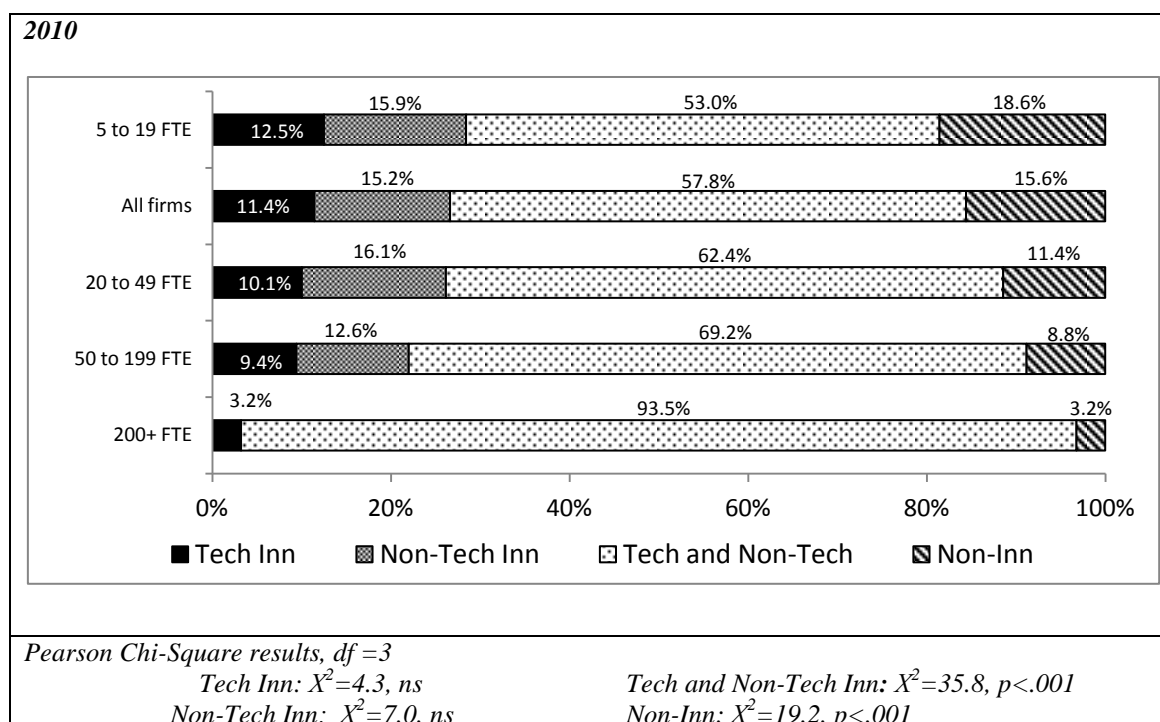
### 5.3.5 TECHNOLOGICAL MODES BY SIZE

There are statistically significant differences between size and the share of firms in two mode categories: Technological and non-technological innovators, and non-innovators only. However this is simply confirmation of a known relationship between firm size and the rate of innovation. The share of non-technological only innovators is fairly similar across smaller firms, though the largest size group has no firms in this mode.

The share of mixed mode innovators decreases monotonically with firm size, and as might be expected, this strategy is more likely in larger firms. Firms in the smallest size category have the highest share of technological innovators only, and the share of firms in this mode category decreases monotonically as firm size increases. This likely reflects smaller numbers of product lines and niche markets serviced by some smaller

firms. If a policy goal is to increase mixed modes of innovation in smaller firms, then these indicators presented by size class might provide a useful benchmark.

**Figure 5.32 Technological modes by size, 2010 TIC**



### 5.3.6 TECHNOLOGICAL MODES – PANEL DATA

This section adds to the existing literature by using panel data to determine whether technological modes can reveal useful information about the mix of innovation strategies over time. Table 5.31 presents the panel data results for 2007 and 2010, showing the change in distribution of firms across mode categories. Using the long format panel data allows testing for significant differences in the share of firms in each mode category using year as a grouping variable (a chi-square test). Again the results are potentially useful from two perspectives: firstly, for monitoring broad trends in the distribution of technological modes for all firms, and secondly, for pinpointing trends by sector.

**Table 5.31 Technological modes – 2007-2010 panel data**

	Natural resources	Manufacturing	Infrastructure	Retail, wholesales, accommodation & food services	Knowledge intensive business services	Other services	All Tas
<i>Total (N)</i>	70	181	105	201	178	85	820
<b><i>Technological innovators</i></b>							
2007	27.1%	23.2%	23.8%	12.9%	15.2%	22.4%	19.3%
2010	20.0%	17.1%	6.7%	9.5%	10.1%	11.8%	12.1%
$X^2$	1.0	2.1	11.9**	1.2	2.1	3.4	16.1***
<b><i>Non-technological innovators</i></b>							
2007	8.6%	7.2%	10.5%	23.9%	11.2%	10.6%	13.0%
2010	10.0%	4.4%	22.9%	20.4%	13.5%	21.2%	14.9%
$X^2$	0.1	1.3	5.8	0.7	0.4	3.6	1.1
<b><i>Technological &amp; non-technological innovators</i></b>							
2007	48.6%	57.5%	42.9%	40.8%	62.9%	49.4%	51.1%
2010	52.9%	66.3%	49.5%	52.7%	64.0%	55.3%	58.0%
$X^2$	0.3	3.0	0.9	5.8*	0.1	0.6	8.0**
<b><i>Non-innovative</i></b>							
2007	15.7%	12.2%	22.9%	22.4%	10.7%	17.6%	16.6%
2010	17.1%	12.2%	19.0%	17.4%	12.4%	11.8%	15.0%
$X^2$	0.1	0.0	0.5	1.6	0.3	1.1	0.8

$X^2$ =Chi-square values with 1 degree of freedom. \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$

Source: TIC data, author calculations with the assistance of Dr A Torugsa.

For all firms, there are two significant changes observed. The share of technological innovators only has decreased, while the share of mixed mode innovators has increased. This suggests that firms are expanding their strategies to incorporate soft innovations in marketing or organisational methods. These trends mostly repeat across sectors. However, only two changes at the sector level are significant: the notable drop in the share of technological innovators in infrastructure, and an increase in the share of mixed mode innovators in retail, wholesale, accommodation and food services.

Although these results might be useful for general benchmarking of performance, they are limited in depth, and might not be informative for policy. For example, if a firm employs a non-technological innovation strategy, the modes do not provide any information on the nature of the innovation, in terms of the intensity, specific type, or likely outcome. The technological mode categories are not ordered in any way, which makes it difficult to assess relative strengths and weaknesses from any of the figures

presented. Some authors find that mixed modes of innovation are more likely to lead to success than singular modes, which suggests that the share of mixed mode innovators might provide a benchmark measure relative to comparison industries or economies. Because of the limited qualitative information provided by technological modes, no further results are presented using panel data.

### 5.3.7 SUMMARY DISCUSSION

This section set out to address the research question by exploring how technological mode indicators might improve understanding of innovation. The criteria based framework approach outlined in the methodology chapter guided this task, considering the indicator rationale, quality, method of construction, differences by sector and size, and potential policy relevance. Results suggested value in presenting indicators by sector. As might be expected based on the literature, non-technological innovation modes were more common in services sectors, and technological modes more so in manufacturing and natural resources. The majority of firms were mixed mode innovators, a mode correlated with firm size. This work makes a key contribution to the existing literature, by further disaggregating mode measures by sector and size and using panel data, providing a deeper evaluation of their usefulness as indicators.

The rationale for development and use of these modes is mostly practical, based on the need to differentiate between the four main types of innovation that are commonly bundled up into a single ‘innovation rate’ indicator. Technological modes are useful for differentiating between innovation by type in terms of three main strategies: technological only, mixed modes, and non-technological only, and benchmarking the distribution of firms across these categories against comparison economies. One advantage is that these modes are constructed using survey questions of high quality based on item non response rates. However, there are notable limitations in the usefulness of these indicators that can be related back to the constituent indicators, and draw similar critique to broad innovation ‘rate’ indicators. Thus we can revisit the background before exploring the limitations of technological modes and concluding this discussion.

Inclusion of non-technological organisational and marketing innovations was a key advance in the third Oslo Manual (OECD, 2005), which stemmed from ongoing critique of the early CIS approach, based on the lack of measures relevant to innovation in services sectors. Debate around the inclusion of questions on non-technological innovation, including marketing innovations for example, has been ongoing as the CIS has evolved, and only since the CIS2006 have these questions stabilised in structure and content. One benefit of results using technological modes is they emphasise the importance of non-technological types of innovation across all sectors, and justify the inclusion of related survey questions. However, results are also limited in depth and usefulness in a number of respects.

Firstly, the mode indicators lack any depth in terms of revealing specific types of non-technological innovation, which might have very different implications for firm strategies, skills requirements, performance, and policy relevance. In this regard, the same criticism levelled at innovation rate indicators could apply to results for these modes. For example, it may be that innovations in online marketing are increasing exponentially and driving rapid sales growth across sectors. There is no way of differentiating specific trends such as this from these indicators. They only differentiate broadly between innovation types, and fail to provide any substantial detail. Secondly, the high rates of mixed mode innovators might be misleading, given noted respondent confusion between concepts of process and organisational innovations (Ijichi, 2007), especially for services firms, where confusion between product, process and organisational innovations can also be an issue (Bloch, 2005; 2007; Salazar and Holbrook, 2004). This could partly explain the high rates of mixed mode innovators.

Part of this lack of depth is due to the constituent survey questions. From the CIS2006 on, there have been at least three questions to differentiate specific types of organisational or marketing innovations, as well as questions on the objectives of each. More informative modes could be presented by drawing on all of these questions, and more research is required in this regard. This point also highlights a practical limitation in the technological modes presented in this section, they are based on a smaller set of questions than in the recent CIS (three on organisational innovation and one on

marketing, similar to the CIS3 and 4), and this was one constraint to further exploration for this study.

There is no obvious interpretation of technological modes in terms of the three major strands of innovation theory covered in the literature review, mostly because these measures simply categorise output types, rather than processes, capabilities, intensity or activities, and this represents another limitation. Technological modes do not provide any indication of innovation intensity, or suggest a link between innovation and firm performance. The indicators are not particularly informative in terms of identifying strengths or weaknesses. From a policy perspective, these modes are less informative than those in the previous sections.

Some of the limited empirical research using alternative modes schemes finds that firms employing mixed modes of innovation are more likely to be successful (Hollenstein, 2003; Jensen et al., 2007), and in this respect, the share of mixed mode innovators might provide a benchmark or target measure against comparison economies, if mixed mode innovators are associated with better economic outcomes. Technological mode indicators, for example, the share of mixed mode innovators, might also have use when viewed in the context of other indicators, or in the calculation of composite indices, which are explored in the next chapter. There is a need for further econometric research to explore the links between different types of organisational and marketing innovation and firm performance. This has the potential to inform new mode schemes that capture more meaningful detail in modal categories (for example, in terms of different marketing methods etc.)

In summary, the results presented in this section have demonstrated how technological modes can assist in understanding the broad distribution of innovation types across firm populations, and may have some use for benchmarking, though are also limited in depth. A key drawback lies in the lack of qualitative information provided, and of the three sets of mode indicators presented in chapter 5, technological modes are the most limited in terms of contribution to understanding and informing policy.

## **5.4 CHAPTER 5 OVERVIEW**

This chapter sought to explore how new complex or innovation mode indicators could improve understanding of innovation. Each section focused on a particular set of innovation modes, selected based on relevance to the research objectives, the available data, and to build on recent indicator work (Bloch et al., 2008; Bloch and Lopez-Bassols, 2009). Section 5.1 provided the most in depth review, mapping differences in capability and intensity using output modes, and tracking capability movements over time with panel data. Section 5.2 examined the distribution of creative verses collaborative or diffusion based modes of innovation, highlighting a need for modes with discrete ordinal categories, while section 5.3 explored distributions of firms based on different innovation strategies using the more common technological modes. This chapter provides the key focus for this research project as complex indicators are the main area for new research on innovation survey indicators. In chapter 6, the focus is on the third main category of innovation indicator uncovered in the literature: composite indices.

## **6.0 EXPLORING SECTORAL CAPABILITY WITH COMPOSITE INDICES**

The objective of chapter 6 is to address the research question by considering how composite indices might improve understanding of the distribution of innovation capabilities across sectors, drawing on various indicators calculated from the 2010 TIC data. As discussed in 2.4.1, composite indices involve a single summary measure that encapsulates values across multiple indicators, so are useful for condensing large numbers of indicators into a more readily digestible aggregate measure. They can visually depict overall strengths and weaknesses for one group of interest compared to another, so are often popular for policy makers. Because they provide a single measure, they are typically used to compare performance at an economy-wide level, for instance in cross-country comparisons in the global summary innovation index (Archibugi et al., 2009), or in the European Innovation Scoreboard (EIS), which features indices built using some indicators from the CIS. This chapter makes a key contribution to the measurement literature, by considering how composite indices might better improve understanding of innovation within an economy.

### **6.1 BACKGROUND**

There are multiple data items used in calculating index measures, often from many data sources. Thus there can be differences in underlying methodologies for contributing surveys, and for generating constituent indicators. Issues around data quality and weighting methods for particular indicators are well known in the literature (Grupp and Schubert, 2010; Archibugi et al., 2009; Shibany and Streicher, 2008), and can impact on the comparability of index measures. However, a key advantage that index measures offer is the ability to combine multiple indicators, which can be difficult to collectively interpret from a policy perspective.

In this sense, composite indices have potential benefit for summarising sets of indicators that correspond to a particular dimension of innovation. Here we consider their use for depicting the spread of capabilities across different sectors. This addresses a key need



for indicators that differentiate capability levels, that was exposed in the literature review.

## **6.2 COMPOSITE INDICATOR CONSTRUCTION**

Innovation indicators can be grouped by various themes corresponding to the particular aspect of innovation they aim to measure. The most common distinction is between input and output indicators. Themes for indicator groupings can be chosen dependent on the needs of analysis, though should always be based on a sound theoretical framework (OECD, 2008). The Oslo Manual provides the background conceptual and theoretical framework for the use of composite indices here. Indicators are grouped by five themes: human capital, collaboration, investment (all inputs), outputs, and impacts. Table 6.10 presents the indicators corresponding to each dimension of innovation.

Indices in Table 6.10 align with the common conceptual framework for innovation scoreboards discussed by Arundel and Hollanders (2008)<sup>37</sup>. There are 21 separate indicators included, many of which are simple indicators based on responses to single questions (for example, the share of product innovators).

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<sup>37</sup> The selection of indicators is based on a policy report prepared for a State Government Agency in Tasmania, by O'Brien, Torugsa and Arundel, (2012).

**Table 6.10 Simple indicators used for composite indice calculation**

<i>Composite indice</i>	<i>Constituent indicators</i>	<i>Indicator construction</i>
Human capital	<ol style="list-style-type: none"> <li>1. <i>Share of sector employees with tertiary qualifications in science and engineering disciplines</i></li> <li>2. <i>Share of sector employees with vocational qualifications</i></li> <li>3. <i>Share of firms providing training for innovation</i></li> </ol>	<p>Q19a/ total sector employees (Q28a+Q28b)</p> <p>Q20a+Q20b/ total sector employees (Q28a+Q28b)</p> <p>Percent of firms answering 'yes' to Q12e in sector</p>
Collaboration	<ol style="list-style-type: none"> <li>1. <i>Share of firms with any collaboration</i></li> <li>2. <i>Share of firms collaborating with universities or public research institutes</i></li> <li>3. <i>Share of firms with collaboration partners located outside of Tasmania</i></li> </ol>	<p>Percent of firms answering 'yes' to Q13 in sector</p> <p>Percent of firms answering 'yes' to Q14f or Q14g in sector</p> <p>Percent of firms answering 'yes' to Q14a to Q14g 'outside of Australia'</p>
Investment	<ol style="list-style-type: none"> <li>1. <i>Share of firms with high intensity R&amp;D (&gt;1%)</i></li> <li>2. <i>Sector innovation intensity</i></li> <li>3. <i>Sector R&amp;D intensity</i></li> </ol>	<p>Percent firms reporting R&amp;D expenditure (Q12b1) of 1% or more of the firm's turnover (Q27a).</p> <p>Sector sum of Total innovation expenditure (Q12 a1 to Q12g1)/ sector sum of sales (Q27a)</p> <p>Sector sum of R&amp;D expenditure (Q12 b1)/ sector sum of sales (Q27a)</p>
Outputs	<ol style="list-style-type: none"> <li>1. <i>Share of novel product innovators</i></li> <li>2. <i>Share of novel process innovators</i></li> </ol>	<p>Share of firms answering 'yes' to Q6a</p> <p>Share of firms answering 'yes' to Q10a or Q10b or Q10c</p>
Impacts	<ol style="list-style-type: none"> <li>1. <i>Sales share from innovative products (new to firm or new to market)</i></li> <li>2. <i>% firms that are fast-growing innovators</i></li> <li>3. <i>% product innovative firms that are efficient innovators</i></li> </ol>	<p>(Sector sum of Q7a+ sector sum of Q7b) / sector sum of Q27a</p> <p>Share of firms answering 'yes' to (Q4a or Q4b or Q8a or Q8b) + sales per employee growth of <math>\geq 25\%</math> between 2007/8 and 2009/10 (Q27a Q27b).</p> <p>For firms answering 'yes' to (Q4a or Q4b) -Total innovation investments are 50% less than innovation sales (sum of Q7a + sum of Q7b).</p>

Though there are different methods for calculating composite indices (see for example, OECD, 2008), the min-max method is selected here. This approach is used in the European Innovation Scoreboard work, due to its simplicity and robustness (Hollanders and Van Cruysen, 2008). The method is used here to maintain some consistency with this work, and because of some key advantages offered: it allows indicators measured on different scales to be combined, it re-scales indicator values so that differences in performance across clusters of indicators are revealed, and it circumvents confidentiality issues encountered when producing simple indicators when there are

small numbers of firms in a sample (as measures are combined)<sup>38</sup>. This is particularly useful for summarising relative industry innovation performance drawing on the large number of possible simple indicators for innovation surveys.

In the min-max method, each indicator is re-scaled against the range for that indicator across all sectors, thus each indicator is expressed as a relative share of the maximum observed performance. As all indicators are given the same weight, essentially the indice corresponding to each theme represents the average of the re-scaled values for constituent indicators. Box 1 describes the method for calculating relevant indices.

### Box 1

The composite indices (CI) for each of the five indicator categories are calculated in two steps. The first step determines the rescaled indicator value while the second step calculates the composite index:

$$1) \quad y_{ij}^t = \frac{x_{ij}^t - \text{Min}(x_j^t)}{\text{Max}(x_j^t) - \text{Min}(x_j^t)}$$

In equation 1,  $x_{ij}^t$  equals the value of indicator  $j$  for sector  $i$  at time  $t$  and  $y$  is the rescaled value. Min equals the minimum observed value among the sectors and Max equals the maximum observed value among the different sectors. Using 2010 TIC cross sectional data,  $t$  is identical for all indicators.

$$2) \quad CI_i^t = \frac{\sum_{j=1}^m q_j y_{ij}^t}{\sum_{j=1}^m q_j}$$

The composite index for sector  $i$  is calculated in equation 2. The equation permits the use of different weights ( $q_j$ ), but here all indicators are assigned an equal weight of 1. In effect, the values of the rescaled indicators ( $y_{ij}$ ) are summed and divided by the number of rescaled indicators.

Source: O'Brien, Torugsa and Arundel, (2012), based on guidelines in the OECD composite indicator guide book (OECD, 2008).

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<sup>38</sup> Confidentiality obligations restrict samples to four firms as a minimum.

Highly correlated indicators (coefficients of over 0.7 between two or more indicators) are excluded from the composite indices, unless there are only three indicators left<sup>39</sup>. Most correlation coefficients are less than 0.6. Each of the composite indices is based on three indicators.

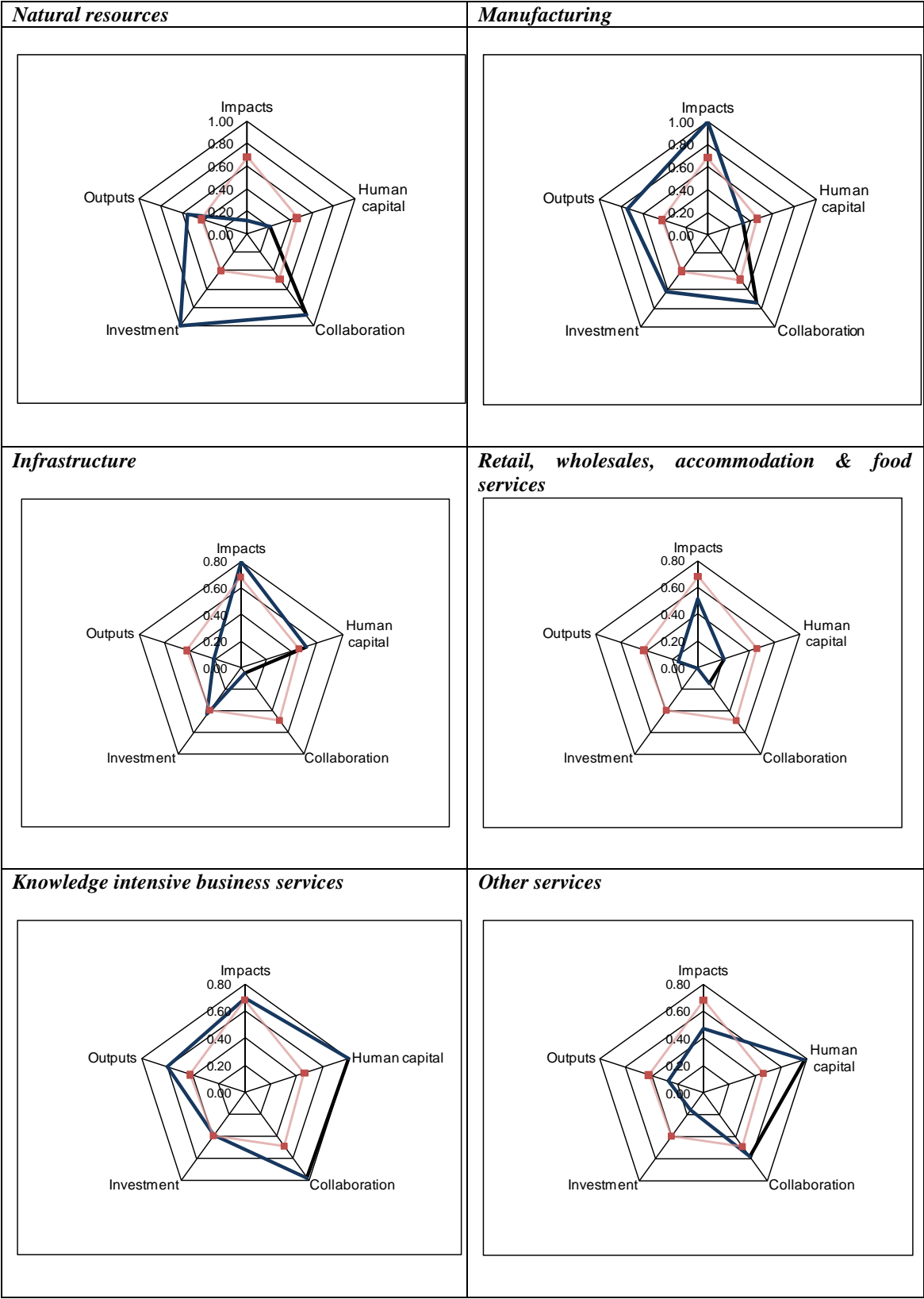
### **6.3 COMPOSITE INDICATORS BY SECTOR FOR TASMANIA**

Figure 6.10 presents the results for the five composite indices for each theme across six different sector groupings. The maximum score on an indice in Figure 6.10 is 1, while the minimum is 0. The dotted line that maps the same shape in each chart represents the average score for all sectors combined. Thus the performance of each sector can be compared to the average. The results have policy relevance in a number of respects. Firstly, they provide a map or innovation profile for each sector. Secondly, they provide scaled values that allow comparison of sector performance relative to the average for all firms and other sectors. Thirdly, they allow the identification of relative sector strengths and weaknesses.

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<sup>39</sup> This occurs for : 1.) impacts, where the share of efficient innovators and innovation sales are highly correlated; 2.) collaboration, where the share of firms collaborating with universities or research institutes is highly correlated with the share of firms with overseas collaboration partners, and 3.) investments, where the share of high R&D intensity firms is highly correlated with sectoral R&D and innovation intensities.

Figure 6.10 Composite indices by industry, 2010 TIC



Of all industries in Figure 6.10, Manufacturing is generally the most innovative, with relatively high scores on all dimensions apart from human capital, which is lower than average. Knowledge intensive business services also shows generally high performance, with average or above performance on all dimensions. Retail, wholesale, accommodation and food services is the least innovative sector, with below average performance over all indices.

There are notable variations in relative strengths and weaknesses across sectors, representing differing sectoral modes of innovation. Manufacturing and KIBS show the highest performance on innovation outputs, based on higher rates of novel product and process innovation. Natural resources shows the best performance on investment and collaboration, though lower performance on impacts and human capital. A key question for policy is whether improvement on human capital measures could translate into greater impacts in this sector.

Infrastructure shows the second highest performance on impacts after manufacturing, and higher than average performance on human capital, though very poor performance on collaboration, which might be a focus for policy support. Knowledge intensive businesses services and other services perform best on human capital, and above average on collaboration. Manufacturing and KIBS also show relatively high performance on innovation impacts, with novel innovations driving sales and a high share of fast growing firms.

Natural resources and manufacturing perform best on collaboration, indicating a need for externally sourced inputs of scientific and technological knowledge in these sectors to drive greater rates of innovation output. Conversely collaboration in retail and infrastructure is very poor, possibly reflecting the highly competitive environments for the former.

These results have policy relevance in depicting the relative strengths and weaknesses in innovation across sectors. The question for policy, which is not addressed here, is whether the focus for policy support is on working to strengths, for example, supporting human capital requirements and collaboration for KIBS and other services, or on

addressing weaknesses, for instance focusing on investment subsidies for infrastructure, other services or retail, wholesale, accommodation and food services. This depends on where the most benefit from support can be yielded. If for example, balanced capabilities are likely to lead to greater economic impacts, then weaknesses might be a target. The focus will also depend on the scope of policy, for example, whether it is economy-wide or sector based. An economy-wide approach might seek to implement measures that will have maximum benefits across multiple sectors given different capabilities. From this perspective, composite indice results can be interpreted in a slightly different way, focusing on each indice performance overall across sectors, rather than sector by sector relativities. For example, three important sectors show low performance on human capital indices: manufacturing, natural resources, and retail, wholesale, accommodation and food services. The first two are important for exports, while the last for local employment and tourism income. This result suggests that a broader policy focus on improving human capital might benefit these sectors capability, with potential for positive economy-wide impacts. A weakness in these measures is they do not indicate a link between capabilities and economic performance. Composite measures can be used for this task, as in the EIS reports. This is not attempted here, as the focus is the usefulness of basic indice measures from a policy perspective. Such analysis would encounter endogeneity issues in the constituent indicators, requiring sophisticated analytical routines that would take the analysis beyond the primary ‘policy relevance’ focus.

#### **6.4 COMPOSITE INDICES FOR 2007-2010 PANEL DATA**

A secondary use for composite indice measures is for mapping changes in innovation performance over time and identifying shifts in capabilities, as the various European Innovation Scoreboards do at the country level. Similarly, composite indices can be calculated using panel data to assess changes in relative sectoral performance over time. Table 6.11 presents the composite indice results again on five innovation dimensions, for the 2007 and 2010 TIC panel data.

**Table 6.11 Composite indices by industry sector, 2007-2010 TIC panel data**

Sector	Four-year change for composite indices from 2007 and 2010, panel firms														
	Innovation Impacts			Human Capital			Collaboration for Innovation			Investment in Innovation			Innovation Outputs		
	2007	2010	Change	2007	2010	Change	2007	2010	Change	2007	2010	Change	2007	2010	Change
Natural resources	0.17	0.10	-42.2%	0.24	0.22	-7.1%	0.35	0.33	-4.1%	0.12	0.13	10.3%	0.62	0.34	-44.6%
Manufacturing	0.26	0.17	-34.6%	0.23	0.20	-15.4%	0.25	0.29	16.2%	0.11	0.09	-14.2%	0.70	0.42	-40.3%
Infrastructure	0.17	0.12	-28.9%	0.20	0.18	-9.2%	0.17	0.16	-3.8%	0.06	0.05	-24.3%	0.55	0.29	-47.4%
Retail, wholesales, accommodation & food services	0.13	0.14	13.5%	0.18	0.18	0.4%	0.16	0.22	35.4%	0.02	0.02	-33.9%	0.44	0.25	-44.4%
Knowledge intensive business services	0.18	0.15	-20.6%	0.37	0.33	-9.9%	0.31	0.30	-2.4%	0.11	0.07	-32.3%	0.67	0.40	-40.6%
Other services	0.17	0.12	-31.0%	0.28	0.24	-12.8%	0.23	0.19	-18.6%	0.08	0.03	-54.1%	0.59	0.32	-45.7%
<b>All sectors</b>	<b>0.19</b>	<b>0.14</b>	<b>-24.2%</b>	<b>0.24</b>	<b>0.22</b>	<b>-8.5%</b>	<b>0.24</b>	<b>0.25</b>	<b>6.2%</b>	<b>0.08</b>	<b>0.06</b>	<b>-21.6%</b>	<b>0.59</b>	<b>0.34</b>	<b>-42.9%</b>



In order to maintain comparability of indices over time, there are some minor differences in the calculated indices presented here compared to those for cross sectional 2010 data<sup>40</sup>. Table 6.11 presents a picture of overall trends in innovation performance for all firms and across sectors between the 2007 and 2010 TICs. There are various approaches to assessing indice performance over time, for example, by categorising firms based on performance against average scores (as featured in the European Scoreboard reports). The approach to assessing changes here is to simply calculate the percentage change in the relevant indices over time. The results are useful from two perspectives. Firstly, for indicating the trends for all firms across time on a particular dimension of innovation, and secondly, for depicting sectoral performance relative to the broader trends.

For all panel firms combined, there is a negative trend over time on four of five composite indice scores. The greatest decrease in performance is for innovation outputs, driven by drops in the share of firms with novel products, followed by impacts, driven by decreasing sales from innovative products, and lower shares of efficient and fast growing innovators<sup>41</sup>. Performance on innovation investment also decreased between 2007 and 2010 TICs, driven largely by decreases in the share of firms with high intensity R&D and by drops in sectoral R&D intensity. There has been an overall increase in performance on collaboration over time, though this is the only positive trend.

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<sup>40</sup> The human capital indice replaces the VET share of employment indicator with an indicator for the share of employees with any type of university education (in either science or engineering disciplines or other disciplines). This indicator is highly correlated with the remaining two indicators for human capital (share of employees with university education in science and engineering disciplines and the share of firms investing in training). The data are also adjusted to technological innovators only for impacts, collaboration and investment indices to maintain comparability over time. This is due to different questionnaire skip routines and definitions used for the 2007 and 2010 TICs.

<sup>41</sup> These references are to constituent indicators, which are not shown here.

There are notable sectoral deviations from the broader trends. KIBS has improved performance on innovation impacts, while retail, wholesale, accommodation and food services shows a small increase in performance on human capital. Natural resources has increased performance on investment, which reflects trends across constituent indicators such as investment in machinery and equipment. The positive trend on the collaboration score is driven by retail, wholesale, accommodation and food services, and manufacturing, as performance decreased on this measure for all other sectors.

The results should be of use from a policy perspective, particularly where negative trends provide a ‘warning sign’ (Arundel and Hollanders, 2008). Negative trends might suggest areas of eroding capability that could affect future competitiveness, for example, in human capital, where policy may play a role in skills provision.

## **6.5 SUMMARY DISCUSSION**

The aim of this chapter was to address the research question by considering how composite indices might improve understanding of innovation capabilities across sectors. While composite indices are typically used at a macro level, drawing on indicators from many different sources to map and compare country level innovation performance, this chapter contributes to the literature by applying the method to map sectoral innovation performance within an economy based on innovation survey indicators only.

Calculating indices against five themes covering inputs, outputs and impacts, the results showed KIBS and manufacturing as the most innovative sectors, and retail, wholesale, accommodation and food services as the least innovative. The results also revealed relative strengths and weaknesses across sectors, with natural resources and manufacturing for instance showing higher performance on investment and collaboration measures, though low performance on human capital, while other services and KIBS showed higher performance on human capital measures. In addition, indices using panel data provide a picture of the relative trends in performance over time.

The Oslo Manual (OECD, 2005) provides the conceptual basis on which to develop composite indices using innovation survey data, and indices should ideally cover the main dimensions of inputs, outputs and impacts allowed by available survey indicators. However, indices are also subject to various limitations, which should be considered when developing measures and interpreting results. Many limitations relate back to the quality levels of the constituent indicators, as indices are often calculated from different data sources using different methodologies. In this case, we draw indicators from two data sources, the 2010 and 2007 TICs. The main results use cross sectional 2010 TIC data, and all constituent indicators are of high quality based on acceptably low item non response rates. For the panel indices, the mix of indicators changed to ensure comparable indicators were used, though all were of the same high quality. This reiterates the need for careful selection of constituent indicators for indice calculation. Indicators should be selected with the analysis or policy needs in mind, and based on a sound conceptual framework and methodology.

There are clear advantages for using composite indices that are highlighted in this brief chapter. Firstly, composite indices can provide a simple, visual picture of the relative strengths and weaknesses of innovation performance across sectors. This is important for informing policies that may impact on some sectors differently than others (for example, R&D subsidies, which might favour natural resources and manufacturing with greater investments). Composite indicators can also have an advantage for studying innovation in small populations of firms, for example, at the disaggregated sector level, as often indicators cannot be published for very small samples due to confidentiality restrictions. Composite indices can avoid this problem when combining multiple indicators into one measure. However, where possible, constituent indicators should be evaluated alongside composite indicators, to fully explain observed patterns across key dimensions. In this sense, there can be a drill down approach, where composite indices provide the high level picture of trends, sector strengths and weaknesses, and individual indicators help to fully explain the trends and direct policy response.

One limitation is that composite indicators featured here do not provide a link between innovation performance and economic performance. They can be used for this purpose, as has been done in many of the European Innovation Scoreboard measurement

exercises. This is an area for future research, though careful attention must be paid to selecting appropriate economic outcome variables, as many of the constituent indicators measure innovation outcomes.

In summary, this chapter has answered the research question by demonstrating how composite indices can improve understanding of innovation within economies and across sectors, by providing a map of relative strengths, weaknesses, and trends in sector innovation performance that may inform policy support.

## 7.0 CONCLUSION

This thesis addressed a need for research on new measures of innovation. Indicators generated from innovation surveys based on a ‘subject’ or firm level measurement approach were the focus. Such surveys are now carried out in approximately 80 countries (OECD, 2012), and resultant indicators provide an important new data resource for understanding innovation performance within and across economies, and for ‘telling a story’ of relevance for developing, monitoring and evaluating policy. However, despite the wide availability of published survey indicators, they lack crucial information content, often portray counterintuitive patterns and results, and are subject to various shortcomings requiring further insight and improvement. These are partly evidenced in the limited uptake by policy makers and in wider measurement exercises.

One of the key problems lies in under exploitation of existing survey data for indicator work, due predominantly to limitations in microdata access. Statistical agencies, who generally administer national innovation surveys and have data access, have limited resources or incentives to develop better indicators. While many academics have access to microdata, their focus is on econometric research rather than producing more useful indicators. Some recent work has made progress developing new indicators, but many unknowns remain in regard to their usefulness.

Indicators are important. They can test or validate theories about innovation (Arundel et al., 2008, Finnbjornsson, 2008), and influence policy discourse and content (as R&D indicators have for instance) that can ultimately impact on societal well-being. The need for further evaluation of current and new indicators provides the rationale for this study, which is motivated by the central question: How can new indicators improve understanding of innovation?

To answer the research question this study utilised cross sectional and panel data from the Tasmanian Innovation Census (TIC), a large scale regional innovation survey based on a methodology defined in the Oslo Manual (OECD, 2005). This provides the international, standardised conceptual framework for conducting innovation surveys, and consequently the research has resonance for any survey based on Oslo Manual

guidelines. Importantly, this thesis makes a number of unique contributions to the growing literature around innovation measurement, building on recent indicator work by Arundel (2007), Bloch et al. (2008) and Bloch and Lopez-Bassols (2009) in a number of ways. Firstly, it demonstrates indicators that depict differing capability, novelty, and intensity levels. It provides further disaggregation and evaluation of new indicators by sector and size variables, and highlights areas for improvement of constituent innovation survey questions and data. Secondly, panel data indicators present a dynamic view of innovation, showing indicators that incorporate non-innovative firms, demonstrating options for producing new indicators with greater policy relevance. Thirdly, results reveal how composite indicators can be useful for mapping sectoral capabilities and can move beyond the usual macro (country) level of analysis.

The thesis was structured in seven main chapters. Chapter one provided an introduction, detailing the rationale and related problems informing the research. Chapter 2 explored the literature in four sections. Chapters 4 to 6 presented results and summary discussions. And finally, this chapter concludes the thesis, by revisiting the core content, contemplating the implications of results and discussions, and considering research limitations and areas of priority for future work.

Literature on the historical evolution of subject approaches to measurement, which covers the background on growth theories and traditional R&D, patent, and bibliometric indicators, importantly demonstrates how innovation survey indicators address a need for economy-wide understanding. Three key streams of underlying innovation theory underpin the interpretation and evaluation of new indicators in this research: the linear, chain-link, and systems approaches. These theories developed in conjunction with three versions of the Oslo Manual (OECD, 1992; 2005). This historical background reveals three key requirements for developing indicators. Firstly, they must be provided at the sector level, to capture industry diversity in underpinning knowledge domains, technologies, and capabilities involved in the production of innovations. Secondly, they must reflect firm heterogeneity and differences in firm size demographics, because these shape challenges and strategies around innovation performance. Thirdly, they must reflect specificities of the relevant innovation system. As the largest and longest

running cross-country survey exercise based on the Oslo Manual, the European Community Innovation Survey (CIS) provides the reference point for exploring the evolution of innovation survey indicators. Early critique as surveys and indicators developed contextualises key gaps that remain and drive this research. This is primarily in terms of the need for indicators with greater policy relevance, which reflect differing levels of capability, novelty, weakness, strength, and different innovation inputs and outputs, or modes of innovating. This literature exposes a clear need for new work to meet these gaps, by exploiting existing data to demonstrate and evaluate innovation indicators at finer levels of disaggregation, and by examining how new indicators might improve understanding and provide valuable information for policy. Recent coordinated work to develop new complex indicators from existing survey data provides a platform for the approach and contribution of this study.

Drawn from the literature, a criteria-based framework guided the production and evaluation of innovation indicators, and the structure of commentary in results and discussion chapters. Key considerations were the historical and theoretical context, indicator quality and method of construction, observed variations across size and sector variables, and potential policy relevance.

Indicator results in the first section of chapter 5 importantly demonstrate three degrees of innovation novelty for both product and process innovations. These differentiated between creation (high novelty) and diffusion (medium and low novelty) based innovation. Deviations across sectors highlight the importance of service sectors as a conduit for diffusing externally produced innovations, such as those embedded in information technology. Natural resources and manufacturing sectors show relatively greater shares of high product novelty innovation on account of their international export status. Bias towards exporters in these indicators should inform interpretation and use from a policy perspective, with implications for comparability and benchmarking across countries. For example, indicators for the rate of product novelty on domestic markets, which represent rates of diffusion, should be used as benchmark measures to understand relative innovation performance for services. High novelty indicators (the rate of new to market product innovators operating on international markets) should be used to benchmark relative innovation performance for tradable

sectors such as manufacturing and natural resources. These indicators should be easy to produce for statistical agencies, based on existing survey data and questionnaires. Results also highlight some practical areas for improving questionnaire logic, some applicable to the CIS, that would improve the quality of data and novelty indicators. This includes better linking of questions on product novelty and market location, so that firms are only asked about product novelty for markets they operate in. In addition, the CIS should change question wording to ask about ‘new to world’ process innovations. However, results also highlight errors in respondent interpretation of novelty concepts, and suggest that around 10% of firms with product innovations fail to correctly understand ‘new to firm’ or ‘new to market’ concepts. This suggests that ongoing work to improve definitions, respondent understanding, and data quality should not neglect these ‘core’ novelty questions, because they provide crucial building blocks for developing more informative indicators.

Significant correlations found between R&D indicators and the likelihood of generating novel product or process innovations demonstrate that R&D activity and intensity indicators from innovation surveys provide good measures of innovation capability – defined as the ability to turn innovation inputs into innovation outputs – and should be included in the range of published indicators released by statistical agencies. This finding also underpins the development of complex indicators in chapter 5. In the panel data, additional indicators also demonstrate that R&D inputs are not essential for all novel innovation, and that non-R&D modes of innovation are more common in service sectors. These results confirm the need for a flexible theoretical approach to understanding and explaining innovation, as neither science-push nor market-pull views can capture all modes of innovating. Results also suggest that indicators for non-R&D modes of innovation should be published by statistical agencies. They are easy to calculate and would help to address the bias towards R&D indicators in policy and academic domains, and to highlight a need for policy to accommodate non-R&D modes of innovating.

Novelty indicators ‘weighted’ by employment showed the share of total employees working for firms with a particular type of novel innovation. Results for these indicators reveal additional information about the distribution and impacts of innovative outputs



by firm size. They indicate that novel product innovation is more likely in larger firms, and novel process innovation more evenly distributed across smaller firms. These results importantly suggest that weighted indicators should be produced as complements to firm share indicators, with potential policy relevance for depicting the distribution of activities across firm populations, and as an indicator for skills demand. They could also reduce the need for indicators to be produced by different firm size ranges, as weighting contains information about the distribution of activities by size. Currently weighted indicators are not produced for CIS data, nor, to the authors knowledge, for most other innovation surveys. These are recommended as a valuable addition to the current range of published indicators.

In chapter 5, three types of complex ‘mode’ indicators demonstrate different patterns of innovation capability across firm populations. They classify firms into different ‘modes’ of innovating based on responses to multiple survey questions, and draw on recent coordinated research by Bloch et al. (2008), Bloch and Lopez-Bassols, (2009) and Arundel (2007). The results and discussion presented in the first and second sections are perhaps the most illuminating for this study, with significant implications for the wider production and improvement of indicators. In the first section, innovation output modes classify firms (on the basis of inputs and outputs) as technology adopters, technology modifiers, novel innovators on domestic markets, or novel innovators on export markets. The results show that modification and adoption are more common modes in service sectors, while high capability modes (novel innovators) are most common in manufacturing and natural resources. Results demonstrate the value of modes for depicting the distribution of innovation capabilities and intensity across economies or at an innovation ‘system’ level, and also across sectors, and firms of different sizes. Three streams of innovation theory all underpin selected measures via constituent indicators. Thus mode indicators overcome a key weakness in the widely available range of rate based indicators and meet a key policy need for benchmarking of capability levels. By highlighting sectoral differences, mode indicators importantly emphasise the dangers of a ‘one size fits all’ policy approach.

Panel data results reveal how mode indicators can provide a dynamic understanding of capability development by tracking specific movement of firms between ordered output

mode categories. The results suggest that for the most part, innovation capability develops cumulatively in line with theoretical thinking (Malerba, 2002; 2005; 2005a), as firms move up one contiguous mode category over time. However, some of the results suggest a need for theoretical approaches to better account for rapid capability development. Mode indicator results reveal information with important implications from a policy perspective, because they offer the capacity to identify both capability development and erosion over time. The former is important, as it could signal areas where policy could accelerate development. Alternatively it might not be required if the focus is on lifting weaker firms. However, modes are just as important in providing measures of capability decline. As an example, it is often argued that the ‘Dutch disease’ is a significant problem for Australia, as the resources boom and high currency value erodes manufacturing capability, which then moves offshore. Given the cumulative nature of capability, and the inevitable demise of the boom, there are very negative consequences for long term competitiveness because of the time taken to rebuild any lost capability. Therefore dynamic mode indicators can provide important ‘early warning’ signals that might elicit policy response. These indicators can be produced for all firms, and ideally at the sector level, although they do require panel data.

Just as importantly, the panel results show how development of innovation capability in non-innovative firms can be monitored by tracking the movement of these firms into different innovation modes over time. This is an important and unique result, as non-innovators have been left out of much empirical and indicator work to date. A key challenge for policy is to determine how to best allocate resources to lift innovation and economic performance, and whether to focus on highly innovative firms, for example, or on encouraging non-innovative firms to develop capabilities. By providing information on the rates at which non-innovative firms develop capability over time, these types of indicator can help inform related policy decisions around increasing performance.

Consequently, a key recommendation of this research is for relevant statistical agencies to produce output modes for innovation surveys. At a minimum, these could be produced for cross sectional data. Ideally though, indicators using panel data should be

produced to track the movement over time of firms between lower capability modes, such as adoption, to higher capability modes, such as technology modification or novel innovation in domestic markets. This depends on the output modes representing discrete, ordered categories of capability. The output modes should also be constructed using ‘core’ questions that repeat over time, and there may be a need for more exploratory work to verify ordered modal categories.

In the second section of chapter 5, status mode indicators classify firms into four categories based on creativity and diffusion inputs: creative collaborators, creative non-collaborators, informal collaborators and informal non-collaborative innovators. Panel data results reiterated the importance of a set of ordered, discrete modal categories for understanding capability movement and optimising the usefulness and policy relevance of indicators. They show that ordered levels of innovation diffusion intensity would be a useful advance, and should be possible to develop from existing survey data. In addition, results across three chapters and different indicator categories clearly show that innovation based on diffusion is the most common mode of innovating in services sectors. The implication of these results combined, is that indicators for ‘diffusion intensity’ should be developed to measure service sector innovation. To achieve this, further work is required to establish categories of diffusion with at least approximate degrees of escalating intensity or capability.

Technological mode indicators classify firms into three categories based on the types of innovations implemented: technological innovators only (product or process), non-technological only (organisational or marketing) and both technological and non-technological. Results show that non-technological modes are more common in services, that relatively more firms innovate with technological only modes in manufacturing and natural resources, and that the majority of firms employ mixed modes. However, results reveal these to be the least useful of the mode schemes. This is mainly due to a lack of depth in information on the specific types of organisational, marketing, or technological innovation, which might have very different implications for firm strategies, capabilities, and performance. Consequently, these modes are of less policy relevance, apart from in a broad benchmarking sense. This is an important result for informing future development of indicators, as it again demonstrates that indicators

should categorise firms based on intensity of activities, rather than on activities alone, which is the main problem with widely available rate based indicators.

A key theme emergent from all mode indicator results was that questions remain about whether particular modes of innovation are desirable. Although theoretically, higher intensity modes should have positive economic outcomes (Verspagen, 2005), there is limited evidence on the impact of modes, for example, on firm level sales growth or productivity improvements (Autant-Bernard et al., 2010). It may well be that a particular ‘low-intensity’ mode of innovating, such as technology adoption, is the most profitable in some sectors. This would imply that improving technology acquisition or inward diffusion capabilities may be a more desirable outcome than to shift upwards along the given capability spectrum. These questions cannot be answered with the results from this study, but they do highlight an area for future work.

In chapter 6, composite indicators measure five dimensions of innovation covering inputs, outputs, and impacts. Each indicator incorporates two to three innovation indicators using the min-max method to rescale values into a single summary indice. The results importantly map the innovation profile for each sector, allowing comparison of sector performance relative to other sectors, and the average for all respondent firms. For example, manufacturing is shown as the most innovative sector, while retail, wholesale and accommodation is the least innovative. The results also reveal relative strengths and weaknesses across sectors. Natural resources and manufacturing for instance, show higher performance on investment and collaboration measures, though lower performance on human capital, while other services and KIBS show higher performance on human capital measures. In addition, indices using panel data provide a picture of mostly negative relative trends in performance over time.

The results demonstrate clear advantages for using composite indicators. Firstly, composite indicators can provide a simple, visual picture of the relative strengths and weaknesses of innovation performance across sectors. This is important for informing policies that may impact on sectors differently (for example, R&D subsidies, which might favour natural resources and manufacturing who perform better on investment). The visual power of these indicators is a key element in defining their contribution to

understanding, and should not be underestimated in terms of policy relevance (OECD, 2008). Composite indicators also have an advantage for studying innovation in small populations of firms, because often individual indicators cannot be published for very small samples due to confidentiality restrictions. Composite indicators avoid this problem by combining multiple indicators into one measure. These results make a key contribution to the literature. They show the usefulness of composite indicators beyond the macro-level of analysis typical for comparisons of such indicators, and also for policies applied at lower levels of geography such as states or regions. An important implication is that a lack of comparable data might not always inhibit the value in these indicators for understanding the distribution of innovation capabilities and performance.

In summary, this thesis showed that new indicators of innovation, in the form of simple, complex, and composite indicators can move beyond the limitations of widely published survey indicators and improve understanding of the distribution of innovation novelty, capabilities, strengths and weaknesses; across sectors, firm sizes, and whole economies. New indicators should be produced to differentiate between levels of novelty and diffusion, and to reveal both capability development and erosion over time. In addition, understanding can be improved with relatively minor improvements in existing data and indicators, as well as the development of entirely new indicators generated from existing survey data. The contributions of this thesis are an important addition to the literature on innovation indicators, for progressing an empirical and theoretical understanding of innovation, and for promoting the relevance of survey indicators for innovation policies at national, sub-national, sectoral and firm levels. Prior to concluding the thesis, the limitations of the research and future research directions are duly discussed.

## **7.1 LIMITATIONS AND FUTURE RESEARCH PRIORITIES**

There are a number of limitations to this study which warrant consideration, some of which are methodology related. Firstly, results only apply to a sample of respondent firms in a regional innovation survey, and might be impacted by the predominance of smaller firms and those in low or medium low tech manufacturing sectors. Secondly, it

is possible that non response in the 2010 TIC may have some impact on the indicator results presented. In general, non-respondents are thought to be biased towards non-innovators, as innovators are more likely to respond to a study on innovation. Though the non response analysis found no significant bias, this cannot be completely discounted and remains a limitation of the study. Thirdly, the study excludes firms with less than five full time employees, so does not cover innovation in micro-businesses. This limitation extends to most innovation surveys. The reasons are pragmatic, and include the very large number of micro-businesses in most economies, the high level of churn (births, deaths and changes), and prohibitive costs and logistics associated with attempting to conduct representative surveys of these firms.

The most important results are for innovation modes, which were for a very limited set of mode indicators, which were selected based on previous research, rather than on exploratory methods such as cluster or factor analysis techniques. The modes were also limited by the TIC questionnaire content. There could be many other possible modes that better capture differences in innovation capability or intensity, but the results are limited to the few indicators explored here.

There are many practical issues that constrain the capacity for wider uptake of innovation mode indicators. The data access issue remains a problem, and there is a need for greater testing of the validity of particular modes if they were to be produced in any type of ongoing way that was comparable across surveys. An inadvertent spin off from this point, is that a lack of comparable mode indicators may not always inhibit their usefulness for improving understanding, as this research has shown such modes to be useful for informing policy and promoting better understanding using data for one economy. A key contribution then, is to show that when produced for firm groupings within an economy, modes can importantly signal areas of capability strength or erosion that might warrant a policy response.

The links between innovation capability and economic outcomes should be a priority for future research. Linked to this is the need for further work to develop mode categories. Here innovation diffusion and creativity were shown as one area requiring development of better ordinal categories for differentiating intensity levels. Future work

of this type should link in with the literature on innovation taxonomies, and consider limiting the empirical focus to ‘core’ survey questions and indicators based on the Oslo Manual. There is a need for more theoretical and empirical work to evaluate whether mode categories and mode schemes are actually capturing what they intend to. Various results suggested an unobserved innovation capability factor or variable that differentiates highly innovative from less innovative firms. The output modes contribute to the task of mapping capability, but are limited by the selection of indicators. More sophisticated econometric work is required to tease out further information about an unobserved or latent capability variable. This might not be captured in the current suite of survey questions. This type of work could lead to improvements in questions and contribute to the development of better indicators.

In summary, this thesis has exposed issues around theory, policy and practice for shaping a related future research agenda. Results highlight a need for theoretical approaches to better account for the systemic determinants of rapid innovation capability development and decline. From a policy perspective, the research suggests a need to better understand the impact of approaches that focus on existing strengths, or building up capability based on identified weaknesses. Though sector results caution against a ‘one size fits all’ policy approach, they also indicate a need to better understand where a broader focus on generic capabilities might yield benefits across sectors. Finally, on a practical level, there is a need for better access to innovation survey microdata, for research to standardise and produce different indicators for degrees of novelty and capability, and for work to better understand links between innovation modes and firm level performance.

In concluding, a key limitation of this research warrants mention, which is the focus on innovation measurement taking a subject approach. As the literature showed, this is but one of a suite of useful and valid classes of measure, and as innovation is so complex a phenomenon, many different approaches are required to generate ongoing improvements to understanding. Although subject approaches provide a good breadth of indicators and measures, this is at the expense of the qualitative depth and richness offered by alternatives such as the object approach. They are just a part of a much

broader puzzle, and should be used in conjunction with traditional measures and any other sources that may emerge.



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## ANNEX A – 2010 AND 2007 TASMANIAN INNOVATION CENSUS – CORE QUESTIONNAIRE ELEMENTS

### 2010 QUESTIONNAIRE ELEMENTS

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#### A. INTRODUCTION

**Q1. To start with, could you describe the activity from which your business derives its main income?**

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**Q2a. As at June 30 2010, was your business part of a larger business, that is, two or more businesses under common ownership?**

*Please tick one box only*

**Yes** ☐ → Go to Question **2b**

**No** ☐ → Go to Question **3**

**Q2b. Is the head office of your business located in:**

*Please tick one box only*

a. Tasmania ☐

b. Australia ☐

c. Outside of Australia ☐

**Please answer all remaining questions only for the activities of your business in Tasmania.**

**Q3. Can you estimate the percentage of your business's total income in the 2009/10 financial year from the sale of goods or services in:**

a. Tasmania \_\_\_\_\_%

b. Australia \_\_\_\_\_%

c. Outside of Australia \_\_\_\_\_%

## B. Goods and services innovations

The next set of questions asks about **new or significantly improved goods or services** that your business introduced onto the market over the last three financial years, from July 2007 to June 2010.

A **new good or service** is completely new and different to goods and services previously produced by your business. However, exclude the simple resale of new goods or services purchased from other businesses.

A **good or service** can be **significantly improved** in many ways:; it could provide more functions, higher quality or comfort, include improved materials, components, or design; or offer better performance. However, exclude minor changes such as new colours or a software upgrade.

New or significantly improved goods and services **do not need to be new to your market**. They only need to be new to your business. A new good or service can be originally developed by your business, or by other businesses.

**Q4. In the past three financial years to June 2010, did your business introduce any:**

	Yes	No
a. New or significantly improved goods	<input type="checkbox"/>	<input type="checkbox"/>
b. New or significantly improved services	<input type="checkbox"/>	<input type="checkbox"/>

If you answered "No" to Question 4a **and** "No" to Question 4b → Go to Question 8

Otherwise → Go to Question 5

**Q5. Were any of your business's new or significantly improved goods or services developed by:**

	Yes	No
a. Your business through modifying goods or services originally developed by other businesses or organisations	<input type="checkbox"/>	<input type="checkbox"/>
b. Your business in collaboration with other businesses or organisations	<input type="checkbox"/>	<input type="checkbox"/>
c. Your business mainly by itself	<input type="checkbox"/>	<input type="checkbox"/>
d. Mainly other businesses or organisations	<input type="checkbox"/>	<input type="checkbox"/>

Note: "other organisations" include universities, research institutes, etc.



**Q6a. Were any of your new or significantly improved goods or services new to your market? That is, your business introduced them onto your market *before* your competitors?**

Yes ☐

No ☐

**Q6b. Were any of your new or significantly improved goods or services *only* new to your business? That is, they were already offered by a competitor in your market?**

Yes ☐

No ☐

*The next question asks about the distribution of your sales income in the 2009-2010 financial year from goods or services that were only new to your business, new to your market, and unchanged.*

*Unchanged goods or services must not have been changed in any significant way since July 2007. Goods and services that were only new to your business or new to your market must have been new or significantly improved since July 2007.*

**Q7. Using the definitions given above, what percentage of your sales income in the last financial year was from new or significantly improved goods or services that were:**

a. New to your market \_\_\_\_\_%

b. New to your business \_\_\_\_\_%

c. Unchanged \_\_\_\_\_%

**Total sales income in 2009-2010** 100%

### **C. Process Innovations**

*The next set of questions asks about new or significantly improved **processes**. This includes **methods** for producing and supplying goods and services, plus supporting activities for these processes. Exclude purely organisational or managerial changes - these are covered in Question 15.*

*A new or significantly improved process must be new to your business, but does not need to be new to your market. It does not matter if the new process was originally developed by your business or by other businesses.*

**Q8. In the past three financial years to June 2010, did your business introduce any new or significantly improved processes for:**

		<b>Yes</b>	<b>No</b>
a.	Producing or supplying your goods and services	<input type="checkbox"/>	<input type="checkbox"/>
b.	Back office systems such as operations for purchasing, accounting, computing, or maintenance	<input type="checkbox"/>	<input type="checkbox"/>

*If you answered "No" to Question 8a **and** "No" to Question 8b* → Go to Question 11

*Otherwise* → Go to Question 9

**Q9. Were any of your business's new or significantly improved processes developed by:**

		<b>Yes</b>	<b>No</b>
a.	Your business through modifying processes originally developed by other businesses or organisations	<input type="checkbox"/>	<input type="checkbox"/>
b.	Your business in collaboration with other businesses or organisations	<input type="checkbox"/>	<input type="checkbox"/>
c.	Your business mainly by itself	<input type="checkbox"/>	<input type="checkbox"/>
d.	Mainly other businesses or organisations	<input type="checkbox"/>	<input type="checkbox"/>

*Note: "other organisations" include universities, research institutes, etc.*

**Q10. To the best of your knowledge, were any of your new or significantly improved processes new to your industry in:**

		<b>Yes</b>	<b>No</b>	<b>Don't Know</b>
a.	Tasmania	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
b.	Australia	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
c.	The World	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

## D. Incomplete or abandoned innovation activities

**Q11. In the past three financial years to June 2010, did your business have any activities to develop new or improved goods, services, or processes, which were not yet completed or abandoned?**

Yes ☐

No ☐

*If your business did not introduce any new or improved products, processes, **or** have incomplete or abandoned innovation activities (if you answered "No" to all of questions 4a, 4b, 8a, 8b **and** 11)*

→ Go to Question 15

Otherwise → Go to Question 12

## E. Innovation Activities and Expenditures

**Q12. In the past three financial years to June 2010, did your business engage in any of the following innovation activities:**

	Activity	Yes	No
a.	<b>Acquisition of machinery, equipment and software</b> Acquire advanced machinery, equipment, computer hardware or software to produce new or significantly improved goods, services, or processes.	<input type="checkbox"/>	<input type="checkbox"/>
b.	<b>In-house R&amp;D</b> Conduct, on an occasional or regular basis, research and development in-house. This is known as R&D and involves the creation of new knowledge and its application to develop new or significantly improved goods, services, or processes.	<input type="checkbox"/>	<input type="checkbox"/>
c.	<b>External R&amp;D</b> Pay other businesses, universities or research institutes to conduct research and development on your behalf.	<input type="checkbox"/>	<input type="checkbox"/>
d.	<b>Acquisition of external knowledge</b> Purchase or license patents and non patented inventions, know-how, or other types of knowledge from other businesses or organisations.	<input type="checkbox"/>	<input type="checkbox"/>
e.	<b>Training for innovative activities</b> Provide or pay for training for your staff specifically for the development or introduction of new or significantly improved goods, services, or processes	<input type="checkbox"/>	<input type="checkbox"/>
f.	<b>Design</b> Conduct design activities to change the shape or appearance of new or significantly improved goods or services. Design work could have been conducted by your business or contracted out to others.	<input type="checkbox"/>	<input type="checkbox"/>

- |    |  | Yes                      | No                       |
|----|--|--------------------------|--------------------------|
| g. | <b>Market introduction of innovations</b> Conduct activities for the market preparation and introduction of new or significantly improved goods or services? This can include market research, launch advertising, feasibility studies, etc. | <input type="checkbox"/> | <input type="checkbox"/> |

Please estimate your expenditures, for the 2009/2010 financial year only, for each activity in Question 12 for which you answered “Yes”. You may give either a dollar amount or a share of your total 2009/2010 sales income.

**Q12.1. Where relevant, what was your expenditure on activities a1 to g1 below in the 2009/2010 financial year only?**

Activity	Expenditure in dollars on activity in 2009/2010	OR	Expenditure as % of Total 2009/2010 Sales Income
a1. Acquisition of machinery, equipment and software	_____		_____
b1. In-house R&D	_____		_____
c1. External R&D	_____		_____
d1. Acquisition of external knowledge	_____		_____
e1. Training for innovative activities	_____		_____
f1. Design	_____		_____
g1. Market introduction of innovations	_____		_____

## F. Collaboration

The next question is about collaboration between your business and other organisations to develop new or significantly improved goods, services, or processes. Both partners do not need to benefit commercially, or share risks. Exclude pure contracting out and exclude collaboration that does not involve developing new or improved goods, services, or processes.

**Q13. In the past three financial years to June 2010, did your business collaborate with other businesses or organisations to develop new or significantly improved goods, services, or processes?**

**Yes** ☐ → Go to Question 14

**No** ☐ → Go to Question 15

**Q14. Which types of collaboration partner did your enterprise use?**

*Please tick all that apply*

Type of collaboration partner	Tasmania	Australia	Outside of Australia
a. Other businesses within your business group	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
b. Suppliers of equipment, materials, services, or software	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
c. Clients or customers	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
d. Other businesses in your sector, including competitors	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
e. Consultants, commercial labs, or R&D institutes	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
f. Universities or other higher education institutions	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
g. Public research institutes such as CSIRO or Cooperative Research Centres	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

## **G. Organisational and marketing innovation**

**Q15. In the past three financial years to June 2010, did your business:**

	<b>Yes</b>	<b>No</b>
a. Implement a new or significantly changed <b>corporate strategy</b>	<input type="checkbox"/>	<input type="checkbox"/>
b. Implement new or significantly changed <b>business practices</b> such as <i>supply chain management, knowledge management, or quality systems</i>	<input type="checkbox"/>	<input type="checkbox"/>
c. Implement new or significantly changed methods of <b>organising work responsibilities and decision making</b> , such as <i>cross-functional teams or outsourcing activities</i>	<input type="checkbox"/>	<input type="checkbox"/>

- |   |                          |                          |
|---|--------------------------|--------------------------|
|   | <b>Yes</b>               | <b>No</b>                |
| d. Implement new or significantly improved <b>marketing concepts or strategies</b> to increase market share or target new markets | <input type="checkbox"/> | <input type="checkbox"/> |

## H. Basic economic information about your business

*Sales income **includes** exports and taxes, but **excludes** GST.*

**Q27a. What was your business's total sales income from its Tasmanian operations for the 2009-2010 financial year?**

**Q27a. 2009/2010**

\$ \_\_\_\_\_

**Note:** *Informed estimates are fine if exact figures are not available*

**If unable to give a dollar amount, can you identify which of the following six broad sales income categories your business falls into?**

**2009-2010**

**Tick one box only**

- |                                  |                          |  |
|----------------------------------|--------------------------|--|
| \$1 Million or less              | <input type="checkbox"/> |  |
| From \$1 million to 5 million    | <input type="checkbox"/> |  |
| From \$ 5 million to 10 million  | <input type="checkbox"/> |  |
| From \$10 million to 50 million  | <input type="checkbox"/> |  |
| From \$50 million to 100 million | <input type="checkbox"/> |  |
| Over \$100 Million               | <input type="checkbox"/> |  |

**Q27b. What was your business's total sales income from its Tasmanian operations two years earlier, for the 2007/2008 financial year?**

**Q27b. 2007/2008**

\$ \_\_\_\_\_

**If unable to give a dollar amount, can you estimate approximately how much your 2009/2010 sales income changed compared to 2007/2008?**

- |                     |            |                          |
|---------------------|------------|--------------------------|
|                     |            | <b>Tick one box only</b> |
| <b>Increased by</b> | 5% to 9%   | <input type="checkbox"/> |
|                     | 10% to 24% | <input type="checkbox"/> |

<b>Increased by</b>	25% to 49%	<input type="checkbox"/>
	50% or more	<input type="checkbox"/>
<b>Unchanged</b>		<input type="checkbox"/>
	5% to 9%	<input type="checkbox"/>
<b>Decreased by</b>	10% to 24%	<input type="checkbox"/>
	25% to 49%	<input type="checkbox"/>
	50% or more	<input type="checkbox"/>

**Q28. For the last pay period of June 2010, how many employees were working for your business that were:**

- a. Full time, defined as 35 or more hours per week \_\_\_\_\_
- b. Part time, defined as less than 35 hours per week \_\_\_\_\_

**Q29. And two years earlier, for the last pay period of June 2008, how many employees were working for your business that were:**

- c. Full time, defined as 35 or more hours per week \_\_\_\_\_
- d. Part time, defined as less than 35 hours per week \_\_\_\_\_

**If unable to give employment numbers for June 2008, can you estimate approximately how much your total employees have changed since then:**

**Tick one box only**

<b>Increased by</b>	5% to 9%	<input type="checkbox"/>
	10% to 24%	<input type="checkbox"/>
	25% to 49%	<input type="checkbox"/>
	50% or more	<input type="checkbox"/>
<b>Unchanged</b>		<input type="checkbox"/>
	5% to 9%	<input type="checkbox"/>
<b>Decreased by</b>	10% to 24%	<input type="checkbox"/>
	25% to 49%	<input type="checkbox"/>
	50% or more	<input type="checkbox"/>

**Q30. Finally, would you briefly describe your business's most important innovation in the past three financial years to June 2010?**

## 2007 QUESTIONNAIRE ELEMENTS

In this survey, the questions are about [business name]'s whole business enterprise in Tasmania.

Q1. To start with, could you describe the activity from which [business name] derives its main income?

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Q2a. Is [business name] part of an enterprise group, that is, two or more enterprises under common ownership?

*Please cross one box only*

Yes ☐

No ☐

Q2b. Is your headquarters in Tasmania, in mainland Australia or Outside of Australia:

*Please cross one box only*

In Tasmania ☐

In Mainland Australia ☐

Outside of Australia ☐

(If the enterprise is part of an enterprise group) In the rest of these questions "your enterprise" refers only to [business name] in Tasmania.

Q2c. Does [business name] have more than one location or establishment in Tasmania?

*Please cross one box only*

Yes ☐

No ☐ → Go to Q3

Q2d. (If yes) What was the number of locations operated by [business name] as at 30 December 2006?

---



The next question asks for the percentage distribution of sales revenue between markets in Tasmania, Australia and Overseas.

**Q3. Please estimate the percentage of your revenues in the 2005-2006 Financial Year (ended June 30 2006) that came from the sale of goods or services in:**

- a. Tasmania \_\_\_\_\_%
- b. Mainland Australia \_\_\_\_\_%
- c. Outside of Australia \_\_\_\_\_%

**The next section is about new or improved goods or services at [business name]**

*When we say that, we are talking about the market introduction of a good or service that is new or significantly improved.*

*That could mean that the good or service is completely new and different to goods or services previously produced by the enterprise.*

*That can also mean that the good or service is significantly improved in terms of quality, functions or intended uses; or significantly improved through changes in materials, components, design, or other characteristics that enhance performance.*

*For example, we would exclude superficial changes (such as new colours or patterns on a label), but include new packaging that improves shelf-life, or reduces costs.*

*The new good or service does not need to be new to your market, only to your enterprise, and it does not matter if the new good or service was originally developed by your enterprise, or by other enterprises.*

*We don't include the simple resale of new goods purchased from other enterprises.*

**Q4. During the past three calendar years, 2004, 2005 and 2006, did your enterprise introduce:**

		Yes	No
a.	New or significantly improved goods.	<input type="checkbox"/>	<input type="checkbox"/>
b.	New or significantly improved services	<input type="checkbox"/>	<input type="checkbox"/>

**(If 'no' to both options above go to Question 8, otherwise Q5a:)**

**Q5a. During the 3 years from 2004 to 2006, were any of these goods or services new to your market, that is where your enterprise introduced a new good or service onto your market before your competitors?**

*Please cross one box only*

Yes ☐

No ☐

**Q5b. During the 3 years from 2004 to 2006, were any of these goods or services only new to your enterprise, that is where you introduced a new good or service similar to a product already available from your competitors?**

*Please cross one box only*

Yes ☐

No ☐

*The next question applies to goods or services during the three calendar years 2004 to 2006.*

*The question asks how much of your turnover is due to goods or services that were unchanged during 2004 to 2006, and how much of your turnover is due to goods or services introduced during 2004 to 2006 that were new or improved.*

*We ask about turnover for the 2005-2006 financial year only (ended June 30 2006), and we ask for a percentage of turnover.*

*We are interested in the distribution of turnover between sales of goods or services that were unchanged, significantly improved, new to your enterprise but not your market, and new to your market.*

**Q6.**

- a. What percentage of your 2005-2006 turnover, was from goods or services that were **unchanged**, or only marginally modified during 2004 to 2006? \_\_\_\_\_%
- b. What percentage of your 2005-2006 turnover, was from goods or services introduced during 2004 to 2006, that were **significantly improved**? \_\_\_\_\_%
- c. What percentage of your 2005-2006 turnover, was from goods or services introduced during 2004 to 2006, that were **new to your enterprise but not to your market**? \_\_\_\_\_%
- d. What percentage of your 2005-2006 turnover, was from goods or services introduced during 2004 to 2006 that were **new to your market**? \_\_\_\_\_%

**Total turnover in 2006** 100%

**The next section is about Process Change**

*A New Process is the use of new or significantly improved **methods** for the production or supply of goods and services. Purely organisational or managerial changes should not be included - these will be covered shortly.*

*The new process must be new to your enterprise, but it does not need to be new to your industry. Again, it does not matter if the new process was originally developed by your enterprise or by other enterprises.*

**Q8a. During the three calendar years 2004 to 2006, did your enterprise introduce any new or improved processes for producing or supplying goods or services?**

Yes ☐

No ☐ —————→ Go to Question 9

**Q8b. Were any of these processes new only to your enterprise and not to the industry?**

Yes ☐

No ☐

**Q8c. Were any of these processes new to the industry?**

Yes ☐

No ☐

**Q9. Does [business name] plan to introduce a new good, service or process within the next three calendar years 2007, 2008 or 2009?**

*Please cross one box only*

Yes ☐

No ☐

**Now a few questions about expenditure**

**Q10, Q11, Q12.** During the three years 2004 to 2006, did your enterprise engage in [...]?  
(When 'yes') What was your approximate expenditure on [...] in the 2005/6 financial year only?

*Please cross one box for each category*

		Yes	No	\$ 2005/6	% of Turnover in 2005/2006 Financial year
<b>a.</b>	<b>In-house research and development for new products or processes, that is, creative work undertaken within your enterprise on an occasional or regular basis to increase the stock of knowledge and its use to devise new and improved goods, services and processes</b>	<input type="checkbox"/>	<input type="checkbox"/>  If no skip to Q15		

**Q15, Q16, Q17.** During the three calendar years 2004 to 2006, did your enterprise engage in [...]? (When 'yes') What was your approximate expenditure on [...] in the 2005/6 financial year only?

		Yes	No	\$ 2005/6	% of Turnover in 2005/2006 Financial year
<b>b.</b>	<b>Acquisition of research and development from other organisations, that is, RESEARCH purchased by your enterprise and performed by other companies, including other enterprises within your group or by public or private research organisations.</b>	<input type="checkbox"/>	<input type="checkbox"/>		
<b>c.</b>	<b>Acquisition of advanced machinery, equipment, computer hardware or software to produce new or improved goods, services, production processes, or delivery methods</b>	<input type="checkbox"/>	<input type="checkbox"/>		
<b>d.</b>	<b>Acquisition of external knowledge: Purchase or licensing of patents and non-patented inventions, know-how, and other types of knowledge from other enterprises or organisations.</b>	<input type="checkbox"/>	<input type="checkbox"/>		
<b>e.</b>	<b>Internal or external training for your personnel specifically for the development and/or introduction of new or improved goods, services and processes.</b>	<input type="checkbox"/>	<input type="checkbox"/>		
<b>f.</b>	<b>Design activities, outside of the RESEARCH phase for the development or implementation of new or improved goods, services and processes.</b>	<input type="checkbox"/>	<input type="checkbox"/>		

		Yes	No	\$ 2005/6	% of Turnover in 2005/2006 Financial year
<b>g.</b>	<b>Activities for the market preparation and introduction of new or improved goods and services, including market research and launch advertising.</b>	<input type="checkbox"/>	<input type="checkbox"/>		

The next question is about collaboration. We define collaboration as active participation with other enterprises or non-commercial institutions aimed at developing new goods, services or processes. Both partners do not need to benefit commercially, or share risks. Exclude pure contracting out of work with no active collaboration.

**Q18. Did [business name] engage in any collaboration with other enterprises or institutes during the three calendar years 2004 to 2006?**

Yes ☐

No ☐ → Go to Question 20

The next question asks for a “yes” or “no” response to whether your enterprise has collaboration partners, and whether they were located in Tasmania, Australia or Outside of Australia. Collaboration partners can be in more than one location.

**Q19. Did [business name] collaborate with (read for each category a to g).**

**(If ‘yes’ ask ) Were they located - within Tasmania ... in Mainland Australia ... Outside of Australia?**

Type of collaboration partner		Please cross all that apply		
		Within Tasmania	Mainland Australia	Outside of Australia
<b>a.</b>	Other enterprises within your enterprise group	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<b>b.</b>	Suppliers of equipment, materials, services, or software	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<b>c.</b>	Clients or customers	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<b>d.</b>	Competitors or other enterprises in your industry	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<b>e.</b>	Consultants, commercial labs, or private RESEARCH institutes	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

<b>f.</b>	Universities or other higher education institutions	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
<b>g.</b>	Public research institutes or CRCs (Cooperative Research Centres)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

In this next section we ask about new forms of organisation, business structures or practices aimed at improving efficiency, or new approaches to markets and customers. The question asks for a “yes” or “no” response to a number of answer categories.

**Q21. During the three calendar years 2004 to 2006, did your enterprise make major changes in the following areas of business structure and practices?**

*Please cross one box for each category*

	Yes	No
a. Implementation of a new or significantly changed <b>corporate strategy</b>	<input type="checkbox"/>	<input type="checkbox"/>
b. Implementation of <b>advanced management techniques</b> within your enterprise, e.g. knowledge management systems	<input type="checkbox"/>	<input type="checkbox"/>
c. Implementation of major changes to your <b>organisational structure</b> , e.g. introduction of cross-functional teams, outsourcing of major business functions.	<input type="checkbox"/>	<input type="checkbox"/>
d. Implementation of changes in <b>marketing concepts or strategies</b> (e.g. packaging or presentational changes to a product to target new markets, or new activities to open up new markets)	<input type="checkbox"/>	<input type="checkbox"/>

**And finally some basic economic information about your enterprise**

Turnover is defined as the market sales of goods and services based on the amount earned; **include** exports and taxes, but **exclude** GST.

**Q22. What was your enterprise’s total turnover from its Tasmanian operations for the 2005-2006 financial year? What was it two years earlier, for the 2003/4 financial year?**

**a. 2005/6**

\$ \_\_\_\_\_

**b. 2003/4**

\$ \_\_\_\_\_

**Informed estimates** are fine if exact figures are not available

(If unable or unwilling to estimate) can you tell us which of the following six broad categories your enterprise falls into? (Read all categories and circle relevant code)

<b>2005-2006</b>	<b>Code</b>	<b>2003-2004</b>	<b>Code</b>
\$1 Million or less	1	\$1 Million or less	1
\$5 Million or less	2	\$5 Million or less	2
\$10 Million or less	3	\$10 Million or less	3
\$50 Million or less	4	\$50 Million or less	4
\$100 Million or less	5	\$100 Million or less	5
Over \$100 Million	6	Over \$100 Million	6

The next question is about the number of employees at [business name].

**Q23. During the last pay period ending in December 2006, how many employees were there who worked [ ask for a to c below ]?**

a.	Full time that is 35 or more Hours per week	
b.	Part time, that is less than 35 hrs per week on a regular basis	
c.	Irregular hours or were there for seasonal work	

If there were employees working irregular hours or there for seasonal work, then ask d:

d.	For employee's working irregular hours or there for seasonal work, could you estimate how many full time people they were the equivalent of during the whole 2006 calendar year?	
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Next, we ask the same questions about the number of employees two years earlier:

**Q24. During the last pay period ending in December 2004 how many employees were there who worked [ ask for a to c below ]?**

a.	Full time that is 35 or more Hours per week	
b.	Part time, that is less than 35 hrs per week on a regular basis	
c.	Irregular hours or were there for seasonal work	

If there were employees working irregular hours or there for seasonal work, then ask d:

d.	For employee's working irregular hours or there for seasonal work, could you estimate how many full time people they were the equivalent of during the whole 2004 calendar year?	
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**Q25. During the last pay period ending in December 2006, approximately what number of your enterprise's employees were educated to degree level or above in science or engineering subjects? ... What about other subjects?**

Note: If respondent has difficulty providing a number, then ask if they can provide their answer as a percentage of total no of employee's

	December 2006	
a. Science and engineering subjects	___ (Number) OR	___%
b. Other subjects	___ (Number) OR	___%

The final question is an open ended one.

**Q26. Could you briefly describe your most important innovation in the past three years?**