FIRM-LEVEL PRODUCTIVITY GROWTH IN NORTHERN IRELAND: THE IMPACT OF EXPORTING, INNOVATION AND PUBLIC FINANCIAL ASSISTANCE

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THESIS SUMMARY

Motivated by the historically poor productivity performance of Northern Ireland firms and the longstanding productivity gap with the UK, the aim of this thesis is to examine, through the use of firm-level data, how exporting, innovation and public financial assistance impact on firm productivity growth. These particular activities are investigated due to the continued policy focus on their link to productivity growth and the theoretical claims of a direct positive relationship.

In order to undertake these analyses a newly constructed dataset is used which links together cross-sectional and longitudinal data over the 1998-2008 period from the Annual Business Survey, the Manufacturing Sales and Export Survey; the Community Innovation Survey and Invest NI Selective Financial Assistance (SFA) payment data. Econometric methodologies are employed to estimate each of the relationships with regards to productivity growth, making use in particular of Heckman selection techniques and propensity score matching to take account of critical issues of endogeneity and selection bias.

The results show that more productive firms self-select into exporting but there is no resulting productivity effect from starting to export; contesting the argument for learning-by-exporting. Product innovation is also found to have no impact on productivity growth over a four year period but there is evidence of a negative process innovation impact, likely to reflect temporary learning effects. Finally SFA assistance, including the amount of the payment, is found to have no short term impact on productivity growth suggesting substantial deadweight effects and/or targeting of inefficient firms.

The results provide partial evidence as to why Northern Ireland has failed to narrow the productivity gap with the rest of the UK. The analyses further highlight the need for access to comprehensive firm-level data for research purposes, not least to underpin robust evidence-based policymaking.

Keywords: Self-selection; learning by exporting; CDM-model, propensity score matching

Dedication

Dedicated to my two children, Aimee and Cillian

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LIST OF ABBREVIATIONS

2SLS	Two-stage Least Squares
ABI	Annual Business Inquiry
BERD	Business Expenditure on R&D
BERR	Department of Business, Enterprise and Regulatory Reform
CCMS	Client Contact Management System
CIS	Community Innovation Survey
CDM	Crépon, Duguet and Mairesse
CoE	Census of Employment
DED	Department of Economic Development
DETI	Department of Enterprise, Trade and Investment
DID	Difference-in-difference
DIUS	Department for Innovation, Universities and Skills
ERC	Enterprise Research Centre
GMM	Generalised Method of Moments
GPS	Generalised Propensity Score
GVA	Gross Value Added
HMRC	Her Majesty's Revenue and Customs
IDB	Industrial Development Board
IRTU	Industrial Research Technology Unit
LEDU	Local Enterprise Development Unit
LEP	Local Enterprise Partnership
LPS	Local Productive System
MNE	Multinational Enterprise
MSES	Manufacturing Sales and Export Survey
NI	Northern Ireland
NIEC	Northern Ireland Economic Council
NIERC	Northern Ireland Economic Research Centre

PPI	Producer Price Index
R&D	Research and Development
ROEU	Rest of European Union
ROW	Rest of World
ROI	Republic of Ireland
RSA	Regional Selective Assistance
SDS	Secure Data Service
SFA	Selective Financial Assistance
SFIE	Selective Finance for Investment in England
SIC	Standard Industrial Classification
SMART	Small Firm Merit Awards for Research and Development
TFP	Total Factor Productivity
UKDS	UK Data Service
UK	United Kingdom
VML	Virtual Micro-Laboratory

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1 INTRODUCTION

1.1 Introduction

> *"Productivity isn't everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise output per worker" (Krugman, 1994, pg. 13).*

Productivity is a measure of the efficiency of production, quantifying how an economy or firm uses the resources it has available, and is typically defined as a ratio of a volume measure of output to a volume measure of input use. According to the OECD (2008) productivity, as an indicator, offers a dynamic measure of economic growth, competitiveness, and living standards within an economy.

At the firm level growth in productivity drives the growth of real wages and enables firms to remain competitive, or indeed improve their competitiveness. Firms can increase output either by increasing inputs or by increasing productivity; the latter allowing the firm to generate a higher level of output, and hence income, using existing resources.

Given its importance then at both the firm and economy-wide level in improving incomes, wages, and standards of living it is unsurprising that economic policy in industrialised countries has become increasingly focussed on productivity and its growth over the last number of decades. This was particularly the case in Northern Ireland (NI) where, during the 1990s, it was recognised that productivity growth was key to long term sustainable growth, but that the region performed poorly in this measure (DED, 1990, 1995, 1999). In particular, it was observed that there was a prevailing productivity gap between NI and the rest of the UK; whereby labour productivity had remained at around 80 per cent of the national level since the 1980s (DETI, 2005a; NI Executive, 2008).

In response to the productivity gap and overall low levels of productivity, policies to improve business productivity growth were set out in the various Northern Ireland economic strategies from the 1990s onwards, which were to be enacted through programmes provided by the region's economic development agencies. These policies were arranged through a framework, as set out in national Government policy, and centred around specific drivers of productivity growth, namely investment, innovation, skills, enterprise and competition (HM Treasury, 2000). It was also recognised within Northern Ireland, that as a small regional economy, a further measure, exporting, was key to regional productivity growth (DED, 1990, 1999; DETI, 2007).

In conjunction with re-orientation of policy towards productivity growth so the objective of regional financial assistance in NI also switched from a general employment creation role towards that of improving productivity. This shift was characterised by the provision of discretionary assistance to 'high-quality knowledge-based' projects that would improve regional competitiveness (Wren, 2005), rather than the previous focus on those investment projects that would create or safeguard jobs. In NI this was characterised by assistance for capital projects gradually being reduced and replaced by softer forms of assistance such as those for marketing, management, exporting and R&D activities. Such assistance, provided under the remit of Selective Financial Assistance (SFA)[1] in NI, resulted in levels of spend of more than £200 million between 2002/03 - 2007-08 targeted specifically on innovation, training and trade related programmes designed to improve productivity (IREP, 2009).

These new policies represented a step change from those which had traditionally sought to generate employment (Wilson, 1965; Quigley, 1976). Notably, though, none of the Northern Ireland economic strategies set out the empirical evidence nor the underlying economic theory which provided the causal link between such drivers and productivity growth[2]. Indeed, despite the radical change in focus and the fact that by 2010 there had now been more than a decade of policy specifically aimed at improving productivity; the productivity gap in NI was no better than it was in 2000. In fact in 2010, GVA per hour worked in NI was 80.9 per cent of the UK's level compared to 84.1 per cent in 2000 (ONS, 2011). This suggested that the new policy levers and associated financial assistance aimed at improving productivity growth

[1] SFA is the Northern Ireland equivalent of Regional Selective Assistance (RSA) which was introduced in the UK in 1972 as one of the main regional policy instruments. Its main aim on its introduction was to safeguard and create employment in "disadvantaged" regions.

[2] For example, in the Draft Regional Economic Strategy (DETI, 2007) there are no references to any theoretical or empirical academic studies relating to innovation or exporting and their impact on productivity growth but merely statements to the effect " Improving and enhancing NI's overall innovation and R&D performance will lead to increased productivity and prosperity, moving the NI economy up the value-added chain" (DETI, 2007, pg.58). Rather the document makes statements relating to how the Strategy will meet UK and EU policy objectives and how it will be implemented and measured.

within firms were not having the desired effect, and if anything the gap between the NI and UK levels had actually widened.

This apparent lack of impact on the productivity gap in NI prompted the initial interest in firm-level productivity and, combined with the paucity of detailed empirical work examining NI productivity growth and providing any causal evidence as to its drivers, provided the motivation for this research. Using uniquely linked micro-data the research seeks to examine how specific activities undertaken by firms and targeted by policy, namely exporting and innovation, influence productivity growth at the firm level in NI. In addition it seeks to measure the impact, if any, that SFA had on productivity growth over the 1998-2008 period; this particular programme of assistance selected for investigation due to its function as a highly flexible policy instrument used to provide direct financial support to private profit-making firms in order to achieve either employment or productivity growth (SQW, 2013).

A literature search to uncover the potential impacts of exporting, innovation and public financial assistance on productivity growth has revealed limited evidence for NI, both in terms of the number of empirical studies, particularly up-to-date studies, and findings relating to a productivity effect. For example, Roper et al. (2006a) and Bonner et al. (2006) provided the most recent evidence (up to 2001) on the firm-level determinants of exporting but there have been no studies on the impact of exporting on productivity growth. With regards to innovation Roper et al. (2006b, 2008) reported negative effects from product innovation on productivity levels but no effect on productivity growth within the service sector (Roper et al., 2007; Love et al., 2010), whilst productivity effects from grant assistance, and in particular SFA assistance has provided mixed results (Harris et al., 2002; Hart et al., 2007; SQW, 2013).

The wider related empirical work examining these specific areas at the firm level has only become feasible in the last two decades, with the increasing availability of micro-level data, and suitable software and techniques to enable its manipulation (Doms and Bartelsman, 2000). Where empirical studies have been undertaken, the results also appear to be somewhat inconclusive despite the compelling theoretical arguments as to how each of these activities should increase productivity within firms. The empirical literature on the link between exporting and productivity growth, which is now relatively vast, provides a more compelling argument for firms becoming more productive prior to exporting than it does for higher productivity growth resulting from exporting (see Wagner, 2007; and Singh, 2010 for a summary of the literature). Likewise the empirical literature on the innovation-productivity argument fails to reach a consensus on the effect on productivity growth (Hall, 2011); this is particularly important with regards to NI, as the only available micro-studies on the subject suggest a negative impact (Roper et al., 2007; Love et al., 2010). The effect of public financial intervention on firm performance has also had mixed results, with suggestions of rent seeking amongst firms (Bergstrom, 2000, Harris and Trainor, 2005) and the prevention of the natural creative destruction process (Criscuolo et al., 2012; Koski and Pajarinen, 2013), and no consensus, as yet, on the direct impact on productivity growth (Bernini and Pellegrini, 2011). In addition it is recognised that measuring the direct impact remains a challenge due to "the many factors involved and the fundamental evaluation problem, the general lack of data available for outcomes in the case of the counterfactual situation" (GEFRA, 2010, pg. 12).

Given the apparent lack of consensus empirically on the productivity-enhancing effects of exporting and innovation, and the shortage of evidence with regards to a positive public financial assistance impact on productivity growth, this research offers the opportunity for a detailed examination of these activities at the firm level. This is particularly pertinent for NI as countless economic strategies have encouraged such activities with the expectation that it would result in improved productivity, but without any subsequent evaluation upon which such claims can be validated (NIEC, 1999b).

The ensuing objectives, and hence the contributions of this thesis are thus expected to be manifold. Firstly by undertaking a comprehensive literature review, detailing the theoretical arguments and reviewing the empirical evidence of the relationships between exporting, innovation and public financial assistance the aim is to draw together in one study these distinct literatures, providing the basis for a greater understanding of how these firm-level drivers impact productivity growth. This is particularly important for the productivity discussion in NI whereby exporting and innovation have been advocated as the main drivers of productivity and competitiveness, but with no formal framework setting out how this occurs. Indeed, efforts to reduce the productivity gap with the UK will be undermined without an understanding of the mechanisms operating at the firm level.

A second unique contribution concerns the development of the dataset, which is constructed by linking together, for the first time, a range of administrative survey data with financial data on public (SFA) grant payments. The dataset combines firm-level records, linked via unique reference number, from a number of official NI government business surveys. These include the Annual Business Inquiry (ABI), the Manufacturing Sales and Export Survey (MSES) and the Community Innovation Survey (CIS), which when linked together provide both a longitudinal and comprehensive set of data for each firm, further enhanced by the addition of any SFA payments that these firms received. This latter addition is particularly valuable given the extent of support firms in NI receive, its inclusion enabling the level of financial support to be modelled in isolation above and beyond other contributing effects.

Currently, the survey data is held by Government across separate datasets, and is generally not utilised for research in the same vein that the ONS makes available its firm-level survey data[3]. It is anticipated then that by demonstrating the benefits of linking together this administrative data, to provide a unique resource, it can be shown that research can be undertaken at a relatively low cost with zero additional burden to the firm. Indeed if the resulting pooled dataset can be maintained and updated in future, then any results arising from this research can be re-visited as necessary, as more data and perhaps other methods of evaluation become available. In fact using the results of the analysis conducted here, along with the identified limitations, it is expected that future analyses can be fine-tuned to take account of developments in the wider empirical literature.

A third contribution is that of the empirical analyses undertaken; it will contribute to the existing literature by providing evidence, for the first time, on the self-selection and learning-by-exporting hypothesis for NI. The analysis will adopt best practice methodologies, to include quantile regression and propensity score matching, to test hypotheses on which there is continued debate. The combination of advanced estimation methods, and a dataset which has been newly constructed and never before utilised, providing an original insight.

Likewise the estimation of the links between R&D, innovation and productivity will be modelled for NI, for the first time, using a structural model. This will take account of endogeneity and selectivity bias issues, which are key concerns. The results will provide evidence for NI which is comparable to other similar studies, allowing the results to be understood in a wider context.

[3] The ONS makes available its micro-level business surveys to approved researchers via the Virtual Micro-Laboratory and UK Data Service.

Due to data limitations, the impact of public financial assistance is rarely estimated using the value of payments[4]. Its inclusion here represents a unique contribution, moving the estimation beyond analysing the impact of support as a binary measure, to one which explicitly takes account of actual amounts received by firms. This permits a separation of the general effect of being a 'supported' firm, to that which allows an estimate of the elasticity of support on productivity growth, again using best practice methodologies.

Overall it is anticipated that the thesis will help not only fill a knowledge gap in NI, on the strategic activities of local firms and their impact productivity growth, but will also set these results within an international context. The use of up-to-date, and best practice, methodologies together with a uniquely constructed dataset will provide novel contributions to the ongoing debates, both empirically and in policy circles.

1.2 Context

Northern Ireland represents an interesting, and representative, case study for examining these issues in that manufacturing firms in Northern Ireland have enjoyed a higher level of subsidy from government than firms in any other UK region since the mid-1960s (Roper, 1996), and it has a proportionately larger level of public expenditure than any other UK region (IREP, 2009) however typically the region performs poorly on most of the aggregate performance indicators:

- NI's productivity has lagged behind the rest of the UK with GVA per employee at around 80 per cent of the UK average for the last thirty years (Oxford Economics, 2009).
- NI's GVA per job filled is, after Wales, the lowest amongst the UK regions in 2010 and the gap with the UK level has widened since 2000 (Fig. 1.1).
- At 7 per cent NI firms have one of the lowest shares of turnover attributable to new, improved or novel products in 2008 (BIS, 2011b)[5]
- The value of exports of goods per workforce job in NI in 2010 is £6,330 which is around 25 per cent lower than the UK average (BIS, 2011a).

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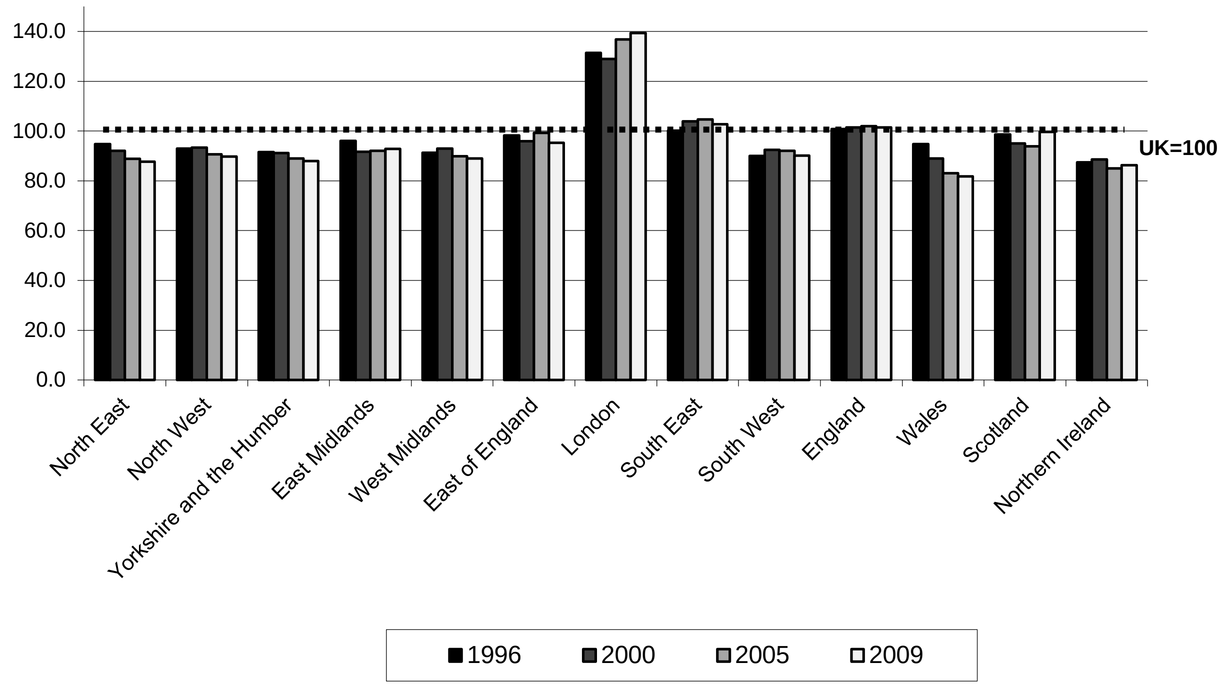
[4] Girma et al. (2007) suggest that, to date, due to lack of such data, the empirical evidence of the effect of grant assistance on productivity has been based largely on whether a firm participated in a government scheme or not rather than examining the effects of the actual payments.

[5] The South West had the lowest percentage at 5% followed by Scotland at 6%. Northern Ireland's share of 7% was equal to that of the East Midlands. The UK average was 11%.

- The value of goods exported is less than 20% of GVA in 2011 (BIS, 2012), which is below the UK average and also well below other comparable regions including the North East and Wales[6].

Figure 1.1: Gross Value Added per job filled in the UK regions (Index UK=100)



Source: ONS 2011

The above findings thus suggest that firm performance in NI with regards to productivity, and its drivers, is somehow different to or inferior to other regions, and its output is of a lower value-added nature, despite being heavily assisted by government. Peripherality may in part explain these findings (Boddy et al., 2010); however the underlying nature of firms, the industrial structure and/or the nature of industrial policy may also play a part. The research questions in this study will therefore contribute to a better understanding of these issues, and will be addressed by the availability, for the first time, of detailed firm-level linked data incorporating SFA grant payment information. The research questions will attempt to uncover the nature of the relationships between firm level activities and productivity growth, which

[6] Northern Ireland's export of goods accounted for 19.4% of GVA in 2011 compared to a UK average of 21.5%. The North East had the highest share at 31.4%.

are important from a policy perspective in that in order to set appropriate policy goals it is necessary to understand the characteristics of firms; what influences their decision to undertake business activities such as R&D, innovation and exporting, and how this impacts on their performance. This understanding will help to target assistance more specifically; identify the potential impacts of such policies and avoid setting targets for activities which potentially have no direct impact on the ultimate policy goals.

1.3 Policy Background

Within NI Government support for industry has progressed over the last fifty years from being strongly interventionist towards a more focussed role in helping industry overcome market failure. The nature of assistance to firms has evolved from direct forms of support for capital investment to a more targeted approach aimed at the underlying obstacles to firm growth. Traditionally, the policies to emerge under the industrial structure heading were aimed largely at promoting new employment to compensate for the loss of jobs in older, declining industries, and hence reduce unemployment. However in the 1990s, due to a recognition that the NI economy was lagging that of other UK regions, policy shifted towards achieving higher levels of growth, to be attained through measures to develop the knowledge economy; promote innovation; improve competitiveness, and shift the economy up the value chain, all of which would be facilitated through the private manufacturing and tradeable services sectors (DED, 1990).

This radical change in policy persisted over the following decade, and in fact the 2008 Programme for Government reiterated the continued need to improve productivity, aiming to halve NI’s private sector productivity gap with the UK average (excluding the Greater South East) by 2015 (NI Executive, 2008). The region’s economic development agency also remained committed to the policy goal, their ultimate objective to

> *“…improve the competitive position of our client business, thereby contributing towards an increase in regional productivity, as measured by Gross Value Added per head” (Invest NI, 2009, pg.23.).*

This radical policy change, in part, reflected the national Government's actions, whereby the pursuit of higher productivity growth as a means of ensuring long-term economic growth had become central the policy agenda in the late 1990s. The concern at the UK macro-level was the UK's prevailing productivity gap with other industrialised nations, such as France, Germany and the US (HM Treasury, 2000, pg.6). In response to this, and based on recently developed theoretical arguments, supporting endogenous-based knowledge-driven growth, the UK Government developed a set of five drivers of productivity growth, upon which is would base policy, namely investment, innovation, skills, enterprise and competition (HM Treasury, 2000).

The means by which the UK Government sought to fund this new economic goal remained consistent despite the policy change. Regional Selective Assistance (RSA), of which SFA is the Northern Irish variant, continued to be provided. RSA/SFA had been a long-standing element of the UK economic development infrastructure, originally set up in the early 1970s to create or safeguard employment opportunities by providing discretionary grants to firms in disadvantaged regions. These regions, known as 'Assisted Areas' were typically characterized by relatively low levels of per capita GDP and high unemployment. Assistance could be provided to establish a new business, to expand, modernize or rationalize an existing business, to set up research and development facilities or to move from development to production (Criscuolo et al., 2012). The new policy focus on productivity meant that the aim of RSA shifted from employment creation towards projects that could improve regional competitiveness, suggesting that RSA was in essence a flexible tool, which could shift in reaction to the progressing agendas

In NI SFA was used to provide direct financial support in the form of grants, loans, or share options to both indigenous and foreign owned firms. It was intended to be the "assistance of last resort"; all other commercial sources and public sector funding having been fully explored beforehand[7]. Where it was given, SFA could only fund a proportion of total project cost with Gross Grant Equivalent (GGE) limits in place – typically the maximum level in NI ranged from 50% (for small firms) to 30% (for large firms) of the total project cost. As a flexible tool SFA was used to support a wide range of eligible projects which were intended to lead to higher levels of business

[7] http://www.investni.com/selective_financial_assistance_guidelines_sfa_smp.pdf

growth, and deliver long-term high quality employment across the region (SQW, 2013).

1.4 Theoretical and Empirical Background

Exporting, innovation, and public financial assistance can all be thought to be interlinked, working directly and indirectly through various mechanisms, to impact on firm productivity performance. It is difficult to unpick the relationships when considered as a whole, as firms that export may also be more likely to innovate, and vice versa (Love and Roper, 2013); likewise those that seek grant assistance may also be more likely to export and/or innovate as such behaviour suggests a proactive nature with regards to the pursuit of opportunities to improve growth. Given the potential for numerous endogenous relationships within the system it is therefore difficult to identify the causal relationships between these activities, and to distinguish which has the greater impact on productivity growth, when considered together. The intention of the thesis is thus to evaluate each of the individual relationships separately, whilst controlling for the other factors, where possible. Each of the individual relationships has its own underlying theoretical and empirical literature; thus this research seeks to utilise and build on these to identify how these firm-level activities drive productivity growth and to validate, or otherwise, the underlying theoretical principals.

1.4.1 Exporting and Productivity Growth

The links between international trade and growth are relatively well established at the macro-economic level; at the micro-economic level the relationship between exporting and firm growth has only been established relatively recently, and in fact a seminal paper by Bernard and Jensen (1995) was the first to examine in any great detail, the characteristics of exporting firms. From that initial study there developed a body of literature that sought to examine the nature of firms that exported; how they differed from those that did not, and how exporting impacted on their growth. A number of stylised facts were drawn up based on those studies along with two central, but not mutually exclusive, hypotheses regarding exporting and productivity. The first hypothesis proposed that exporters are more productive than non-exporters prior to exporting and thus they self-select into exporting activity. This was termed the ‘self-selection’ argument and was deemed to occur due to the sunk costs involved in selling to external markets and the necessity to already be highly efficient prior to competing in the wider export marketplace; factors which create an entry barrier for less successful firms (Clerides et al., 1998; Melitz; 2003). The second hypothesis proposed that firms learn to become more productive through exporting, by exposure to other more advanced techniques and technologies, and feedback from international customers and suppliers. This was termed the 'learning-by-exporting hypothesis and suggested that through such learning exporting would improve the productivity growth of firms (Jovanovic and Lach, 1989; Fafchamps et al., 2002).

Empirical evidence for the self-selection argument is comprehensive and has been widely found in the literature. In fact Wagner (2007; 2012) and Singh (2010) in summarising the relevant literature both conclude that there exists strong evidence for the self-selection of more productive firms into exporting. In contrast the evidence for learning-by-exporting has been less conclusive, with many studies reporting no such impact (Delgado et al., 2002; Wagner, 2002; Arnold and Hussinger, 2004; Wilhelmsson and Kozlov, 2007; Pisu, 2008). Within NI there has been a paucity of evidence in relation to the export behaviour of firms and in fact none have sought to look at the evidence as to whether more productive firms self-select into exporting and/or whether exporting leads to improved productivity growth. Rather the only empirical studies undertaken have sought to distinguish the characteristics of exporters from non-exporting firms (Roper and Love, 2001; Roper et al., 2006a; Bonner et al., 2006) and although they have established particular characteristics amongst exporters, it is not known whether this is a cause or effect. Given the lack of empirical evidence for NI, and the wider contestable evidence for learning-by-exporting, the thesis seeks to substantiate the two key hypotheses in the literature and thus provide further support, or contest the findings in the wider empirical body of work. The proposed methodologies will reflect those widely used in the literature, taking account of heterogeneous firms, where necessary (Melitz, 2003; Bernard et al., 2003) and using stochastic dominance and propensity score matching techniques to test the main hypotheses.

1.4.2 Innovation and Productivity Growth

It is acknowledged that current understanding of the relationship between innovation and productivity growth came about through the work of Solow (1957) who identified a residual, attributed to technical change that was responsible for more than four fifths of growth in the US economy. His findings led to the development of a new theoretical literature, termed endogenous growth, which provided an explanation of the mechanism through which long term growth occurs. These endogenous growth theories proposed that knowledge embodied in human capital together with investment were responsible for firms learning to produce more efficiently (Arrow, 1962; Romer, 1986; Lucas, 1988; Rebelo, 1991), leading to higher productivity levels within the firm. The theories provided explanations as to why profit-seeking firms would invest in R&D despite the apparent risk and lack of protection, and demonstrated how monopoly rents could be achieved. Indeed they explained how knowledge spillovers arising from innovative activities could drive the Schumpeterian process of creative destruction and hence long-term growth, whereby inefficient firms exit the market to be replaced with a continuous cycle of more technologically advanced innovators.

The empirical evidence to support the innovation-productivity growth relationship was bolstered greatly by the introduction of the Community Innovation Survey (CIS) which was a Europe-wide initiative to study the innovation activities of firms. It identified various types of innovation behaviour; two of which, product and process innovation, have been examined widely in the literature with regards to their impact on productivity. A novel paper by Crépon, Duguet and Mairesse (1998) set out the framework through which innovation impacts productivity growth; showing it to be a multi-stage process whereby firms make a decision to invest in R&D; they decide how much to spend; the impact of this spending on innovation output is then measured, and finally the impact of the innovation output on productivity growth is assessed. The literature following this approach, termed the Crépon, Duguet, Mairesse Model (CDM-model), has been found to have largely consistent results for the R&D elements, in that R&D spending is found to positively affect innovation outputs. The impact on productivity growth is less well supported; innovation where it has been measured as a continuous variable[8] is generally found to have a positive impact, where it has been measured as a dummy, the impact is slightly less so, and where process innovation has been included separately the results of its impact have been inconclusive (Hall, 2011).

There have been several studies looking at the impact of innovation on firm performance in NI; those looking specifically at productivity impacts have come to a somewhat surprising conclusion. Generally it has been found that innovation,

[8] For example where innovation has been measured as innovative sales, or innovative sales per employee.

measured as a continuous variable[9] has a negative effect on productivity levels, (Roper and Love, 2004); where it is measured by dummy variables, it has either a negative impact (from product innovation) or an insignificant impact (from process innovation) (Roper et al., 2006b, 2008). Looking specifically at the service sector there were found to be no direct impacts from innovation, either on productivity levels or growth, although there was some evidence of an indirect effect working through exporting (Roper et al., 2007; Love et al., 2010).

Again due to the inconsistent evidence with regards to a positive productivity effect from innovation, the thesis seeks to test the hypotheses for NI. As discussed, the results thus far for NI have been shown to be either negative, insignificant or indirect. Re-running the analysis on a different, potentially more comprehensive dataset may help to clarify the argument, and re-establish the link between the empirics and the theory. The methodology will follow that of the augmented-CDM model[10] as it allows for the problems of selection and endogeneity to be controlled for.

1.4.3 Public Financial Assistance and Productivity Growth

The final element of the analysis is to establish the link between public financial assistance received by firms and their productivity growth. The theoretical justification for public subsidisation of firms lies within the body of literature concerning market failure. Here government intervention is said to be justified and required in situations where the market is unable to achieve allocative efficiency, resulting in the waste of resources. The justification for intervention with regards to productivity growth is explained by three alternative propositions (Beason and Weinstein, 1996); the first (Schumpeterian) is linked to innovation and concerns both the public good and incomplete markets arguments; the former leading to an under-investment in innovation due to lack of appropriability, and the latter due to a difficulty in sourcing the required finance. The second (Marshallian) and third (strategic trade) arguments both promote intervention in the form of protection, so that infant industries, or struggling domestic industries, can be allowed to grow and reap economies of scale without the threat of external competition.

[9] Innovation is measured as the percentage of sales derived from new products and termed 'innovation success'.
[10] The empirical methodology used in the dissertation follows the version of the CDM model as used in Griffiths et al. (2006), hence it is referred to as the augmented-CDM model.

The theoretical justification for intervention would suggest that it is only undertaken in practice where it can have a positive outcome. The empirical literature regarding the impact of intervention, in the form of financial assistance, or subsidies, does not necessarily support this proposition, particularly with regards to productivity growth. In fact, in those studies in which subsidies have been grouped together and their impact estimated, the results have overwhelmingly reported either a negative or insignificant impact; the targeting of inefficient declining firms seen as the principal cause of this (Beason And Weinstein, 1996; Criscuolo et al., 2012; Martin et al, 2011; Koski and Pajarinen, 2013). Where positive productivity impacts have been reported it has been when the assistance has been targeted towards specific firms, and/or when it has been separated into those programmes specifically targeted towards productivity improvements (Girma et al., 2007; Colombo et al., 2011; Grilli and Murtinu, 2011).

The NI evidence with regards to the impact of financial interventions on productivity growth is relatively limited. There is evidence of substantial impacts on output but not necessarily on productivity improvements, and in fact the only positive findings have been short-term in nature and again only detected when the assistance has been separated into specific categories (McGuinness and Hart, 2004). The aim of this final element of the thesis is to add to the relatively small existing body of literature on the subject, and to provide updated evidence for NI. Given the degree of public subsidisation of firms in NI and the policy focus on raising productivity growth to close the gap with the UK, the region provides a strong basis for an in-depth analysis. A number of different techniques are proposed to undertake this stage of the analysis due to the difficulties involved in estimating the counterfactual, and the associated endogeneity and selectivity bias issues.

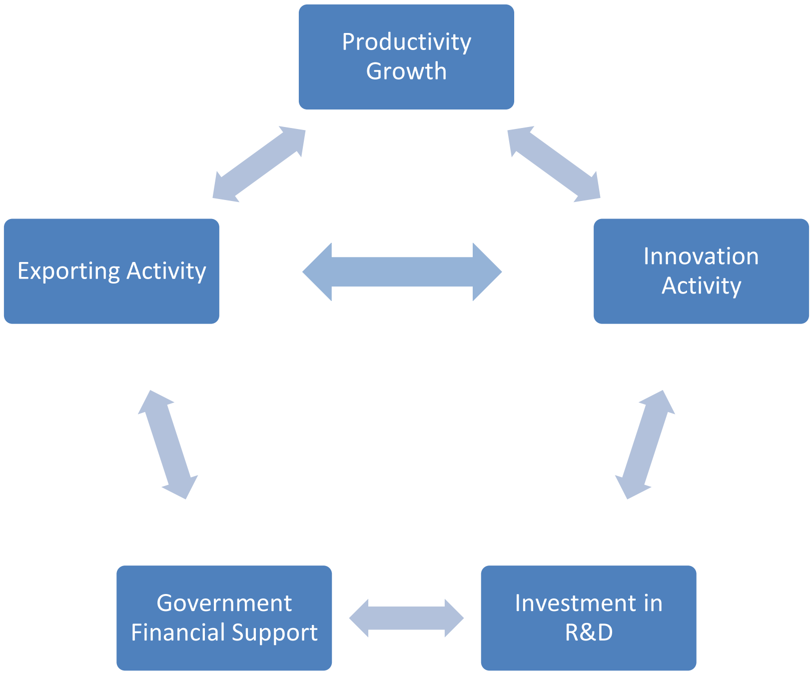
1.5 An Integrated Approach

The approach taken here to separately analyse the relationships between productivity growth and exporting; innovation; and public business support was due to the desire to gain a fuller understanding of the mechanisms through which each of these activities could be expected to fuel growth in firm-level productivity. Indeed the vast separate literatures on each and their theoretical underpinnings suggest different mechanisms through which this occurs. Despite this it is recognised that each of these activities are also related at the firm level, and may be undertaken either simultaneously or in a sequential fashion.

A more comprehensive approach therefore, which would take account of such inter-relatedness between these activities, would have been to consider an integrated method, whereby each of these activities are included within a single structural-type model. This type of analysis would then allow the estimation of the effect of each activity on the next, thus allowing both direct and indirect causal effects to be analysed. Indeed, consideration of firm-level productivity as endogenous within the export-productivity relationship, operating through innovation activity, would have represented a major contribution, as hypothesised in the theoretical literature (Yeaple, 2005; Bustos,2005).

A difficulty with this approach, and the main limitation with regards to its use here, is that there are *many* endogenous relationships within the system, as suggested in Figure 1.2. In order to model such a scenario a detailed panel level dataset would be required, which would need to encompass sufficient lags to allow for identification of the stages of the process, and to enable reverse causality effects to be considered. Unfortunately the data available for use here (as outlined in Chapter 5) did not have a full panel element thus making it impossible to correctly model each of these stages in a step-wise process.

Figure 1.2: Relationship between Firm-level Activities; Government Financial Support and Productivity Growth



Until recently the empirical literature has tended to also analyse these relationships in isolation, even when only considering innovation, exporting and productivity, as highlighted by Castellani and Zanfei (2007):

> "*Several studies have produced evidence on the relationship between firm heterogeneity and internationalisation modes. However, most of them have focused on firm diversity either in terms of productivity or in terms of innovation, but they do not examine them both*" (Castellani, D and Zanfei, A., 2007, pg. 161).

Indeed their study was novel in this respect showing that multinational firms were significantly more productive than exporters and non-internationalised firms even after controlling for innovation inputs and outputs. Siedschlag and Zhang (2015) adopt a similar approach, modelling the effects of firms' internationalisation activities, as measured by FDI and exporting, on their innovation and productivity levels. Their contribution is the use of an integrated model, similar to Crepon et al. (2008) and Griffith et al. (2006) but augmented by including internationalisation activities in each stage of the model, as well as considering various types and combinations of innovative activity. They confirm previous findings that foreign owned firms and domestic exporters have higher productivity than firms that serve only the domestic market; these firms are also more likely to invest in innovation. In addition they report that innovation output is positively associated with labour productivity even after controlling for other determinants. Cassiman and Golovko (2011) analyse these same relationships within a set of three models. The first exploring the relationship between exports, product innovation and productivity for the full sample of firms; the second using two subsamples based on the firm's previous innovation status: and the third decomposing the effect of product innovation into its direct and indirect effects on the decision to export. They find that R&D and product innovation positively affect the firm's export decision in two ways, firstly, and directly, through a demand expansion effect and secondly, indirectly through its impact on productivity, with firms with higher productivity self-selecting into export markets. Importantly, their use of this integrated approach also allows them to detect that the effect of productivity on exporting is no longer significant once the firm's previous innovation status is controlled for; this latter finding having implications for the learning-by-exporting hypothesis. Monreal-Perez et al. (2012) also examine the learning-by-exporting and self-selection hypotheses in the context of an integrated approach, controlling for endogeneity. They find that that innovation increases firms' export activities, but that exporting does not make it more likely that firms will develop product or process innovations. They also find no evidence of a moderating effect from productivity on these results.

These studies represent important advances in the empirical literature, in which the endogenous relationships between exporting, innovation and productivity are considered. The Cassiman and Golovko (2011) paper in particular, makes important discoveries with regards to the moderating effect of innovation on the productivity-export relationship which is a key omission that cannot be detected when the relationships are modelled within a singular rather than an integrated framework. In each case the authors use panel datasets and highlight their approaches to deal with the endogeneity issues. As explained above, and detailed in Chapter 5, the dataset constructed here was based on a combination of voluntary and compulsory surveys; and did not cover the same firms annually. As a result it was not possible to construct a panel element which would have allowed for a similar analysis. Indeed the estimation proposed here imposes a further complication in that it also includes the effect of public financial assistance on productivity growth. To date, to the author's knowledge, there has been no attempt to include such data on public support for business within these formal integrated models. In fact had it been possible to construct a panel dataset incorporating this data this would undoubtly have enhanced the contribution of the thesis both empirically and in terms of policy implications, and may present an opportunity for future work.

As a result, it could be argued that a less comprehensive approach has been taken in this thesis in which each of these relationships is estimated separately, thus omitting potential indirect effects. However, given that several of these relationships have never been formally examined within NI, it is felt that as an exploratory analysis using a newly constructed dataset and best-practice methodologies, the thesis still represents a valid contribution in understanding the drivers of productivity growth at the firm level.

1.6 Structure of the Thesis

The overarching aim of this research is to examine the ways in which exporting, innovation and government financial assistance impact on firm-level productivity growth. Prior to examining these relationships Chapter 2 discusses the measurement of productivity and its associated difficulties, and describes the definition as applied throughout this thesis. Chapter 3 details the policy background with respect to productivity, specifically how policies aimed at improving productivity evolved in NI in the post-war period.

Chapter 4 provides an overarching literature review, covering the three strands of the study separately. The first provides an overview of the exporting-productivity relationship, detailing the theoretical background; the nature of the self-selection and learning-by-exporting theories and then focussing on the empirical literature which evolved from the pioneering work of Bernard and Jensen (1995). The second strand deals with the literature surrounding the innovation-productivity relationship, discussing the development of endogenous growth theory; and then focussing on the empirical literature which has evolved largely since the introduction of the Community Innovation Survey (CIS) and which has the work of Crépon, Duguet and Mairesse (1998) as its basis. The final strand of the literature review is the grant assistance-productivity relationship. Here market failure theories are discussed as well as the arguments for intervention with regards to productivity growth. The empirical literature review covers relevant studies focused on the impact of public subsidies on productivity. Within each of the literature summaries is a discussion of the NI context, examining the empirical work undertaken to date; the findings and resulting conclusions. Each section of the literature review also concludes with a summary of the key findings and a discussion of the subsequent hypotheses which have been developed for analysis here.

A key element of this research is the construction of a unique linked dataset to undertake the empirical work. Chapter 5 details the underlying datasets from which the data is drawn and describes the mechanics of constructing the new ‘linked-up’ dataset. The necessity of compiling such a unique dataset is discussed along with the drawbacks and associated problems experienced in its construction.

Chapter 6 presents the methodologies and individual empirical models for each of the research questions and hypotheses. As with the literature review it is split into three sections; the first focuses on the relationship between exporting and productivity growth, initially examining the differences between exporters and non-exporters and testing specifically, using modern econometric techniques, for evidence of self-selection and for learning-by-exporting; the latter providing the rationale for increased productivity growth from exporting. It ends with a summary of the findings; a discussion of how it sits within the literature and the limitations.

Sub-section B tests how innovation impacts productivity growth; it sets out the modelling process which is based on the augmented-CDM model of four related equations; namely, the decision to spend on R&D; the decision about how much to spend; how R&D expenditure impacts innovation and how innovation impacts productivity growth. The results are discussed within the context of other findings for NI, and the wider empirical literature. Finally, in sub-section C the impact of public financial assistance on the productivity growth of NI firms is tested and its contribution, if any, separated from that of other firm level effects. This section discusses the various methodological approaches available to test the relationship, and the related complications and limitations associated with each. It ends with a summary and a discussion of the implications of the findings and how they fit within the literature.

The final chapter incorporates a summary of the main findings and discusses how the results relate to the underlying theoretical arguments and how they compare to the wider empirical literature. The wider impact the findings have for NI are also discussed, particularly with regards to the policy implications. Finally, the potential drawbacks and limitations of the empirical analysis are assessed, as well as a discussion of ongoing further research in the area.

2 MEASUREMENT OF PRODUCTIVITY

2.1 Introduction

The growth of firm level productivity is at the core of this study. At its broadest interpretation, productivity is meant to capture the efficiency by which inputs are turned into outputs (Hulten, 2001). Productivity is not directly observed and is thus a derived measure which can be calculated in a number of different ways, the choice of which usually depends on the purpose of the measurement and the unit of observation, for example the firm versus the economy.

At the firm level, there are a number of ways in which it can be measured, either through single factor productivity measures, such as labour productivity, in which a measure of output is related to a single measure of input; or through multi-factor productivity measures, such as total factor productivity, in which a measure of output is related to a group of inputs. Within each of these measures is also the choice of inputs and outputs; output typically measured through either a gross output measure, or through a measure of value added, the latter attempting to capture the movement of output (Schreyer, 2001). Inputs are generally measured as labour or capital, or in the case of multi-factor measurements, include intermediate inputs such as energy, materials and services.

Productivity is thus not a straightforward concept to capture and, according to the ONS "measuring productivity is one of the more difficult challenges in economic statistics" (ONS, 2007, pg. 2). Each of the productivity measures, even at the firm level, can have inherent difficulties, with the choice of productivity measure and the variables which are used for its estimation often driven by the availability of data. This chapter discusses the two main productivity measures at the firm level, labour productivity and total factor productivity, how they are calculated and the benefits and drawbacks of each. The chapter ends with a summary of the discussion, the choice of measure used for this study and the potential implications.

2.2 Labour Productivity

Labour productivity is a single, or partial, productivity measure, defined as the quantity of goods and services produced per unit of labour input (Barnett et al, 2014).

According to Schreyer (2001, pg. 48) labour productivity is useful as "it relates to the single most important factor of production, is intuitively appealing and relatively easy to measure". At its most basic, labour productivity can be measured through the gross output method using, for example, total revenue, divided by the labour input, measured as either the number of employees, or by the number of hours worked. This measure is perhaps the easiest to obtain from firm-level datasets, particularly as it can be estimated using just two variables, revenue and employment; however due to its very basic nature it runs into a number of problems.

On the input side, using a simple measure of labour input, such as the number of employees, fails to take account of the number of hours worked by different employees or the quality of that labour, which can result in an over or under-estimation. Counting all employees together in one 'total employment' figure is problematic in that there is likely to be considerable variation in how firms in different sectors use their part-time staff, for example there is likely to be a much higher share of such staff in the service sector (Mayes, 1996). This can be somewhat alleviated by weighting part-time employees into their full-time equivalents before summing together however again there are difficulties with how this is done, with part-time staff often counted as 'half' a full-time employee, despite the fact that their hours may be more or less than this, and again it may vary across firm or industry.

Using employee hours worked is a preferable means of capturing labour input, and remedies the full-time/part-time problem; however this measure itself has its drawbacks, namely that not all hours are homogeneous, firstly, marginal hours may be less productive than the average as workers begin to tire (Denison, 1989) or workers may become less productive in the hours prior to overtime rates starting (Leslie and Wise, 1980). Furthermore the use of hours worked doesn't account for human capital or skill levels. The various type of employees, in terms of their skills and tasks, are not homogeneous, either within or across firms, but are considered to be so when using the hour worked (or total employment) figure as the measure of labour input. In this case the hour worked of the most qualified staff member is treated as equal to that of the new start. Thus in order to properly account for labour input within a firm one would ideally have data not only on the number of hours worked, but the hours worked for each employee (or occupation) within the firm, however data on occupation or skill levels and hours worked by the various employees within a firm is not routinely collected in the same survey as data on output measures thus it is difficult to incorporate such elements into the firm labour productivity measure[11].

In terms of the output measure for labour productivity, total revenue (turnover) is frequently used as the data is most widely available (Gal, 2013). However the use of total revenue is problematic in that it fails to take account of intermediate inputs in the production process which can differ markedly across sectors in terms of quantity, quality and cost. It is a particular problem in sectors where re-selling is a key feature, such as in Wholesale and Retail; here overall revenue may be high but the purchase of intermediate products may account for a large proportion. An alternative measure, which remedies this, is value added, a net figure which captures the difference between output and intermediate inputs. At the firm level value added is defined as the difference between the firm's sales and its purchases of raw materials and external services. It has been argued by Kathuria et al. (2011) that value-added is the preferred measure in the literature, specifically as it accounts for the intermediate input issues.

Despite being preferable in terms of labour productivity, the use of value added per employee (or employee hour) remains a partial productivity measure, looking at the efficiency of labour only. As with other single productivity measures the deficiency lies in the fact that it can provide a distorted view of the factor's contribution if the proportion undergoes a change relative to other inputs. For example, capital deepening can lead to a rise in labour productivity and fall in capital productivity over time; the resulting change in labour productivity reflecting the substitution of one factor by another rather than any improvement in labour efficiency (Majumdar, 2004). Given that such partial measures do not account for other factors of production, particularly differences in capital intensity amongst firms, their use can be thought of as incomplete.

2.3 Total Factor Productivity

Total factor productivity (TFP) is perhaps a more complete measure of productivity, defined as the ratio of output (or value added) to a weighted sum of the inputs used

[11] The Annual Survey of Hours and Earnings (ASHE) in the UK collects information on occupations, sectors, hours worked and earnings. It is based on a sample of firms and thus would only be suitable for providing the labour input measure on a sectoral basis or for a representative firm rather than for each individual firm in the analysis.

in the production process (Kathuria et al., 2011). Given its inclusive nature it overcomes the problem of changing factor intensities in production however it is more difficult to estimate than labour productivity, requiring detailed firm level and price data.

Conventionally TFP is regarded as measuring the rate of technical change (Krugman, 1996), however, this has been the subject of some contention and in fact has been described “as much a measure of our ignorance as it is a measure of anything positive” (Lipsey and Carlaw, 2001, pg. 39), others have also questioned its usefulness (Metcalfe, 1987, Griliches, 1995). Despite these doubts TFP as a measure of firm level productivity is widespread in similar types of research (Bergstrom, 2000; Duguet, 2006; Goodhueys, 2007; Grilli and Murtinu, 2011; Colombo et al., 2011; Harris and Li, 2012) and is thus a valid measure to consider for this study.

TFP accounts for both intermediate inputs and capital intensity, and as with labour productivity, can be measured in a number of manners. Typically, it can be calculated in a deterministic manner using index numbers, such as the Solow-Residual or Superlative Index, based on the Törnqvist and Fisher indices. In these measures, which assume perfect competition and constant returns to scale, output is related to a weighted sum of inputs, with each firm benchmarked to a reference point, such as the median. Such measures are, however, thought be sensitive to measurement error (Gal, 2013).

Alternatively TFP can be estimated, using econometric techniques, through the use of a production function. Historically this was done using OLS, however it suffered from simultaneity and endogeneity bias. More modern techniques involve the use of semiparametric techniques, as introduced by Olley and Pakes (1996), and developed by Levinsohn and Petrin (2003); Ackerberg, Caves and Frazer (2005); and Wooldridge (2009). These techniques estimate a measure of TFP, proxied by the use of capital and investment.

The estimation of TFP in such a manner is data intensive and requires detailed information on the capital stock, depreciation, and price levels for individual firms. The problem arises in that such information is not always available, for example data on capital stocks is not routinely collected. Where capital stocks data is unavailable, data on investment can be used as a proxy, however capital is composed of different asset types of varying ages, the value of which, and the services they provide changing over time, eventually reaching a point at which they have no further value or productive use. It is virtually impossible to measure this accurately so estimates are typically made on measuring the rate at which new assets are acquired (i.e. gross investment); the price of those new assets, and making a range of assumptions about how the quantity and value of older assets changes over time (i.e. depreciation) (Oulton and Srinivasan, 2003). There are a number of crucial problems with such approximation methods, particularly the fact that investment at the firm level tends to be highly volatile. As Wagner (2010) argues high values are often reported in some years and very low values in others, leading to rather different values for the capital stock proxy variable depending on the year(s) used. A further concern is that the capital stock measure typically only captures investment in tangible assets due to the measurement, and conceptual difficulties, surrounding the valuation of intangible assets. Sargent and Rodriguez, (2000) also highlight the fact that capital goods are not used at full capacity during the whole business cycle and thus, much like the argument in the labour productivity measure for accurately reflecting number of persons employed, so the measure of the capital stock should also only include capital employed.

Aside from the problems with capital, another important issue which arises with this measure of TFP concerns the use of price indices. Outputs are known to typically vary within industries; the use of a single industry-level price deflator in industries in which outputs have a considerable variation in quality can result in output measures which are underestimated. In addition, measured productivity differences within the same industry may also reflect differences in market power which are embodied in prices (Syverson, 2011). A remedy to this would involve individual firm level prices, however these are typically unavailable and would be difficult to correctly construct.

2.4 Summary

Productivity is difficult to capture accurately at the firm level, not least because there are competing estimates; one, labour productivity, which is relatively straightforward to measure but suffers from only being a partial measure and the second, TFP, a more complete measure but one which is open to interpretation and has a heavy data requirement. In deciding which measure is most appropriate a balance has to be struck between the purpose of the productivity measure and what is available given data constraints. For empirical reasons it is also necessary to use a measure which can be compared to other similar studies in order to draw conclusions.

There has been academic debate about the most appropriate measure of productivity Syverson (2011, pg. 332) advocates that the choice “is a matter of asking oneself which assumptions one is comfortable making”, reiterating that making assumptions is an essential part of estimating a production function for a TFP measure. Sargent and Rodriguez (2001) make an important point when they suggest that labour productivity measures are preferable to TFP if there are any biases in the estimates of the capital stock. They suggest that this is particularly important when making cross-country comparisons, as methods to deal with depreciation and aggregation can vary, although it is noted that their conclusions relate more closely to aggregate productivity measures than to firm level estimates. They also suggest that that TFP is only preferable when examining issues over the long term, such as several decades, and that for the short to medium-term that labour productivity should be used (Sargent and Rodriguez, 2001, pg. 13).

The purpose of this research is to examine how specific factors impact on productivity growth at the firm level over a relatively short time period. The rationale for the study is to understand the factors underlying the prevailing productivity gap between NI and the UK which, as Fig 1.1 showed, can be seen in the measurement of gross value added per job filled. Thus if the idea is to understand the reasons behind this gap then it follows to use a similar, if not the same, measure of productivity. Using such a labour productivity measure can also perhaps be more easily understood in general terms in that it relates to specific variables that can be drawn from company accounts; one can quite easily imagine the concept of output per employee however it is more difficult to explain and calculate what TFP is in relation to data that a company has at its disposal. Indeed as Jorgenson and Griliches (1967) report, if we had access to all the required data to measure inputs then there would be no residual and hence no TFP measure.

Given the concern then with what TFP actually captures at the firm level, and the associated data and measurement difficulties, the preferred measure used in this study is labour productivity, measured as gross value added per employee. This closely follows the measure as reported in Fig 1.1 and captures the rate at which inputs are turned into outputs, thus it is easily interpreted, and arguably more intuitive. It also fits with the recommendation of using labour productivity for relatively short time periods.

As discussed previously using such a partial productivity measure does have its drawbacks, not least because the ‘total employees’ variable as the labour input fails to take into account differences in working hours of employees and their skill levels. Given that this research study is concerned with productivity growth then unless we expect hours of work or skill levels to radically change between or within sectors over a relatively short time period then we can be relatively confident that the results will not be unduly affected as the difference in skill levels and hours worked between sectors should remain relatively constant over the time period in question.

The issue of different use of capital across sectors and indeed across firms remains the major caveat with using such a partial productivity measure; a limited solution here is to control for sector in any analysis. Indeed due to issues with data availability at the micro-level use of this labour productivity definition is quite common across the empirical literature and similar measures been used to effect in other studies examining firm productivity growth (Kraay, 1999; Fryges and Wagner, 2007; Castellacci, 2009; Crespi and Zuniga, 2012; Mairesse et al., 2012). As the results of these studies will be used for comparison purposes the use of the labour productivity measure is justified within the analysis here.

3 PRODUCTIVITY AND INDUSTRIAL AND REGIONAL POLICY

3.1 Introduction

The study of productivity growth and the firm-level factors that impact on it are at the heart of this thesis; the interest arising from the continued focus on productivity improvements by successive NI Governments and particularly the desire to reduce the longstanding productivity gap with the rest of the UK, as outlined in Chapter 1. The aim of this chapter is therefore to provide a more detailed discussion of the policy context, showing in particular how productivity became the central aim of policy, and how this incorporated both export and innovation goals. Furthermore the chapter seeks to highlight the lack of evidenced-based policymaking that underlies most of the industrial strategies in NI; factors that together provide the main rationale for undertaking the analyses in this thesis.

Prior to the 1970s, post-war industrial policy in the UK can be considered to have been mainly concerned with the restructuring of the economy. The extensive state intervention during the period sought to correct the principal economic deficiency of the interwar years, that of high unemployment (Woodward, 1995) and in fact, the policy emphasis on improving productivity really only came into effect in the late 1960s and 70s, when Britain's GDP per capita had fallen behind that of its European counterparts (Nickell & Van Reenen, 2002).

Post-war industrial policy in NI generally mirrored that of the UK and was also largely focussed on employment creation throughout the period. However unlike the UK, concerns about productivity really only emerged in the 1990s as NI's own enduring productivity gap with the rest of the UK was acknowledged as an issue (DED, 1990). Subsequent policy to eradicate this productivity problem was generally centred around similar themes to the 'five drivers of productivity', as identified by the UK Government in response to its productivity gap (HM Treasury, 2000) and following the UK lead, the role of Government in NI progressed from being strongly interventionist to a more focussed role in helping industry overcome market failure. In tandem, the nature of assistance to firms also evolved from direct forms of support for capital investment to a more targeted approach at the underlying obstacles to firm growth.

In NI the policies to improve productivity were operated through a series of successive strategies, with often recurring aims (NIEC, 1999a) and although each were aimed at making firms more competitive in order to help close the productivity gap with the rest of the UK it appears that in reality they were more aspirational in nature than analytical (IREP 2009) and undertaken with little empirical grounding, or ex-post evaluation. In fact where evaluation was undertaken, particularly with regards to financial assistance programmes, the impact was seen more so through employment gains than any productivity improvements (MacFlynn, 2015).

The following discussion summarises the development of policy with regards to productivity in NI. It details the repetitive ambitions of each of the strategies since the early 1990s and the associated criticisms with regards to the lack of detail on the underlying economic model; the accompanying policy goals and whether these goals had been met. The lack of such evidence coupled with the short-term nature of each strategy perhaps explains why NI has failed to close the productivity gap with the UK and further reinforces the need for empirical studies, grounded in theory, to provide the evidence for robust policy-making decisions.

3.2 NI Industrial Policy

Throughout history the overarching aim of industrial policy in NI has been the targeting of the perceived inherent weaknesses of the economy. In fact until the 1990s the policies that emerged could be broadly classified into three areas, namely improving industrial structure and performance, the physical infrastructure and the functioning of the labour market (NIEC, 1991).

Traditionally, the main economic policy to respond to such issues was the promotion of new employment to compensate for the loss of jobs in older, declining industries, and hence reduce unemployment (NIEC, 1983). This was achieved largely by promoting NI as a location for foreign inward investment using a range of financial incentives; and secondly by encouraging the expansion of existing industry. The former of these, inward investment, was devised as a means of diversifying the industrial base in NI while financial assistance was also offered to indigenous existing firms for the purposes of advanced factory building (Harris and Trainor, 2005a). One of the earliest NI industrial policy documents the Wilson report (Wilson, 1965) further integrated physical and industrial policy and introduced a third approach, namely support for small firms with regards to employment creation and start-ups.

Despite this three-strand approach, increasing violence coupled with the oil price shocks in the mid-1970s rendered existing policies inadequate to counter the recession in NI and led to the preparation of the 'Quigley Report' (Quigley, 1976). In response to the political risks and the high levels of unemployment in the region (Brownlow, 2014) this report encouraged further government intervention in the economy and a strengthening of the assistance available to local industry by advocating 'a heavily subsidised Northern Ireland economy, with the State playing a much greater role, both direct and supportive' (Quigley, 1976, p.17) and whilst the report itself was never formally adopted as a strategy a number of its recommendations with regards to government intervention were subsequently implemented.

During the 1980s the effectiveness of economic development policy in NI was again called into question as it was felt that the region was not recovering from the effects of the recession in line with the rest of Great Britain. As a result the Department of Economic Development (DED) set up a number of working groups to examine the deficiencies of the NI economy. This process known as 'Pathfinder' identified six key causes of deficiency in the economy namely, the lack of an enterprising tradition; deficiencies in training and managerial skills; the peripherality of the economy; the combination of a small manufacturing sector producing non-tradeable goods coupled with a large public sector; an over-dependence on public funds in the private sector and the unstable political situation (DED, 1987). The purpose of this process was to stimulate wider discussion, rather than being a formal policy proposal, and formed a key element of the subsequent strategy 'Competing in the 1990s – the Key to Growth' (DED, 1990).

The 'Competing in the 1990s' document marked a radical departure from previous economic strategy in NI in that its aim was no longer simply that of employment creation but rather of achieving growth through making NI more competitive. It was developed in line with the overhaul of regional policy in the UK in 1988 whereby the goal had switched from one which sought to reduce mainly employment disparities amongst the regions, to one which would help disadvantaged regions increase their competitiveness and productivity, not least in the face of the increased competition that was anticipated with the opening up of the Single European Market in 1992 (Griffiths and Wall, 2007, pg. 198).

In NI's case the fundamental change wasn't restricted to simply the overall direction of policy but also in the way it would be administered, in that it sought to ensure that government assistance to indigenous industry would act only to counteract situations of market failure (DED, 1990, pg.15), as opposed to the previous pragmatic approach of industrial development whereby government had a strong interventionist role as a provider of advice, resources and leadership. The Strategy document acknowledged that existing policies in the promotion of enterprise contained both displacement and deadweight effects, in that many of the firms would have started trading anyway without government assistance (pg. 42). Thus the new focus of policy was higher levels of growth for the Northern Ireland economy which would be achieved through measures to improve the competitiveness of the economy and which would be facilitated through the private manufacturing and tradeable services sectors. The new strategy emphasised that policy would seek to reduce the overdependence of firms on public assistance and instead it would be targeted on helping them overcome the obstacles to growth which could not be addressed through the normal operation of the market.

The new strategy also paved the way for a different type of assistance than had gone before; previously industrial development assistance had been geared towards investment in plant and machinery whereas this new strategy stressed that softer forms of assistance would be favoured and would be conditional on evidence that companies were actively taking the required steps to improve competitiveness (pg. 17). The creation of employment was no longer to be the key concern for firms however it was hoped that these softer forms of assistance, such as grants for management and workforce skills, R&D and other such activities, which companies would find difficult to develop on their own, would permit efficiency gains from which employment would arise.

This new strategy, and its associated forms of assistance, was directed specifically at indigenous industry as support for inward investment firms was to remain as it had been i.e. pursuing projects with employment growth prospects using a range of financial inducements. This differing policy for the two sets of firms was based on the idea that inward investment was good for the economy not only because of the employment opportunities it offered but also due to the associated technology and knowledge it brings and the opportunities for knowledge transfer to indigenous firms. Government assistance for these firms, in the form of financial inducements, was thought necessary to offset NI's position as a risky location due to its unstable political environment (pg. 20).

The 'Competing in the 1990s' document was the starting point for the subsequent 'Growing Competitively' strategy (DED, 1995) and then 'Strategy 2010' (DED, 1999) and was the first to mention NI's productivity problem. Quoting a NIERC report (Hitchens and Birnie, 1989) it stated that average output per head in NI manufacturing was around 80 per cent of that in GB (pg. 43) and although the Strategy generally sought to improve competitiveness it did not specifically mention any targets to reduce this gap.

The two subsequent strategies again focussed on the competitiveness of NI industry and reinforced many of the 'Competing in the 1990s' aims, for example some of the main elements of 'Growing Competitively' were the improvement of the competitiveness of indigenous companies and a shift in emphasis from capital grants to assistance in overcoming obstacles to growth (DED, 1995). Strategy 2010 further emphasised the need for the economy to be "fast growing, competitive, innovative and knowledge-based", and amongst its aims were a reduction in the total industrial grants to the same firms, and a re-balancing of grants away from capital and towards R&D, marketing, management and training development (DED, 1999). In a step up from 'Competing in the 1990s' the Strategy again cited NI's productivity gap with the rest of the UK but this time had a central goal of reducing the gap to 90 per cent of the UK's level by 2010.

Whilst the aim of reducing the productivity gap with the UK appeared a worthy goal, and on the face of it, a relatively long-term one, there were several criticisms of the Strategy itself, and in particular, the aim of raising NI's GDP per head towards UK levels:

> *"..the strategy document has no clear economic model, indicates no baseline projections as to what would happen in the absence of implementation of the strategy and, in most cases, fails to demonstrate connections between the strategy's recommendations and it goals" (NIEC, 1999b, pg)*

Furthermore, there appeared to be little post-Strategy evaluation into whether goals were met and if not, the reasons why. This was not a unique occurrence, indeed the same was said for ‘Competing in the 1990s’. Commenting on that particular Strategy the NIEC (1999b) reflected on the fact that no working group was ever charged with reviewing and evaluating the Strategy (pg.1) and suggested that such an exercise would have presented an analysis as to whether the underlying economic model was appropriate; whether the strategy had been implemented and whether the goals had been met. The lack of such evaluation in both cases is particularly alarming but perhaps not surprising given that the targets from previous strategies had all failed to be met (Kingon, 1999). Nevertheless, the fact that the same criticism was levelled at two strategies that were almost a decade apart in timing showed a general lack of in-depth analysis with regards to economic growth in the region.

Strategy 2010 was followed by two subsequent policy documents in short succession, both of which again had similar aims. The “Economic Vision” (DETI, 2005a) set out the details of the type of economy that was sought for NI by 2015. The “Draft Regional Economic Strategy” (DETI, 2007) then set out the framework for delivery of this goal and highlighted the fact that growth in the NI economy would be improved by increasing the employment rate and improving productivity. In a slight departure from national Government policy, four drivers were identified in order to achieve this, namely infrastructure, enterprise, skills and innovation[12]. Government intervention in the economy would, again, only be undertaken where there was demonstrable market failure, and one of the key interventions would be to refocus business support on exports, R&D and innovation.

In conjunction with the “Economic Vision” the NI Executive published its 2008 Programme for Government which included the economy as its top priority, and in particular had one overarching aim, which was a direct follow through from the Strategy 2010 objective:

> *“raising private sector productivity in order to close the gap between Northern Ireland and the rest of the UK (excluding the South East) by 2015” (NI Executive, 2008, pg.10).*

[12] Competition was not included as one of the drivers, as was the case in the UK national policy, as it was regarded to be a product of the other four drivers named here (DETI, 2007, pg. 14).

As a means of achieving this goal the DETI minister decided to review the existing economic policies and programmes which were being administered through the Department and its delivery body, Invest NI, as it was felt that although previous policies to generate jobs had been successful the same could not be said for those which had sought to improve productivity performance.

Indeed, despite the continual moves since the 1990s towards producing a higher productivity economy this review again emphasised how successive strategies had failed to demonstrate how their delivery frameworks would achieve this goal, or point to any existing evidence or relevant empirical studies on which they modelled their argument, a critical omission as pointed out by the subsequent policy review panel:

> *"Having reviewed NI's existing economic policies, the Panel believe that a future strategy should include a much stronger analysis of the issues being addressed and the proposed impact of measures being proposed. This would ensure that policies and strategies are more analytical and less aspirational in nature*", (IREP, 2009, pg. 53).

> *"Indeed, following its assessment of relevant documents such as Strategy 2010, Economic Vision, the draft Regional Economic Strategy and the more recently produced Programme for Government, the Review Panel consider that insufficient attention has been given to the most basic and fundamental question – what drives economic growth in NI?" (IREP, 2009, pg. 104)*

By failing to address the basic question of what actually drives economic growth in Northern Ireland the Review suggested that NI had instead relied too heavily on the Treasury's frameworks for UK growth. The report suggested a realignment of policy; it highlighted that firms are the agents through which growth occurs and as such economic development policy should be built around the needs of business. It further stated that the UK Government's five drivers were a necessary but insufficient framework for growth in NI that they failed to prioritise exports and inward investment. Furthermore it stated that the promotion of innovation and R&D were the most important long-term drivers of productivity. To this end it was suggested that SFA should be redirected towards providing greater levels of support for innovation and R&D; that grants for business expansion should be phased out and those for company training be reduced in favour of support for small firms and projects with a high innovative content; and that export assistance should be more dedicated and professional.

3.3 Export and Innovation Policy

Export assistance had historically been available to firms in NI, operating through Invest NI and its predecessors IDB and LEDU, however it had been acknowledged by government that whilst export assistance was comprehensive[13], export performance was a key weakness of the economy (DED, 1987). Rather than setting up a new policy for exporting, each of the Strategies, with the aim of promoting higher levels of growth, all concluded that the continued promotion of exports, particularly from indigenous firms, would be a key element in its success (DED, 1990; DED, 1995; DETI, 2005a, 2007). Notably, none of these documents spelt out explicitly the process by which exports would lead to growth, rather it was suggested that it would be beneficial to companies if they were more outward-oriented and that they should "adopt the export route as a means of developing and growing their business" (DETI, 2007). In fact the Review of Economic Policy contained a greater discussion of both export base theory and the mechanisms through which exports can create growth in the economy than any of the predecessor strategy documents (IREP, 2009, pg. 108-109).

The latter document suggested that a strong export base would help finance imports and would also help "provide a link to fast growing economies through access to rapid demand growth and also potentially through inward investment and the attraction of skilled migrants" (IREP, 2009, pg. 108). The report alluded to the fact that export sectors are important for productivity and growth and indicated that the role of the export base would be to help with knowledge spillovers and in expanding the capacity to undertake R&D and innovation through the anticipated high value-added inward investment and skilled workers that would be attracted to the region.

As with the growing importance of exports in achieving productivity growth so innovation had also been recognized throughout the various Strategies, and became a specific focus of industrial policy in the early 1990s, with the formation of the Industrial Research Technology Unit (IRTU). This institution was set up on the back

[13] Acting under the remit of the DED, the IDB and LEDU were responsible for delivering the export promotion policies. Their central strategies were focussed on helping firms with their marketing, design and quality practices to enhance export potential, as well as organising trade missions and providing improved market intelligence. Invest NI took over the responsibilities of both IDB and LEDU in 2002; the promotion of exports remained a particular focus, with Invest NI citing "being international" as one of three economic drivers for its client companies (Invest NI, 2005).

of concerns about low levels of R&D and innovation in the region, and sought to bring together responsibility for all the programmes concerning R&D and innovation under one roof for the first time (Roper and Love, 2004). The initial policy document (IRTU, 1992), set out how the institution would help increase firms' technological capability, R&D and innovation, using a combination of its own resources, EU Structural Funds and DED schemes by providing similar types of innovation support as in the UK.

Following this initial document, several Innovation Strategies, dating back to the start of the decade, were launched, each of which aimed ultimately to create an R&D and innovation infrastructure; enhance the use of R&D and innovation by the business sector and, develop a culture of innovation and enterprise (DETI, 2003, 2005b, 2008). The third action plan, was developed "in recognition of the contribution that innovation can make to Northern Ireland's productivity growth" (DETI, 2008, pg.12); and as such set out four "imperatives" and a number of associated objectives which sought to, amongst other things, increase innovation and R&D.

Again as with the export policies and economic policy in general, there was a lot of repetition in each of the successive Innovation Strategies. References to any particular theories or relevant studies linking innovation to productivity growth were of an indirect nature, typically citing UK Government White Papers or reports. Indeed, it was often taken for granted that there was a direct link between innovation activity and productivity growth:

> *"The Action Plan has been developed in recognition of the contribution that innovation can make to Northern Ireland's productivity growth. Therefore its overall success will be measured in terms of its contribution to the Programme for Government goal of halving the private sector productivity gap with the UK average (excluding the Greater South East of England" (DETI, 2008, pg. 12).*

Again, it took the Review of Economic Policy (IREP, 2009) to set out the arguments with regards to the importance of innovation and R&D including its perceived direct impact on productivity and its role in technology transfer and raising the absorptive capacities of firms. Whilst the importance of R&D had been recognised in previous strategies from "Competing in the 1990s" onwards, the Review set out how this could be achieved and emphasised the need to look upon innovation as a commercial process, encouraging the development of products and processes new to the region rather than new to the industry. This, it was felt, would play a central role in promoting productivity growth amongst firms in the region and again reinforced the notion that policy should be tailored specifically to the NI economy, rather than simply adopting the national strategy:

> *"Furthermore, a more commercially orientated view would help switch the emphasis from Innovation and newness per se toward the introduction of products and processes new to the region. Hence the encouragement of imitations, adaptations, improvements and adoptions of products and processes into the region would appear to be much more relevant to the promotion of productivity growth in NI than the pursuit of newness per se." (IREP, 2009, pg. 110).*

3.4 Summary and Discussion

Industrial policy in the UK has been focussed on improving productivity as far back as the 1960s the rationale being the country's poor performance relative to competitor countries such as the USA, France and Germany. A similar problem was identified in NI; that of a productivity gap with the rest of the UK. This gap, in the order of around 80 per cent of the UK level, was officially recognised in policy documents in the early 1990s, although its reduction not set specifically as a policy target until the end of the decade.

This shift in priorities away from employment creation towards productivity growth was due largely to a change in national UK policy where, in the late 1980s, competitiveness and improved productivity levels became the goal of regional policy in place of the traditional concerns about employment disparities. Due to this policy re-orientation assistance for softer forms of support such as grants for R&D, training and management were favoured over those for capital projects, whilst assistance was to be given only in cases of market failure. This marked a radical change in NI, as previous policy documents had actually suggested heavier government intervention to industry to alleviate NI's high unemployment levels (Quigley, 1976).

As the economy developed the eradication of the prevailing productivity gap with the rest of the UK became an increasing priority, with a renewed focus on increasing export behaviour and innovative activity amongst firms as a means of achieving this aim. However, despite the radical changes in policy there was a noticeable lack of detail in each of the policy documents about the means in which competitiveness would be achieved and the productivity gap reduced. Criticisms were levelled at the successive strategies for failing to evaluate whether they were built on appropriate economic models and in particular whether the goals set were achieved. Indeed it was felt that the strategies were typically aspirational in nature rather than truly analytical. The fact that most of the economic strategies since the early 1990s contained the same sorts of aims, without any theoretical underpinning or empirical evidence as to whether they were being met, further reinforced this notion.

Importantly, and in recognition of these limitations and the enduring productivity gap, a policy review document declared that for too long industrial policy in NI had simply followed suit with the UK with no recognition of whether this was the right course of action for improving NI's economy (IREP, 2009). The subsequent strategy document focusing on firms as the drivers of productivity growth coupled with the theoretical arguments as to how firms' activities would help strengthen productivity performance showed, for the first time, an understanding that policy should be formulated on a more robust basis, taking note of deficiencies in the underlying structure of the economy and using existing theoretical and empirical evidence as a means of deriving appropriate policies.

The shift in NI towards this type of evidence-based policy making represented a step in the right direction, and was further enhanced by the recommendation of the need to regard economic policy as a long-term plan (IREP, 2009, pg. 122). However at the national level wider events in the economy during 2008 led to a re-focusing of policy away from productivity towards general economic growth whilst in NI the goal of reducing the productivity gap with GB by 2015 fell by the wayside in the 2011-15 Programme for Government as it was felt the target wouldn't be met[14]. Given that this had been central to economic policy for around a decade its sudden withdrawal meant that once again there was no immediate demand for follow-up evaluation[15]; once again perpetuating the previous problem with regards to how strategies are linked to goals and gaining an understanding of why they do, or do not, work.

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[14] The target to close the gap is a notable omission from the 2011-15 Programme for Government however there is little documentation providing the rationale or reason for its omission. Evidence from the Public Accounts Committee provides partial details: "The Committee was surprised that a key 2008-11 Programme for Government target to halve the productivity gap between Northern Ireland and the rest of the UK by 2015 was discontinued in the current Programme (2011-2015), seemingly because it was not on course for achievement. This is a measure which helps provide strong evidence that the work of Invest NI is having a meaningful impact on improving the local economy". http://www.niassembly.gov.uk/assembly-business/committees/public-accounts/reports/report-on-invest-ni-a-performance-review/

[15] There was an evaluation of Selective Financial Assistance in NI over the 2004/05 – 2010/11 period carried out by SQW, in conjunction with Aston Business School and Ipsos Mori, however the purpose of the evaluation was primarily to inform the discussion with BIS and the European Commission about NI's Assisted Area status (SQW, 2013, pg. 2) rather than to solely provide an evaluation of economic policy.

As the economy recovers it is likely that productivity growth will at some point become the focus of policy once again. Within NI it is imperative that up-to-date research is undertaken in order to provide, at a minimum, evidence as to whether the strategic activities that firms undertake, such as exporting and innovation, do indeed have a productivity impact, or whether the focus of intervention for productivity improvements should be elsewhere. Without that, one has to rely solely on evidence from other economies which will not necessarily have the same underlying industrial structure or macro-economic context as NI. Indeed given that one of the main criticisms of policy was that it had blindly followed the UK national approach rather than being tailored specifically to NI then it would seem imperative that any evidence on the effectiveness of policy should also be undertaken at the NI level.

Given the vast amount of firm level data that is collected in NI, this is something that could easily be remedied were better access to the data allowed. Indeed this thesis proposes a potential approach that could be undertaken, merging existing datasets to provide a fuller picture of micro-level activity and using this to assess the effectiveness of policies. The analyses carried out in Chapter 6 seeks to do this exactly, providing NI-specific evidence on exporting and innovation, activities that have been identified as productivity enhancing but for which there is little existing evidence . Likewise, the analysis of the impact of public financial assistance seeks to look solely at its effects on productivity growth; this type of policy evaluation providing the necessary empirical evidence that is currently lacking in NI policy documents.

4 ASSESSMENT OF THE THEORETICAL AND EMPIRICAL LITERATURE

The aim of this chapter is to provide an overarching literature review covering the three separate strands of the analysis; as such the chapter is divided into three sub-sections. The first assesses the theoretical and empirical literature regarding exporting and productivity growth at the micro level. Sub-section B discusses the literature regarding the innovation activities of firms and its link to productivity. Thirdly, sub-section C presents the theoretical arguments for government intervention in the market and assesses the empirical literature with regards to the relationship between public financial assistance to firms and productivity growth.

Sub-Section A: Exporting and Productivity Growth

4.1 Introduction

The links between exporting and economic growth can be traced back to the work of Adam Smith in the 1700s and the concept of specialisation for economic growth. Such classical theories were quite basic, with simplistic assumptions, however as the nature of world trade has evolved so trade theory has been re-visited and modified to take account of empirical findings such as technological progress, intra-industry trade and increasing returns to scale. As a result, the theoretical link between trade and growth at the macro level has become relatively well established but, until relatively recently, said little about the role of the firm in the process. It was only as recently as the 1990s that the notion of the firm, as a conduit of exporting, became the focus of international trade research. In fact, empirical work in the field indicated that exporting firms differ substantially from firms that solely serve the domestic market, with productivity differences playing a key role. Such findings of the microeconomic studies were not well explained by existing theories of international trade particularly with their assumption of a representative firm within industries. As a result, new hypotheses have been put forward in the last decade which address these empirical challenges, by introducing the notion of the heterogeneous firm.

The remainder of this chapter discusses the development of international trade theory in brief and then focuses on the more recent theoretical and empirical literature regarding exporting and productivity at the firm level. The aim of the chapter is to set out the key theoretical arguments in terms of the relationship between exports and firm-level productivity growth and the evidence in support, or otherwise, of these theories. The rationale for this approach is to develop some central hypotheses for testing in a NI context, using the available literature to identify key gaps in the current knowledge, and in a more general context, to add to the body of existing empirical literature in areas where there is a lack of consensus or where the evidence diverges.

4.2 Development of Trade Theory

International trade theory is a distinct branch of general economic theory which connects trade with economic growth. The field of study originated in the work of Smith (1776) who suggested that free trade could be beneficial to countries, basing this on the concept of absolute advantages in production. His model was based on a scenario whereby there are two countries, two products and one factor of production, namely labour. The theory suggested that countries differ in their ability to produce goods efficiently thus a country should specialise in producing and exporting goods in areas where it has an absolute advantage and import goods in areas where other countries have an advantage. This notion was further extended by Ricardo (1817) in his theory of comparative advantage which suggested that trade between two countries would be possible and profitable as long as comparative cost differences exist, even if a country has no absolute advantage in the production of at least one commodity. Ohlin (1933) developed this further, proposing a new model, which was not solely restricted to a single factor of production, but was based on the general theory of value. The Heckscher-Ohlin model, or factor endowment theory of trade, accepted the notion of comparative advantage however it improved on the Ricardian model by focusing on two factors of production, namely labour and capital, and identified the difference in these factor endowments as the cause of trade.

Whilst these classical theories pinpointed the gains from trade, they were criticised on the basis that they were static theories where resources and technology are held constant and production functions are assumed to be the homogeneous across countries. They failed to take into account dynamic factors whereby the stock of productive factors in a country can increase over time and technological innovation can occur, making the existing stock of factors more efficient. They also ignored the fact that the economies of countries change and develop over time. This latter point was a particular concern during the 1960s whereby there was significant technological progress and the rise of the multinational enterprise. Such new features resulted in a call for new theories of international trade to reflect changing commercial realities (Leontief, 1966).

To respond to the above concerns a body of trade theory emerged during the 1950s and 1960s which accounted for these dynamic elements, although based on the classical framework (Hicks, 1953; Myint, 1958; Haberler, 1959; Posner 1961; Caves, 1965; Vernon, 1966). These theories included those which introduced the concept of technological progress as the basis for comparative advantage, dubbed the neo-technology hypothesis, or technological-gap model (Hicks, 1953, Posner, 1961) and also those based on product life cycle (Vernon, 1966,1971; Wells, 1968, 1969).

Haberler's (1959) model was developed based on the static theory of comparative advantage which describes the indirect dynamic benefits of the gains from trade. He proposed that trading in the world market brought indirect benefits such as the provision of capital goods and raw materials indispensable for economic growth. In addition he proposed that trade acts as a vehicle, both for the dissemination of technological knowledge, the transmission of ideas, skills, managerial talents and entrepreneurship, as well as the international movement of capital. Trade also acts as an anti-monopoly policy, helping maintain a degree of competition. Haberler's conclusion was that gains can be made from international trade directly by the division of labour and specialisation, and indirectly, by the above mechanisms, leading to the development of the productive capabilities of countries.

Myint (1958) developed his model on a 'productivity' theory of international trade. He based his theory on two ideas, both attributable to Adam Smith; international trade overcomes the narrowness of the home market and provides an outlet for the surplus product above domestic requirements (known as the vent-for-surplus theory); and by widening the extent of the market, trade improves the division of labour and raises the general level of productivity within the country (known as the productivity theory). This second idea purported that international trade was a dynamic force which, by widening the size of the market, encouraged technical innovation, raised the skill of the workers, and allowed the country to enjoy increasing returns to scale. Myint's vent-for-surplus theory stated that if a country possesses a surplus productive capacity then engaging in trade provides an effective demand for the output of the surplus resources, which otherwise would have remained unused. In this way export production is increased without necessarily reducing domestic production. Caves (1965) expanded on the vent-for-surplus theory. He proposed the idea that under autarky, it is possible that certain factors in a country would be under-utilised or perhaps not used at all due to the smallness of the domestic market. The country would therefore be at a point inside its production possibility frontier. Opening the economy up to trade would encourage more intensive use of the resource and of factors of production. Hence trade would act as a vent for the surplus product.

Vernon's (1966) theory of the product cycle can be regarded as an extension of the Heckscher-Ohlin model whereby trade is based on changes in relative factor abundance (technology) over time. This theory puts less emphasis on the factor-proportion theory of comparative advantage and more emphasis on the product, the timing of innovation and the dynamic changes of technology in influencing trade patterns. The product cycle of Vernon is a long-run theory that emphasises changes in the trade position of a nation over a number of years. The theory is an extension of the technological gap model, as proposed by Posner (1961) and earlier by Hicks (1953), which suggested that trade amongst industrialised countries is based on the introduction of new products and new production processes, giving innovating nations a temporary monopoly in the world market. This monopoly is eroded as foreign producers acquire the new technology and begin to export the product themselves, by which stage the original innovating nation has introduced newer products, thus establishing a continuous technological gap.

Vernon extends on Posner's theory by suggesting that the product and the methods for manufacture go through three stages of development with comparative advantage, and hence location, shifting from one nation to another as the product matures. Product innovation and initial use occurs in high income, highly skilled countries first and then spreads to middle and lower income countries as technology and skills are diffused and the product becomes standardised and hence can be mass produced by less skilled labour. The process is therefore that of an advanced country developing and exporting a particular good, losing the export market share to other countries who imitate the innovation, and then ending up as a net importer of the product. Central to the theory is the assumption that diffusion of new technology occurs slowly enough to generate temporary differences between countries in available production technology.

4.3 New Trade Theory

A radical departure in the 'traditional' way of thinking about international trade came in the form of New Trade Theory, developed by Krugman (1979), and later expanded on by Lancaster (1980), Helpman (1981) and Ethier (1982). The development of the theory was motivated by the failure of more traditional theories to explain some of the most significant facts about post-war trade, specifically that the ratio of trade to GDP had increased; that trade had become more concentrated among industrialized countries; and that trade among industrialized countries was largely intra-industry trade. The theory, which had its roots in Heckscher-Ohlin, thus proposed a link between trade and industrial organisation, based on the central idea of increasing returns to scale and imperfect competition. It suggested that these provide the reasoning for specialisation and trade even when regions are similar in factor endowments.

The underlying theory suggests that nations with similar factor endowments i.e. little or no comparative advantage differences may still find it beneficial to trade because they can take advantage of massive economies of scale. A country can develop an industry that has increasing returns to scale, produce that good in great quantity at low average unit costs, and then trade those low-cost goods to other nations. By doing the same for other increasing-returns goods, all trading partners can take advantage of large economies of scale through specialization and exchange.

The theory of increasing returns to scale and their subsequent effects was categorised into three approaches in the literature (Krugman, 1987). The *Marshallian approach* proposes that increasing returns to scale are external to the firm and arise in the form of price externalities associated with the desire of firms to locate near large markets and the desire of workers to live near areas in which production is concentrated due to lower prices and relatively higher wages. The *Chamberlinian approach* incorporates the notion of product differentiation and product variety into the analysis; the interaction between demand for product variety and economies of scale leading to intra-industry trade (Helpman, 1981). The *Cournot approach*, focuses on imperfect competition and emphasises the market failure arguments for protection. Previously Heckscher-Ohlin theory advocated free trade as it encouraged specialisation in the production of goods that could be produced most efficiently, thus improving welfare. These new models however, as they are based on increasing returns, suggest cost advantages with the introduction of protective tariffs. Tariffs or subsidies that protect the home market can help increase the volume of local production, providing home firms with long-term cost advantages over foreign competitors.

In a further development, combining elements of both old and new trade theory Helpman and Krugman (1985) devised an ‘integrated’ model whereby horizontal product differentiation and increasing returns to scale are combined and operate within the factor-endowment comparative advantage framework. This model was found to be quite representative of actual patterns of international trade, particularly when modified to allow for differences in technology, factor prices and trade costs.

Endogenous growth theory was one of the more recent economic growth theories to emerge, a strand of which deals with the international trade aspect. Romer (1986) and Lucas (1988) were amongst the key proponents of the theory which explains long-term economic growth endogenously, by relaxing the assumption of diminishing returns to capital and by assuming technological progress as endogenous to the model. Technological progress is viewed as a product of economic activity whereas previous theories treated technology as a given, or a product of non-market forces. The key notion is then that unlike physical objects, knowledge and technology are characterized by increasing returns, and these increasing returns drive the process of growth, allowing it to continue indefinitely.

Endogenous growth theory was developed as a response to the empirical shortcomings of the neoclassical model as developed by Solow (1956), which emphasised the role of capital accumulation in the growth process. In his model the accumulation of physical capital is seen as the key factor underlying growth in a perfectly competitive economy with constant returns to scale, and an exogenous savings rate assumed to be a constant fraction of total national income. In the model a sustained increase in capital investment increases the growth rate only temporarily due to diminishing or constant returns to scale. A steady-state growth path is reached when output, capital and labour are all growing at the same rate; a key prediction is that growth rates of countries will converge over time. Technological progress enters neoclassical growth theory as an exogenous factor that grows at a constant rate and is essential to economic growth in the long run. The advancement of technology enhances the productivity of labour so that the marginal product of capital does not decline as the capital-labour ratio increases. In the long run, as there is no upper limit to the growth of technology and thus to the growth in labour productivity, the growth rate of real income per capita does not decrease to zero. Economic growth is therefore sustainable; the long-run growth rate is equal to the assumed constant growth rate of technological progress.

The new endogenous growth theories resemble Solow's model but suggest that technological change lies at the heart of economic growth and that technological change arises largely because of the intentional actions of profit-maximising people or firms responding to market incentives, thus explaining its endogenous nature (Romer, 1986). In these innovation-based models new ideas are generated by investment in R&D; these ideas lead to new products and processes that are used as inputs in the production of final goods. This R&D based innovation raises productivity, as the input goods produced are more specialised or are of higher quality; additionally it generates external effects such as knowledge spillovers whereby the new knowledge generated by the R&D activities stimulates the development of knowledge by others or enhances their technological capabilities.

Grossman and Helpman (1994) suggest that when such models of endogenous innovation are expanded to include international trade in goods, capital and ideas they produce theoretical frameworks that are consistent with observed phenomena. These theories emphasise the point that the economic processes which create and diffuse new knowledge are critical to shaping the growth of nations, communities and individual firms, suggesting that free international trade can speed up growth. The theory proposes that the development and production of new goods for export have externality effects which promote economic growth, and that each export product has different potential for externality effects; countries that specialise in exports with the highest export potential experiencing the most rapid growth. The flow of new information by way of openness to foreign investment or foreign trade and thus the extent to which ideas can move freely from place to place is also an issue of considerable importance in shaping knowledge spillovers. Additionally the proposed link between trade and technical efficiency suggests that lowering trade barriers can benefit nations by allowing nations to absorb new technology at a faster rate; increase the benefits that arise from R&D; reduce price distortions; and encourage greater specialisation and more efficiency in the production of intermediate outputs leading to a more rapid introduction of new products and services.

4.4 Microeconomic Theories of International Trade

The development of the above theoretical arguments was aided by empirical studies which showed there to be a strong positive relationship between export expansion and the economic growth of a country or region (Balassa, 1978, 1985; Caves et al., 1980; Feder, 1983; Chow, 1987). However, neither the theoretical nor the empirical studies said much about the links between exporting and the growth of the firm, despite the fact that firms are the intermediaries through which exporting occurs. It wasn't until the mid-1990s, and a seminal paper by Bernard and Jensen (1995) that encouraged a strand of literature in which the causes and effects of exporting, at the firm level, were examined.

During the 1990s, as the topic of globalisation and regional economic competitiveness became increasingly important, the strand of research focussing on exporting firms took off, with a growing body of literature using firm-level data to focus on the microeconomic effects of exporting, and more specifically the links between firm characteristics and exporting. Bernard and Jensen (1995) discovered, using data from the American Annual Census of Manufacturing, that exporters and non-exporters were essentially different in their underlying characteristics. This was followed up, in the subsequent decade, by a raft of studies worldwide that sought to corroborate these initial findings and identify whether there was a profile that differentiates exporters from non-exporters, based on their firm-level characteristics (for example: Aw & Hwang, 1995; Westhead, 1995; Roberts & Tybout, 1997; Clerides et al., 1998; Jalvagi et al, 1998; Bernard & Wagner, 1998; Bernard & Jensen, 1999, 2001; Gourlay & Seaton, 2004, Harris and Li, 2005; Bernard et al., 2007). These studies overwhelmingly concluded that there does exist substantial differences between the two groups of firms. These differentials, which include measures such as performance, productivity, size, R&D expenditure, and wages indicated that exporting firms have preferable characteristics, and perhaps more importantly, these characteristics exist before exporting begins[16].

The resulting empirical literature identified two key, but not mutually exclusive, hypotheses in relation to productivity[17] and exporting at the firm level; one which suggests that exporters are already more productive prior to exporting – the self-selection argument (Melitz, 2003; Bernard et al., 2003); the other that exporting improves the productivity of firms – learning-by-exporting (Lucas, 1988; Clerides et al., 1998).

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[16] Both Greenaway & Kneller (2005) and Wagner (2007) provide detailed surveys of the relevant literature. The latter summarising findings from 54 empirical studies published between 1995 and 2006 based on firm-level data from 34 countries; and overwhelmingly concluding that exporters are better firms.

[17] Although different measures of productivity are used in the various studies i.e. labour productivity versus total factor productivity, the results appear to be robust across measures.

The first, the self-selection argument, suggests that the actual process of selling outside the domestic market involves certain costs which create a type of entry barrier; only firms which are already successful can overcome this barrier and as such, they self-select into export markets. Roberts and Tybout (1997), building on the work of Dixit (1989) and Krugman (1989), suggest that the sunk costs involved in entering new foreign markets include establishing distribution systems; market research about demand conditions abroad; and product modification and compliance. These entry, or sunk, costs are estimated to be substantial thus they argue that only efficient firms enter the export market as only they have the means to incur these costs. Fafchamps et al. (2002) arrive at the same conclusion, suggesting that, in the case of Morocco, firms that export are more productive before exporting starts and this is driven by the sunk costs in achieving market familiarity, whereby firms learn to design products that appeal to foreign customers.

As part of the argument, research suggests that the exporting process requires firms ex-ante to be efficient due to the fact that they will be operating in a wider marketplace, the argument being that participation in world markets exposes a firm to more intensive competition, thus firms need to learn how to produce domestically and reach high levels of productivity in the home market before they try and enter export markets (Bernard and Jensen, 1999, Clerides et al., 1998). This hypothesis is also supported in the development economics literature which states that product market competition in export markets is greater than competition in domestic markets, resulting in a lack of opportunities for inefficient firms (Aw and Hwang, 1995). This lack of opportunities results in the failure of lower-productivity non-exporting firms who exit the market; such reallocation resulting in a rise in aggregate productivity in the economy (Bernard et al., 2007).

Hirsch (1971) and Clerides et al. (1998) also use the sunk costs argument in explaining why larger firms (in terms of sales volume and capital stocks respectively) are more likely to be exporters; they suggest that due to these fixed costs only producers of larger batches can keep unit costs low by spreading these fixed costs over a large number of units sold. Similar arguments are made in relation to those other characteristics which indicate firm superiority, for example the size, age, ownership and innovative nature of the firm, each of which has been found to have a particular influence on export performance, the latter of which is linked to technology-based models of competitive advantage.

The second key hypothesis, learning-by-exporting, argues that through their activities abroad, exporters gain access to information about more productive techniques of production and distribution. They also receive feedback from international customers, suppliers and competitors and learn from, and adopt, best practice methods. This hypothesis thus predicts that firm productivity rises with exposure to international markets (Jovanovic and Lach, 1991; Fafchamps et al. 2002). The hypothesis is also recognised in the endogenous growth literature which postulates that exports drive productivity growth through innovation (Grossman and Helpman, 1991); technology transfer and adoption from leading nations (Barro and Sala-i-Martin, 1995) and learning-by-doing gains (Lucas, 1988; Clerides et al., 1998). Driven by intense competition in foreign markets, firms have a strong incentive to upgrade their technology so as to reduce costs, improve product standards, and remain competitive. Again exposure to leading-edge technology and managerial skills from international competitors enables firms to learn how to operate more efficiently whilst the economies of scale from functioning in numerous international markets can also improve productivity.

The notion of learning-by-exporting is based on the concept of learning-by-using as hypothesized in Rosenberg (1982). This concept suggests that knowledge is only attained after a product or process has been used, thus in the exporting arena it refers to knowledge spillovers which have been acquired from being in the export market continuously and interacting with competitors and consumers (Yasar et al., 2006).

Although this latter hypothesis is still subject to debate, there has been a general consistency in the empirical findings surrounding the differences, and in particular the productivity differences, between exporting and non-exporting firms. However, as Bernard et al. (2003) highlighted, traditional international trade theory has little to say on the stylised facts unearthed by these studies, or in some cases is inconsistent with it, suggesting that in general, the empirical work tends to focus on the microeconomics only and typically ignore its setting within macroeconomic trade theory. Given this, new trade theories based on heterogeneous firms, their role in generating international trade and also inducing aggregate productivity growth, through the reallocation effects of entry and exit, have since been developed.

Melitz (2003) introduced the concept of firm heterogeneity into Krugman's (1980) monopolistic competition model of intra-industry trade. The model states that firms must endure sunk costs in order to enter the domestic market; prior to entry they also face uncertainty as to how productive they will turn out to be. Firms produce a variety of differentiated products but face fixed production costs; increasing returns to scale means that following entry they produce with different productivity levels, although they also face a constant exogenous probability of death. The fixed production costs lead to the exit of inefficient firms whose productivities are lower than a threshold level known as the 'zero-profit productivity cut-off', as they do not expect to earn positive profits in the future.

As with the domestic market there are also fixed costs and variable costs associated with entering export markets however the decision to export occurs after firms observe their productivity levels. A firm will enter export markets only if the net profits generated from its exports are sufficient to cover the sunk costs. As in the case of the domestic market only those who have a productivity level above a higher threshold - the 'export productivity cut-off' - find it profitable to export in equilibrium, the others will exit. Typically, the combination of fixed and variable export costs ensures that the exporting productivity threshold is higher than that for production for the domestic market, resulting in only a small share of firms with high productivity engaging in exports markets. There is a steady-state mass of firms active in the industry, thus the mass of new firms who enter and have a productivity level above the zero-profit productivity cut-off equals the mass of exiting firms that die.

In the model the reallocation of output and employment, from low to high productivity firms, also results in average industry productivity increases. This happens through the following mechanism; reductions in barriers to trade increase profits that existing exporters can earn and reduce the export productivity cut-off above which firms export. Labour demand within the industry rises, due to expansion by existing exporters and new firms beginning to export; this increase in demand bids up factor prices and reduces the profits of non-exporters. This reduction in profits in the domestic market induces some low-productivity firms who were previously marginal, to exit the industry. As low-productivity firms exit, and as output and employment are reallocated towards higher-productivity firms, average industry productivity rises.

Bernard, et al., (2007) further incorporate this notion of heterogeneous firms into Helpman and Krugman's (1985) seminal model and use it to explain some commonly observed trade patterns. As in the previous integrated model the concept of endowment driven comparative advantage explains why some countries export more in certain industries than in others; the concept of horizontal product differentiation with increasing returns to scale explains why there is two-way trade within industries and the notion of self-selection driven by trade costs explains why only some firms export within these industries that engage in two-way trade.

4.5 Empirical Findings

The empirical studies in the realm of exporting and productivity growth often jointly consider the evidence for both the self-selection and learning-by-exporting hypotheses and whilst there are numerous empirical results to back up the self-selection theory across various countries, the latter has more mixed results. Amongst the plethora of empirical studies the following highlights some of the key papers and results.

Self-selection of more productive firms into exporting is widely reported in the literature (for example, Baldwin and Gu 2003; Greenaway et al., 2003; Girma et al., 2004; Hahn, 2004; Damijan et al., 2004; Greenaway and Kneller, 2004, 2007, 2008; Van Biesebroeck, 2005; Farinas and Martin-Marcos, 2007; Serti and Tomasi, 2008; Kox and Rojas-Romagosa, 2010; Yang and Mallick, 2010; Sharma and Mishra, 2011; Haidar, 2012; Temouri et al., 2013). Indeed the International study group on Exports and Productivity (ISGEP, 2008) overwhelmingly conclude that in their study of 14 countries using micro-level panel data that there is strong evidence for self-selection of more productive firms into exporting. This is also confirmed by Singh (2010) who concludes his literature review by stating that studies supporting self-selection overwhelm studies supporting learning-by-exporting.

Amongst those reporting such evidence Arnold and Hussinger (2004) indicate that the self-selection of more productive German firms into exporting supports the theoretical models of international trade with heterogeneous firms, as formulated by Melitz (2003). Alvarez and Lopez (2005) not only find evidence for self-selection in their study of Chilean plants, but importantly they find that it is an active and conscious process carried out by firms. They argue that firms consciously increase their productivity by investing in physical and human capital as well as new technology with the explicit purpose of becoming exporters. Manez-Castillejo et al. (2010) also test for both self-selection and learning-by-exporting amongst Spanish firms and, although they find evidence for both they report that self-selection occurs only amongst small firms. Interestingly, Muuls & Pisu (2007) furthermore indicate that although there is a productivity differential for exporters compared to non-exporters, and that self-selection occurs, they believe the effect, as reported in the literature, may be overstated because typically imports are not considered.

One of the few studies to contradict the finding on self-selection is that by Girma et al. (2004) who use plant level data on Irish firms to compare productivity and profitability across three types of firm; namely those that serve only the domestic market; those that export and those that engage in FDI. The results indicate that the authors cannot reject the hypothesis of identical distributions of sales per employee, value added per employee and net profit per employee for exporters relative to non-exporters. However they do find that domestic FDI plants stochastically dominate both domestic exporters and non-exporters in terms of labour productivity and profits per employee. Despite these findings a separate study, also centred on Republic of Ireland-owned industrial firms (Ruane and Sutherland, 2004) found that exporting enterprises were superior to those that do not export, in the sense of being larger and having higher productivity. In support of self-selection they find that it is enterprises that are initially superior that tend to become exporters, whereas there is no evidence that firms develop superior characteristics as a consequence of exporting. The difference in findings between these two empirical studies suggesting that the choice of methodology and time period may influence the results; the former based on plants in the year 2000 and using stochastic dominance tests and the latter based on firms over the period 1992-97 and using regression methods[18].

Despite the support for the self-selection theory, evidence for the learning-by-exporting theory is less conclusive. One of the earliest papers to test explicitly for learning-by-exporting was based on data from the American Census of Manufacturers (Bernard and Jensen, 1999). Over annual horizons, exporters were found to grow faster in terms of employment and shipments; however productivity growth was either the same, or grew more slowly for exporters, whilst wages also showed mixed results. Over longer time frames, the advantages from exporting were more limited. Exporters still had higher employment growth rates, of around 0.4 - 1.1 per cent per year, however the growth in shipments was no longer significant and productivity growth was lower for initial exporters. Overall the authors concluded that

[18] This point is also made by Martins and Yang (2009) who conduct a meta-analysis of the relationship between exporting and productivity in which they state that care should be taken when comparing estimates from papers that adopt different methodologies.

success leads to exporting and that exporting is associated with growth in plant size and higher plant survival rates, however firms entering export markets are unlikely to see any productivity gains. Their results implied that exporting per se may not enhance productivity, but rather it simply provides wider market opportunities for more productive firms and may result in the reallocation of resources from less productive to more productive activities. The more direct benefits lie in the creation of new jobs and, through higher survival rates, the stability of these jobs.

Other empirical studies rejecting the learning-by-exporting hypothesis include early papers such as those by Aw and Hwang (1995), Bernard and Jensen (1995), Bernard and Wagner (1997), and Clerides et al. (1998) whilst Wagner (2002) and Arnold and Hussinger (2004), both using matching techniques, also found no evidence for post-exporting productivity improvements in their separate studies of German manufacturing plants/firms. Similarly, Delgado et al. (2002) who found evidence to support the self-selection theory for their sample of Spanish manufacturing firms in the early 1990s did not find the same evidence for the learning-by-exporting hypothesis.

Such findings were highlighted by Alvarez and Lopez (2005) and Crespi et al. (2008) as potentially being problematic in that the authors failed to take account of the indirect links between exporting and productivity growth. Both stated that if exporting affects learning and it is this learning that subsequently affects productivity growth, then unless learning is accounted for in the modelling process the true relationship between exporting and productivity growth may not be uncovered. Using data on a panel of UK firms Crespi et al. (2008) examined whether firms who export are more likely to report learning from customers; they then examined whether such learning is related to later productivity growth. The results suggest that past exporting is associated with more learning from buyers (but not with learning from other sources) but past learning is not associated with more exporting. Importantly, past learning is associated with higher productivity growth. This latter result provides support for the learning-by-exporting hypothesis however the results are somewhat qualified by the authors, in that due to the nature of the data causality cannot be inferred, and that pre-exporting sorting may be affecting the results. The Alvarez and Lopez (2005) paper also finds evidence of learning-by-exporting, however only for new entrants to exporting and not for continuous exporters. They suggest that there may be externalities from exporters to domestic firms, or indeed from consolidated exporters to firms that initially do not export, generating a downward bias on the effect of exports on firm performance.

Studies which did provide evidence for learning-by-exporting include that by Girma et al. (2002) who found that exporting may boost the productivity of UK exporters, although they suggested this could be the consequence of the matching analysis methodology used in their study. Other evidence of productivity improvements after exporting have been found for firms in the UK (Greenaway and Kneller, 2004, 2007, 2008; Girma et al., 2003, 2004; Harris and Li, 2007); China (Kraay, 1999, Yang and Mallick 2010; Dai and Ju, 2013); Canada (Baldwin & Gu, 2003); Italy (Castellani, 2002; Serti and Tomasi, 2008) Slovenia (De Loecker, 2004, 2007) Turkey (Yasar and Rejesus, 2006) and African nations (Van Biesebroeck, 2005). Typically these studies examine the post-entry productivity performance of new exporters and report that productivity growth is higher for new exporters typically only up to two years after entry, with the productivity improvements ranging from 2 per cent to 5 per cent annually. This finding is also confirmed by Martins and Yang (2009) who in a meta-analysis of more than 30 papers conclude that the learning-by-exporting effect is higher in the first year after starting to export than for later years.

Studies which suggest longer productivity effects include Greenaway and Kneller (2007) for the UK who report higher productivity growth for up to three years after entry; four years for Slovenia (De Loecker, 2007) and six years for Italian firms (Serti and Tomasi, 2008). For China (Kraay, 1999), the learning effects were largely insignificant for new entrants however for established exporters the effects were relatively large: with the results suggesting that a ten percentage point increase in a firm's export to output ratio in a given year leads to 13 per cent higher labour productivity, 2 per cent higher total factor productivity, and 6 per cent lower unit costs in the following year. In contrast, Yang and Mallick (2010) reported, for their sample of Chinese firms, that productivity growth was higher for new exporters the second year after starting to export whilst Dai and Yu (2013) indicate that starting to export has an instantaneous effect in raising productivity by 2 per cent, but there are no significant long-run effects. Girma et al. (2003) who looked at exiting plants in the UK found evidence of a temporary instant negative impact of exit on productivity, with more persistent negative effects on employment and output.

Manez-Castillejo et al. (2010) found evidence for post-entry productivity growth amongst Spanish manufacturing firms, both large and small. However the time span over which the improvements occur differed by size; small exporters take more than a year before productivity improvements are seen and reach their maximum extra productivity growth (over non-exporters) after two years. Large exporters take more than two years to gain extra productivity growth over non-exporters, at which point productivity growth is 14 per cent higher. After four years productivity growth for large firms is 15-16 per cent higher for exporters compared to non-exporters. They suggest that the productivity gains from starting to export are therefore more intense for large firms.

The reasons for the difference is time span for the effects of learning on productivity growth are not yet well understood; for those where an immediate one year impact is detected it is thought that this may be due to the fact that firms are exposed to foreign competition and advanced technologies for the first time and thus the impact on learning is immediate. Alternatively the increase in productivity may be due to the access to foreign demand and the resulting immediate improved use of the firm's capacity (Damijan and Kostevc, 2006). Where the productivity effects take longer to filter through it is likely that this reflects a longer time lag between learning and being able to put that learning into practice.

In a move away from considering the aggregate effects of exporting on productivity, De Loecker (2004) suggests that the actual export market should also be considered. By doing so he was able to show that there was a significantly higher productivity premia for firms exporting their products from Slovenia to high income regions, indicating that the characteristics of the destination export market makes the difference with regards to learning. His finding was an important development in the literature and led to a new wave of empirical studies focussing on the export destination market. The findings of these studies were again generally supportive of self-selection, but remained mixed for the learning-by-exporting hypotheses, however they did appear to reaffirm the importance of the geographic market.

Those confirming the evidence of self-selection included Wagner (2007) and Verardi and Wagner (2010) who found German exporters selling within the euro-zone to be more productive than those selling within the domestic market only, but less productive than those selling outside the euro zone. Lawless (2009) who found that

Irish firms with the greatest export market coverage tended to be more productive[19]. Bellone et al. (2010) who found that French firms selling to global markets had higher productivity growth than those selling within Europe only, but no difference in the productivity distribution of the latter compared to non-exporters. Three separate studies for Italy also found that firms exporting to a larger number of countries; more industrialised countries and high-medium income countries were all more productive (Serti and Tomasi, 2009; Castellani et al., 2010; Conti et al., 2010).

Those studies considering evidence for both self-selection and learning-by-exporting by market destination included Wilhelmsson and Kozlov (2007) who found Russian firms that exported to the OECD were more productive than those who simply exported within the former Soviet Union countries; however they found no definitive proof for subsequent productivity effects. Pisu (2008) found higher ex-ante productivity levels amongst Belgian firms that exported to more developed countries compared to those selling to less developed countries and to non-exporters, although he also found no such impact on subsequent productivity growth. Damijan and Kostevc (2006) reported a one off increase in productivity growth the year after starting to export for Slovenian firms, and this was the same for those that exported to former Yugoslav countries as well as those exporting to the EU. However in a later paper Kostevc (2008) reported higher productivity amongst Slovenian firms exporting to more demanding markets, but inconclusive evidence for learning-by-exporting. Silva et al. (2010a) found those starting to export to only developed countries were more productive in the pre-entry period, however in contrast to these other studies they also found that there was a learning-by-exporting effect. They reported that those selling to EU markets had a post-entry productivity increase but there was no such effect for those selling to non-developed countries (Silva et al., 2010b). Martins and Yang (2009) conclude in their meta-analysis that the impact of exporting upon productivity is higher for developing than developed countries, which appears to reaffirm the notion that those selling to markets more developed than their own have a greater potential for learning and thus a greater likelihood of increased productivity growth.

Given the inconclusive evidence for learning-by-exporting subsequent important contributions to the literature included observations from Fryges and Wagner (2007),

[19] Indeed Ruane and Sutherland (2004) in an earlier paper had previously suggested that the destination market mattered, in that the performance characteristics of Irish enterprises that exported globally differed from those that exported locally to the UK.

and separately De Loecker (2010), who both noted that the methodologies typically used for the detection of learning-by-exporting were flawed. Using a continuous treatment approach, based on generalised propensity score methodology, Fryges and Wagner (2007) found that exporting improves labour productivity growth, but only within a sub-interval of firms' export-sales ratios[20]. They suggest that the reason previous empirical studies found no positive link between exporting and productivity growth is due to the fact that export status, measured as a binary variable, was typically used in the various analyses, whereas their results show that one needs to take account of varying levels of export intensity to model the relationship properly. The paper lends its support to both the self-selection and learning-by-exporting hypotheses, although the latter is qualified to a certain extent. The study finds that a firm's export activities have a causal effect on its labour productivity growth rate at an export-sales ratio of 19 per cent, deemed the 'threshold of internationalisation'. If export intensity falls below this then productivity growth will be lower (although still higher than non-exporters), and in fact productivity growth will only be positive as long as the firm's export intensity does not rise above 52 per cent. At intensity levels above 52 per cent firms see no productivity benefits from exporting compared to those who do not export at all. The authors also find that the relationship between labour productivity growth and export intensity is not stable over time. In fact running the model for 2002-05, they find that firms that export more than 76 per cent of their total sales have a negative labour productivity growth rate. Without the data to support their hypothesis, the authors suggest that the reason for this particular finding is that firms are possibly selling to India and China and as such, are less likely to benefit from exporting if they are selling to technologically less advanced countries.

Using an alternative proposition De Loecker (2010) suggested that the previous methods used to detect learning-by-exporting were biased into rejecting the hypothesis, by failing to take account of previous export experience. He produced a model whereby output growth is related to capital growth and the firm's lagged export status, showing that if productivity gains from exporting occur simultaneously with investment, it biases the capital coefficient upwards and thus underestimates the productivity effect from exporting, by attributing it to a growth in capital. In this way it could lead to the assumption that exporting has no effect on subsequent productivity

[20] Castellani (2002) also found that export intensity was key to the productivity impact of exporting rather than simply the act of exporting; this was tested by including a variable measuring export intensity in the regression.

growth. By incorporating past exporter status into his model, he finds for Slovenian firms, that exporting and investing do indeed raise future productivity, and the average ranges from 1 to 8 per cent. He also finds that the productivity gains are lower when firms are already very productive. Using a similar methodology Manjón et al. (2013) also find that learning-by-exporting is only detected when they allow past export experience to affect productivity. They use a Cobb-Douglas production function to estimate firm productivity by generalised method of moments (GMM) for their sample of Spanish firms, taking account of the fact that exporters and non-exporters have different demands of intermediate materials. They find that exporting results in yearly gains in productivity of around 3 per cent for up to four years after entry. In addition, export intensity only matters for those who continue to export, with the extent of the productivity gains dependent on the amount that they export.

Based on a similar idea Harris and Li (2012) examine the extent to which productivity within UK manufacturing and tradeable service firms may be affected by entry and exit, and repeated entry/exit behavior in international markets. Overall, the results, weighted to the population, indicate that firms new to exporting experience an increase in TFP of 3 per cent in the year following entry; firms exiting export markets experience a 10 per cent decrease in the year after exit; whilst firms that enter then exit experience an 11 per cent increase in productivity in the year of entry but just a 0.03 per cent increase in the following year. Importantly, they note that when they use unweighted data the results are largely insignificant; they suggest that widespread use of unweighted data may be the cause of the reported lack of impact on productivity from exporting, as reported in the literature. They find that their results differ across and within industries, with post-entry productivity improvements generally higher for service sector firms.

4.6 NI Empirical Evidence

Despite the promotion of exports being a key feature of the various economic strategies in NI, there have been few empirical studies examining the productivity position with regards to exporting firms. Indeed, the relationship between exporting and productivity growth in terms of either self-selection or learning-by-exporting has never been estimated. Studies which have been undertaken have primarily sought to understand the differences between exporters and non-exporters, and have confirmed the hypothesis that exporters are generally better firms. Roper and Love (2001) and Roper et al. (2006a) were the first to examine the determinants of export performance[21] for manufacturing plants in both NI and the Republic of Ireland (RoI) over the 1991-99 period. They found that large, externally-owned plants with higher skill levels had the highest export propensities. In particular, they noted a strong positive effect from the strength of plants' internal resource base, suggesting that those with a high proportion of graduate employees and those with an in-house R&D capability had a higher export propensity. Interestingly for indigenously-owned plants in-house R&D was more important; for externally-owned plants it was R&D conducted elsewhere in the group (particularly outside Ireland). Plant size and external ownership were also found to be important determinants, as was age, with younger firms also found to have a higher export propensity.

Bonner et al. (2006) in a follow-up study looking at the 1998-2001 period found that the firm-level characteristics that profile the type of firms that export are not the same as those that influence export intensity, suggesting that export promotion policies should make a clear distinction between those designed to promote non-exporters to participate in export markets and those aimed at increasing the export share of current exporters. In terms of the likelihood of being an exporter larger firms, more productive firms and those undertaking R&D were all found to be significant. The determinants of export performance, in this case export intensity, were shown to be linked to superior firm characteristics such as higher productivity levels and larger firm size; there also appeared to be specific sectoral influences. Export intensity was found to be higher amongst the externally-owned group of firms however R&D was no longer significant in this model. In contrast, those with lower labour costs were found to export higher shares of total sales suggesting that once firms began to export they used their low cost basis, rather than technological advancement, as a means of being competitive. Neither this nor the previous studies examined whether these characteristics were the cause or consequence of exporting.

4.7 Summary

The links between trade and growth are well established at the macro-economic level, with the theoretical literature developing in line with observed real world phenomena such as the notion of heterogeneous firms, intra-industry trade and endogenous technological change. Surprisingly, the micro-economic relationship between trade and growth has only been examined relatively recently, and whilst the

[21] Export performance is measured as export intensity i.e. the proportion of plant total sales made outside the UK and Ireland.

empirical literature has burgeoned, there remain outstanding issues for which there is no definitive consensus.

There exist two main hypotheses surrounding the exporting-productivity relationship, that concerning self-selection, whereby more productive firms are thought to self-select into export markets; and that concerning learning-by-exporting whereby there are assumed to be productivity increases post-entry to export markets, whereby firms learn to produce more efficiently due to the exposure to foreign competition and methods. Evidence for the former is widespread, with most empirical studies confirming the existence of self-selection, due to the existence of sunk-costs and/or the deliberate actions of firms who ramp up productivity before entry so as to be able to compete effectively. The latter hypothesis however is still subject to debate; many studies report no evidence for learning-by-exporting although more recent studies have suggested that the destination market is of key importance, with those firms selling to markets more developed than their own experiencing subsequent productivity increases due to a catching-up effect. Alternative arguments concern notions surrounding the degree of export intensity, with productivity effects being detected only after a certain threshold of exporting has been reached; and when previous export experience, including the different intermediate input demands of exporters versus non-exporters, are taken into account.

The lack of consensus on the latter hypothesis suggests that it is a worthwhile area to investigate further. This is particularly the case for NI, where there is a dearth of evidence on exporting firms in general, and a particular gap in the knowledge surrounding the productivity effects of exporting. This is somewhat surprising given the stated policy focus on exports as a means of raising productivity in NI (IREP, 2009), added to the fact that NI is unique amongst the UK regions in collecting data on the value and destination of exports from NI manufacturing firms since the 1990s.

Given this, the thesis aims to undertake an analysis of exporting firms, the resulting hypotheses firstly testing the widely held assumption that exporters differ in characteristic from non-exporters; and more specifically whether NI exporting firms are associated with value-added activities such as R&D. This latter proposition attempting to test the notion that NI exporters are selling to more advanced economies[22]. It is proposed that three slightly differing definitions of exporter will also

[22] Although export destination data is collected in NI it was not made available for this research. Thus in order to try and establish whether NI firms are exporting to more developed

be used (based on broad market destination) in a further attempt to unearth this destination effect. The notion of heterogeneous export firms will also be incorporated into the analysis using both binary and continuous export measures.

H1: Exporting firms display a different set of characteristics than non-exporters, suggesting they are 'better' firms

H2: Exporters are more likely to undertake R&D due to the technology-based competitive markets in which they operate

The second set of hypotheses then examines the key arguments with regards to the productivity impact by testing for both self-selection and learning-by-exporting:

H3: Due to the sunk costs or 'self-selection' argument, exporters are more productive than non-exporters, prior to exporting

H4: Exporting has a positive effect on a firm's productivity growth, as suggested by the 'learning-by-exporting' notion.

countries, R&D activity is used as a proxy, the idea being that those selling to less developed markets would have less need for R&D (if their export good is already more advanced than those currently available in the export market), compared to those selling to more advanced and technologically-driven economies.

Sub-Section B: Determinants of Innovation and its Impact on Productivity Growth

4.8 Introduction

Innovation has been defined as the "transformation of knowledge into new wealth-creating products, processes and services" (Porter and Stern, 1999, pg.12), and is widely considered, particularly by endogenous growth theorists, to be a long–term driver of economic growth. The theories linking innovation to growth can be traced back to the work of Schumpeter, who introduced the notions of creative accumulation, and destruction however it was not until the work undertaken by Solow that growth through technological change was formally introduced into the growth modelling framework.

The period since the late 1980s saw a development in the theoretical literature moving from macro-level studies to those focussing on the link between innovation and firm growth. In these models investment in R&D, and human capital were seen as endogenous to the growth process as they were the engine through which firms could grow by producing output more efficiently. These models also introduced the notion of government support for R&D activities in that the appropriable nature of innovations suggest that where they can be reproduced the incentive for firms to invest in such activities is lowered.

As a result of these endogenous models, studies which measure and quantify the impact of innovation activities at the firm level have become more widespread, particularly since the 1990s, and have been facilitated in particular, by the introduction of the Community Innovation Survey (CIS) which was initiated in European countries to investigate enterprises' innovation activities. According to the definitions used in the CIS an innovation is "the implementation of a new or significantly improved product (good or service), process, new marketing method, or new organisational method in business practices, workplace organisation or external relations" (OECD, 2005, pg. 46). The CIS survey has now been conducted seven times, the last in 2011, (each survey spanning a two or three year period) and has spawned a variety of research on innovation behaviour amongst firms across Europe.[23]

[23] Examples of such studies include Camacho and Rodriguez, 2005 who look at the innovative activities of service sector firms in Spain; Cefis and Marsili, 2005 who examine the survival probability of innovator versus non-innovator firms in the Netherlands; Hall et al.,

This literature review seeks to summarise the developments in the theoretical literature surrounding innovation and growth, leading up to the adoption of endogenous growth theory as central to long-term growth. The empirical literature review then focuses on those studies which link innovation to productivity at the firm level, in terms of the impact on productivity levels and on productivity growth. The aim of the literature review is to provide an indication of where the academic thinking currently stands on the subject and where gaps in the knowledge are in relation to NI. The chapter ends with the development of the resulting key hypotheses to be tested.

4.9 Innovation and Growth Theory

In theory terms there have been a number of different, and developing, arguments explaining how innovative behaviour fuels growth, and indeed at the micro-level there has been discussion about the type of firms that are more likely to undertake innovative activities. The pioneer of studies on innovation, Joseph Schumpeter, developed two competing theories about how the innovation process occurs. After studying the capitalist market model Schumpeter developed a theory of innovation which was based on a company's size. Initially he stated that innovation occurred through small firms as they have more flexibility, with larger firms held back by their bureaucratic structure. He proposed that innovation was an uneven and random process with technological opportunities available to a pool of homogeneous firms; the process driven by a perpetual renewal of entrepreneurs at the frontier of technology replacing incumbent firms, and holding temporary monopoly power, thus disrupting production and organization in an industry – a process known as creative destruction (Schumpeter, 1934).

Several years later Schumpeter argued that as innovation activities were costly, risky and led to uncertain outcomes for firms, that the process of innovation was in fact driven by large companies that had better resources and more market power to develop innovations than smaller firms. He believed that knowledge was specific to individual firms and applications, with innovation resulting from the in-house

2009, who examine the links between innovation and productivity amongst Italian SMEs; Damijan et al, 2010 who look at the relationship between exporting and innovation in Slovenia; Raymond et al, 2010 who examine the persistence of innovation in Dutch manufacturing firms; and Iversen, 2011 who assesses the impact of patenting on collaboration amongst Norwegian firms.

accumulation of technological competencies of heterogeneous firms. This cumulative knowledge built up over time thus creating barriers to entry for new firms – a process known as creative accumulation (Schumpeter, 1942). These barriers, accompanied by the weak appropriability conditions of the benefits of innovation meant that innovation was more suited to large firms than it would be to fully competitive markets populated by small firms (Freeman and Soete, 1997).

It was not until the late 1950s, and the work of Solow that the role of innovation was formally introduced into economic growth models[24]. Through the use of a production function Solow (1957) sought to measure the share of growth that was attributable to increases in capital. He found that output per hour in the US economy approximately doubled between 1909-49 however capital accumulation accounted for just 12.5 per cent of this growth. The residual, (accounting for 87.5 per cent) was attributed to technical change, known as total factor productivity.

In Solow's model long-term growth was thus determined exogenously by technical change. Critics of this neo-classical model argued however that there had to be a source for this technical change, and that it should be explicit within the model;

> *"A view of economic growth that depends so heavily on an exogenous variable, let alone one so difficult to measure as the quantity of knowledge, is hardly intellectually satisfactory". (Arrow, 1962, pg.155)*

Proponents of alternative models suggested that growth was instead the result of continuous investment in knowledge, human capital and innovation. They postulated that firms undertake innovative behaviour only if "the expected revenue of the invention exceeds the expected cost" (Nelson, 1959, pg. 300). In addition, they suggested that the profits from R&D may not be secure if externalities occur, whereby the profits spill over the boundary of the firm and become public. In this case the profits are no longer appropriable (Nelson, 1992) and as such market failure discourages firms from undertaking innovation.

Theories, based on these assumptions and centred on microeconomic foundations, were termed under the umbrella of endogenous growth theory and became popular

[24] Previous studies, pioneered by Tinbergen (1942) had also decomposed the sources of growth into their factor inputs, whilst Fabricant (1954) and Abramovitz (1956) had shown that the majority of labour productivity growth in the US was attributable to the residual of total factor productivity. However Solow is credited with formally bringing technical change into growth accounting and bringing the subject to fore.

in the 1980s, through the work of Romer (1986) and Lucas (1988), and latterly Barro (1990); Rebelo (1991); Grossman and Helpman (1991) and Aghion and Howitt (1992), whose assumptions were based on the pioneering work by Arrow (1962) on learning-by-doing. He suggested that learning is the product of experience, which itself is a function of cumulative gross investment. The central idea of his model is thus that firms, unintentionally, learn from experience how to produce more efficiently.

Romer (1986) built on this initial idea by emphasising the role of knowledge spillovers in growth, and allowing a role for public policy in the process. In his model firms utilise human capital to undertake R&D because they expect it to be profitable; in doing so they create knowledge which is both appropriable and non-appropriable, the latter, the knowledge spillover, having the properties of a public good. His model postulates increasing returns to growth from investments in human capital and R&D due to these knowledge spillovers. In addition, and building on the work of Arrow (1962), his model suggests that due to the public good argument there may be underinvestment in R&D because the benefits cannot be reaped due to these non-appropriability and spillover issues, and hence a justification for public subsidisation of R&D investment.

The later Aghion and Howitt (1998) model was based on a similar proposition to Romer's and also alluded to Schumpeter's notion of creative destruction, their focus centred on the notion that industrial innovations improve the quality of goods. The central idea of their paper was that firms undertake R&D, despite it being an uncertain activity, as successful R&D allows them to hold temporary monopoly rents over the innovation through the use of patents. The successful innovation renders the previous one obsolete, which can have positive and negative externalities. In terms of growth, the innovation of intermediate goods can be used to produce final output more efficiently than before, whilst the monopoly power that arises from the new innovation incentivises other firms to also undertake R&D, with growth arising from this continuous cycle of innovators. The expected growth rate of the economy thus depends on the amount of research undertaken in the economy as a whole.

The Lucas (1988) model further emphasised the role of the accumulation of human capital as the engine of growth, raising the productivity of both labour and physical capital. In his model human capital is defined as the skill embodied in workers; they face a trade-off, they can either use their current skills in the production process or withdraw effort from production to undertake further training to enhance their future productivity; the subsequent increased wages associated with the training giving a greater incentive to train. With constant returns to human capital, the resulting productivity increases from knowledge accumulation seek to raise the overall growth rate.

These initial models were expanded on to include other key variables such as allowing public policy to impact on long-term growth (Barro, 1990), whereby it was shown that public investments can increase private capital marginal productivity, and hence economic growth; and Rebelo (1991) who showed that the taxation of income can substantially reduce growth rates. As mentioned in the previous section, Grossman and Helpman (1994) furthermore included international trade in their model showing that the development and production of new goods for export can result in externality effects which promote economic growth; the flow of new information by way of openness to foreign investment or foreign trade increasing knowledge spillovers.

The endogenous growth theories thus postulated that firms will invest in R&D if they expect future profits generated by the new products to exceed the cost of undertaking the research. Arising from these models were competing theories as to the process by which firms continue to innovate. One approach suggests that it is explained by the existence of sunk costs whereby R&D facilities are established at fixed cost, producing a stable flow of innovations (Sutton, 1991). Alternatively it is argued that persistence in innovative activities are the result of 'success breeds success' processes whereby innovations that have met a commercial success in the past generate profits that may be invested in current innovation activities (Mansfield, 1968). Building on the learning-by-doing model (Nelson and Winter, 1982) Malerba and Orsenigo (1993) further predict that the production of innovations is subject to dynamic economies of scale in that knowledge that has been used to produce past innovations can, assuming that the depreciation rate of innovative abilities is small, be used to produce current and even future innovations, each one improving on the original. These alternative theories suggesting that firms possess certain characteristics which make them more likely to innovate, and more likely to continue to innovate, for example, firm size, financial resources, technological opportunities, managerial abilities and risk attitudes.

Whilst such endogenous theories characterise R&D or innovation as an activity undertaken by firms, they also allow external parties to act as influencers, such as in the case of market failure. A separate strand of innovation literature, that of innovation systems, further encompasses the role of *all* actors in the process to include “the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies” (Freeman, 1987, pg. 1). The literature highlights that innovation occurs due to the interaction of these players, and is not solely restricted to the decisions or activities of firms.

The key elements of the innovations systems literature, as developed by Freeman (1987), Lundvall (1992) and Nelson (1993), is summarised by Soete at al. (2010); it builds upon elements introduced in the theories discussed above and, although not the focus of the analysis in this thesis, is nevertheless relevant as it sets the context in which the study is positioned. Their review highlights that the innovation systems literature expanded the innovation discussion away from its narrow traditional focus on R&D to encompass wider forms of innovative activity; the collection of data on such activities, as suggested by this more systemic approach, a key feature of the CIS. They highlight the role of institutions and organisations, as they provide the structure against which innovation can occur. As suggested by Nelson and Winter (1982) these include the practices that shape the way things are done and how innovation is perceived, and the way in which agents act and interact. They assert that continuous learning is central to innovation systems, both in terms of the learning by individuals and by firms and they indicate that, due to the risk involved in innovative activity, that social capital is an important determinant of investment in innovation (Akcomak and ter Weel, 2009). Finally, they reinforce the importance of interaction and co-operation between innovating firms and external actors, including their customers and suppliers.

This latter point about interaction is key to systems of innovation, as a lack of such co-ordination between the different actors gives rise to ‘systemic failure’. This is a departure from the notion of ‘market failure’ that is commonly discussed in terms of the innovation sphere, as it suggests a wider policy response, and not simply those responding to market imperfections. Thus whilst market failure can lead to policies to spur innovation at the firm level; its success or otherwise is influenced by the other elements of the system and how well they are co-ordinated, and indeed whether they are appropriate or even exist (Edquist, 2001). In fact government itself is endogenous within the innovation system, thus necessitating the need for policies to be adaptive, to respond to local conditions, and to cover a wider remit including science, technology, education, industrial and regional policy (Soete et al., 2010).

As a result, it is deemed that the impact of innovation at the macro-level is due to the various interactions at the micro-level; the combination of investment in human and social capital and the research capacity of a region or country, together with opportunities for local spillovers, and the extent of absorptive capacity, all working together to determine its outcome. Bearing this in mind, innovative activities at the firm level, as analysed in this research, may affect individual firms' productivity, but tell only part of the story when considering the impact on aggregate productivity. This is important in the NI context, particularly as the productivity gap with the UK, is as much a macro problem as it is for individual firms and sectors. Indeed Cooke et al. (2003) have suggested that the regional innovation system in NI is weak; with underdeveloped knowledge-mediating and knowledge transfer institutions; weakly embedded externally owned plants and a lack of clustering or networking among smaller firms. Although outside the remit of this study it will be important to consider the results of the firm-level analysis in this context, as, without a broader support system for innovation any impact will therefore be muted.

4.10 Empirical Findings on Innovation and Productivity

The relationship between innovation and firm growth can differ depending on the performance measure under analysis, for example the impact on sales growth can differ markedly from that on employment growth if the innovation is labour saving (Roper and Love, 2004). The impact on productivity growth is one such measure in which innovation is expected to have a positive effect, due to the role that innovation has in making the productive effort more efficient. Process innovation in particular, which is defined as "the implementation of a new or significantly improved production or delivery method" (OECD, 2005, pg. 49) can result in improved productivity by enabling firms to produce output at a lower cost (generally through a reduction in labour). This can also result in higher profits at the existing market price or allow firms, depending on the elasticity of demand, to both lower prices and raise profits. In this way firms can gain a cost advantage over competitors, allowing them to increase market share and seek further rents under increasing returns to scale.

Product innovation, defined as "the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses" (OECD, 2005, pg.48) can increase productivity if the new product creates additional demand and gives rise to scale economies in its production. In contrast it could also be argued that the product innovation could have a negative impact if the additional demand generates a growth in employment that initially outpaces the growth in output leading to a temporary reduction in overall productivity growth until the method of output production can be made efficient.

Pioneering work analysing innovation and quantifying its effect on productivity growth stretches back decades, and was undertaken typically through the use of a production function framework (Griliches, 1958; Mansfield, 1965), however most of the early empirical work used R&D as the measure of innovation. This was later criticised on the basis that R&D expenditure does not encompass all the innovative efforts of firms such as learning-by-doing, or the knowledge embodied in investment in new machinery and human capital (Hashi and Stojcic, 2012). Indeed, Crépon, Duguet and Mairesse (1998) were one of the first to show that the traditional method for estimating the relationship was inappropriate in that R&D is an innovation input, and that it is not innovation input, but actually innovation output, that increases productivity. They put forward the idea that firms invest in R&D to either launch new products or reduce production costs, and it is the resulting success or otherwise of these innovations that impact on firms' productivity and other economic performances. Their model encapsulated four relationships:

1) the research relationship linking R&D to its determinants
2) the decision about how much to spend on innovation activities (innovation expenditure equation);
3) the innovation equation relating expenditure on innovation to innovation output measures (innovation production function) and,
4) the productivity equation relating innovation output to productivity (output production function).

The knowledge-production function model used by Crépon et al. (referred to in the literature as the CDM-model) has subsequently formed the basis for this line of empirical research linking innovation to firm performance (see for example Klomp & Van Leeuwen, 2001; Criscuolo & Haskel, 2003; Janz et al., 2004; Benavente, 2006; Griffith et al., 2006; Jefferson et al., 2006; Loof & Heshmati, 2006; Mohnen et al., 2006; Parisi et al., 2006; Van Leeuwen & Klomp, 2006; Masso and Vahter, 2008; Polder et al., 2009; Criscuolo et al., 2010; Mairesse and Robin, 2010; Hall et al., 2009; Castellacci, 2009; Damijan et al., 2010; Crespi and Zuniga, 2012; Mairesse et al., 2012). The CDM approach is thought to be a superior model through which to measure the relationship as it enables econometric issues surrounding selectivity bias and endogeneity to be controlled for; the former issue arising due to the use of sample data which will include firms with no reported R&D expenditure.

The empirical evidence using the model, a large proportion of which uses CIS data, reveals a number of common findings with respect to each of the elements of the CDM-model. The decision to undertake R&D is usually modelled with the same variables as the related innovation expenditure relationship (linking expenditure on R&D to its determinants); one of the key variables with a positive impact is firm size, with larger firms more likely to undertake R&D (Cohen and Klepper 1996). Interestingly however, the intensity of R&D spending is found to be associated with either a U-type relationship with regards to size; or with smaller firms (Janz et al., 2004) or having no impact at all (Benavente, 2006). Lin and Lin (2010) state that whilst firm size has a positive impact on innovation, the impact follows an inverse U-shaped effect, with small and medium size enterprises most likely to undertake technological innovation, although the finding differs if patents are used to measure innovation, in that larger firms are more likely to generate a larger number of valid patents. Driffield et al. (2010) also report a U-shaped relationship between firm size and R&D, for UK firms, with larger (and older) firms tending to increase investment in R&D to a certain point after which the increase in investment slows down.

The international focus of the firm is also found to be an important determinant, with those operating in export and international markets more likely to be doing R&D (Loof and Heshmati, 2002; Kemp et al., 2003) as postulated by the theoretical literature, although Driffield et al. (2010) is a notable exception. Hashi and Stojcic (2012) suggest that the nature of the foreign market is key to this finding, with those selling to developed markets more likely to experience a positive relationship but those selling to less developed markets showing either no relationship, or a negative relationship between R&D and exports[25].

Other key variables in the R&D decision include receipt of national government financial support, which supports the theory regarding under-investment in R&D due its public good characteristics; a high degree of market share; product diversification

[25] This is tied in with the notion that learning-by-exporting is more prevalent when the export market is more highly developed.

and the absorptive capacity of the firm, particularly regarding those with a high proportion of skilled labour. Importantly, the impact of all these variables fluctuates across the empirical literature, with some only significant for the probability of undertaking R&D but not for the intensity with which it is undertaken, and vice versa.

The second stage of the model – the innovation production function – was also found to show largely consistent results across the empirical literature despite the use of various different measures of the dependent variable, such as innovation dummy variables; measures of innovative sales per employee; and measures of patents. Where the results differed from the norm it was typically for less developed countries or where innovation had been spilt into product and process innovation, the results not necessarily the same for both. The key explanatory variable in the innovation production function, expenditure on R&D, was found to positively and significantly affect the probability of product innovation (or innovation where it was considered as a single measure) in the majority of the studies. Key exceptions to this were Benavente (2006) who found current R&D expenditures to have no significant impact on current innovation in Chilean firms, although this was explained by the fact that there are likely to be lags involved in the process which were not built into the model. Parisi et al. (2006) who found no significant impact on process innovation (although spending on new fixed capital had a strong impact) and Alvarez et al. (2010) who reported no effect on product innovation for their study of Chilean firms, although they found a positive effect for process innovation.

The extent to which R&D intensity affected the likelihood of innovating depended on the measurement of the dependent variable; Janz et al (2004) suggested that a 10 per cent increase in innovation expenditure per employee increased innovation output per employee by 5 per cent, which was slightly higher than that reported by Loof and Heshmati (2003) and Crépon et al. (1998) who both estimated an effect of around 3 per cent. In contrast, OECD (2009) reported an elasticity of between 14 to 35 per cent across 15 different countries worldwide, and more than 40 per cent in Australia, New Zealand and Norway. Increasing R&D intensity from zero to the average increased the likelihood of introducing a product innovation by 5 - 6 percentage points (Parisi et al., 2006). Lederman (2010) suggested that investing in R&D (measured as a dummy variable) increased the probability of product innovation by 0.18 per cent, whilst Roper et al (2006b) also using a dummy variable found that enterprises undertaking in-house R&D were 27.5 per cent more likely to develop product innovations and 11.9 per cent more likely to develop process innovations.

Bishop and Wiseman (1999) suggested that, for a sample of defence-related UK firms, establishments with an R&D function were over three times more likely to have introduced a commercially significant innovation, than those who did not possess such a function.

As suggested by Roper and Love (2001) it is not just R&D spending that influences innovation activity but also external linkages or so-called 'network effects', which include sourcing information from and co-operation with, suppliers, clients, universities and public research centres. A number of studies found such effects to be significant for innovative activity although the results were not consistent across the board, for example external co-operation and the use of internal information sources were found to be important determinants for UK firms but there was no such effect from government information and non-financial support (Criscuolo and Haskel, 2003). Suppliers were found to be an important source of information for process innovation in a number of European countries, but the only influence on product innovation was from information derived from customers (Griffith et al., 2006). Indeed, in a review of innovation surveys Bogliacino et al. (2010) found clients and suppliers to act as important sources for innovation across a number of developed and developing countries, whilst knowledge internal to the firm acted as the dominant source of information. The positive link was confirmed by Lin and Lin (2010) who found, for Taiwanese firms, that undertaking internal R&D, and technological co-operation with other firms, was positively associated with product innovation. Interestingly, they noted that internal R&D is crucial for manufacturing firms, whilst for service sector firms, co-operative R&D is more important. In contrast, Alvarez et al. (2010) found no effect from supplier or client sources and reported that only university sources had an impact in their study of Chilean firms; they also stated that formal co-operation was also only significant for university and/or technological institutes. Studies reporting no such impacts at all included Janz (2004) who found no impact on co-operation or the use of customers and clients as information sources for firms in Germany and Sweden.

Other key results from the innovation equation included firm size, appropriability and absorptive capacity. Absorptive capacity, reflected by the amount of highly qualified employees, and/or the presence of an R&D department, was also found to be strongly related to innovative activity, in those papers where it was captured (such as Klomp and Van Leeuwen, 2001; Criscuolo and Haskel, 2003; Benavente, 2006; Roper et al., 2006b; Criscuolo, 2009) and in the wider innovation literature (Lund

Vinding, 2006). The findings with regards to firm size were mixed, innovation was generally associated with larger firms however, importantly, Crépon, Duguet and Mairesse. (1998), found no significant impact from firm size on innovation output in French firms, likewise Janz et al (2004) found no impact for Swedish firms and a negative impact for German firms and Roper et al. (2006b) reported that size had no impact on product innovation but a positive effect on process innovation. Jefferson et al. (2006) also found that the elasticity of new product sales with respect to R&D expenditure declined with firm size in China.

Appropriability conditions are noted in the theoretical literature as being important for innovation activities in that firms are more likely to innovate if they can protect the innovation and thus derive the benefits from it (Arrow, 1962, Spence, 1984, Becker and Peters 2000) however again the findings from the empirical literature were not conclusive. Those confirming the proposition included Castellacci (2011) who reported that the complex design of new products was important in the commercialisation of the innovation for Norwegian firms and Alavrez et al (2010) who reported that patenting activity as a means of protecting the innovation were strongly associated with higher innovative activity across six South American countries. Alternatively Griffith et al. (2006) found that the ability to protect an innovation through formal or strategic methods was less important for process innovation than for product innovation, and that neither were important for the UK and Janz et al. (2004) found that such protection measures were only significant in Sweden, with no impact on German firms' likelihood of spending on innovation.

The final stage of the model – the output production function – is perhaps of most interest as it captures the impact of innovation activity on the firm performance variable, here productivity. Importantly, the results of this stage were somewhat mixed across the empirical studies. There were notable differences depending on whether the productivity measure was in levels or whether it concerned productivity growth, with stronger impacts generally found for productivity levels. There were also differing results for product and process innovation, the latter typically having less, none or a negative impact on productivity levels but a generally positive impact on growth. This finding is perhaps surprising as we would generally anticipate that process innovation leads to efficiency improvements in the production process and thus would lead to an increase in both productivity levels and productivity growth.

Crépon, Duguet and Mairesse (1998), the originators of the model, estimated the output equation as the impact of knowledge capital on productivity (and included a further advanced model controlling for labour quality). The results revealed constant returns to scale; the estimated elasticity of knowledge capital was 0.13 when proxied by the number of patents and 0.1 when proxied by the share of innovative sales. In their extended model skill composition variables were found to be highly significant, with a coefficient of 1.7, implying the productivity of engineers and administrators were higher, by a factor of 2.7, than the other categories of employees. The estimated elasticities of knowledge capital decreased by one third when these controls for skill were included, thus the estimated elasticity of the number of patents dropped to 0.09 and the number of innovations to 0.06. Similarly, Jefferson et al. (2006) found that after controlling for inputs of capital, labour and materials, new product sales were associated with higher productivity; the estimated elasticity of output with respect to new product sales 0.04 which translated into an 18 cent increase in output for every one dollar increase in new product. The marginal productivities of new products were furthermore found to be comparatively high in the state owned sector.

Other positive and significant findings with respect to productivity levels included Crespi and Zuniga (2012) reporting on a study of six South American countries, who found that technological innovation was positively associated with labour productivity for all except Costa Rica; the coefficients ranging from 0.24 to 1.95; the relatively high elasticities a result of the use of dummy variables as well as higher rates of return for developing countries. Castellacci (2009) reported a positive impact from product innovation to labour productivity in Norwegian firms, with coefficients ranging from 0.24 to 0.56 depending on the methodology used. Mairesse et al. (2012) reported positive elasticities on labour productivity ranging from 0.24 to 1.11 across four different sectors in China and Correa et al. (2005) reported that a 10 per cent increase in the portfolio of new products increased value added by 5 per cent in their sample of Brazilian firms. Chudnovsky et al. (2006) furthermore found that labour productivity (measured as sales per employee) was 14.1 per cent higher for Argentinian innovators than non-innovators; Arza and Lopez (2010) also reporting on Argentina, found that technology innovators had 17–27 per cent higher labour productivity than non-innovators.

Criscuolo (2009) looked at the relationship across 20 countries and reported a positive and significant coefficient from sales from product innovation (per employee) on productivity in all but one country, Switzerland. The coefficients ranged from 0.3 to 0.7 and they summarised that

> *"On average, across this universe of heterogeneous innovating firms in different institutional contexts, a 1% increase in firms' innovation sales per employee is associated with a productivity increase of 0.5%" (Criscuolo, 2009, pg. 120).*

Their findings with regards to the impact of process innovation were less conclusive, and except for Austria, the coefficient was either not significant or was negative. These, perhaps surprising, findings were explained as being possibly due to the adjustment costs and associated learning involved with process innovation which may result in temporary lower productivity. Alternatively, they suggested that firms may be more likely to introduce process innovations in times of difficulty or during lower production cycles due to the lower opportunity costs and hence the greater expected gains. Their findings were consistent with previous studies such as Griffith et al. (2006) who found significant positive effects from product innovation on labour productivity in three out of four European countries (with elasticities ranging from 0.06 to 0.18) but a significant effect from process innovation in just one of the countries (France), with an elasticity of 0.07.

Other studies reporting no impact from innovation on productivity levels, or a mixed impact when spilt into product and process innovation include Benevente (2006) and Alvarez et al. (2010) for Chile, the latter reporting no impact from product innovation, but a positive impact for process innovation. Raffo et al. (2008) who reported no impact from product innovation on labour productivity in Argentina but significant impacts for Brazil and Mexico; Mairesse and Robin (2010) for France who found only significant impacts for process innovation but not product innovation, and Hall et al. (2011) who reported a positive and significant effect for product innovation but a negative significant impact for process innovation for Italian firms.

Hall (2011) summing up the empirical evidence reports that where innovative sales have been used as the measure of innovation output the elasticities with regards to productivity levels for Western European countries generally lie between 0.09 and 0.13; where a dummy variable has been used for product innovation the values range from 0.05 to 0.10, whilst for process innovation the results are too inconclusive to arrive at a summary range.

With regards to the impact of innovation on productivity growth, rather than levels, the reported elasticities are not as strong; however there appears to be more favourable results with regards to process innovation. Parisi et al. (2006) find that process innovation has a large impact on productivity growth; the estimated coefficient lying between 0.11 and 0.17; in contrast product innovation has no significant effect. Goedhueys (2007) also reports no impact from innovation on TFP growth in his Brazilian study. Freel (2000) reports on small innovating firms in the West Midlands region of the UK and finds higher productivity levels for innovative firms, although no impact on productivity growth. He also suggests that his findings point towards higher returns to innovation for larger firms. Chudnovsky et al. (2006) find that innovation has a positive impact on productivity growth amongst Argentinian firms when it is measured as a combination of product and process innovation (with an elasticity of 0.14) however when considered on their own only process innovation has an impact. Huergo & Jaumandreu (2004) report on process innovation only and find there to be an immediate impact on TFP growth, with an elasticity of 0.015, however they find that this effect declines over time. Loof and Heshmati (2006) find that productivity increases with an increase in innovative sales per employee, with an elasticity of 0.07 for manufacturing firms and 0.08 for service sector firms. Cassoni and Ramada-Sarasola (2010) in their study of Uruguay report that a 10 per cent increase in the degree of relevance of the innovation product results in an increase in the growth rate of labour productivity of 3 per cent, with a 5 per cent increase for process-only innovators.

Criscuolo and Haskel (2003) make a distinction between novel and non-novel innovations, with some interesting results. They find that novel process innovations reduce total factor productivity growth initially, whilst non-novel process innovation raises it; and the overall effect is positive. They suggest the reasons for this are that novel process innovations take time to be implemented, leading to a fall in measured productivity growth initially. Their findings for product innovation are less conclusive; in general the effect of product innovation is positive but in terms of the weight of point estimates there are mixed findings. Duguet (2006) taking a similar approach also finds that only radical innovations increase TFP growth, with no effect from incremental innovations.

Interestingly Huergo and Moreno (2010) point out that the effect on TFP growth is significant for product and process innovation but only when persistence in innovation is not taken into account; when it is the effect from process innovation drops by around 50 per cent (the coefficient dropping from 7.2 to 2.7) whilst there is no longer an effect from product innovation.

Damijan et al., (2008) highlight the importance of distinguishing between the impact on productivity levels and productivity growth. For their sample of Slovenian firms they report evidence of a positive link between firm productivity levels and their propensity to innovate, however evidence for a positive correlation between innovation activity and productivity growth is less conclusive and depends largely on the econometric methodology employed. Their standard OLS estimates provide some empirical support for a positive impact of innovation on productivity growth but robustness checks, which include estimating the regression at various quintiles of firms by their characteristics, suggest that the results are due largely to the exceptional performance of a specific group of service sector firms. Indeed further robustness tests, which include estimation by matching techniques, do not find any evidence for an effect from innovation to productivity growth and this holds for both product and process innovation.

Again summarising the relevant literature Hall (2011) concludes that the impact of innovation on productivity growth is generally lower than for the level version of the equation, with an innovative sales elasticity of 0.04-0.08, and a product innovation dummy of about 0.02. As suggested above she also reaffirms the point that the effect from process innovation is typically negative when included with product innovation in the equation, although positive when considered on its own. This latter conclusion is likely to reflect the fact that, due to a demand effect, product innovation may likely result in employment growth (at the expense of productivity growth), while process innovation is likely to have labour saving effects (increasing productivity growth); when considered together the effect on productivity growth could thus be either positive or negative depending on which of the innovation types is stronger.

The lack of consensus across the literature on this final stage of the model may thus be attributed to the exclusion of certain key variables (such as persistence), as noted above, or due to the methodologies employed. In fact it is noted that where negative process innovation effects have been found that the period of analysis has typically been only over a short (usually two year) period. This leads into a key issue, which is highlighted by Knell and Nas (2006), and which is of particular concern for those studies which have used the CIS, that of timing issues. The CIS questions regarding innovation inputs and outputs refer to activities undertaken by the firm over a three year period, and thus to link the inputs and outputs one has to make assumptions that current innovation efforts are a continuation of past efforts. However Raymond et al. (2006, 2010) has suggested that there is limited evidence for persistence in innovation effort and thus it cannot be assumed. Thus unless the authors have been able to build the CIS responses across a number of waves into a panel dataset, then the results when measured in one cross-section, are open to question. In addition where the impact on productivity is measured across the same time period or slightly later time period means that the dynamic cannot be traced; the inability to include lags in the model is of key importance and may explain the lack of impact on productivity levels or growth as found in certain studies.

4.11 NI Empirical Evidence

Despite the continued policy focus on innovation and a number of studies examining innovation activities in NI, few studies actually confirm the positive impact of innovation on productivity at the firm level. Harris and Trainor (1995) were one of the first to look at the determinants of innovation activities amongst manufacturing firms in NI, and specifically the links between R&D and innovation. They focused on the impact of profitability rather than specifically on the productivity impacts, and found that firms with higher levels of R&D spending were more likely to innovate, and that innovating firms experienced, on average, 17.5 per cent higher excess profits (as measured by the price-cost margin) than non-innovating firms. This, they concluded, suggested that R&D and innovation outputs are positively linked to the long term growth of firms.

Roper and Love (2004) looked at the innovation impact on four measures of business performance in the Republic of Ireland and NI, namely profitability levels, productivity levels, sales growth and employment growth, whereby innovation was measured as the percentage of sales derived from new products, and termed ‘innovation success’. They found positive and significant results for the effect of innovation success on sales and employment growth, no effect on profitability and a significant (but very small) negative effect on productivity. This latter effect explained as likely due to disruption or timing effects caused by the introduction of new products. In a similar study Roper et al. (2006b, 2008) used a CDM-type approach and focussed on the impact of innovation on productivity levels, sales growth and employment growth amongst manufacturing firms in NI and the RoI. In this study innovation was again measured as innovation success, but dummies for product and process innovation were also used. The authors found that product and process innovation had a strong positive impact on sales and employment growth however they found insignificant process innovation effects on productivity and negative product innovation effects. The latter findings were again explained as resulting either from a 'disruption' effect whereby the introduction of new products to a plant may disrupt production and hence reduce productivity, or as a product-lifecycle type effect whereby newly introduced products are initially produced inefficiently with negative productivity consequences before becoming established through process innovations to improve productive efficiency. Importantly, they suggested that their results may have been affected by the methodology used; that by pooling the data, as opposed to utilising panel data estimation, they may have reduced the ability to allow for lagged innovation and performance effects which could have reversed the negative productivity impact from product innovation.

In later studies concentrating on the service sector in Northern Ireland Roper et al. (2007) and Love et al. (2010) used the CIS and merged it with the Annual Business Inquiry to look at the determinants of service innovation, and its subsequent impact on business performance. They found service sector innovators to be more likely, than non-innovating services firms, to be exporters; to have higher labour productivity and higher sales per employee than that of non-innovators, and to have faster sales and employment growth than their non-innovating counterparts. However, they found that innovation in itself had no direct impact on productivity or productivity growth which was similar to that found for business services in the US (Mansury and Love, 2008). This finding, they suggested, may be due to the fact that the impact of service innovation on productivity takes longer to manifest itself than the period they were able to observe. Importantly, they also found that both R&D and exporting were positive and significantly related to productivity and productivity growth and thus they concluded that there is an indirect link between innovation and productivity via exporting, which is underpinned by performing R&D.

4.12 Summary

Endogenous growth theories have been developed over the last thirty years to explain the relationship between knowledge, innovation and the long-term growth of the economy; their development arising due to a need to explain the source of technical change which Solow had credited as key to economic growth but which had previously been considered as being exogenously determined. Endogenous growth theories are based on micro-economic principles and provide the rationale for the profit-maximising firm to engage in innovative activities which are risky to undertake due to uncertain outcomes. Firms can undertake innovative activity to enhance or defend their competitive position; process innovation improving productivity and allowing the firm to gain a cost advantage over its competitors, and increased market share; and product innovation enabling the firm to capture monopoly rents and thus hold temporary power over competitors until the product can be imitated. The theories also provide reasoning as to how investment in human capital leads to increased wages for the profit-maximising individual and how this leads to long-run increases in living standards and generates additional demand in the economy.

With regards to productivity growth the theories suggest that there is an effect at both the firm level and the economy-wide level. Through learning, firms are able to produce output more efficiently and thus increase their productivity, either by improving the processes they use or through the use of innovative intermediate goods which are more specialised or of a higher quality than those used previously. At the macro-level the temporary monopoly power that can arise through the innovations incentivises other firms to also invest in innovative activities, producing a continuous cycle of innovators. This cycle of ever-increasing technologically advanced firms entering the market results in a loss of market share for incumbent firms, and an eventual exit from the market; their exit raising the overall level of productivity in the economy, this element of the theory reinforcing the Schumpeterian notion of creative destruction.

Given the importance of innovation in increasing productivity and long-run growth the theories furthermore underline the need for government intervention in situations where there would be underinvestment in innovation due to the benefits being only weakly appropriable, or where there the knowledge would spill over outside the firm.

Empirical evidence examining such links between knowledge, innovation and productivity suggests a positive relationship between spending on R&D and undertaking innovative activity. The subsequent relationship between innovative activity and productivity growth is perhaps less well substantiated. In general, product innovation has been found to increase productivity levels but not necessarily productivity growth; whilst process innovation is associated more-so with productivity growth, although with less of an impact, if at all. The finding suggests that the intended outcome of product and process innovation may be competing; the former potentially generating additional demand which is employment enhancing for the firm, and the latter generating labour savings. As a result of this dual effect the overall impact on firm-level productivity is largely dependent on the nature of the innovation i.e. product or process; the intended outcome and a sufficient time lag to evidence its impact.

The studies looking at the impact of innovation on productivity growth in NI have overwhelmingly found no evidence of a direct positive link. Rather the effect from product innovation has been typically negative, and suggested either a disruption effect, or a need to measure the effects over a longer time period. The impact from process innovation has also been reported as insignificant. Instead the studies found that any effects from innovation to productivity were indirect in nature and only found when the firms undertook innovation in conjunction with exporting.

Given the lack of support for the productivity-enhancing aspect of innovation theory at the NI level, and the overall mixed messages of support across the empirical literature, the innovation-productivity relationship warrants further investigation. This is particularly important for NI, whereby policy has been specifically focussed on increasing innovation activity amongst firms, as a means of both raising their productivity and overall productivity growth in the economy. The hypotheses derived from this literature will follow the augmented-CDM model; firstly focusing on the firms that undertake R&D, and specifically whether they exhibit certain characteristics.

H1: Firms that invest in R&D are more likely to be larger, more productive and have more skilled employees

H2: Firms that invest in R&D are more likely to be exporters

The relationship between innovation activity and its determinants will then be examined; firstly testing the relationship between R&D (as an innovation input) and innovation outputs, and secondly, testing whether R&D activity in firms is associated with government assistance due to the associated risk and appropriability issues.

H3: Product and process innovation is positively affected by R&D expenditure

H4: Firms that innovate are more likely to have received government assistance

Finally the relationship between the outputs of innovation activity and productivity growth will be estimated. The results of the latter seek to add to the existing empirical knowledge where there remains a lack of consensus on the nature of the impact and whether it is of a direct or indirect nature. The results will also be useful in a NI context in providing a more robust evidence base for policymakers, given the sustained emphasis on innovation activity within economic policy circles:

H5: Innovation (measured as either product or process) has a positive effect on productivity growth.

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Sub-Section C: Impact of Public Financial Assistance on Productivity Growth

4.13 Introduction

The provision of government assistance to firms is a feature of most economic policies around the world. Typically the argument for government intervention is to overcome some type of market failure or address specific business need, for example SMEs and start-ups are often viewed as most in need of assistance due to their limited internal resources and perceived vulnerability to external competition (Holm-Pedersen et al., 2009). However, despite the prominence of these policies, research analysing the impact of government financial assistance on firm performance is still somewhat limited due to a lack of required data, and/or or due to the difficulties in isolating the effects of subsidies from the confounding effects induced by other factors (Bernini and Pellegrini, 2011). Where the effects have been estimated problems concerning endogenous participation and selection bias have to be overcome, which is not always possible, particularly when seeking suitable instruments to properly identify the models (Criscuolo et al., 2012). The actual impact of the value of subsidy is also not always possible to estimate with most studies estimating the assistance impacts through the use of dummy variables (Girma et al., 2007).

The aim of this section is to introduce the theoretical reasoning behind government intervention in the economy, and specifically, the justification in terms of why it is needed to help increase the productivity of firms. This is followed by a discussion of the relevant empirical literature in which the impact of grant assistance, or business subsidies, on firm-level productivity has been estimated. The resulting conclusions of the empirical literature will be used to develop the key hypotheses for testing in a NI context, underpinned by the theoretical arguments. Areas of dispute or unanswered questions from the empirics will form the basis for the hypotheses.

4.14 Market Failure

A key argument for the justification of government interference in the economy lies in the ‘market failure’ concept. Neo-classical economic theory suggests a world with certain idealised conditions, namely perfect competition in which no participant influences the price of the product it buys or sells; where there is perfect information and where entry and exit to the market is free and available to everyone. According to the first fundamental theorem of welfare economics, when these conditions are met it gives rise to a Pareto optimal outcome i.e. labour, land and capital are used efficiently in such a way that it would not be possible to use them in a different way to make someone better off without making someone else worse off. The welfare theorem thus supports the case for letting the market do the work, and therefore suggests there is no need for any intervention[26]. Market failure is said to arise however when such an unregulated market is unable to achieve, in all circumstances, such allocative efficiency, thus resulting in a waste of some resources.

The market failure can take a number of different forms; Stiglitz (1988) identifies five conditions relevant to the market for goods and services, under which the market is not Pareto efficient: uncompetitive or monopolistic market structures; public goods; externalities; incomplete markets; and finally, information asymmetry. Government intervention is said to be justified if it can counteract the inefficiency arising from such market failures and provide a welfare-enhancing outcome[27].

Taking each of the market failures in turn, a summary of the justification for government intervention is provided. Uncompetitive or monopolistic market structures are thought to act against the public's interest and generate more costs than benefits. The lack of competition can result in productive inefficiency, whereby, without competitors, there is no incentive to reduce average costs to a minimum. Likewise there may be allocative inefficiency, in that monopolists can be price makers rather than price takers, and set prices well above marginal costs. Monopolistic market structures also result in less choice and restricted output for consumers. Government intervention may thus be justified, in this case, to increase the number of competitors in order to prevent firm(s) from dominant positions that are immune from the self-correcting forces of the market mechanisms. As stated above, for the welfare theorem to be proved, the market has to do the work, and this can only happen when sufficient competition exists.

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[26] The first theorem of welfare economics is cited as the analytical confirmation of Adam Smith's 'invisible hand' hypothesis, whereby competitive markets tend towards an efficient allocation of resources.

[27] Of course, government intervention may not always lead to a Pareto-optimal outcome; in fact, the intervention can lead to a more inefficient allocation of goods and resources, a term known as government failure (McKean, 1965).

Public goods are those for which the total cost of production does not increase as the number of consumers increase. They have two distinct features; one person's consumption does not reduce the amount available for someone else i.e. it is non-rivalrous; and no one can be excluded from sharing the consumption of such a good even if they refuse to help towards the cost i.e. it is non-excludable. The existence of public goods thus gives rise to the free-rider problem, in that an individual or firm has insufficient incentive to pay for a product when the payment has no impact on the quantity of the product that is consumed. It pays for everyone to free-ride and therefore little or no revenue would be raised from the sale of a public good if it was privately provided. Government intervention is thus justified in this case to provide the public good, paid for through taxation.

Externalities arise when the production or consumption of a resource has an effect on the cost of a producer, or on the utility of a consumer, who are not concerned with the activity, and which is not taken into account by the party undertaking the activity. It is the discrepancy between private benefit and social cost and its presence causes output to diverge from its socially optimal level. Negative externalities can arise when an individual or firm does not bear the costs of the harm it imposes, whilst positive externalities arise when an individual or firm provides benefits for which it is not compensated. Government intervention can be used in the presence of externalities to establish private property rights (Coarse, 1937) or to encourage bargaining between the parties concerned, either through taxes (for negative externalities), subsidies (for positive externalities) or through regulation (Pigou, 1932).

Incomplete markets arise when the private sector supplies only part of the whole market demand. In order to achieve complete optimality there has to be a market in which each good and service can be traded to the point where marginal benefit equals marginal cost. Incomplete markets are typically experienced in markets where there is risk, for example the insurance and credit markets, due to the problem of adverse selection. The provision of credit from private finance providers is one such example, whereby firms may have limited access to credit due to a) inadequate collateral; b) constraints on the supply of funds from other private sector benefactors, and high interest rates; and c) the inherent risks associated with new firms or new projects resulting in the reluctance to lend, or a restriction on the amount of finance available. In this instance government may intervene to subsidise inputs so as to lessen the need for such credit.

Information asymmetry is a problem in that the availability of information is an essential part of efficient market behaviour. Incomplete information means that producers or consumers are unlikely to secure the maximum amount of utility from a product that they would secure with perfect information. Information is often regarded as a public good, as once the information is provided to one individual, it does not reduce the amount available to others. The ease with which others can then access the information makes it difficult to charge users enough to cover the costs of production, such a scenario results in the private sector producing too little information. In addition, where information is not a public good, market failure can still arise due to moral hazard, where one individual in a transaction takes advantage of the special knowledge in ways that change the nature of the transaction itself. Government intervention can thus be justified if positive externalities arise through the dissemination of information by government, for example on starting a business, accessing export markets, or accessing finance.

4.15 Government Intervention and Productivity Growth

The main aim of government intervention with regards to productivity is to promote its growth. The theoretical arguments that specifically justify the need for government assistance in achieving this growth are based on the arguments above, and can be summarised by Beason and Weinsten (1996) who group them into three categories, namely, Schumpeterian, Marshallian and strategic trade arguments. The Schumpeterian case suggests the need for the subsidisation of technological development and is based on two types of market failure. Firstly, knowledge is a public good and therefore the returns to investment in knowledge and innovation for one firm may spill over to others and thus lower the incentive to invest. Alternatively, the private benefits from investing in innovation may be lower than social ones and thus lead to an under-investment in innovation. Secondly, there is the problem of incomplete markets; investing in innovation can be a risky and uncertain business which the external private sector may not be willing to finance. In this case innovation can only be undertaken by large firms who dominate product markets and who can take advantage of economies of scale in the R&D process. Technological progress is thus driven by large firms, with small and start-up firms finding it difficult to raise the necessary finance in external capital markets. In such cases, where there is an underinvestment in innovation, government may support R&D expenditure; subsidize knowledge producing sectors, and grant firms temporary monopolies by protecting intellectual property. Innovators can thus take monopoly rents, giving them greater incentives to invest in new technologies and processes.

Marshallian theories promote infant industry protection for those sectors or industries that exhibit local externalities which increase with the size of the industry. Such protection can allow the firm or sector to develop its comparative advantage thus giving rise to economies of scale, network effects and agglomeration economies, all of which can lead to increases in output and productivity. Finally strategic trade theories argue that in order for productivity to increase, domestic firms must be protected from foreign firms if they are not as efficient or because of market failure they are unable to grow. Under increasing returns to scale, productivity growth can arise when import protection is used as export promotion (Krugman, 1984). Alternatively government R&D subsidies can be used to help domestic firms capture rents from their foreign competitors, particularly for high technology sectors (Brander and Spencer, 1983).

It is naturally assumed that government intervention to counteract the inefficiencies arising from this market failure will result in a positive outcome; however this is not necessarily the case. In fact government failure can arise when the intervention results in inefficiencies. Hoekman and Javorcik (2004) suggest that in order to take advantage of government intervention firms may purposely underinvest so that they are awarded subsidies; such subsidies may result in corruption, bad corporate governance, and rent seeking behaviour. Harris and Trainor (2005b) furthermore state that intervention can result in allocative inefficiencies if firms are encouraged to invest, through lower relative capital costs, leading to an overinvestment in capital. In addition, unless the subsidies result in additional investment expenditure it can lead to deadweight and displacement effects and a culture of rent seeking. They further suggest that subsidies can lower efficiencies as firms become over-reliant on them, and have no incentive to improve their own performance.

4.16 Empirical Findings on Public Assistance and Productivity

Whilst the theoretical arguments can be made in terms of justifying government intervention the empirical evidence of its success, in terms of its impact on productivity growth, is relatively unfavourable; most studies rely on whether a firm took part in a programme rather than analysing the impact of the actual payments or subsidies received (Girma et al., 2007) and few studies find conclusive evidence of a positive relationship between assistance/subsidies and productivity growth. Instead the evidence suggests that intervention can in fact hamper productivity growth by preventing the exit of inefficient firms, particularly when it is targeted by lobbying towards less productive declining industries.

Beason and Weinstein (1996) were one of the first to use aggregated data to examine the impact of industrial policy tools on Japanese mining and manufacturing firms between 1955-90. They explored how tariffs, loans, subsidies and corporate tax breaks had been used to target sectors and the impact this had had on total factor productivity. Overall they found little evidence that these policies positively affected productivity growth, and in fact they suggest that this occurred because policies were targeted wrongly, in that they sought to aid declining sectors and protect large unproductive industries. Likewise Lee (1996) examined the impacts of industrial policies such as tax incentives, capital subsidies and credit policies on the productivity growth of firms in the Korean manufacturing sector. He found that whilst tax incentives had a positive impact on output and capital growth, there was no such impact on TFP growth. He concluded from his findings that industrial policy may in fact have decelerated growth in the country due to the targeting, and resultant protection, of low productivity industries.

Early work on the UK's main government support scheme to businesses, that of Regional Selective Assistance (RSA) focussed on the employment effects and associated cost-per-job (see King, 1990; Swales, 1997; Wren, 2005). Harris and Robinson (2004) were the first to examine the impact on output; their study examining the effects of two UK government industrial support schemes, RSA and the Small Firm Merit Awards for Research and Development (SMART) on the total factor productivity (TFP) of British manufacturing plants between 1990-98. They found that when comparisons were made between RSA-assisted plants and those in the whole of Great Britain that assistance did improve productivity compared to average levels. However, when the comparison group was restricted to only include other plants within assisted areas then RSA assistance did not significantly improve plant productivity (although there was an effect for certain sectors and for Scotland). Additionally firms in receipt of SMART support did not experience any improvement in performance, although the authors argue that this may be due to the fact that the benefits from this scheme would be expected over a longer time frame than was analysed.

The impact of RSA and its successor, Selective Finance for Investment in England (SFIE) was also evaluated by Hart et al. (2008). Using RSA data from 2000-2004 they examined the impact on employment growth, sales growth and productivity growth for 2004-06, using both econometric and case study evidence. A number of econometric approaches were used such as OLS, Heckman selection and Instrumental Variables, for both robustness purposes and also to take account of issues concerning selection bias (amongst UK single-site firms) and endogeneity (amongst multinational firms (MNEs)). In general, across the different estimation techniques, RSA was found to be positively related to employment growth however the size of the RSA grant was not found to significantly affect employment growth in general, but did impact employment growth in single domestic plants (a 10 per cent increase in grant size increased subsequent employment by less than 1 per cent) and for MNEs, (a 9 per cent increase in grant size increased subsequent employment by 1 per cent). Notably, the selection methods indicated that, amongst UK single-site firms, support was given to those who performed worse than average. The impact on sales and productivity growth was estimated using the self-reported case study evidence; approximately 80 per cent of RSA recipients stated sales improvements, and the same share cited productivity improvements as a direct result of the assistance.

Criscuolo et al. (2012) also focussed on the impact of RSA in the UK, and in particular its effect on employment, investment, productivity and entry and exit. Using a matched dataset covering the period 1985-2004 they employed an instrumental variable approach, with area-level eligibility as the identification variable. They found that RSA increased investment and employment, particularly for small firms, but once an increase in these factor inputs were controlled for there was no causal effect on total factor productivity. In fact, they found that firms that received RSA were relatively large and had low productivity prior to receiving the assistance, thus RSA actually dampened reallocation effects from more productive to less productive plants and lowered aggregate productivity growth across the economy.

Koski et al. (2013) reported similar findings for their sample of Finnish firms. Using three different types of government subsidy, namely R&D, employment and other (which typically targeted investment or expansion) they looked at the impact on productivity, using both an instrumental variables approach and a conditional difference-in-difference approach; the former using annual government budgets for each type of subsidy as instrumental variables for the endogenous subsidy variables.

The results of the instrumental variables model suggested that R&D subsidies had no impact on labour productivity, while employment and other subsidies were negatively related to labour productivity. Using the difference-in-difference approach they found no impacts from any of the subsidies even up to five years after receipt of the subsidy. Instead, they found that those firms that had received subsidies were less productive than firms on average, prior to the receipt of employment and/or other subsidies. They concluded that employment and other subsidies tended to be targeted to less productive firms, and that this prevented their exit from the market, hindering the process of creative destruction.

Further studies focussing specifically on R&D subsidies include Sorenson et al. (2003) who looked at the impact of public support for innovation on private R&D and productivity in Danish manufacturing firms. They found that whilst public support increased expenditure on R&D by firms, it had an insignificant (although positive) long run effect on productivity. Irwin and Klenow (1994) also looked at the impact of high-tech R&D subsidies on a consortium of 14 leading US semi-conductor producers, known as Sematech. They also were unable to provide any definitive evidence of a productivity effect.

Other studies reporting no impact or a negative impact on productivity growth include Morris and Stevens (2010). In their study of New Zealand firms from 2000-2006 they find that participation in a government programme has a positive effect on sales, particularly for those receiving assistance prior to 2004, but they find no effect on value added or productivity. They do recognise however that their results are sensitive to methodology used. Similarly Pellegrini and Centra (2006) and Bernini and Pellegrini (2011) using a matched difference-in-difference approach on firms in Southern Italy find that labour productivity growth is slower in assisted firms, the latter study reporting that productivity growth and labour productivity are around 8 per cent higher in non-subsidized firms. They suggest that this may be due to the fact that firms increase their employment in order to gain a subsidy, as a higher employment level puts them higher up the ranking. However they suggest that the results highlight the trade-off that firms have with regards to employment growth and productivity growth. In addition they also note that there are methodological limitations in their study, specifically that the performance of new firms or start-ups cannot be evaluated.

Martin et al. (2011) looked at the impact of public policy to promote industrial clusters on the productivity of French firms. Using a difference-in-difference approach they found that firms that were supported through this cluster policy, denoted as being in a 'local productive system' or LPS, were less productive than other firms, and that they had a negative and significant drop in productivity once they became a member of this LPS. They noted that their methodology did not control for the fact that such LPS firms were on a downward trend prior to receiving the benefits of the policy however when this was controlled they found evidence at best for a weak, short-run effect. As with the other results above, they suggested that their results were consistent with a political economy interpretation in that the objective of the policy was to protect some large firms in declining regions and sectors.

Bergstrom (2000) was one of the few empirical studies to report a positive relationship between public subsidies and productivity. He examined the effects of government capital subsidies on firm level productivity in Sweden over the 1987-93 period. Using panel data on both subsidised and non-subsidised manufacturing firms he found that subsidisation was positively correlated with productivity growth but only for the first year after subsidies were granted. After that, the more subsidies a firm received, the worse its total factor productivity growth. He therefore suggested that although there may be market failure arguments for offering subsidies, it is not certain that resources will be efficiently allocated upon their receipt, confirming the proposition made by Harris and Trainor (2005b).

Duch et al. (2009) using a propensity score matching approach on Spanish firms also found a positive link between public subsidies and value added. Focussing specifically on R&D subsidies and using a two stage approach they found firstly that assisted firms had 3.5 – 5.6 per cent higher value added growth rates than non-assisted firms. To test the robustness of these results they re-ran the analysis with three additional types of control group; again they found a positive and significant effect from the public assistance variable on value added growth, with an elasticity of around 10 per cent. They also found that larger firms, exporters, and those with a lower initial value added had faster growth. Importantly, they noted that there may have existed other factors that they could not control for, which influenced the productivity impact, including the receipt of other forms of financial assistance by the firms in their study.

In a novel study Girma et al. (2007) investigated whether government subsidies stimulated productivity growth in manufacturing plants in the RoI over the period 1992-98. Their paper was unique in that they had data on all grant payments that were made to plants and thus were confident that their results were not biased due to other unobserved financial assistance payments. In this way their paper represented a departure from other similar studies, and was also unique in that the grant payment data was used in the model rather than assistance being measured simply as a dummy variable. Their results showed that when all the grant payments were added together as a total in any year they had no significant impact on total factor productivity growth. However, when the grants were categorised into whether they were likely to affect productivity directly or not, it was only those that were likely to be directly productivity enhancing that had a significant positive impact. The effects of productivity enhancing grants were also found to be higher in those plants that were most financially constrained, up to a certain point.

In a similar vein Colombo et al. (2011) and Grilli and Murtinu (2012) also distinguished between different types of subsidy in their respective studies, and again reported only significant results when the subsidies were separated in this way. Colombo et al. (2011) examined the impact of R&D subsidies on the TFP growth of New Technology-Based Italian firms, distinguishing between automatic and selective subsidies. Using a GMM-system estimator, with instrumental variables, they reported no effect on TFP growth when all subsidies were combined. However when they were separated they found that only selective schemes had a significant positive impact, with an estimated TFP increase of 31.4 per cent.

Grilli and Murtinu (2012) adopted a similar approach although extended it further, analysing the differential impact of selective and automatic subsidies according to the goal of the subsidy (R&D-enhancing versus others) on a sample of Italian New Technology-Based Firms. Using a GMM-system estimator to control for endogeneity of the subsidy they also found that when subsidies were lumped together they did not have a significant positive effect on firms' TFP growth, however when subsidies were split into selective versus automatic, and R&D-enhancing versus others (such as those supporting employment growth, job training, and general purpose investments) that only the R&D enhancing selective schemes had a significant positive impact, increasing TFP growth by 24.5 per cent. Interestingly, they also reported that such selective awards have indirect beneficial effects, beyond the amount of the subsidy, in that they provide a 'certification effect' to third parties as to the quality of the firm.

This ‘stamp of approval’, as proposed by Lerner (2002), makes it easier for them to obtain external additional resources due to the lower perceived investment risk. Interestingly, they noted that the use of the actual amount of the subsidies received, as opposed to the use of dummy variables, would have further enhanced their study by allowing for direct and indirect effects to be separately estimated and would have also enabled them to test whether the relationship between subsidies and TFP growth was non-linear.

4.17 Empirical Evidence for NI

Given the historical importance of employment creation in the Northern Ireland policy arena most of the early evaluation work on the effect of government assistance tended to focus on the impact on employment, with the impact on turnover growth investment and exports also eventually being considered (see Gudgin et al, 1989; Hamilton, 1990; Sheehan, 1993; Hart and Hanvey, 1995; Hart and Scott, 1994; Roper and Hewitt-Dundas, 1998, 2001; Hart and Gudgin, 1997,1999; Hart et al., 1998; Bonner and McGuinness, 2007). Overall there has been less work focusing on the productivity impact; those studies that did focus on productivity tended to look at the effects of grant assistance on small firms only (Hart et al., 2000, Hart and McGuinness, 2003; McGuinness and Hart, 2004) and found mainly employment impacts but little or no effect on productivity growth. It is only relatively recently that productivity has become a prominent feature of the evaluation work, although to date the number of academic studies on its relationship with grant assistance is relatively sparse.

Early examples of the evaluation of public policy support for small firms were based largely on comparisons of the performance of groups of assisted and non-assisted companies (Gudgin et al, 1989, Hart and Hanvey, 1995, Hart and Scott, 1994), with a substantial employment growth differential usually identified between the two groups. These studies, whilst indicative, were criticised by Roper and Hewitt-Dundas (1998) as having a number of limitations, for example, although an employment growth differential was generally found, the statistical significance of these differentials was not usually established; the studies also tended to focus on employment growth, with little or no attention given to the impact on turnover or profitability growth; where it was found that assisted firms grew faster than non-assisted firms it was not made clear whether this reflected the benefits of assistance, a tendency for faster growing firms to select themselves for assistance or whether assistance was successfully targeted on faster growing firms (selection bias); finally, the studies made no attempt to differentiate between the different types of assistance which may have been received. It was only in the late 1990s that the evaluation process began to use more sophisticated techniques in order to properly assess the impact of government policy.

A paper by Roper and Hewitt-Dundas (1998) was one of the first to evaluate the impact on business performance of different types of grant support, using a methodology which overcame many of the previous limitations. In particular the paper examined the structure of grant support for small firms over the 1991-95 period and assessed its impact on a range of performance indicators. Using the approach adopted by Bates (1995), the paper also separately identified the selection and assistance elements of the performance differential between assisted and non-assisted firms, a feature which the previous literature on NI firms had failed to take into account, but which was one of Storey's six steps in the evaluation process (Storey, 1998). The dataset utilised in the analysis contained information on small firms in NI and the RoI over the 1991-95 period, and was taken from the Competitive Analysis Model which conducted interviews with small firms between April and September 1995.

Around half of all small firms in NI and 29 per cent of those in the RoI were found to have received some grant support over the 1991-95 period. Cluster analysis was used to profile the type of grant aid that firms were receiving; the results suggested there were three assisted clusters in NI and two in the RoI, each with a differing degree of the amount of support received. Comparison of these assisted firms against the non-assisted group, in terms of characteristics, revealed that the assisted firms tended to grow faster, be more profitable and more active in terms of sales, market and strategy development than non-assisted firms. In order to test whether the improved performance of the assisted group was due to their underlying characteristics or whether the assistance they received was driving their performance, selection models were estimated for turnover growth, employment growth and return on assets. The analysis revealed that the selection terms were largely insignificant, although there was some evidence that in NI assistance was focussed on firms with above average productivity growth. The effects of assistance on turnover growth and profitability were also insignificant, suggesting that the difference between assisted and non-assisted firms was due to their business characteristics rather than the assistance they received. However an effect was found for employment growth, with grant support in both NI and the RoI found to have a significantly positive effect on employment, although the authors suggested that the positive impact on employment and lack of impact on turnover had worrying implications for productivity growth.

The impact on productivity growth was further examined by McGuinness and Hart (2004) using a dataset provided by LEDU on small firms. This paper examined the impact of grant assistance to NI small firms delivered through the 1994-97 period by LEDU through its Growth Business Support Programme, examining in particular the ways in which different types of assistance and their lagged structures impact on the business performance of small assisted firms. The central objective of the work was to understand the extent to which the value of financial assistance influences growth (employment, turnover and productivity measures) and if differential impacts arise depending on the nature and timing of the grant assistance. The dataset used comprised 324 surviving LEDU growth firms over the period 1994-97 who were in receipt of assistance between 1994-96. The impact of assistance provided in 1994-1996 was assessed on firm growth in 1997 using a standard OLS procedure. The models were run separately on employment, turnover and productivity and were estimated on the aggregate dataset and for subsamples based on employment size. Selection problems were explicitly accounted for in the analysis using the standard Heckman two-step approach.

The results indicated that firm size was inversely related to growth in employment and turnover, whilst employment growth was also higher in the urban areas. The impact of financial assistance on employment growth was found to be positive and significant, suggesting the effectiveness of such interventions in stimulating employment increases in the short term. However the regression results indicated that not all types of financial assistance were designed to ultimately yield a positive influence on growth, for example the provision of ad hoc assistance in the previous year was found to exert a positive influence on employment growth whereas marketing or working capital programmes exerted a lagged negative effect. Similar discrepancies were found in relation to the different types of assistance on turnover and productivity growth. Marketing and working capital assistance were found to exert a significantly positive influence on productivity growth in the year following assistance however after three years the gains had disappeared. In contrast, ad-hoc assistance was found to reduce productivity growth in the year following assistance.

When split by firm size, the results for larger firms indicated that the level of assistance was not significant within the model, suggesting that, for these firms, the nature of the assistance package was of more importance than the actual amount received. For small firms the control variables indicated that employment growth was more rapid amongst urban and manufacturing firms, whilst the actual value of assistance was found to be important in employment growth.

Overall the results indicated that after controlling for firm size, sector, location and legal status there were differential impacts on firm growth associated with the timing and nature of the various assistance packages received from LEDU. The results were not the same for smaller and larger firms in the sample, underlying the complexities of the relationship between business support mechanisms and the drivers of small firm growth. Productivity growth in larger small firms assisted by LEDU appeared to be associated with marketing and management assistance whereas for smaller LEDU-assisted small firms the actual amount of finance received was of greater importance.

More comprehensive evaluations, covering both large and small firms, looking explicitly at the effect of SFA on output and productivity came to differing conclusions about its impact. Using aggregate data Harris (1991) found that if there had been no capital grants available then the output of manufacturing firms in NI would have been 25 per cent lower between 1955-83. Harris et al. (2002) and Harris and Trainor (2005a) used plant level data to estimate a policy-on/policy-off model and found that total manufacturing output would have been between 7-10 per cent per annum lower throughout 1983-98 if SFA had not been in operation. Hart et al. (2007) used a two-step model on firm level data to assess the impact of SFA on employment growth, sales growth and productivity. They found that growth in GVA per employee was lower amongst SFA beneficiaries than non-beneficiaries, although not significant. However, growth in GVA was higher amongst beneficiaries and this was statistically significant. Looking at the differential impacts on sales and employment they found positive and significant employment effects; there were also sales effects but these were weaker than for employment, implying no observable effects on productivity. One of the reasons highlighted for this latter finding was that the impact period may have been too short, in that they examined the effect of assistance received between 1998-04 on the performance in 2004-06.

A descriptive study analysing the growth of SFA recipients versus non-assisted firms (Hart and Bonner, 2012) and splitting the beneficiaries into newly-assisted versus previously assisted firms found that previously assisted firms were larger, had higher GVA and higher employment costs than both newly assisted and non-assisted firms. In addition, they had the highest turnover per employee and GVA per employee growth rates over the 2007/08 – 2009/10 period, whilst new assists had the biggest increase in employment. This study whilst indicative of better performance amongst SFA-assisted firms alluded to the fact that the results were descriptive only and implied no causality.

A more sophisticated analysis determining the causal impacts of SFA assistance (SQW, 2013) over a five year period from 2007-12 (for those in receipt of offers prior to 2007) and over a one year period from 2011-12 (for those in receipt of offers prior to 2011) looked at the employment and turnover impacts. They found that SFA had a positive impact on the growth of beneficiary firms, but only in the one year period. Assistance was found to have a negative impact on employment growth over the longer time frame, particularly if it was targeted at poorly performing firms. Importantly, they found that it was that amount of SFA support *offered* that made a difference to employment and turnover growth, with the amount *paid out* only impacting on turnover growth, suggesting that the offer acts as the incentive, generating confidence within the firm, much like the 'stamp of approval' effect as mentioned by Grilli and Murtini (2012) and Lerner (2002).

4.18 Summary

Financial assistance to firms provided through grants, loans and other public subsidies are typically justified on the basis that they are given to overcome some form of market failure. Where they are provided to enhance productivity the arguments made generally fall into three categories; the first concerns underinvestment in technological innovation, whereby public good and incomplete markets arguments suggest a need for intervention. The second strand concerns the protection of infant industries for whom such protection allows the development of comparative advantage; and the third strand argues for the protection of domestic firms in the face of advanced and efficient foreign competition.

Whilst the theoretical arguments may be strong, and the propensity to provide subsidies widespread, actual empirical evidence on the positive productivity effects of public assistance is scarce. In addition, there has been little work carried out using data at the firm level in conjunction with individual data on subsidy payments, the Girma et al. (2007) academic paper being quite novel in this respect. More often than not the findings suggest that subsidies can result in the inefficient allocation of resources, particularly amongst repeat beneficiaries, or indeed can serve to dampen overall productivity growth in the economy if largely unproductive firms are the recipients of assistance and are helped to remain in existence. This appears to have been a feature of many of the public subsidy programmes where lobbying has resulted in assistance targeted towards older, declining industries, preventing the natural creative destruction process from occurring.

Where positive effects on productivity have been found, it appears to be short-term in nature, and only apparent when the subsidies have been targeted specifically to productivity-enhancing projects, and where the recipients have been carefully selected. Automatic provision of grants and the combined effects of financial support appear to have no impact on firm's productivity growth.

There has been considerable research done on the various impacts of government subsidies within NI, although typically, and for historical reasons, mostly examining the impact on employment growth. The reported impacts on output have been relatively large however the impact on productivity growth has been mixed, with few studies considering this performance measure. Where positive results have been reported it has been when specific grant types have been assessed, although again the impacts are found to be short-lived.

The lack of recent evidence on the causal productivity impacts of public assistance for NI firms provides the incentive to examine the issue within the context of this thesis, adopting techniques to properly identify the true effects of policy support, as highlighted by Storey (1998) in which the need to control for selection bias is emphasised. The resulting hypothesis will thus focus on the direct effect on productivity growth:

H1: Controlling for firm effects, public financial assistance payments increase the productivity growth of recipient firms.

The aim of this exercise will be to fill a knowledge gap within the NI policy arena, the importance of which was highlighted by the emphasis on productivity improvements within the economy, and in particular the need to reduce the productivity gap with the rest of the UK. The results will also provide a useful addition to the academic literature on the subject, the high level of public subsidisation in the region providing a strong justification for the analysis, and the inclusion of payment data in the model, reflecting a little-used variable.

5 DATASET AND DATA-LINKING METHODOLOGY

5.1 Introduction

One of the key aims of the study is to create a unique firm-level dataset for NI which allows the research questions to be addressed. At present, there is no one dataset available that includes the range of variables required, this gives rise to two potential options a) collection of the required data via a bespoke survey or b) collating and merging data on firms that has already been collected. The former option would be costly, burdensome on firms and unlikely to yield high response rates given the detailed nature of data that would be required. The second option has therefore been chosen, with datasets sourced from official Government Department surveys, each with a varying number of observations and sampling structures.

The datasets in question were provided for the period 1998-2008 and contain information on firm-level employment, financial attributes, exports, R&D and innovation. The datasets are owned by the Northern Ireland Department of Enterprise, Trade and Investment, and include the Annual Business Inquiry (ABI), the Manufacturing Sales and Export Survey (MSES), the Business Expenditure on R&D Survey (BERD), the Census of Employment (CoE) and the Community Innovation Survey (CIS).

Each of these surveys has its sampling frame drawn from the Inter-Departmental Business Register (IDBR); a business register that contains information on all businesses in the UK which are VAT registered or operating a PAYE scheme[28]. The IDBR holds a unique identifying reference number for each individual firm. Actual returns from these surveys can thus be linked together using this reference number as the unique identifier. Once the data from these surveys has been linked together in this way, the resulting pooled[29] dataset can then be merged with financial data from Invest NI in order to identify which firms received assistance and also to quantify the amount of grant assistance received.

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[28] The IDBR includes details of around 2 million companies in the UK and covers around 99% of economic activity http://www.adls.ac.uk/ons/inter-departmental-business-register/?detail

[29] The terms pooled data and panel data are often used interchangeably to refer to cross-sectional time-series datasets. For the purposes of this thesis the term pooled data is used to indicate the unbalanced nature of the data (as opposed to a balanced panel of firms).

The following discussion describes each of the datasets that were linked together for use in the analysis. General issues with linked datasets are presented, along with the methodology and issues confronted here. The chapter concludes with the results of the data-linking exercise.

5.2 Issues with Linked Datasets

The use of linked data to conduct analyses has become more widespread over recent years as governments have recognized the cost saving measures and the richness of data that can be achieved by linking across datasets. Statistical agencies have also become more amenable to opening access to the data they have collected. In fact the Scottish Government, in particular, has recently highlighted such benefits:

> *"We have an ambition to fully realise the benefits that can be achieved through data-linkage to maximise the value of administrative and survey data. By enhancing the data standards and statistical capacity we will improve the quality of data that exists and make advances on the evidence base, particularly in terms of a joined-up understanding of how outcomes are achieved, allowing for more informed spending on public services and early interventions that save money in the long run." (Scottish Government, 2012, "Joined-up Data for Better Decisions: A strategy for improving data access and analysis", pg. 9)*

The use of such linked data, whilst undoubtedly of great value, is however not without its problems and potentially poses a number of difficulties, both ethical and statistical, not all of which are always addressed in the literature.

Ethically, linking a range of datasets together can provide detailed information on company makeup and performance which a company may not be aware of, or have given permission to be created. Such in-depth information could be of value to competitors, and thus researchers have to be mindful of the need to preserve confidentiality when working with such data. Statistical methodologies and secure modes of working are generally utilized, or imposed, when dealing with such data and these include methods which prevent disclosure of cell counts below a certain threshold, or where individual firms dominate particular categories. In addition, most open access datasets are anonymised so that the researcher is unable to identify specific companies, however this in itself can create problems in the data linking process, as discussed below.

On the statistical side, there are a number of problematic issues which can arise from the nature of the underlying survey and/or the nature of the resultant linked dataset. The underlying surveys can cause measurement and linking issues due to differences in choice of sampling frame; non-response; wrong/missing identification numbers; the handling of changes to identification numbers; and the level at which the data is collected, for example firm versus plant. The subsequent linked dataset can have issues with erroneous inclusion or exclusion of matches, measurement error, and representativeness. Chesher and Nesheim (2007) have categorized these into five specific statistical issues concerning linked data, namely 1) the impact of contributing survey designs and non-response; 2) measurement error issues 3) impact of excluding unmatched units; 4) impact of including erroneously matched units, and 5) consequences of linking when there are no units in common.

As indicated above, the two main issues, ethical and statistical, may appear unrelated however preservation of the former can actually impact on, or cause, the latter. Typically datasets are anonymised before being provided and whilst this helps prevent unauthorized release of, or use, of company information, it can lead to problems involving the exclusion of unmatched units which can occur when firms cannot be matched by unique identifier. In these cases a lack of other specific company data relating to name or address means that non-matches, or false negatives, are discarded when in fact such additional contact details would provide enough information for the correct match to be located. Discarding such information represents a loss of data, and may induce bias if the discarded data is particular to any specific group of firms, such as smaller firms, or firms within a particular sector.

In contrast to this there is also the issue of false positives, whereby erroneous records are matched. This is more likely to occur where matching has been done on name, or address, rather than on unique identifier. In these cases, particularly when the use of fuzzy matching is undertaken, whereby a match is made if the name or address doesn’t exactly match, but mostly matches for example Mr John Smith versus John Smith, care has to be taken to ensure that the link is correct. This can be done by comparing other variables common to both datasets for example number of employees in a given year; sector of main business activity etc. but can be a time consuming task; in addition the match is ultimately made based on the decision of the researcher and may not be easily replicated.

In terms of issues with survey design, the underlying surveys that have been linked can take a number of different sampling frames; for example they can be random samples of the population or they can be based on stratified sampling methods. In the latter, weighting is usually undertaken to relate the results back to the population, however when such data is linked to other, perhaps non-weighted, data the question arises as to how to ascertain representativeness, and how to correct for missing data due to non-sampling or non-response. The answer depends largely on what the data is intended for, how linking has affected the original sample designs, and, if data is missing, which method of imputation or estimation has been used.

Typically missing data is a common problem with datasets, and is particularly the case for linked data due to the non-sampling or non-response in the original datasets; and non-matches in the linked data. The problem can be overcome by either discarding the missing data or through the use of imputation methods, the choice of which depends on how the data is missing. According to Little and Rubin (1987) there are three mechanisms that lead to missing data, namely 1) missing completely at random (MCAR); 2) missing at random (MAR); and 3) non-ignorable missing. The first of these occurs when the probability of missingness is the same for all units, and response probabilities are unrelated to any variables in the study. The second, missing at random, is more common and occurs when response probabilities depend on the other fully-observed variables. The third type of missingness is the non-ignorable, this is perhaps the most important, and typically occurs when response probabilities depend on missing variables themselves, for example when those with high salaries refuse to reveal them and thus do not respond.

The simplest approach to dealing with issues of missing data is to discard cases with incomplete information, which can be done on a complete-case basis i.e. dropping an entire record if data is missing for any of the variables, or on an available-case basis whereby subsets of the data for which information is available are used and the rest are discarded. Whilst these are straightforward methods they can result in a substantial reduction in the sample size, and hence large standard errors; in addition inference is only valid if the missingness is completely at random, otherwise the estimates may be biased (Horton and Kleinman, 2007).

As mentioned, imputation is an alternative method for estimating missing data; again there are multiple ways of doing this. Mean imputation is the most straightforward, whereby for each missing value of a given variable the mean of the observed variables, or a sub-group of the observed variables, is substituted. The downside of this is that is distorts the underlying distribution of the data, in that adding values equal to the mean makes the distribution more peaked around the mean and hence reduces the variance. Alternative methods which avoid this include ‘cold-deck’ and ‘hot deck’ imputation; the former replaces a missing value with a constant value from an external source, for example the population mean, but as a result underestimates the variance and sampling error. The latter is used for categorical variables and replaces each missing value with a randomly selected value form the observed data, but it also distorts the correlations and covariances.

Regression imputation represents a slight improvement on the above in that it imputes missing values with predicted values drawn from a regression based on observed variables in the dataset, however due to the methodology imputed values will always lie on the regression line and hence the standard errors will be reduced and correlations and covariances inflated. In addition this approach is more complicated when more than one variable has missing data which is more likely in a linked dataset. For panel data specifically, other imputation methods involve using the last observed value for the unit; using the mean of previous values; or indeed the mean of the previous and following value, surrounding the missing value. However as with the other methods, these have the potential to induce bias and underestimate the variance. As a result of the disadvantages associated with such approaches they are generally not recommended (Greenland and Finkle, 1995; Jones, 1996; Carpenter et al, 2004; Cook et al, 2004; Jansen et al., 2006).

Approaches which are thus deemed most appropriate for missing data cases, particularly those missing at random, include those involving maximum likelihood or multiple imputation. Maximum likelihood is particularly suited to large samples; it uses the EM algorithm (Dempster, Laird and Rubin, 1977) which involves two steps; an estimation step and a maximisation step. The method works through an iterative process, whereby missing values are replaced by estimated values; parameters are estimated using this full-data; the missing values are re-estimated based on the new parameter values; the steps are then repeated until convergence is achieved. This approach, whilst superior to the previous imputation methods, can however be quite complex, both computationally and mathematically. Multiple imputation (Rubin 1976) thus represents a viable alternative, and can be used in cases of low sample size or high rates of missing data; the method is also used only to impute the missing data rather than estimating other parameters, as in maximum likelihood methods, and so is less sensitive to the choice of model. The process works by estimating imputed values for the missing values; the imputation procedure is repeated independently a number of times, typically around 3-5 times (Schafer, 1997), with each dataset containing the same observed values but different sets of imputations for the missing data; as a result a number of complete datasets are created. Each of these datasets is analysed using complete-data methods and the results are then combined; the variability across the datasets allowing for the uncertainty of the imputations to be taken into account and hence providing inferences that are generally valid.

Whilst the above thus shows that procedures do exist for estimating missing data, typically it has been found that their use, in all types of study and not just those concerning linked data, is limited. In fact, Horton and Kleinman (2007) report on a study undertaken by Burton and Altman (2004) who review cases of missing data in 100 papers concerning cancer prognosis; they find that 81 per cent had missing data and, of these, just 1 paper used a multiple imputation approach. In fact one of their conclusions stated:

> *"We are concerned that very few authors have considered the impact of missing covariate data; it seems that missing data is generally either not recognised as an issue or considered a nuisance that is best hidden (Burton and Altman, 2004, pg. 6)*

A further study they report on by Horton and Switzer (2005) also looked at the statistical methods used in 331 papers in the New England Journal of Medicine, just 8% of which listed some type of method for addressing missing data, of which just 2 were multiple imputation methods. More recently, Jelicic et al. (2009) analysed 100 papers in the field of developmental psychology and found that 57 of the studies had either missing data or discrepancies in sample sizes; of these 82 per cent had just removed the missing cases either through case wise or pair wise deletion.

In terms of addressing the issue of missing data in linked datasets, the evidence is also limited; most papers simply state the resultant number of observations in their linked dataset, or just state that they have dropped missing observations (Hasumi et al., 2013), with no mention of the degree or impact of any potential missing data. Buddelmeyer et al. (2010) suggest that non-matches in their dataset on Australian firms cause an under-representation of two of the industries, however they proceed with the analysis on the basis that the matched sample "appears quite representative of the population" (pg. 268). Those which do account for, and address the missing data issue include Thornberry et al. (2010); and Abowd, Finer, and Kramarz (1999) who use multiple imputation; and Abowd, Crepon, and Kramarz (2001) who use a dynamic attrition model to model the missing data process.

In addition to the missing data problem, there is also little discussion in the empirical literature where linked data is used about how measurement error problems have been overcome, and in fact Chesher and Nesheim (2007) themselves suggest that solutions typically used for measurement error are of limited use as the measurement error processes for linked data are complex and often involve non-linear models. Instead much of the literature, rather than try to correct for it, highlights that bias, due to measurement error from missing, non-sampled, or non-matched data may be a feature of their analysis.

5.3 Dataset Details

The datasets used here were made available by DETI, and Invest NI, for the purpose of undertaking this research study. The DETI surveys were all conducted under the Statistics Act (1988) and are a combination of statutory and voluntary surveys, each of which has its own sampling frame.

The ABI is a statutory survey, conducted by DETI (and its predecessors), that has been undertaken annually since 1998. It provides information on the value of the economic activity that businesses generate and associated expenditure, costs, and incomes. The survey includes data on turnover, gross value added, employment levels, employment costs and purchases. In NI the survey is undertaken on a sample of firms; until 2007 typically all businesses in the Production industries employing twenty or more employees were selected to contribute to the survey; within the Construction sector all businesses employing fifty or more employees were selected and within Services, an employment threshold of one hundred employees was applied, with businesses falling below the threshold of complete enumeration selected on a random stratified basis. For the 2008 survey all businesses with 50+ employees, or 20+ employees and more than one local unit, were fully enumerated. Businesses falling below the threshold of complete enumeration were once again selected on a random stratified basis. The data provided for the purpose of creating the dataset was obtained from actual returns; on average, data was provided for around 2,000-4,000 firms per ABI survey between 1998-2008.

The MSES is a voluntary survey that has been carried out annually in Northern Ireland since 1991/92. The Northern Ireland Economic Research Centre (NIERC) conducted the survey until 2003; it has since been conducted by DETI (and its predecessors). The survey provides information on total sales, external sales and exports by Standard Industrial Classification (SIC) Division and market destination. Currently the sample for the survey is all manufacturing firms with 5 or more employees, although this is then boosted to ensure all assisted firms (both in manufacturing and business services are included). Previously, until 2001/02, all firms with 20 or more employees were surveyed (and usually a sample of 500 firms with employment less than 20). The data provided for the purpose of creating the dataset was obtained from actual returns; on average; data was provided for around 1,500 to 2,500 firms per MSES survey between 1998-2008.

The BERD survey is a voluntary survey, conducted by DETI (and its predecessors), that has been carried out triennially in NI between 1993-99; and collected annually since 2001. The survey contains a range of data including types of R&D expenditure; type of research undertaken; sources of funding and types of R&D employment. The survey is undertaken on a sample of firms however it includes all those known to be engaged in R&D and thus represents a census of all known R&D performers in NI[30]. The data provided for the purpose of creating the dataset was obtained from actual returns and estimates. R&D estimates were made by the survey statisticians for non-responding businesses; estimates for Invest NI companies were based on the value of offers made to promote R&D investment; the amount remaining to be claimed against these offers; the frequency of claims and the contribution of Invest NI's assistance to total planned R&D expenditure. Non-Invest NI firms' estimates were based on historical information and other administrative surveys within the Statistics Research Branch (DETI, 2009). On average, data was provided for around 300 firms per R&D survey between 1999-2005 and over 600 firms for 2007-08.

The CoE is a statutory survey, conducted by DETI (and its predecessors), which has been carried out in NI every two years since 1978 (it was carried out annually between 1971-78). It is a full count of the number of employee jobs in all industries except for agriculture (and excludes the self-employed). The survey provides data on male, female, full-time and part-time employees up to a five-digit Standard Industrial

[30] The information that identifies which firms carry out R&D is sourced from previous surveys and other sources such as the Office for National Statistics (ONS), Invest NI and filter questions on the ABI and the CIS.

Classification (SIC92) level. The units to be surveyed are drawn from the IDBR, with all units considered to be live on the IDBR at September in the year of the survey selected. The data provided for the dataset was given at local unit level, which had to be amalgamated into reporting unit or firm level to link in with the other datasets. On average, data was provided for around 50,000-60,000 local units bi-annually which was amalgamated into 33,000-42,000 firm-level records per Census survey.

The CIS is a voluntary survey carried out by EU member states that allows the monitoring of Europe's progress in the area of innovation. The survey is conducted in NI by DETI (and its predecessors) and was originally conducted every four years (the first in 1993), but since 2005 has been conducted every two. It is based on a core questionnaire developed by the European Commission (Eurostat) and Member States and provides a range of information related to innovation activity among enterprises, including the extent of innovation activity; the impact of innovation on businesses; expenditure on innovation; sources of information and co-operation; and the barriers to innovation. A sample of firms drawn from the IDBR is surveyed; typically it covers enterprises with 10 or more employees in sections C to K of the (SIC) 2003. Due to a change in the ownership of the CIS data, which transferred from DETI to the ONS, the only data available from the CIS for the pooled dataset is from CIS 4 which covers the period 2002-04; data was provided on approximately 1,300 firms.

The Invest NI data is collected by the agency through their Client Executives, the agency's client-facing account management team. Data is stored primarily on the Client Contact Management System (CCMS) and contains contact and background information on the client companies; letters of assistance awarded; proposed new jobs to be created or promoted, and jobs to be safeguarded. A longitudinal dataset has also been developed, by Invest NI, from this, containing information on financial assistance *offered* to companies and expected jobs created or safeguarded. The payments data on Invest NI clients is held by them on a separate database and at the time of writing, was being reconciled with client company information; however historic payments data on the largest client companies was made available (drawn from Invest NI's predecessor, the Industrial Development Board's databases). This payment data contains information on the acceptance date of offer; amount offered and amounts paid out on an annual basis covering the period 1983/84 – 2008/09. Both the payments and client data contain a unique identifying company reference number, as assigned by Invest NI. Work has been undertaken to match these reference numbers to the unique IDBR reference. The data provided for the pooled dataset includes information on 2,900 client companies (of which 1,400 were significantly assisted firms in 2006[31]); the payments data covers 640 client companies.

5.4 Methodology and Data Issues

The methodology for constructing the pooled dataset was to link each of the annual DETI datasets via the IDBR reference number to create, in the first instance, annual cross-sections. These annual cross-sections were then linked together to provide the longitudinal element. The CIS and Invest NI data were matched in at the end as they did not follow the format of the other datasets. Initially data was provided on actual returned survey information, however during the period of the study subsequent data containing official estimates for non-sampled, and in a few cases, non-returned data, also became available. These were merged into the dataset after the initial pooled dataset had been created.

In principle, the matching process should be fairly straightforward, however prior to matching a number of exercises had to be carried out on the data to reduce the risk of error.

- Firstly all the common variables, including the reference numbers, had to be checked and standardised to ensure all had the same variable name on each dataset, and were of the same length and format;
- data variables had to be checked, and in some cases recoded, to ensure that they were assigned the correct format and those that were common across years were measured consistently i.e. financial variables had to be numeric rather than string, and all had to be measured in £000s or in actual values;
- values coded as zero had to be checked to ensure that this indicated a valid value rather than a non-response;
- outliers had to be checked to ensure they were valid and not a result of keying-in error;
- SIC codes had to be checked to ensure they were recorded on a systematic basis for example 5 digit versus 2 digit. The SIC codes on the 2008 datasets

[31] Significantly assisted clients are defined as those client companies that were in receipt of an offer of assistance worth £25,000 or more in the previous five years, and/or £250,000 in the previous ten years.

used the SIC2007 classification so they had to be recoded to SIC92 to maintain consistency.

- each annual dataset had to have the reference year appended to the end of the variable names so that when matched longitudinally the specific year could be identified;
- finally where the datasets were not all measured on the same time frame for example calendar year versus financial year, these had to be reconciled so that the linked data was matched to the most appropriate time period. In this instance data collected on an annual basis such as the 1998 ABI, which reflected values for the 1998 calendar year, was matched to the 1998/99 MSES which reflected data for financial year covering April 2008 – March 2009.

Annual cross-sections of the linked data were created first by matching together the unique reference numbers of each dataset. The matching was done this way, rather than creating panels of each individual dataset and then merging them together, for a number of methodological reasons. Firstly, the earlier datasets did not contain IDBR reference numbers for each firm, thus matching across datasets had to also be undertaken by name[32] and, following that, manual matches had to be undertaken comparing address and turnover data[33]; this was much more straightforward to carry out on an annual basis (as variables common to the surveys should report identical values for the same year) than would be after the data had been linked longitudinally. Additionally, it allowed for gaps in reference numbers to be imputed from other surveys (where it was available) and thus led to easier linking longitudinally. Secondly, for a number of administrative reasons[34], the IDBR reference numbers tend to change over time which can create problems when creating time-series data. As the reference numbers for each survey came from the same source it was more likely that any reference number that changed would appear, under the new reference, across all the survey data in any given year. Linking cross-sectionally first meant that data was matched together, under the new reference, across the surveys; when linking longitudinally it then was easier to spot any gaps due to reference

[32] Names of companies are not always recorded the same way on survey returns, differences can arise with trading names used instead of owner names and also differences in spelling/use of abbreviations.

[33] The ABI, MSES and R&D surveys all contain data on sales/turnover so where there was no match on reference number or name, matches were manually identified for the largest firms based on identical address and turnover data.

[34] Reference numbers can change due to merger and acquisition activity and when the firm ownership changes.

changes (for example the entire linked data for a particular year would be missing for a firm whilst simultaneously a 'supposed' new firm would appear in that year under the new reference number), thus once these were identified the linked data could be slotted correctly into the record of its previous reference number (and thus removed as a new firm)[35].

A further methodological problem which had to be accounted for was that, whilst the majority of the survey return data was provided at firm/reporting unit level[36], the Census of Employment was not. This data was provided at local unit/plant level[37] and also contained its own Census plant and firm-level reference numbers, as assigned by the Department. The accompanying IDBR reference numbers were only provided in full for the 2007 dataset[38]. Thus a number of steps had to be taken before the data could be linked into the other datasets. Firstly the plant level data had to be amalgamated into firm level, this left an issue as to which SIC code to be assigned to the firm level version, where it differed across plants. A decision was made to retain the SIC of the largest plant within the firm by employment size (although for the purposes of the pooled dataset the SIC code from the ABI was used to define sector as it was thought to be more consistent over time). Amalgamating into firm level data also provided a difficulty when it came to assigning a postcode; this was not remedied as it was felt that the postcode provided by the other surveys would also suffice. Once the data was at firm level, measures had to be undertaken to assign IDBR reference numbers to the earlier years (by applying the 2007 reference numbers to earlier years where the firm was alive) and by manual identification of firms. This proved more problematic than anticipated due to the sheer number of

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[35] This method may not have captured all firms in cases whereby there was a reference number change and an accompanying name change, resulting in the failure to recognise the firm as an existing one.

[36] On the IDBR the reporting unit holds the mailing address to which inquiry forms are sent. There are two types of reporting units in NI - (i) an enterprise reporting unit reports for all the local units within the enterprise (ii) a local unit list reporting unit reports on a specified list of local units and these usually distinguish multinational companies operating in NI. For example, Marks and Spencer have one reporting unit for activity in Great Britain and another for activity in NI (source: http://www.detini.gov.uk/stats_bus_register_3.doc)

[37] The local unit is an enterprise or part thereof (for example a workshop, factory, warehouse, office, mine or depot) situated in a geographically identified place. At or from this place economic activity is carried out for which - save for certain exceptions - one or more persons work (even if only part-time) for one and the same enterprise. On the IDBR, a local unit is an individual site (factory, shop, office, etc.) at which an enterprise conducts its business (source: http://www.detini.gov.uk/stats_bus_register_3.doc).

[38] This difference in referencing created further issues for a number of firms (mostly containing subsidiaries) whereby the firm was recorded under the IDBR as one entity with one reference number but was recorded under the CoE referencing as a number of distinct firms each with its own reference number, and vice versa.

firms on the dataset and an inability to attach reference numbers for the earliest datasets due to firm death; as a result the CoE data was used more as a tool to verify employment against the other datasets (in cases of outliers) and was not matched into the dataset.

Other issues which arose, due to the nature of the underlying surveys, was that of missing data. The MSES, BERD and CIS data are all voluntary surveys and thus the response rates vary. Smaller firms in particular are less likely to reply due to the administrative burden of form-filling and also if they do not perceive themselves to undertake the activities the survey is concerned with, for example exporting or innovation (i.e. resulting in non-ignorable missingness). In addition many of the surveys conduct stratified sampling beneath a particular sizeband and thus there will also be missing values for years in which firms are not surveyed.

Missing data can be estimated by a range of imputation methods, as discussed in Section 5.2. For linked data of the scale used here the preferable method would have been multiple imputation however there was a significant number and range of data, including both continuous and categorical variables that would have had to be estimated for each individual dataset that contributed to the overall pooled dataset. Due to the very nature of the linked dataset the estimation of missing values would have been extremely complex; firstly due to sample design, missing data for firms not sampled every year would have had to have been estimated; then missing data for firms that were sampled but did not respond; finally missing data for non-matches would also have had to be estimated. This was further complicated by the fact that linking was done longitudinally and cross-sectionally, involving numerous annual datasets, indicating the creation of a substantial number of imputations for each missing value, as per the multiple imputation method. Indeed it has been noted that it is difficult to combine datasets for analysis after the multiple data sets have been generated in the MI method (Scholmer et al., 2010). As a result no attempt was made to impute or estimate missing data prior to the linking stage. Rather the data was linked as it was, and available case analysis was then undertaken, in which a sub-dataset of available data was used for each research question. These sub-datasets were assessed as to the representativeness compared to the population, and to the extent of missing data for each of the predictor variables. Where missingness of variables was found to be high, caveats are mentioned to highlight the likely bias in the analysis.

5.5 Results of Data Linking

As stated above in the methodology the individual datasets used for the analysis were first merged cross-sectionally by year; the resultant annual waves were then linked longitudinally. Due to the inability to match the majority of the CoE to the pooled dataset the ABI was thus used as the anchor dataset upon which the others were matched. The ABI was favoured for a number of reasons; the ABI is a compulsory survey and had the largest and most representative sample (in terms of the population of firms) of all the contributing datasets (excluding the CoE); the ABI contained the variables needed to derive the productivity measure; and the ABI data was provided at the reporting unit level which was consistent with the other datasets.

Table 5.1 displays the results of the initial data linking exercise, showing the number of firms on the ABI dataset and the number of, and percentage of, firms from each of the annual MSES, and R&D datasets that matched. The matches include those done via unique reference number; those matched by name and those matched manually by a combination of name, address and turnover.

The initial match rates appear relatively low, at least for the MSES data; whereby the match rate, which equated to around 700 firms per year, ranged from around 27 per cent to 52 percent annually. One of the main reasons explaining the low rates is that the MSES focuses predominantly on Manufacturing firms; the only Service sector firms included are those which are Invest NI clients. In contrast the ABI covers Manufacturing and Other Production industries; Construction and Services. The proportion that linked between these two datasets are thus most likely to be the largest firms (as those with 20 or more employees were fully sampled for the majority of the period, on both surveys), assisted firms, and predominantly manufacturing; the non-matched from the MSES survey more likely to be smaller manufacturing firms.

The match rate for the R&D firms was more promising, particularly in the earlier years, with around two thirds of firms matching to the ABI. As the number of firms on the R&D surveys expanded, the match rate declined, to less than 40 per cent, however the actual number of matched firms rose, to around 300 firms in the latter two years.

Table 5.1: Results of Data Linking Exercise – Matching to ABI 1998-2008

	ABI	*MSES*		*R&D*	
	N	**Total N**	***% matched to ABI***	**Total N**	***% matched to ABI***
1998	***2,395***	1,527	*43.9*	-	-
1999	***2,273***	1,489	*48.4*	253	*66.4*
2000	***2,260***	1,499	*51.9*	-	-
2001	***2,688***	1,640	*44.4*	264	*66.7*
2002	***3,537***	1,662	*49.4*	281	*66.6*
2003	***3,490***	2,350	*36.2*	285	*60.7*
2004	***3,371***	2,237	*37.0*	312	*58.7*
2005	***3,614***	2,346	*37.0*	348	*49.4*
2006	***3,720***	2,501	*37.7*	291	*50.9*
2007	***3,749***	2,647	*34.5*	601	*46.8*
2008	***4,099***	2,659	*26.7*	811	*36.6*

Source: Authors estimates of DETI data

Once these annual waves were created the data was linked longitudinally. Each annual wave was matched to the subsequent one, creating a pooled dataset from 1998 – 2008; once duplicates had been removed this covered 16,176 unique firms with each firm on the dataset having at least one annual record (derived from at least one survey).

The CIS and Invest NI datasets were subsequently matched in as they did not follow the format of the others. The CIS dataset covered the period 2002-04 and contained data for 1,359 firms; these firms were matched to the dataset resulting in a match for 1,196 or 89 per cent. The Invest NI dataset contained data for 2,937 firms; of these 1,402 matched to the dataset, equating to a match rate of 48 per cent. The majority of the non-matches were due to missing unique reference numbers on the Invest NI dataset.

5.5.1 Linking with Estimated Data

After the initial dataset had been created further data from the ABI, MSES and R&D surveys were made available for use in this analysis. This additional data contained the actual returned information, as provided previously, as well as estimates for non-sampled data, and larger non-returned data. These estimates were undertaken by the statistics agency gathering the data; ABI estimates were undertaken for non-returns above a selected employment threshold; data was imputed using a methodology which takes account of previous returned data and the performance of other similar businesses (DFP, 2010, pg.9). MSES estimates were made for those companies with 50 or more employees that failed to respond to the survey. Estimation was carried out based on previous year returns, if available, by applying growth rates, calculated from changes over the year in similar businesses. If no previous year data was available, a sales value was derived from another comparable survey; export destination information was estimated based on the returns of the industry to which the non-respondent belonged. If no data were available, an estimate was made based purely on the returns of similar businesses (DETI, 2008b). As before, the additional R&D data was estimated separately for Invest NI and non-Invest NI firms (see 5.4 for details).

Given that this new data would in part help address the issue of missing data which is a key issue in such linked datasets, due to non-sampling and non-response, the decision was made to incorporate this new data into the existing pooled dataset, rendering it more representative of the population of firms in the NI economy. Rather than start from the beginning and re-create annual cross-sections incorporating this additional data, each revised annual dataset (containing estimates) was merged incrementally to the existing pooled data. This additional data was provided at local unit level and thus had to firstly be amalgamated into reporting unit level to be consistent with the original data. The new data didn't cover the entire 1998-2008 period, but was available from 2002 onwards. As well as adding the extra firms to the pooled dataset, this estimated data was also used to fill gaps in the existing data due to non-response for specific questions. Table 5.2 replicates that of the initial matching and shows the new matching rates for the ABI, MSES and R&D, based on the supplied actual and estimated data. As is obvious from the table virtually all of the firms on the MSES and R&D datasets were subsequently matched to the ABI.

Table 5.2: Results of Data Linking Exercise (incorporating estimates) – Matching to ABI 2002-2008

	ABI	***MSES***		***R&D***	
	N	**Total N**	***% matched to ABI***	**Total N**	***% matched to ABI***
2002	***46,006***	2,331	*96.8*	281	*98.6*
2003	***46,664***	2,350	*99.4*	285	*99.3*
2004	***48,186***	2,237	*99.7*	558	*98.4*
2005	***50,396***	2,758	*98.2*	857	*98.1*
2006	***51,884***	2,879	*99.0*	340	*97.6*
2007	***53,575***	3,012	*97.8*	601	*96.2*
2008	***54,556***	3,024	*97.8*	811	*96.0*

Source: Authors estimates of DETI data

Incorporating these additional firms into the original dataset of 16,176 firms resulted in a final dataset covering 82,974 firms. Again this was checked for duplicate observations, and when these were removed it resulted in a total number of 82,889 unique firms. The CIS and Invest NI datasets were once again matched against this expanded dataset to try and locate additional matches; matching the CIS to this resulted in a match for 1,340 firms, representing a match rate of 99 per cent; matching the Invest NI dataset resulted in a match for 2,198 firms, a rate of 75 per cent. Whilst these rates represented an improvement on the first-stage matching, as stated previously, the Invest NI firms suffered from a lack of complete reference numbers, hence the lower matching rate.

6 METHODOLOGY AND RESULTS

As with the literature review in Chapter 4 the methodology and results chapter is subdivided into three sections each covering one aspect of the productivity growth analysis. Sub-section A focuses on the relationship between exports and productivity growth; sub-section B that of innovation and productivity growth and finally, sub-section C examines the impact of public financial assistance on productivity growth.

Sub-Section A: Relationship between Exports and Productivity Growth

6.1 Introduction

As evidenced in the literature review (Chapter 4), there is a generally accepted consensus that exporting firms exhibit particular characteristics that differentiates them from non-exporters. In fact the literature appears to conclude that "exporters are better than non-exporters" (Bernard and Jensen, 1999, pg.1) and that they exhibit these desirable characteristics several years before they ship any goods abroad. However there is no such agreement regarding the effect of exporting on the firm; this is particularly the case for productivity effects, whereby it has not been conclusively proven that exporting enhances the productivity growth of firms; it may be that the perceived link is simply a case of more productive firms becoming exporters. It is important to look at the causality issue from both sides, particularly from a policy perspective, as there is a need to understand what type of firms become exporters in order to set appropriate policy goals, and secondly, in order to set reasonable expectations about the impact of these policies, there is a need to understand how exporting affects firms' performance; factors that have been lacking in official policy documents in NI.

This chapter thus seeks find answers to these questions; the key hypotheses with regards to exports and firm level productivity growth are set out followed by the methodologies that will be used to test them. A more detailed description of the dataset and variables used for the analysis is discussed alongside the key results. This section of the chapter concludes with a summary and discussion.

6.2 Testable Hypotheses

As discussed at the end of Chapter 4, and based on the findings of the empirical literature, the first set of hypotheses will examine the differences, if any, between exporters and non-exporters in NI, as per the stylised facts. The hypotheses are that:

H1: Exporting firms display a different set of characteristics than non-exporters, suggesting they are 'better' firms

H2: Exporters are more likely to undertake R&D due to the technology-based competitive markets in which they operate

The third and fourth hypotheses will then examine the effects of exporting on the subsequent performance of the firm, and test for the presence of self-selection and learning-by-exporting:

H3: Due to the sunk costs or 'self-selection' argument, exporters are more productive than non-exporters, prior to exporting

H4: Exporting has a positive effect on a firm's productivity growth, as suggested by the 'learning-by-exporting' notion.

6.3 Data and Descriptive Statistics

The first stage of the exports-productivity question is to examine the determinants of exporting – are exporters better firms and how do they differ from non-exporters? Once this is established the effects of exporting on productivity growth can then be examined. The aim of this chapter is to seek an answer as to whether more productive firms become exporters, that is to accept the self-selection hypothesis, and/or whether exporting increases productivity growth, the learning-by exporting hypothesis.

The empirical work for this chapter utilises a subset of the overall pooled dataset i.e. those for whom exports data is available. As stated in Chapter 5 the exports data is sourced from the MSES which is a voluntary survey and sampled on a stratified basis. The response rate for the survey was typically around 80% annually over the period to which the data refers; estimates of non-returned data for those with employment of 50 or more were calculated individually by the statisticians collecting the data. The dataset used here contains both the actual returned data and the estimated data for larger firms, as described in Chapter 5.

Of the 82,889 firms in the pooled dataset, there are 4,732 firms with sales and export data; equating to 20,457 observations over the 1998-2008 period. In order to ascertain whether missing data is an issue, this subset of data was analysed against the published population figures to test for representativeness. The published data do not give an indication of the number of firms that export, therefore representativeness is tested against the value of exports, market destination and size of exporting firms. The data was found to account for over 90 per cent of the total value of sales and exports, as per the annual published figures, from 2002 onwards. The data was also found to be representative of the grossed-up published figures in terms of sales by market destination and by size. Table 6.1 shows the comparator figures by market destination for 2008/09, and Table 6.2 the comparator figures by size of firm.

Table 6.1: Destination of Sales by Market: Sample versus Published Population Data 2008/09

	Sample Data %	**Full Population %**
Northern Ireland	26.6	23.2
Great Britain	37.7	40.6
Republic of Ireland	10.5	10.4
Rest of Europe	9.0	9.6
Rest of World	16.1	16.2

Source: DETI 2009 and author's own estimates of DETI data

The sample data slightly over-represents the share of sales within NI and under-represents sales to Great Britain. Sales to the other three main destinations are almost identical. The reason behind this may be that due to its voluntary nature, and the associated burden with form filling; those that responded annually were more likely to be engaged in exporting (those that didn't, regarding the questionnaire as not applicable) meaning that the data from respondents is slightly skewed in favour of exporters. It is also probable that smaller firms are less likely to fill in questionnaires of a voluntary nature and, indeed we can see that the sample data under-represents the share of sales made by small firms by around 2 percentage points (Table 6.2). Based on these comparisons, the data is deemed to be sufficiently representative of exporting firms to proceed with the analysis.

Table 6.2: Share of Total Sales by Sizeband: Sample versus Published Population Data 2009

	Sample Data %	Full Population %
Small (0-49 employees)	15.9	18.1
Medium (50-249 employees)	28.1	24.4
Large (250+ employees)	56.0	57.5

Source: DETI 2009 and author's own estimates of DETI data

6.3.1 Exporter Definition

One of the conceptual issues for this Chapter is that of the definition of an exporter. Export sales are regarded, in the official statistical sense, as sales outside the UK, however as Table 6.3 shows for selected years, around two-thirds of firms sell to the Republic of Ireland (ROI market) whilst around half sell to Great Britain (GB market), with these figures remaining consistent over the period[39]. The share exporting to the rest of Europe (ROEU market) and the rest of the world (ROW market) is markedly lower, at less than one fifth of all firms.

Given that NI is uniquely located as a region of the UK but also as a neighbouring region to a Eurozone country i.e. the ROI it may be the case that for many of these NI firms, the process of selling to the ROI is the equivalent of serving a natural domestic market, due to a similar customer base and zero shipping or air transportation costs. Regarding the ROI as an export market, in this study, may miss part of the reasoning behind why exporters are different, for example, due to the self-selection argument, which postulates that there are significant costs involved in the adaptation of products to foreign customers' demands and standards, and the establishment of distribution networks abroad. In the case of NI firms it is much easier to sell into, and set up distribution channels, to a market which may only be miles away from the domestic base, than it is to set up in one in mainland Europe or further afield, in which there are language barriers and in which transportation and distribution channels need to be organised.

In addition, research has found that the share of exporting firms in a country varies considerably; the ISGEP (2008) report suggests export participation rates[40] ranging

[39] The figures prior to 2002 do not include estimates and refer to returned surveys only, as a result the market destination data is somewhat skewed. The data is considered consistent from 2002 onwards.
[40] Defined as the percentage share of exporting firms.

from 27 per cent of manufacturing firms in Colombia to 83 per cent in Sweden. The relatively high share of exporters in NI is more akin to the rates observed by ISGEP in small open economies, such as the ROI (70%), Denmark (77%) and Slovenia (81%), and is primarily driven by the share of firms exporting to the ROI. Given this high proportion selling to the ROI, as opposed to markets further afield, common barriers to exporting, such as language and cultural issues, may not be encountered. As a result the typical findings regarding export behaviour may differ in NI due to the absence of such issues and their implications for sunk costs.

To reflect NI's unique position geographically; the issues raised above; and developments in the literature, various definitions of exporter are therefore incorporated into the analysis. The first definition to be used is the standard one i.e. exporters are firms that sell outside the UK (termed exporters); under this definition those selling to the ROI are deemed exporters. The second definition refers to those who sell outside NI (termed external sellers); under this definition sellers to both GB and the ROI are deemed exporters; this definition is used to reflect the fact that sales to GB involve shipping or air transport costs whilst sales to the ROI involve non-sterling currency transactions, both of which could be expected to influence the sunk costs involved in starting to export. The third definition refers to those selling outside the UK and ROI (termed overseas sellers); under this definition those selling to the ROI are not exporters. This definition is used to explore whether firms selling to markets in the EU and further afield exhibit any particular characteristics which are not observed under the normal exporter definition and also, as noted in the literature review, whether destination market influences whether learning-by-exporting occurs. Ideally the actual individual markets would be identified (as well as their level of technological development) for the latter analysis, but in the absence of such detail this broader measure is incorporated as a trial measure to establish whether there are any learning effects that are not detected under the other definitions.

Of the sample of 4,732 firms with export data there are a total of 3,439 that can be classed as exporters (72.6%); 3,631 external sellers (76.7%) and 1,294 firms selling overseas (27.3%).

Table 6.3: Share of Firms Selling to Main Market Destinations 1998-2008

	NI market %	GB market %	ROI market %	ROEU market %	ROW market %	N firms
1998	87.7	69.6	70.9	32.0	28.2	657
2000	87.2	67.4	72.4	32.0	28.0	749
2002	87.7	45.4	62.0	15.8	15.6	2,352
2004	90.7	44.2	65.0	17.2	15.5	1,922
2006	89.4	43.6	64.8	17.2	16.1	2,886
2008	87.7	44.7	64.1	17.0	16.4	3,029
Overall	89.3	47.8	65.8	18.8	17.7	4,732

Source: Author's own estimates of DETI data

6.3.2 Descriptive Statistics

The subset of data used for this chapter covers all manufacturing sectors, as per the SIC 92 classification, and a number of service sectors, excluding public services (see Table 6.4). The monetary variables used in the dataset are expressed in thousands of pounds sterling; those in manufacturing have been converted from nominal to real values by sector by deflating with the Producer Price Index (PPI), obtained from the Office of National Statistics, whilst service sector monetary values have been deflated using implicit deflators derived from chained volume indices of GVA.

As mentioned above, the dataset contains observations back to 1998 however the estimates for larger firms that did not respond to the survey were only provided from 2002 onwards. In addition, R&D variables which take account of human capital inputs are only available on an annual basis from 2002 onwards. Given both these conditions the analysis is restricted to the 2002-08 period; this reduces the dataset to 16,183 observations or 4,571 firms, of which 3,301 (72.2%) are exporters; 3,478 (76.1%) external sellers and 1,188 (26.0%) overseas sellers. The representativeness of the dataset is thus retained.

Table 6.4 displays the sectoral composition of the three different types of exporter firm, pooling the data as a whole. Given the nature of the MSES data it is unsurprising that around three quarters of all firms are in Manufacturing; Business Services constitutes the next largest grouping, at around one tenth of all firms and Wholesale and Retail at 8 per cent. The composition of exporters and non-exporters by sector broadly match the overall sectoral share and this is consistent across the different definitions for example, under the standard export definition 74 per cent of non-exporters are in Manufacturing and 72 per cent of exporters; likewise 11 per cent of both are Business Services firms.

Table 6.4: Sectoral Composition of Exporters and Non-Exporters 2002-08

	Exporter		External Seller		Overseas Seller		
	0	**1**	**0**	**1**	**0**	**1**	**Total**
Manufacturing	3,387 *[29%]* *(74%)*	8,299 *[71%]* *(72%)*	2,907 *[25%]* *(77%)*	8,779 *[75%]* *(71%)*	9,214 *[79%]* *(72%)*	2,472 *[21%]* *(72%)*	11,686 *(72%)*
Construction	186 *[24%]* *(4%)*	582 *[76%]* *(5%)*	160 *[21%]* *(4%)*	608 *[79%]* *(5%)*	706 *[92%]* *(6%)*	62 *[8%]* *(2%)*	768 *(5%)*
Wholesale & Retail	292 *[22%]* *(6%)*	1,036 *[78%]* *(9%)*	230 *[17%]* *(6%)*	1,098 *[83%]* *(9%)*	1,048 *[79%]* *(8%)*	280 *[21%]* *(8%)*	1,328 (8%)
Business Services	498 *[29%]* *(11%)*	1,249 *[71%]* *(11%)*	329 *[19%]* *(9%)*	1,418 *[81%]* *(11%)*	1,220 *[70%]* *(10%)*	527 *[30%]* *(15%)*	1,747 *(11%)*
Other Services	234 *[36%]* *(5%)*	420 *[64%]* *(4%)*	169 [26%] *(5%)*	485 *[74%]* *(4%)*	544 *[83%]* *(4%)*	110 *[17%]* *(3%)*	654 (4%)
Total	4,597 *[28%]*	11,586 *[72%]*	3,795 *[23%]*	12,388 *[77%]*	12,732 *[79%]*	3,451 *[21%]*	16,183

Note: Square brackets represent row percentages by exporter category; round brackets represent column percentages by exporter category
Source: Authors own estimates of DETI data

Table 6.5 shows the key descriptive statistics for the data; indicating the differences between exporters and non-exporters, using the three different definitions. As described above, the data has been restricted to the period 2002-08, and contains 16,183 observations across the period. Pooling the data together, it can be seen that exporters and non-exporters differ across several metrics and these differences are highly significant. Looking at the standard exporter definition we see that on average exporters are larger, in terms of both sales and employment, with sales around four times higher, and employment twice as high as non-exporters. Their spending on R&D is more than ten times higher than non-exporters, on average, whilst labour productivity (GVA per employee) and employment costs per employee are also higher. A similar pattern emerges for those selling outside NI (external sellers) whilst for the overseas sellers the differences are even more pronounced. Employment amongst overseas sellers is three times larger than for those just selling within the

UK and Republic of Ireland; sales are around seven times larger and R&D spending more than thirty times higher.

Table 6.5: Key Descriptive Statistics for Exporters and Non-exporters 2002-08

	Exporter (n=11,586)		***Non-exporter (n=4,597)***		
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	***T-Test***
Employment	56.4	206.9	29.8	159.6	7.8***
Employment costs per employee	16.1	9.3	13.5	7.9	16.5***
GVA per employee	30.7	27.4	27.2	25.5	7.6***
R&D spending	119.3	1,360.8	9.2	102.0	5.5***
Sales	8,189.1	84,677.0	2,343.8	20,761.3	4.6***
	External seller (n=12,388)		***Non-external seller (n=3,795)***		
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	***T-Test***
Employment	55.5	202.8	27.1	165.4	7.9***
Employment costs per employee	16.0	9.3	13.1	7.8	17.5***
GVA per employee	30.6	27.0	26.6	26.3	8.0***
R&D spending	113.0	1,316.8	6.3	84.9	5.0***
Sales	7,980.6	82,524.7	1,789.1	13,477.6	4.6***
	Overseas seller (n=3,451)		***Non-overseas seller (n=12,732)***		
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	***T-Test***
Employment	108.7	347.7	32.6	119.8	20.6***
Employment costs per employee	18.7	12.1	14.4	7.7	24.9***
GVA per employee	35.9	39.5	28.0	22.0	15.3***
R&D spending	367.6	2,449.2	12.2	198.5	16.2***
Sales	19,688.3	153,544.8	2,961.8	15,511.6	12.1***

Note: Sales, R&D spending, employment costs and GVA per employee are in £000s at 1995 prices. Labour productivity defined as GVA per employee
Source: Authors own estimates of DETI data

Table 6.6 shows the percentage share of firms in each export intensity size band by the three types of exporter status, where export intensity is measured as exports as a share of sales. The corresponding average labour productivity for each of these intensity size bands is also displayed in the lower half of the table. The Table reveals that, for the standard definition, just over one quarter of firms do not export i.e. their export sales intensity is zero. Around one third of firms sell less than 20 per cent of their output to export markets, and less than one fifth of firms export more than half of their production.

The external sales definition of exporter indicates that around three quarters have external sales however just 35 per cent of firms sell more than half of their produce outside NI. The final definition, overseas sellers, indicates that one fifth of firms sell to overseas markets; of these around one in ten sell less than 10 per cent to overseas markets, whilst only 6 per cent sell more than half of what they produce overseas.

The average labour productivity figures are interesting in that, for each exporter measure, they show that firms that sell more than 50 per cent of their products to export markets tend to have higher average productivity levels than those who export a smaller share. Below this 50 per cent intensity mark the pattern of average labour productivity is quite stable across intensity bands, particularly for the external and overseas sellers, suggesting that the relationship is not monotonic.

The fact that there are relatively low shares of firms with high export intensity may suggest that the extent of any learning that is associated with exporting is somewhat limited, however the fact that those selling more than 50 per cent of sales to export markets have higher labour productivity does further suggest a need to examine whether this is a cause or effect from exporting.

Table 6.6: Share of Firms and Mean Labour Productivity by Export Intensity Size Band 2002-08

	Export Definition	**External Seller Definition**	**Overseas Seller Definition**
Export Intensity	**% of firms**	**% of firms**	**% of firms**
0%	28.4	23.5	78.7
1-9%	21.8	15.1	9.1
10-19%	11.9	9.0	2.6
20-49%	20.6	18.0	3.7
50+%	17.3	34.5	5.9
Intensity	***Mean Labour Productivity*** **£000s**	***Mean Labour Productivity*** **£000s**	***Mean Labour Productivity*** **£000s**
0%	27.2	26.6	28.0
1-9%	30.1	27.8	31.9
10-19%	27.5	28.1	31.5
20-49%	29.7	28.2	33.4
50+%	34.9	33.8	45.8

Note: Labour productivity defined as GVA per employee
Source: Authors own estimates of DETI data

6.4 Methodology

The central aim of this chapter is to firstly examine the difference between exporters and non-exporters and secondly, to analyse whether exporting has any impact on a firm's labour productivity growth. The first step has been widely examined in the empirical literature, typically using some form of binary choice model. For example, early work by Roberts and Tybout (1997) makes use of a probit with random effects. Bernard and Wagner (1998) model the export decision using both a linear probability model with fixed effects and a probit with random effects. Bernard and Jensen (1997, 2001) use a fixed effects linear probability model and control for the lagged endogenous variables by estimating the model with first differences and instrumental variables. Later models concentrate on export intensity and use techniques to account for the dependent variable which is bounded between 0 and 1, for example Roper and Love (2001) use Tobit models whilst Wagner (2001) employs fractional logit models. In more recent developments, rather than modelling the difference between the two sets of firms at the means, studies have estimated the difference between exporters and non-exporters along the entire export intensity distribution (for example, Fryges and Wagner, 2007). Here both approaches are used; a binary choice model is selected to examine the difference in characteristics between exporters and non-exporters; and quantile regression is used to examine the differences at varying levels on the export intensity distribution to take account of the heterogeneous nature of exporters.

For the second part of the analysis, the literature has typically employed two main techniques to model self-selection into exporting and to test for learning-by-exporting. These techniques include testing for stochastic dominance for the former (for example, Delgado et al., 2002; Girma et al., 2004; Wagner, 2012; Cassiman et al., 2010; Temouri et al., 2013; Engel and Procher, 2012) and propensity score matching for the latter (Girma et al. 2004; Greenaway and Kneller, 2007; Damijan et al., 2010; Yang and Mallick, 2010; Eliasson et al., 2012; Manjon et al., 2013). Both these approaches are utilised here, with non-parametric Kolmogorov-Smirnov tests used in the stochastic dominance approach, and propensity score matching used to test for evidence of learning-by-exporting.

6.4.1 Logistic Regression

Following Gourlay and Seaton (2004), Westhead (1995) and Javalgi et al. (1998) a Logit model is employed to test for differences between exporters and non-exporters. Logistic regression allows one to predict a discrete outcome, in this case export participation, from a set of variables. The dependent variable in the logistic regression is dichotomous, taking the value one with a probability of success, or the value zero with a probability of failure. The logistic regression makes no assumption about the distribution of the independent variables and hence they can take any form (continuous, categorical etc.). The relationship between the predictor and response variables is not a linear function but rather the logistic regression function is used which is the logit transformation of Y, the dependent variable. The logit is the natural logarithm (ln) of odds of Y, and odds are ratios of probabilities (π) of Y happening, to probabilities (1 – π) of Y not happening. Maximum likelihood estimation (MLE) is the preferred method used to calculate the logit coefficients by authors such as Haberman (1978) and Schlesselman (1982); this method seeks to maximise the log likelihood, which reflects how likely it is (the odds) that the observed values of the dependent variable (exporting) may be predicted from the observed values of the independent variables (firm characteristics).

The simple logistic model has the following form:

$$\text{Logit (Y) = natural log (odds) = } \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta\chi \qquad (6.1)$$

The regression coefficient (β) is the logit. Taking the antilog of (6.1) on both sides, one derives an equation to predict the probability of the occurrence of the outcome of interest:

$$\pi = \text{Probability}(Y = \text{outcome of interest} \mid X = x, \text{ a specific value of X}) = \frac{e^{\alpha+\beta_x}}{1+e^{\alpha+\beta_x}} \qquad (6.2)$$

where π is the probability of the outcome of interest, in this case exporting, α is the Y intercept, β is the regression coefficient, and e = 2.71828 is the base of the system of natural logarithms.

We can extend this simple logistic regression to incorporate multiple predictors:

$$\pi = \text{Probability (Y=outcome of interest} \mid \text{X}_1 = x_1, X_2 = x_2 \ldots X_i = x_i$$
$$= \frac{e^{\alpha+\beta_1\chi_1+\beta_2\chi_2+\ldots\beta_i\chi_i}}{1+e^{\alpha+\beta_1\chi_1+\beta_2\chi_2+\ldots\beta_i\chi_i}} \quad (6.3)$$

where π is the probability of the event, α is the Y intercept, βs are regression coefficients, and Xs are a set of predictors. The null hypothesis underlying the overall model states that all βs equal zero. A rejection of this null hypothesis implies that at least one β does not equal zero in the population, which means that the logistic regression equation predicts the probability of the outcome better than the mean of the dependent variable Y. The interpretation of results is rendered using the odds ratio for both categorical and continuous predictors (Peng, et al., 2002).

In the logit model used here the binary dependent variable is defined, equal to one if the firm is an exporter and zero otherwise. The decision to export is modelled as a function of firm-level and sectoral characteristics, thus the basic model is given as:

$$Y_{it} = \beta_0 + \beta_1 \text{ltotalemp}_{it-1} + \beta_2 \text{totalempsq}_{it-1} + \beta_3 \text{lgvaperemp}_{it-1} + \beta_4 \text{lempcostsperemp}_{it-1} + \beta_5 \text{rdspendsh}_{it-1} + \beta_6 \text{Assist}_{it} + \beta_7 Z_{it} + \varepsilon_i \quad (6.4)$$

where subscript *i* denotes firms, and *t* denotes time.

In the model Y is the decision to export; **ltotalemp** is the log of firm size; **totalempsq** is the quadratic of firm size; **lgvaperemp** is the log of labour productivity; **lempcostsperemp** is the log of labour costs per employee; **rdspendsh** is R&D spending as a share of turnover; **SFAasst** is a dummy indicating receipt of SFA financial assistance and Z is a vector of sectoral characteristics. The continuous variables are all transformed into natural logs prior to estimation and are estimated with one lag (excluding the sectoral variables and SFA assistance which are simultaneous).

The regressors in the model were selected based on *a priori* reasoning that certain firm attributes influence export performance, as discussed above in the relevant literature; descriptive statistics for the model (based on the standard export definition) are given in Table 6.7. Given the widespread evidence for larger and more productive firms to be exporters, both are included as key variables in the analysis. The log of firm size (**ltotalemp**) is measured by employment size and is expected to be positively related to the likelihood of a firm being an exporter. The reasoning for this is that larger firms have greater resources and hence greater capability to overcome sunk costs to expand into foreign markets; larger firms might also be able to take advantage of economies of scale in production, show higher capacity of taking risks and obtain credit at lower costs (Wagner (1995). A quadratic of firm size is also included (**totalempsq**) to account for the fact that the size-export relationship may be a non-linear; this is most likely to be the case in which very large monopolistic firms have a low inclination to export (Wakelin, 1997).

The productivity variable (**lgvaperemp**) is defined as the log of GVA per employee. As per the self-selection theory more productive firms are deemed the most likely to become exporters due to the sunk costs argument and are also more likely to be able to compete effectively in a wider marketplace. Given this we would anticipate a positive effect from the productivity variable.

Labour costs are measured in logs per employee (**lempcostsperemp**) and are included to act as a proxy for the human capital and hence quality of the workforce, in the way that the wage level is used as a proxy in the literature (Bleaney and Wakelin, 1999; Bernard and Jensen, 2001). The notion is that the higher the wage/labour costs the more sophisticated the product and therefore the more likely the firm is to be an exporter.

The R&D variable is measured as R&D expenditure as a share of turnover (**rdspendsh**). The expected sign on the coefficient is positive in that firms who have a high R&D spend ratio are expected to be more likely to be actively involved in developing their products and/or processes, and may be doing so in order to retain export market share to remain competitive or expand into new (more technologically advanced) export markets.

A variable to represent SFA assistance to industry (**Assist**) is included in the model to take account of the fact that NI firms are heavily assisted, particularly with regards to export promotion. The variable is coded as 1 if the firm is an Invest NI client and 0 otherwise; the anticipated sign on the coefficient is positive reflecting the fact that those firms that export are likely to have received assistance to do so.

Sectoral dummies are included which distinguish twelve major groups of manufacturing and service activity[41]. It is likely that the ability to export and the share

[41] The sectors and their corresponding SIC codes are detailed in Appendix 1, Table A1.15.

exported will differ across sectors due to the nature of the product on offer, therefore we would anticipate a positive sign on the sectors which have a limited home market, such as heavy manufacturing and transport equipment, compared to the base case of other services.

Table 6.7: Descriptive Statistics for Exporter / Export Intensity Models

stats	*N*	*Mean*	*median*	*sd*	*Min*	*Max*
Exporter (1/0 dummy)	12,374	0.74	1.00	0.44	0.00	1.00
Export Intensity *(export value / sales)*	12,374	0.23	0.10	0.28	0.00	1.00
Labour Productivity *(GVA per employee)*	12,374	30.9	26.0	28.6	2.7	705.3
Size *(total employment)*	12,374	57	16	216	0	6,524
R&D Intensity *(R&D spend / turnover)*	12,374	0.08	0.00	3.09	0.00	1.00
Employment Costs *(emp costs per employee)*	12,374	16.1	15.1	8.7	1.3	232.6
Assisted (1/0 dummy)	12,374	0.10	0.00	0.30	0.00	1.00
Food	12,374	0.12	0.00	0.33	0.00	1.00
Textiles	12,374	0.05	0.00	0.21	0.00	1.00
Paper	12,374	0.07	0.00	0.25	0.00	1.00
Rubber	12,374	0.06	0.00	0.24	0.00	1.00
Metal	12,374	0.17	0.00	0.38	0.00	1.00
Machinery	12,374	0.07	0.00	0.26	0.00	1.00
Electrical	12,374	0.05	0.00	0.21	0.00	1.00
Transport	12,374	0.03	0.00	0.17	0.00	1.00
Other Manufacturing	12,374	0.09	0.00	0.29	0.00	1.00
Construction	12,374	0.04	0.00	0.19	0.00	1.00
Wholesale & Retail	12,374	0.07	0.00	0.25	0.00	1.00
Business Services	12,374	0.09	0.00	0.28	0.00	1.00

Note: Employment costs and labour productivity are in £000s at 1995 prices
Source: Author's own estimates of DETI data

6.4.2 Export Intensity Model

Rather than simply modelling the differences between exporters and non-exporters as a binary choice variable many studies have sought to analyse the differences by using export intensity i.e. share of sales exported, as the dependent variable. Use of this method has typically been done with a Tobit model (see Wagner, 1995; Bleaney and Wakelin, 1999; Roper and Love, 2001) which allows linear relationships between variables to be estimated when there is either left- or right-censoring in the dependent variable. The dependent variable in this model is defined as exports as a percentage (or ratio) of total sales, therefore by definition, it lies between zero and one hundred percent (or zero and one); the use of OLS regression in this instance can result in estimates which imply predictions outside of the zero to one range. However Wagner (2001) has criticised the use of Tobit in such analyses, stating that Tobit is only appropriate when the value of the dependent variable can be less than a lower limit, but observations with such values are not observed because of censoring. Thus he states it is not suitable for instances when the dependent, as in this case, is bounded by zero and one by definition. As a result in his subsequent analyses of the firm-exports relationship he employs fractional Logit models (see Wagner, 2001, 2002, 2008, 2010; and Fryges and Wagner, 2007.)

The fractional logit methodology was developed by Papke and Wooldridge (1996) in a study of employee participation rates in pension plans, and basically enables models, for which the dependent variable is a fraction (thus bounded between zero and one), to be estimated without the need to adjust the data at the extremes, and which allows the predicted values to lie in the required range.

However, rather than take either approach to model export intensity the preferred method used here, which has only been used relatively recently in modelling the relationship between exports and productivity growth, is that of quantile regression. As Wagner (2007) states this method was first introduced to the exporting-productivity literature by Yasar et al. in 2003 and has been used, to date, to model export intensity in a relatively small number of studies, for example,: Wagner (2006), Yasar et al. (2003, 2006); Cassiman and Golovko, (2007); Serti and Tomasi (2009); Bellone et al. (2010); Powell and Wagner (2011); and Velucchi and Viviani (2011). .

Given the variation in export intensity across firms, and the associated average labour productivity levels, as shown in Table 6.6, it seems sensible to model the export decision across the entire export intensity distribution, rather than just comparing the means. The method would also appear to be justified based on Wagner's (2004; pg. 1) observation that "there is no such thing as a representative exporting firm" and in fact he points out that this very fact was the basis for the construction of new trade theory models based on heterogeneous exporting firms (Melitz, 2003, and Bernard, Redding and Schott, 2004). The notion behind using this method is such that if exporters are heterogeneous, then it is likely that the effects of the variables explaining export behaviour is not the same across firms, for example R&D intensity may have a bigger impact on firms that export a small share of output compared to those exporting a large share or vice versa. Regressing the export intensity share on firm characteristics can only account for such differences across the export intensity distribution if it based on the quantile regression technique; OLS, which gives information about the effects of the regressors at the conditional mean of the dependent variable only, assumes that the conditional distribution is homogeneous.

6.4.2.1 Quantile Regression

The quantile regression model was first introduced by Koenker and Bassett (1978); the method is used when an estimate of the various quantiles (such as the median, 90th percentile etc.) of a population is desired. The technique is appropriate to use for modelling the export intensity-firm characteristic relationship for a number of reasons. Firstly, it is likely that export intensity levels vary across the distribution of firms; typically the optimal properties of standard regression estimators, such as OLS, are not robust to modest departures from normality, however quantile regression results are characteristically robust to outliers and heavy-tailed distributions. In fact, the quantile regression solution βˆθ is invariant to outliers of the dependent variable that tend to ± ∞ (Buchinsky, 1994). In addition, while conventional regressions focus on the mean, as stated above, quantile regressions are able to describe the entire conditional distribution of the dependent variable. Thirdly, a quantile regression approach avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. Relaxing this assumption allows for firm heterogeneity and the possibility that estimated slope parameters vary at different quantiles of the conditional export intensity distribution.

The quantile regression model is as follows:

$$y_{it} = \chi'_{it}\beta_\theta + u_{\theta it} \qquad \text{with} \qquad \text{Quant}_\theta(y_{it} \mid x_{it}) = x'_{it}\beta_\theta \tag{6.5}$$

where y_{it} is the dependent variable, x is a vector of regressors, β is the vector of parameters to be estimated, and u is a vector of residuals. $\text{Quant}\theta(y_{it}|x_{it})$ denotes the θth conditional quantile of y_{it} given $x_{it.}$. The θth regression quantile, 0 < θ < 1, solves the following problem:

$$\min_\beta \frac{1}{n}\left\{ \sum_{i,t:y_{it}\geq\chi'_{it}\beta} \theta \mid y_{it} - \chi'_{it}\beta \mid + \sum_{i,t:y_{it}<\chi'_{it}\beta} (1-\theta) \mid y_{it} - \chi'_{it}\beta \right\} = \min_\beta \frac{1}{n}\sum_{i=1}^{n} \rho_\theta \upsilon_{\theta it} \tag{6.6}$$

where ρθ(.), which is known as the ‘check function’, is defined as:

$$p_\theta(\upsilon_{\theta it}) = \begin{cases} \theta\upsilon_{\theta it} & \text{if } \upsilon_{\theta it} \geq 0 \\ (\theta - 1)\upsilon_{\theta it} & \text{if } \upsilon_{\theta it} < 0 \end{cases} \tag{6.7}$$

Equation (6.7) is then solved by linear programming methods. As one increases θ continuously from 0 to 1, one traces the entire conditional distribution of y, conditional on x (Buchinsky, 1998). The estimated regression coefficients can be interpreted as the partial derivative of the conditional quantile of the dependent variable (the share of exports in total sales) with respect to a particular regressor (for example, R&D share of sales), i.e. the marginal change in the export/sales ratio at the kth conditional quantile due to a marginal change in the R&D/sales ratio. For each quantile it can be shown whether the effect of a particular independent variable is positive or negative, and how large this effect is compared to other quantiles which provides information about the heterogeneity of firm behaviour.

The equation used for the export intensity model replicates that for the exporter model as in (6.4) and is given as:

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 \text{ltotalemp}_{it-1} + \beta_2 \text{totalempsq}_{it-1} + \beta_3 \text{lgvaperemp}_{it-1} + \\ &\beta_4 \text{lempcostsperemp}_{it-1} + \beta_5 \text{rdspendsh}_{it-1} + \beta_6 \text{govasst}_{it} + \beta_7 Z_{it} + \varepsilon_i \end{aligned} \tag{6.8}$$

In this model Y is export intensity (measured as exports as a share of sales); the regressors remain as before. We would expect a positive sign on the size, productivity; labour costs, R&D spend and SFA assistance variables, for the reasons given in the binary model. Higher R&D spending is particularly likely to be associated, not just with exporting, but a higher intensity of exporting as the continuing development of products may be undertaken in response to perceived profit opportunities abroad, and so influence the share of sales that are exported. The labour costs variable is also expected to be positively related to export intensity in that, as a proxy for the quality of the good/service, firms with a more sophisticated product may have a limited domestic demand and thus be more likely to sell a greater share in the wider export marketplace.

6.4.3 Self-selection Model

Whilst both the logit and quantile regression models can reveal differences in the characteristics of exporting versus non-exporting firms, they are less informative in terms of policy design as they do not address the issue of causality i.e. whether more productive firms become exporters and/or whether exporting makes firms more productive. These next two sections discuss the modelling techniques used to test for this, under the self-selection and learning-by-exporting concepts.

Stochastic dominance is a form of ordering; the test for it is a useful statistical method of determining the superiority of one distribution over another. The technique has been used extensively in the literature concerning income distributions and inequality (for examples see, Anderson, 1996; Maasoumi and Heshmati, 2000, 2013; Davidson and Duclos, 2000, 2013) however more recently it has been used as a means of testing for self-selection in the exporting-productivity relationship (Mánez-Castillejo et al, 2010; Wagner, 2010b; Vogel and Wagner, 2010; Manjón et al., 2013). In this case, the ex-ante productivity distribution of new exporters and non-exporters is compared and tested.

Stochastic dominance has its roots in decision theory and in particular, where there is uncertainty over the choice between random payoffs. If one payoff or prospect is preferred over another, due to certain outcomes for example more favourable outcomes, better value outcomes or less risky outcomes, then it can be said to be superior to, or stochastically dominate the other payoff. There are different types of stochastic dominance; first order refers to a 'stochastically larger' relationship while second order refers to a 'stochastically less volatile' relationship. A random variable X is said to first order stochastically dominate the random variable Y, given as $X \geq_{FSD} Y$, if for any outcome z, X gives at least as high a probability of receiving at least z as does Y, and for some *z*, X gives a higher probability of receiving at least z. In notation form this is given as:

$$\Pr\{X > z\} \geq \Pr\{Y > z\} \text{ for all z,} \qquad (6.9)$$

And,

$$\Pr\{X \geq z\} > \Pr\{Y \geq z\} \text{ for some z} \qquad (6.10)$$

Or equivalently, in terms of cumulative distribution functions:

$$\overline{F}(z) \geq \overline{G}(z) \text{ for all z, with strict inequality at some z} \qquad (6.11)$$

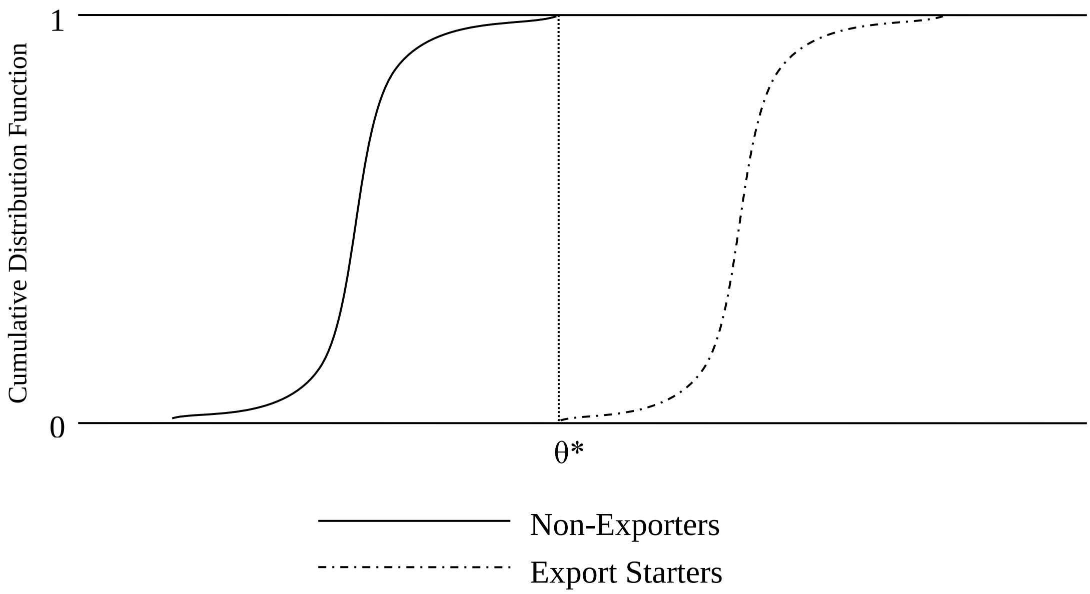
Where F and G denote distributions, and where:

$$\overline{F}(z) = 1 - F(z) \text{ and } \overline{G}(z) = 1 - G(z) \qquad (6.12)$$

As stated in the literature review in Chapter 4, the self-selection hypothesis suggests that the more productive firms self-select into exporting. Manez-Castillejo (2010) summarises how this becomes testable within the stochastic dominance framework and bases it on Melitz's (2003) model of heterogeneous firms. The model suggests that for firms to export they much reach a certain threshold of productivity, given as θ*, which is the lowest level that will allow firms to obtain positive discounted expected profits over future periods, the 'export productivity threshold'. Firms with productivity levels < θ* will not find it profitable to export and hence will not do so whilst those with productivity levels > θ* will export. Thus the threshold represents the dividing line between the productivity distribution functions of exporters and non-exporters.

The productivity threshold is not directly observable, however if self-selection occurs, then we would expect to find that the ex-ante productivity distributions of new exporters dominate those of non-exporters. This is captured visually by Fig. 6.1 whereby the productivity distribution of new exporters is to the right of non-exporters; if the hypothesis is accepted we would expect to find a similar pattern for our data.

Figure 6.1: Stochastic Dominance of Productivity Distributions



In order to statistically test for first-order stochastic dominance the Kolmogorov-Smirnov test is used. In particular, tests of stochastic dominance of a given distribution F(z) (the productivity distribution of export starters) with respect to another distribution G(z) (the productivity distribution of non-exporters) is undertaken by testing two hypotheses:

$$H0: F(z) - G(z) = 0 \ \forall z \in \Re \ \text{ versus}$$
$$H1: F(z) - G(z) \neq 0 \text{ for some } z \in \Re \qquad (6.13)$$

$$H0: F(z) - G(z) \leq 0 \ \forall z \in \Re \ \text{ vs versus}$$
$$H1: F(z) - G(z) > 0 \text{ for some } z \in \Re \qquad (6.14)$$

The first hypothesis is tested through the two-sided K-S test with the second hypothesis tested through the one-sided K-S test. To have first order stochastic dominance of F(z) with respect to G(z) the null needs to be rejected in the first test and the null failed to be rejected in the second test. In other words, we need to verify that the two distributions are different and that this difference is not due to the F(z) distribution lying above G(z).

6.4.4 Learning-by-exporting model

In order to determine whether firms become more productive through exporting (learning-by-exporting) one can look at the post-entry performance of exporting firms[42]. However, it is not a case of assuming that more successful growth post-entry means that there is a causal link between exporting and productivity growth, rather the scenario can also suggest two potential outcomes; firstly that firms have self-selected into exporting or secondly that there is reverse causality, or simultaneity, whereby exporting increases productivity growth and this in turn increases exporting activity. Both these problems are classed as types of endogeneity bias.

The self-selection problem can be thought of as an omitted variables issue; firms have made a choice to start exporting (hence it is not random) but the reasons behind this choice may also impact productivity growth. If these reasons are unobserved in the model then the explanatory variables and the error term will be correlated, hence any results on productivity growth, using OLS, will be biased upwards. Likewise in the simultaneity issue the regressor and the error term will also correlated; in this case OLS estimation picks up both forwards and backwards effects, thereby leading to biased and inconsistent coefficients (Wooldridge, 2006).

In order to remedy the selection and simultaneity bias issues one must try and find the counterfactual productivity position for exporters had they not entered export markets. Obviously this cannot be observed so, one option, in line with typical evaluation studies, is to construct a control group whereby each firm that has exported (been treated) is matched to a non-exporter (untreated) that is similar in nature (in terms of the observed variables) prior to treatment. Using this method any observed differences between the two groups can then be attributed solely to the treatment (Heckman et al., 1999).

Typically, propensity score matching is the technique adopted to construct control groups when estimating the export-productivity relationship (see Wagner, 2002; Girma et al., 2002, 2003; De Loecker, 2004, 2007; Arnold and Hussinger, 2004; Yasar and Rejesus, 2005; Greenaway and Kneller, 2007; Yang and Mallik, 2010; Manjón et al., 2013). A novel approach which takes the notion of matching and

[42] Alternatively one could look at the performance of exporters after leaving export markets and compare them to continuous exporters (for an example see Yasar and Rejesus, 2005). The dataset for this study did not contain enough years to construct post-export performance.

extends it to allow for continuous treatment is that used by Fryges and Wagner (2007). In this method, known as the generalised propensity score (GPS), the traditional propensity score technique is modified so that it allows for the estimation of different levels of firms' export-sales ratios on productivity growth, rather than just the binary treatment (exporter vs non-exporter) method. The methodology was developed by Imbens (2000) and Hirano and Imbens (2004) who defined it as the conditional probability of receiving a particular level of the treatment given the pre-treatment variables. Conditioning on the GPS is sufficient to remove the bias associated with differences in pre-treatment variables, as long as the pre-treatment variables are balanced across the various treatment levels.

The propensity score method was introduced by Rosenbaum and Rubin (1983) who defined the propensity score as the conditional probability of being assigned to a binary treatment group given a vector X of observed covariates. In the analysis a propensity score is computed for each firm in the sample, based on their background covariates; the method then constructs an artificial control group from those not experiencing the treatment; those chosen to be in the control group selected on the basis that their propensity score, i.e. the estimated probability of being in the experimental group, matches that of a firm or individual in the experimental group (Kennedy, 2003). By comparing firms from different treatment groups with the same or a similar propensity score, causal effects of the treatment can be estimated. As propensity scores can only match those background covariates that are observed, unmeasured differences between firms cannot be accounted for, however using post-estimation statistical techniques, sensitivity analysis can be conducted to assess the extent of hidden bias that would need to exist in order to substantively alter the findings (Braitman and Rosenbaum, 2002).

In order to make some inference then about the impact of starting to export on the productivity growth of firms we must speculate about how these firms would have performed had they not started to export. In this study there is a binary treatment, $D_i = 1$ if firm *i* receives treatment (starts exporting) and $D_i = 0$ if firm *i* does not receive the treatment (is a continuous non-exporter). The potential outcome, productivity growth, can be written as $Y_i(D_i)$ for each firm *i*, where *i* = 1: N and N denotes the total population. The treatment effect τ for firm *i* is:

$$\tau = Y_i(1) - Y_i(0) \tag{6.15}$$

The fundamental problem of causal inference arises however in that only one potential outcome is observed for each firm, we cannot observe the counterfactual for exporters had they not started to export and thus we have to estimate the average treatment effect at the population, or sub-population level.

The 'average treatment effect on the treated' is given as:

$$\tau_{ATT} = E(\tau \mid D=1) = E\left[Y(1) \mid D=1\right] - E\left[Y(0) \mid D=1\right] \tag{6.16}$$

As explained above, the counterfactual mean outcome $E\left[Y(0) \mid D=1\right]$ is not observed. We cannot simply look at the mean outcome of untreated firms $E\left[Y(0) \mid D=0\right]$ as there may be an element of self-selection bias, in that the components that determine the treatment may also determine the outcome (Caliendo & Kopeining, 2005). We must therefore find a way to construct the counter-factual, which we can do, making some identifying assumptions to eliminate this self-selection problem.

The first assumption is that of conditional independence, which Foster (2003) states is the critical assumption for propensity score matching. The assumption states that for a given set of covariates X, participation is independent of potential outcomes. Among firms with the same characteristics used for matching, the model thus assumes that these firms are sorted into different treatments as if randomly assigned:

$$Y(0), Y(1) \amalg D \mid X, \ \forall \ X \tag{6.17}$$

A further assumption, or requirement, is that matching has to be performed over the common support, or overlap, area. This means that there must be a substantial overlap between the characteristics of beneficiaries and non-beneficiaries. It thus ensures that persons with the same X values have a positive probability of being both participants and non-participants in the treatment (Heckman et al., 1999):

$$0 < P(D=1 \mid X) < 1 \tag{6.18}$$

When the assumptions of conditional independence and common support are met, the propensity score match (PSM) estimator for the average treatment effect on the treated (ATT) is given as:

$$\tau_{ATT}^{PSM} = E_{P(X)|D=1}\{E\,|[Y(1)\,|\,D=1, P(X)] - E[Y(0)\,|\,D=0, P(X)]\} \quad (6.19)$$

where the PSM estimator is the mean difference in outcomes over the common support, appropriately weighed by the propensity score distribution of participants. According to Caliendo and Kopeinig (2005) the framework for conducting propensity score matching contains five steps:

1. Conduct the propensity score estimation
2. Choose the matching algorithm
3. Check overlap / common support
4. Analyse the matching quality / effect estimation
5. Conduct sensitivity analysis

The first stage is typically estimated using either a probit or logit model, as the treatment is generally of a binary form[43]. The variables to be selected in the propensity score estimation should be those that are either time invariant or measured before participation in order to ensure that they are unaffected by participation, or the anticipation of it. Typically the choice of variables is guided by previous empirical studies and/or economic theory.

The subsequent matching algorithm can take a number of forms; the algorithms differ with regards to how the neighbourhood for each treated individual is defined and also differs with respect to the weights assigned to these neighbours. The nearest-neighbour match is perhaps the most straightforward match; where one individual from the comparison group is selected as a matching partner for a treated individual that is closest in terms of its propensity score. Nearest-neighbour matching can be done with or without replacement; with replacement means that an untreated individual can be used more than once as a match, whereas without replacement means that it can be considered only once. Dehejia and Wahba (1998) find that

[43] Typically either logit or probit models can be used, as both generally give the same results however in cases of multiple treatment the choice between multinomial logit and probit becomes more important (Lechner, 2001).

allowing for non-treatment group members to be used more than once as comparators improves the performance of the match. Furthermore, it is less demanding of the data than permitting non-treatment group individuals to be used only once.

Variants of nearest-neighbour matching include radius and caliper matching; these overcome the main problem with nearest-neighbour i.e. the risk of bad matches if the nearest neighbour is far away. Caliper matching (Cochrane & Rubin, 1973) imposes a tolerance level on the maximum propensity score distance; where the propensity score of a treated individual falls beyond the bound set for a near comparator, the treated individual will remain unmatched. Caliper matching thus increases the quality of matches, however if fewer matches can be made as a result then the variance of the estimates increase. A further practical problem may be that it is difficult to judge in advance what choice of tolerance level is appropriate (Smith and Todd, 2005). Radius matching (Dehejia and Wahba, 2002) extends on this and uses not only the nearest neighbour within each caliper but also all of the units within the caliper.

Stratification matching works by ranking both the treated and the control individuals on the basis of their propensity score and then grouping them into K strata, or intervals. The impact within each strata is then calculated by taking the mean difference in outcomes between treated and control observations. The overall impact is obtained by calculating a weighted average of the strata effects, with weights proportional to the number of treated individuals in each stratum.

Unlike the above matching approaches Kernel matching and local linear matching are non-parametric matching estimators that use weighted averages of *all* individuals in the control group to construct the counterfactual outcome. As more information is used in these approaches, lower variance is achieved, however like the nearest-neighbour approach, a drawback is that observations may be used that are bad matches. Kernel matching can be seen as a weighted regression of the counterfactual outcome on an intercept with weights given by the kernel weights (Smith and Todd, 2005) In kernel matching the estimated intercept provides an estimate of the counterfactual mean whilst local linear matching includes, in addition to the intercept, a linear term in the propensity score of a treated individual.

The range of matching approaches available thus presents the dilemma of which to choose although theoretically they should all give the same results using a large dataset. Indeed Smith and Todd (2000) have shown that the choice makes little difference in such scenarios however Heckman et al. (1997) state that in small samples the approach chosen is of key importance. Generally, one should use a number of the approaches depending on the size and structure of the dataset, for example, based on the size of the control group compared to the treated, and the distribution of the propensity scores.

Once the matching and outcome estimation has been conducted sensitivity analysis can be used to examine the extent of any hidden bias which would occur if there were unobserved variables that simultaneously affected assignment into treatment and the outcome variable. Rosenbaum (2002) proposed a bounding approach to test for such selection bias, which, if present, would alter the inferences one could make about the effect of the treatment. There are two types of command (in Stata) which test for such sensitivity, the first –rbounds- is used for continuous-outcome variables and secondly, -mhbounds- is used for binary-outcome variables. The null hypothesis of the approach is that there is no hidden bias.

The rbounds command calculates Rosenbaum bounds for average treatment effects on the treated in the presence of unobserved heterogeneity (hidden bias) between treatment and control cases. rbounds takes the difference in the response variable between treatment and control cases and calculates Wilcoxon signrank tests that give upper and lower bound estimates of significance levels at given levels of hidden bias. Under the assumption of additive treatment effects, rbounds also provides Hodges-Lehmann point estimates and confidence intervals for the average treatment effect on the treated. Rbounds implements the sensitivity tests for matched (1x1) pairs only.

6.5 Regression Results

The following provides the results of the analysis for the four key hypotheses as set out in Section 6.2. The results of the Logit models are presented first; these set the context for exporting in NI by examining the differences in characteristics between exporters and non-exporters. This is followed by a discussion of the quantile regression results which provide an alternative measure of examining these differences, analysing firms at different degrees of exporting intensity rather than the simple binary ‘export or not’ approach. The discussion then moves on to the link between exporting and productivity; presenting firstly the results of the stochastic dominance tests and then the propensity score matching, allowing for an assessment of whether self-selection and/or learning-by-exporting occurs. A discussion of the results along with the limitations of the study and recommendations for further analysis concludes.

6.5.1 Logistic Models

In order to determine whether there are differences between exporters and non-exporters in NI logistic models are run. Separate models are produced for the three different definitions of exporter as identified above, namely exporter, external seller and overseas seller. Table 6.8 reports the results; odds ratios are reported, along with standard errors, and the models' test statistics. The odds ratios are preferred over the coefficients as they have a more meaningful interpretation; an odds ratio greater than one indicating that the odds, or likelihood, of a firm being an exporter increases when the independent variable increases.

The Chi-sq. statistic is examined first in order to test the null hypothesis that all the regression coefficients in the model are simultaneously zero in the population. In each of the models the statistic is highly significant (with 23 degrees of freedom), thus the null hypothesis can be rejected and the conclusion drawn that the joint impact of all the explanatory variables on the dependent variable is significant in each of the models.

Regarding the explanatory variables the results for the exporter model (column 1), show that the odds ratios for size, employment costs per employee, gva per employee and public assistance are all positive and significant. Odds ratios for continuous variables do not have as obvious an interpretation as binary variables because there is no natural baseline group to compare the odds, however the results can be interpreted as:

- the likelihood of being an exporter increases with size of firm, ceteris paribus,
- the likelihood of being an exporter increases as employment costs rise, ceteris paribus, and
- the likelihood of being an exporter increases as labour productivity rises, ceteris paribus.

- the likelihood of being an exporter is higher for assisted than non-assisted firms

Regarding the sectoral variables, where Other Non-manufacturing is the base case, there are a number of positive and significant results. These include highly significant results for the Textiles; Electrical and Optical manufacture; and Other Manufacturing sectors, indicating that relative to the base case firms in these sectors are more likely to export.

The other two models, for external sellers and overseas sellers (columns 2 and 3), are remarkably similar to the original exporter model; the key differences being amongst the sectoral variables. Given that the dependent variable in these models is based upon destination of sales we would expect differences to arise based on sector, indeed the results show that firms involved in certain types of heavy manufacturing including Rubber, Machinery and Electrical and Optical are more likely to be selling in overseas markets due to a limited home demand. Another interesting observation is that the impact of public assistance is larger (in terms of size and significance) for the overseas seller model. This would fit in with prior expectations that assistance is sought by firms that aspire to sell in markets further away from home due to information asymmetries in accessing specific overseas knowledge.

Interestingly, amongst all three models, the R&D variable is not significant. The inclusion of this was based on the notion that to retain competitive advantage in export markets firms would have to invest in R&D; or alternatively that learning effects from exporting would induce firms to invest in R&D to make production more efficient and improve quality. The R&D variable included in the model is lagged by one year and its insignificance may suggest that a longer time lag is needed for the effects to be seen on exporting[44]. Despite this finding, it may be feasible to interpret the employment costs variable as proxying the quality of the product/service offered by the firm, its significance suggesting that firms with higher wage costs, and thus with a potentially higher value added product, are more likely to be exporters.

At this stage causality is not being determined but rather the statistical relationship between certain firm characteristics and exporting is being examined. The results

[44] The R&D variable is available annually from 2001, thus we use a lag of one year for our analysis period of 2002-08. To extend the lag beyond one year would have resulted in dropping a number of observations.

permit acceptance of the first stated hypothesis, that a difference does exist between the two sets of firms, based on a binary definition of the exporter/ non-exporter firm and are consistent with previous empirical findings, as initially put forward by Bernard and Jensen (1995). The second hypothesis, that exporter firms are more likely to undertake R&D cannot be accepted, based on these models. We proceed with the quantile regression analysis to re-test both these hypotheses under the assumption that exporting firms are not homogeneous.

Table 6.8: Logistic Regression for Export Activity 2002-08

	(1)	(2)	(3)
Dependent Variable	**Exporter**	**External Seller**	**Overseas Seller**
Explanatory Variables			
Log Size	1.620***	1.635***	1.562***
	(0.0826)	(0.0901)	(0.113)
Size squared	1.000	1.000	1.000
	(1.03e-07)	(1.08e-07)	(2.22e-07)
Log Employment costs	1.579***	1.726***	1.541***
	(0.170)	(0.204)	(0.215)
Log Labour Productivity (t-1)	1.278***	1.233**	1.218*
	(0.107)	(0.116)	(0.123)
R&D Intensity (t-1)	1.003	1.017	1.003
	(0.023)	(0.0718)	(0.0171)
Assisted	1.473*	1.540*	1.882**
	(0.298)	(0.342)	(0.526)
Food	0.306***	0.302***	0.699
	(0.111)	(0.117)	(0.293)
Textiles	7.350***	9.380***	107.8***
	(3.358)	(4.880)	(77.40)
Paper & Printing	0.487*	0.427*	0.557
	(0.211)	(0.197)	(0.268)
Rubber	1.844	1.750	2.277*
	(0.764)	(0.787)	(1.130)
Metal	1.002	0.914	0.284***
	(0.324)	(0.316)	(0.107)
Machinery	1.438	2.002	2.803**
	(0.574)	(0.862)	(1.352)
Electrical & Optical	3.432***	3.397**	16.51***
	(1.553)	(1.695)	(10.56)
Transport	2.857**	3.598**	2.766*
	(1.473)	(2.051)	(1.502)
Other Manufacturing	2.850***	2.944***	0.720
	(1.044)	(1.134)	(0.303)
Construction	2.851**	3.224**	0.131***
	(1.262)	(1.520)	(0.0786)
Wholesale & Retail	3.005***	3.237***	2.048*
	(1.056)	(1.223)	(0.794)
Business Services	2.649***	5.555***	11.47***
	(0.915)	(2.071)	(4.874)
Constant	0.442*	2.294*	9.85e-05***
	(0.195)	(1.146)	(5.28e-05)
Observations	12,374	12,374	12,374
Log likelihood	-4601.7037	-3959.2328	-3614.3598
LR Chi-Square (23)	251.12***	240.94***	259.42***

Note: year dummies were also included but are not reported here for space issues
Odds Ratios are reported
Model estimated using xtlogit (in Stata) with random effects
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10

6.5.2 Quantile Regression Models

The results of the quantile regressions on export intensity (exports as a percentage share of sales) are presented in Table 6.9[45]. The pseudo R^2 for goodness of fit is very small in each of the models, ranging from 0.0089 in the 25th percentile model to 0.0691 in the 75th percentile model, suggesting that the explanatory power of the models with regards to export intensity is quite poor. However, in quantile regression the pseudo R^2 is only analogous to the R^2 as given in OLS; it measures the proportional reduction in the sum of the absolute value of the residuals and is not bounded by 0 and 1, as in the OLS R^2 (Koenker and Machado, 1999).

The model is run for the three different exporter definitions; overall each is similar with respect to sign and significance of the explanatory variables. Once again size, employment costs per employee and the first lag of labour productivity are all positive and significant, suggesting the higher the value of these variables, the higher the export share of sales. Likewise, assisted firms have higher shares of export sales. Each of the variables is significant at the 1 per cent level in all of the quantile models; the 75th percentile model has the highest actual coefficients. Using this model we can thus say that for a one per cent increase in employment the value of export intensity will increase by 0.0003 (=0.03/100) units. Likewise for a one per cent increase in employment costs per employee the value of export intensity will increase by 0.0006 units, whilst it will increase by 0.0007 units for a one per cent increase in labour productivity.

Unlike the previous binary models above where they were insignificant, both the employment squared and the R&D intensity variables are significant at different quantiles. The employment squared variable indicates a quadratic relationship between size and export intensity for each of the quantiles except for those with the largest export intensity (90th percentile). The quadratic relationship signifying that the share of exports increases with firm size up to a certain point. This is consistent with *a priori* expectations whereby it was suggested that very large monopolistic firms may have a low inclination to export.

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[45] Given the similarity between the models for each of the three export measures only the export intensity quantile regression results are presented here. Those for external sales intensity and overseas sales intensity are presented in Appendix 1 Table A1.1 & A1.2.

The R&D intensity variable is significant in all but the 75th percentile model, although the size of the coefficients is relatively small. In fact the coefficient is largest in the 90th percentile model, at 0.0337, implying that for a one unit increase in R&D intensity increases export intensity by 0.03 units.

The results for the quantile regressions on external and overseas sellers are tabled in Appendix 1 (Tables A1.1 – A1.2). The model for external sales intensity is similar to that for export intensity in terms of the significant variables and their signs. Importantly however, the quadratic employment variable is only significant in the model for those with a low share of external sales (0.25 model). The model for overseas sales intensity is once again similar; a key difference being that the lag of labour productivity is not significant for the median model (0.5).

Table 6.9: Quantile Regression on Export Intensity 2002-08

Dependent Variable	**Export Intensity**			
	Qreg (0.25)	**Qreg (0.5)**	**Qreg (0.75)**	**Qreg (0.9)**
Explanatory Variables				
Size	0.00453***	0.0211***	0.0310***	0.0158***
	(0.000159)	(0.00187)	(0.00445)	(0.00600)
Size squared	7.15e-09***	2.08e-08***	1.13e-08**	4.97e-09
	(2.43e-10)	(2.88e-09)	(5.01e-09)	(3.47e-09)
Employment Costs	0.00352***	0.0310***	0.0618***	0.0527***
	(0.000491)	(0.00554)	(0.0132)	(0.0158)
Labour Productivity (t-1)	0.00238***	0.0217***	0.0674***	0.0581***
	(0.000410)	(0.00443)	(0.0109)	(0.0143)
R&D Intensity (t-1)	0.000841***	0.000335**	0.000126	0.0337***
	(2.00e-05)	(0.000169)	(0.00109)	(0.000811)
Assisted	.0287264***	.0647146***	.1004772***	.0537476**
	.0028468	.0093404	.0166418	.0221467
Food	-0.00290***	-0.0530***	-0.156***	-0.197***
	(0.00100)	(0.0106)	(0.0238)	(0.0294)
Textiles	0.0148***	0.0416***	-0.0157	0.0149
	(0.00133)	(0.0141)	(0.0315)	(0.0389)
Paper & Printing	-0.00345***	-0.0712***	-0.218***	-0.254***
	(0.00116)	(0.0124)	(0.0276)	(0.0337)
Rubber	0.00715***	0.0101	-0.0415	-0.0927***
	(0.00123)	(0.0130)	(0.0289)	(0.0354)
Metal	-0.00265***	-0.0522***	-0.137***	-0.168***
	(0.000957)	(0.0101)	(0.0226)	(0.0278)
Machinery	0.0136***	0.0532***	0.0440	0.0229
	(0.00118)	(0.0125)	(0.0278)	(0.0342)
Electrical & Optical	0.0212***	0.0698***	0.180***	0.137***
	(0.00137)	(0.0144)	(0.0320)	(0.0398)
Transport	0.0132***	0.0336**	0.0362	0.0171
	(0.00155)	(0.0164)	(0.0367)	(0.0452)
Other	0.00888***	0.0943***	0.0875***	0.0562*
	(0.00108)	(0.0114)	(0.0255)	(0.0313)
Construction	0.0112***	0.0252*	-0.0320	-0.0532
	(0.00142)	(0.0151)	(0.0337)	(0.0417)
Wholesale & Retail	0.0146***	0.0813***	0.0379	0.00942
	(0.00118)	(0.0125)	(0.0280)	(0.0344)
Business Services	0.0136***	0.0591***	0.131***	0.171***
	(0.00109)	(0.0116)	(0.0258)	(0.0318)
Constant	-0.0217***	-0.0960***	-0.0769*	0.314***
	(0.00153)	(0.0165)	(0.0397)	(0.0511)
Observations	12,374	12,374	12,374	12,374
Pseudo R2	0.0089	0.0462	0.0691	0.0663

Standard errors in parentheses
Model estimated using qreg (in Stata)
*** p<0.01, ** p<0.05, * p<0.10

6.5.3 Testing for Self-selection using Stochastic Dominance

In order to test for self-selection, export starters and those who have never exported (over the same period) must first be identified. Due to the small number of years available in the pooled dataset i.e. 2002-2008 and the desire to enlarge the number of observations, several cohorts of export starters and non-exporters were constructed[46]. Export starters in year t are defined as: firms that did not export for two years prior to year t, export in year t, and export in at least one year between t and t+2. Non-exporters, for this cohort, are defined as those firms that did not export for two years prior to year t, nor in any year between t and t+2. As a result of these definitions cohorts for 2004, 2005 and 2006 are able to be constructed. Pooling these cohorts together provides data on 121 export starters and 469 non-exporters[47].

Table 6.10 displays some key descriptives, for the year t-1, for the export starters versus those who have never exported. Export starters were on average larger than the non-exporters as measured by their ex-ante employment size. Employment costs for both groups were more or less equal whilst labour productivity, or GVA per employee, was slightly higher for the export starters.

Table 6.10: Key descriptive Statistics for Export Starters and Non-exporters 2004-06

	Export Starter (t-1)			**Non-exporter (t-1)**		
	N	**mean**	**Std. dev.**	**N**	**Mean**	**Std. dev.**
Employment	121	56.9	276.7	469	17.8	23.4
Employment costs per employee	121	15.2	5.8	469	14.0	6.9
Labour Productivity	121	30.3	22.8	469	25.5	14.6

Note: Employment costs and labour productivity are in £000s at 1995 prices where labour productivity is measured as GVA per employee.
Source: Authors own estimates of DETI data

The cumulative distribution functions of labour productivity for year t-1 i.e. the year before exporters entered the market, is shown for both groups in Fig. 6.2. The distribution of export starters is for the most part to the right of the position for non-

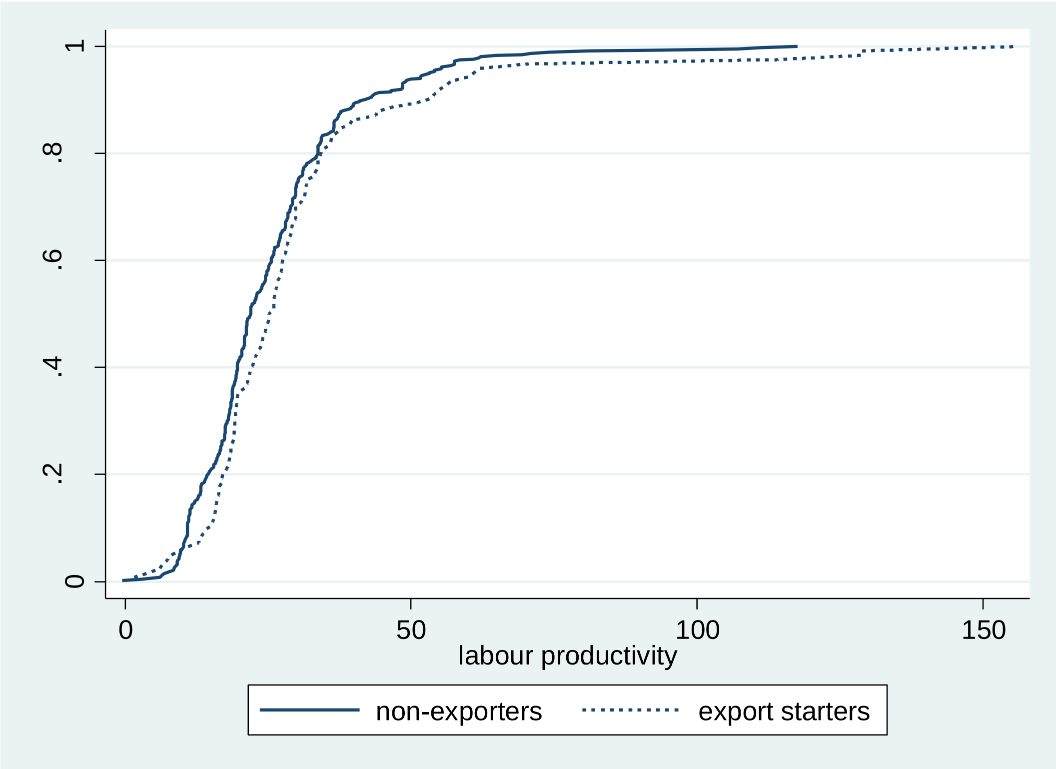
[46] In keeping with the previous analysis we also conduct the stochastic dominance tests for external sellers and overseas sellers. The cohorts are created by the same definition as per the exporters and result in a total of 88 external seller starters, 396 non-external sellers, and 88 overseas seller starters and 2,468 non-overseas sellers.
[47] Arnold and Hussinger (2006) suggest that the asymptotic distribution of both samples independence is likely to be violated if observations are pooled over several years, however due to the small sample size of exporter starters in any one year it is not feasible to consider each year separately here.

exporters, indicating that firms that enter export markets are initially more productive than non-exporters in the year prior to exporting. To formally test if this is the case a Kolmogorov-Smirnov (K-S) test is performed to determine whether the productivity level distribution of export starters stochastically dominates the distribution of non-exporters during the period before entry[48].

Table 6.11 displays the results of the one and two-sided K-S tests. This test is used as it provides a stricter test of productivity differences than a comparison of the means would provide, as it considers all moments of the distribution. To have first order stochastic dominance of export starters with respect to non-exporters the null in the two-sided test needs to be rejected along with a failure to reject the null in the one-sided test. In other words, it needs to be verified that the two distributions are different and that this difference is not due to the export starters distribution lying above that of the non-exporters. The null hypothesis for the two-sided test, that the distributions between the two groups are equal, can be rejected at the 10% significance level. The null hypothesis for the one-sided test, that the labour productivity distribution of non-exporters is stochastically dominated by the labour productivity distribution of export starters, cannot be rejected and thus we conclude that the distribution of labour productivity for export starters lies below or to the right of that for non-exporters, and that the ex-ante labour productivity of starters is higher. We can take this as evidence for the self-selection theory; that the more productive firms self-select into exporting. Interestingly no evidence is found for self-selection using the alternative exporter definitions; for the external seller definition this may reflect the fact that it includes sales to GB, which in effect is a home market. Alternatively, and more likely, the results may be affected by the low sample sizes.

[48] The cumulative distribution functions for external sellers and overseas sellers, and associated Kolmogorov-Smirnov tests, are contained in Appendix 1, Figures A1.1 and A1.2.

Figure 6.2: Ex-ante Labour Productivity Distribution of Export Starters and Non-exporters



Note: Labour productivity defined as GVA per employee
Source: Authors own estimates of DETI data

Table 6.11: Kolmogorov-Smirnov Test for Ex-ante Labour Productivity Differences between Export Starters and Non-exporters 2004-06

	N		Two-sided Test		One-sided Test	
	Export Starters	**Non-exporters**	**Statistic**	**P-value**	**Statistic**	**P-value**
Non-exporters vs Export Starters	121	469	0.1245	0.095	-0.0295	0.843

Notes: The two-sided test is a test of the null that the two cumulative distribution functions are equal against the alternative that they differ. The one-sided test is a test of the null that the cumulative distribution function of the second group lies below (or is equal to) the cumulative distribution function of the first group against the alternative that it lies above.

6.5.4 Propensity Score Matching to Test for Learning-by-Exporting

The results for the various stages of the propensity score matching are reported in Tables 6.12-6.14. The same data on export starters and non-exporters, constructed for the self-selection tests above, is used reducing the sample to 590 firms. To test for the effect of starting to export on productivity growth, a growth variable which is equal to log growth in productivity (GVA per employee) between t-2 and t+2 is constructed, where t refers to the year of starting to export[49].

The propensity score matching was conducted in Stata using the psmatch2 command (Leuven & Sianesi, 2003); the first step in the matching technique was to construct the control group, estimating the propensity score based on a logistic regression, with the variable export starter as the dependent. As stated above, the explanatory variables should be those which are unaffected by treatment, or the anticipation of it, thus variables were selected from the year prior to starting to export (t-1). The variables selected were employment size, employment costs per employee, R&D intensity, sector and year. Labour productivity was not included due to the fact that the self-selection results above pointed to the fact that firms with ex-ante higher productivity self-select into exporting, thus violating the rule that it should be unaffected by the anticipation of treatment (here starting to export). Once the propensity score was computed matching was undertaken using three variations: nearest neighbour matching, with and without replacement, and caliper matching using a caliper of one quarter of the standard deviation of the propensity score. These three types were chosen to allow for sensitivity in the selection of the matching method.

The initial differences in the explanatory variables across the two groups were examined to establish a baseline of standardised bias; likewise the group differences after matching were assessed to detect any remaining selection bias between the two; the results are shown in Tables 6.12 and 6.13. In each of the matching techniques t-tests revealed that the two groups of firms differed significantly in two of the explanatory variables prior to matching, namely employment size and sales. After matching none of the variables were significantly different between the two groups; these tests of equality of the means initially suggesting good balancing. To further check for this the standardised bias was estimated before and after matching; for covariates to be balanced the bias needs to be less than 5 per cent after matching. The results show that in the nearest-neighbour with replacement model the employment size variable was not well balanced, with a bias after matching of 14.5

[49] Propensity score matching techniques were not run on the two other definitions of exporter, namely external seller and overseas seller, as the number of observations was just 88 for each.

per cent. In fact, as shown in Table 6.13 the mean percentage absolute bias for the group was 19.5 per cent before matching and 8.0 per cent after; suggesting that although the matching had reduced the starting unbalance it had not reduced it enough. The nearest-neighbour without replacement also had similar unbalanced covariates with the employment size and sales variables both remaining unbalanced after matching. The reduction in the mean bias for the group was again above 5 per cent after matching and hence the covariates as a whole were unbalanced. The nearest neighbour with caliper matching was the only method in which all of the covariates had a percentage bias below 5 per cent after matching. Indeed the overall bias had reduced from 19.5 per cent before matching to 4.0 per cent afterwards, suggesting that matching using this method was effective in building a good, and well balanced, control group.

Using the results of the caliper matching we can thus be confident that the subsequent results on productivity growth, centred on the difference between the treated and untreated firms, are based on similar firms. The proposition from this is that any impact on productivity growth is not due to any observed differences between the two groups of firms, and is in fact due to the effect of the treatment, that is beginning to export.

Table 6.12: Pre- and Post-matching differences for Export Starters and Non-exporters 2004-06

		N-N with replacement			
Variable	**Sample**	**Treat**	**Control**	**t-test**	**% bias**
Total Employment (t-1)	Unmatched	55.2	17.8	2.97***	19.3
	Matched	60.4	32.5	1.02	14.5
Emp Costs per Employee (t-1)	Unmatched	15.0	14.0	1.40	14.8
	Matched	15.3	16.3	-1.07	-15.8
R&D intensity (t-1)	Unmatched	0.0	0.0	1.22	9.4
	Matched	0.0	0.0	-0.00	-0.0
Sales (t-1)	Unmatched	3,377.3	1,269.3	4.74***	34.5
	Matched	3,753.7	3644.0	0.10	1.8

		N-N without replacement			
Variable	**Sample**	**Treat**	**Control**	**t-test**	**% bias**
Total Employment (t-1)	Unmatched	55.2	17.8	2.97***	19.3
	Matched	60.4	29.7	1.12	15.9
Emp Costs per Employee (t-1)	Unmatched	15.0	14.0	1.40	14.8
	Matched	15.3	15.4	-0.11	-1.6
R&D intensity (t-1)	Unmatched	0.0	0.0	1.22	9.4
	Matched	0.0	0.0	-0.05	-0.8
Sales (t-1)	Unmatched	3,377.3	1,269.3	4.74***	34.5
	Matched	3,753.7	2,292.7	1.54	23.9

		N-N with Caliper			
Variable	**Sample**	**Treat**	**Control**	**t-test**	**% bias**
Total Employment (t-1)	Unmatched	55.2	17.8	2.97***	19.3
	Matched	33.8	31.0	0.41	1.5
Emp Costs per Employee(t-1)	Unmatched	15.0	14.0	1.4	14.8
	Matched	15.4	16.1	-0.79	-11.4
R&D intensity (t-1)	Unmatched	0.0	0.0	1.22	9.4
	Matched	0.0	0.0	0	-0.0
Sales (t-1)	Unmatched	3,377.3	1,269.3	4.74***	34.5
	Matched	3,568.4	3,385.7	0.17	3.0

Note: Employment costs and labour productivity are in £000s at 1995 prices
*** p<0.01, ** p<0.05, * p<0.10
Source: Authors own estimates of DETI data

Table 6.13: Pre- and Post-matching differences in standardised bias

Matching Method	**Sample**	**Mean Bias %**	**Median Bias %**
N-N with replacement	Raw	19.5	17.0
	Matched	8.0	8.1
N-N without replacement	Raw	19.5	17.0
	Matched	10.6	8.8
N-N with caliper	Raw	19.5	17.0
	Matched	4.0	2.2

The matching techniques indicated that there was common support for 582 of the firms; 112 treated firms were matched to 470 untreated firms; the caliper matching dropped one further treated firm. Estimation on the treatment effects are the final stage of the propensity score matching, and although only the caliper matching technique was properly balanced, results are provided for all three methods. Table 6.14 displays the resulting ATT effects; the coefficient on the treated shows the impact on the outcome (productivity growth) for the treatment group (export starters), whilst the control shows the counterfactual, i.e. the impact from the matched control group (non-exporters); the 'difference' thus indicating the impact of the treatment on the treated. The null hypothesis is that there is no difference between the two groups of firms.

Two of the models, the nearest neighbour with replacement and the nearest neighbour with caliper matching have almost identical estimates of the treatment effect in terms of the size and sign of the coefficients, at 0.10; the nearest neighbour without replacement estimates the treatment effect to be 0.02. However the t-tests indicate that these differences are not significant; we thus conclude that starting to export has no significant impact on productivity growth in the period between t-2 and t+2.

Unlike the evidence for self-selection into exporting we therefore cannot provide any evidence for learning-by-exporting, although admittedly the length of the impact time is relatively short and may be better measured over longer time frames. For example, it could be argued that two years after starting to export firms are still in the relatively early stages and may be focussing on improving market position in the export market rather than observing means to make their own processes more efficient. Indeed Mai and Yu (2013) report higher productivity effects three years after starting to export than the immediate effect, and this increases with the number of years of pre-export R&D investment. However overall, the results here are consistent with the literature in which the evidence for learning-by-exporting is weak (Singh, 2010) and may have important policy repercussions, particularly if exporting is seen as a direct causal link to improving productivity growth within firms.

Table 6.14: Propensity Score Matching Results: The Impact of Starting to Export on Productivity Growth

Technique	Sample	Treated	Controls	Difference	S.E.	T-stat	N Treated	N Untreated
N-N with replace	ATT	0.147272	0.047421	0.099851	0.083305	1.20	112	470
N-N without replace	ATT	0.147272	0.132235	0.015038	0.072542	0.21	112	470
N-N caliper matching	ATT	0.146731	0.046997	0.099733	0.082328	1.21	111	470

Note: Model estimated using psmatch2 (in Stata)

Initially sensitivity tests were to be performed after matching using the rbounds command in Stata. This calculates Rosenbaum bounds for average treatment effects on the treated in the presence of unobserved heterogeneity (hidden bias) between treatment and control cases. Essentially it tests that matching has been done on all relevant characteristics and that there is not an unobserved confounder that may account for the difference across the treatment and control groups. However as noted by Hujer et al. (2004), sensitivity analysis for insignificant ATT estimates is not meaningful; thus given that there was no significant difference found between the two groups it is unnecessary to perform the sensitivity analysis here.

6.6 Discussion

The purpose of this element of the analysis was to examine particular differences between exporting and non-exporting firms in NI; firstly to determine whether the stylised fact, that exporters have different firm-level characteristics than non-exporters, held for firms in NI; secondly to ascertain whether more productive firms self-select into exporting and thirdly to identify whether exporting improves the productivity growth of firms. The rationale for the analysis was a lack of evidence on NI firms with regards to exporting, despite the importance in policy terms; and the inconsistency within the literature in terms of the learning effects on productivity growth.

In the analysis three different measures of an exporting firm were used to account for the fact that NI, as a region of the UK, borders a Eurozone country, the ROI, and so may not follow the typical exporter, non-exporter pattern. Sales to the ROI market are technically regarded as exports, despite the fact that to firms in NI, particularly those located in border areas, they may be regarded as similar to local sales. At around 75 per cent, the proportion of firms in NI that export was higher than is generally found in similar national-level studies whereby the share is typically less than 20 per cent. For these reasons, and to try and account for whether learning is more prevalent across distinct export markets, the three different measures were used in the analysis.

Initial examination of the descriptive statistics indicated significant and, in some cases, substantial differences, between exporter and non-exporter firms in the region, and these differences held even when alternative definitions of exporter were used. In order to formally test if these differences were statistically significant two approaches were taken; a logistic regression was run to test for differences in the characteristics of exporter versus non-exporter firms and secondly a quantile regression approach was used to test for differences along the export intensity distribution. The latter was used to account for the fact that exporting firms are likely to be heterogeneous and hence the effects of the variables explaining export behaviour are unlikely to be the same across firms, as recorded at their means. Results from the logistic regression confirmed the different characteristics between the two groups, notably that exporting firms were larger; more productive and had higher employment costs than non-exporters; findings which were consistent with the strand of literature as introduced by Bernard and Jensen (1995). Importantly the logistic models rejected the hypothesis that exporters were more likely to be doing R&D. This was an unexpected result and conflicted with other empirical findings (Greenaway and Kneller, 2005, Wagner, 2007, Singh, 2010) and theoretical arguments, based on international trade theory, (Romer, 1986) which suggest that firms from such developed countries should be competing in export markets based on high quality technologically advanced products.

Re-running the model using quantile regression reaffirmed the findings that exporting firms had superior characteristics than non-exporting firms, and notably, found that those in all but the 75th percentile were more likely to do R&D. The use of quantile regression in this sphere of literature was introduced by Melitz (2003) and Bernard et al. (2003) and is seen to be superior to binary choice for modelling the export decision in that it allows for different types of exporting firms to be accounted for, ranging from those with little exports to those that export virtually all of their sales. The fact that R&D was found to be associated with exporting at both the lower and the highest levels was consistent with Wagner (2004) who found that R&D intensity varied across the export intensity distribution, and suggests that R&D is undertaken for different reasons depending on the scale of exporting within the firm. When firms are starting to export they may undertake formal R&D in order that their products meet compliance regulations in the destination countries. At the other end of the scale, those who are experienced and highly intensive exporters may undertake R&D to improve or expand their existing product range to seek out further profit-making opportunities in the countries in which they already operate. Such results were not able to be detected when testing firms at their means, and thus the findings reiterate the benefit of using the quantile regression method.

The results led to an acceptance of both the initial hypotheses that exporters had different characteristics than non-exporters, and that they were more likely to undertake R&D, confirming the stylised facts as reported in the literature. In particular, the finding that larger firms were more likely to be exporters points to a confirmation that exporting is associated with sunk costs, and that these can be more easily overcome by larger firms who can take advantage of economies of scale to recoup the initial costs.

Regarding the self-selection hypothesis, categorising firms into export starters and non-exporters and using non-parametric Kolmogorov-Smirnov tests provided evidence that exporters (under the standard definition) are indeed ex-ante more productive than non-exporters. The results led to an acceptance of the self-selection hypothesis and are consistent with the wider literature in which evidence for self-selection is widespread (Wilhelmsson and Kozlov, 2007; Loof, 2010; Silva et al, 2010b; Temouri et al, 2013, Vogel, 2011). As reported by Alvarez and Lopez (2005), the results also provide a tentative affirmation of the claim that firms are forward looking and may make a determined effort to be highly productive in the years leading up to entry to export markets so that they may establish themselves in the face of such strong competition and compete effectively. Further detail about the investment activities of firms in the pre-exporting period may confirm this, and suggests a potential avenue for further research.

The evidence for increased productivity growth after starting to export was not as convincing, and in fact no significant differences were found in the productivity growth of new exporters versus non-exporters, even two years after starting. The results rejected the notion of learning-by-exporting, whereby firms operating in foreign markets are thought to become more productive due to the exposure to foreign knowledge, and the necessity to keep up with the intense competition. However this rejection is consistent for the most part with the empirical literature, where a lack of consensus remains about the hypothesis, as summarised by Singh (2010) who asserted that the number of studies in support of self-selection outnumber those in support of learning-by-exporting:

> *"….. this implicitly provides a stronger support for the effects of productivity and growth on trade as compared to the effects of trade on productivity and growth" (Singh, 2010, pg. 1537).*

The overall findings for this section suggest that the export behaviour of firms in NI is no different to those from elsewhere, despite the initial uncertainties about the exporter definition. Firms in NI appear to have the same issue with regards to overcoming sunk costs before entering export markets; they may also gear up their productive efforts in anticipation of entering export markets, which suggests that such firms are forward looking and that the activity is well planned. This is encouraging from a policy perspective in that exporting represents a conscious decision made by the firm and thus the behaviour is more likely to persist. The movement into new markets also reduces over reliance on the domestic market, and can act as a buffer during downturns.

The implicit assumption that exposure to foreign competition will lead to increased productivity growth is not evidenced here, casting doubt on the assumption that activities to support and encourage exporting will directly help to reduce the productivity gap with the rest of the UK. This is important as exporting is often mentioned in the same context as productivity growth, in the various regional and national government growth strategies, despite the lack of conclusive evidence in the empirical literature, for example in BIS (2011c), it is stated:

> *"Exporting stimulates productivity growth through scale economies, through learning from exporting and exposure to new ideas, and through re-allocation of resources across products to focus on the firm's comparative advantage" (BIS, 2011c; pg. xii).*

The ex-ante productivity growth of these firms may indeed raise overall productivity growth in the economy but not necessarily through learning and exposure to new ideas, in fact the latter is likely to occur only where the export destination market is more developed and technologically advanced than the home market of the firm. Instead the economy-wide gains from the ex-ante higher productivity firms will arise if there is a net reallocation effect whereby these new exporters gain market share at the expense of less productive firms who exit the market. For these reasons policies to encourage exporting are to be supported, although perhaps they should differentiate between strategies to encourage and help firms to start exporting and those that encourage existing exporters to sell into highly advanced markets. The former argument is supported by the fact that the propensity score matching was able to construct a group of firms, similar in characteristics to the new exporters, who did not export, suggesting a potential group of firms for whom intervention may be needed.

The UKTI operate a number of schemes on a more targeted basis, whereby export assistance is based on firm size. ‘Passport to Export’, is focussed on small and medium-sized firms (SMEs) who are helped to start export and subsequently given assistance with regards to the different stages of exporting (UKTI, 2014). The ‘Medium-Sized Business Programme’ provides tailored support to larger firms to assess their export capability and get started in international trade, or develop their existing export operations further (UKTI, 2014). In NI, the focus generally appears to be on helping firms to start export, or to increase the value of exports, particularly to emerging economies[50] (DETI, 2014) whereas if the type of learning and knowledge spillovers that are anticipated with exporting are to actually occur then a more tailored package of support to assist with entering highly developed markets should be established.

6.6.1 Limitations and Recommendations

The analysis here has helped to update, and introduce new findings with regards to the export-productivity relationship in NI using techniques which help to account for the heterogeneity of firms. However the results have some limitations which stem from the availability of data; there are a number of other variables which have been used in the literature to model the export decision, notably age of firm, and ownership. These variables were not provided on the contributing datasets, although such information is collected, and their absence is likely to have reduced the explanatory power of the models. In addition it has been reported that the qualities, background and skill levels of the owner/manager are key in the firm’s decision to export, however such information is not collected in the official government surveys and so again, represent a source of omitted variables.

[50] The DETI operating plan has a target of increasing manufacturing exports by 13 per cent and a 60 per cent increase in the value of manufacturing exports to emerging economies.

A new thread of the related literature focuses on the export destination market, with those selling to more developed economies found to have higher ex-ante productivity levels than those selling to less developed economies, and non-exporters. This is an interesting development in the literature and one which could be examined for NI given that the export data is collected at a reasonably disaggregated country level. For the purposes of this study the data provided was disaggregated to just five export market destinations, the broad coverage of the EU and Rest of World destinations too expansive to be able to separate the less developed markets from the more technologically advanced. Despite attempts to try and assess whether learning from exporting differed according to the broad destination, the number of observations was too small to permit reliable results. Again a deeper investigation into the various export markets and, the productivity effects of selling to differentiated markets may represent a worthwhile follow-up study.

In terms of the modelling procedure for the self-selection and learning-by-exporting hypotheses, limitations were largely associated with the reduction in the sample size, and the necessity to pool the data, which is not always optimal (for example in the K_S tests). This arose due to the nature of the source data in which firms were not always sampled, and the voluntary nature of the survey, for which responses were not compulsory. Future work to build a consistent balanced panel of firms over time, with all available variables and detailed destination information would provide further insights into the productivity-exporting relationship and strengthen policy expectations about the outcomes. This will be particularly important in the NI context whereby a rebalancing of the economy, in part through increasing the number of exporting firms, is the long term goal of the current economic strategy (NI Executive, 2012).

Sub-Section B Relationship between Innovation and Productivity Growth

6.7 Introduction

Endogenous growth theories hypothesise the relationship between innovation and productivity growth to be positive, in that R&D and innovative activities help to make the productive effort more efficient and thus raise rates of output per worker, leading to improvements in wages, living standards and economic growth over the long term. The empirical evidence for this relationship is not as clear cut as the theory suggests, with many studies finding no evidence of a positive significant causal link (Hall, 2011). Indeed, Klette and Kortum (2002), who produce a list of stylised facts on the relationship, state that while there is a positive link between R&D and the level of productivity across firms there is no such statistically significant relationship in longitudinal studies of R&D and productivity growth. Although it is now more generally accepted that R&D acts as an input to innovative effort rather than an output, so may not be expected to directly affect productivity (Hall, 2011).

More recent developments also suggest that innovation encompasses more than just the technological aspects, as defined using measures of product and process innovation, with organisational and marketing innovations also recognised as measurable aspects (OECD, 2005). Organisational innovation covers changes in business practices; workplace organisation and with the firm's external relationships whilst marketing innovation covers changes in product design and packaging; product promotion and placement, and in methods for pricing. Empirically, studies have tended to focus on product and process innovation (Hall, 2011); where these other types have been included, organisational innovation in particular has been found to positively affect productivity either in combination with product innovation (Schmidt and Rammer, 2007); or on its own (Polder et al., 2010; Siedschlag and Zhang, 2015).

Over the last decade policy in the UK and NI has endorsed innovation as one of the key drivers of productivity growth, encouraging the take-up of R&D tax credits and grants to boost innovation and ultimately increase productivity growth. In fact the 2005 UK government report on enhancing the R&D tax credit states:

"Productivity growth is central to long-term economic performance and rising living standards. One of its key drivers is science and innovation, as value is increasingly derived not from raw materials and physical production but from creating and exploiting knowledge" (HM Treasury, DTI, HMRC, 2005: pg. 9)

If the empirical evidence on the link between R&D, innovation and productivity growth is weak, or is dependent on a particular type of innovation, it casts doubt on the above assumption that undertaking innovative activities *directly* leads to improved productivity growth which has repercussions on policy expectations. The aim of this section is thus to analyse the underlying relationships and uncover evidence as to whether innovation is indeed a driver of productivity growth in NI.

The remainder of this section sets out the key hypotheses to be tested and the methodologies for doing so. The model is presented along with the descriptive statistics and the results. A discussion of how the results fit with the existing literature concludes the section, along with key limitations and potential for further work.

6.8 Testable Hypotheses

The hypotheses put forward are used to examine all stages of the innovation-productivity growth relationship, as suggested by the augmented-CDM model (Griffiths et al., 2006). That is a) the link between investing in R&D and subsequent innovative activity at the firm level; and b) the link between innovation outputs and productivity growth. The former relationship is often confused, with R&D and innovation often considered to be the same activity rather than as separate inputs and outputs of the innovation process. According to Eurostat (2004)

"R&D relates to the commitment of resources by a firm to research and the refinement of ideas aimed at the development of commercially viable products and processes. The innovation concept is broader than that of R&D. All R&D enterprises are by definition innovative, but all innovators are not automatically R&D performers" (Eurostat, 2004, pg. 11).

The first hypothesis to be tested thus examines the firm's decision to undertake investment in R&D, specifically testing whether firms engaging in R&D have more resources and higher levels of human capital than those that do not invest. The second hypothesis then examines the link between R&D and exporting, as suggested by the international trade strand of endogenous growth theory, as postulated by Grossman and Helpman (1991) whereby scientific and knowledge spillovers arise from engagement in foreign trade. Thus:

H1: Firms that invest in R&D are more likely to be larger, more productive and have more skilled employees

H2: Firms that invest in R&D are more likely to be exporters

Following this, the second stage of the modelling process looks at the innovation process, examining the relationship between R&D engagement and product and process innovation. These two innovation measures are considered to enable comparisons to the empirical literature, the majority of which focuses on product and process innovation rather than organisational and marketing innovation. Given the market failure arguments with regards to innovation, such as the lack of appropriability, and the resulting incentive for governments to support innovative activity amongst firms, the fourth hypothesis examines the extent to which those that undertake innovation have received some form of government assistance:

H3: Product and process innovation is positively affected by R&D expenditure

H4: Firms that invest in R&D are more likely to have received government assistance

The final hypothesis examines the last link in the process and looks at the impact of innovative behaviour on productivity growth:

H5: Innovation (product and process) has a positive effect on productivity growth.

6.9 Data and Descriptive Statistics

The data is once again drawn from the pooled dataset, as described in Chapter 5. The source data for the models are the BERD and CIS surveys, and whilst there are annual observations for the BERD survey unfortunately there is only one observation for the CIS data[51], covering the period 2002-04. This restricts estimation of the

[51] The CIS has been carried out in NI since 1992, however the CIS 4 covering the period 2002-04 was the first usable sample, due to poor response rates for earlier surveys. Since

innovation effects to one point in time; however the effect on productivity growth can still be modelled over a period of time as the post-2002 productivity level observations for the sample are available. As a consequence of the cross-sectional nature of the innovation data, unobserved firm-specific heterogeneity cannot be tested for in the model.

There are 1,341 observations from the CIS 3 data on the dataset. The propensity to innovate is relatively low; of the total 341 (25 per cent) state that they undertook product innovation during the period; 298 (22 per cent) undertook process innovation; 477 (36 per cent) undertook one or the other, and 162 (12 per cent) undertook both. Of the total, 864 (64 per cent) reported that they undertook neither product nor process innovation during 2002-04. These rates are comparable to those published for NI, where 21 per cent of firms were product innovators and 20 per cent process innovators. Additionally, the rates fall within the range as reported for a number of industrialised countries, where the share of firms undertaking product or process innovation in 2002-04 ranged from around 20 to 60 per cent (OECD, 2009, pg.29)

Table 6.15 reports on a number of descriptive statistics for the sample, based on the values in 2002; an innovator variable has been created to equal 1 if a firm undertakes product or process innovation and 0 otherwise, and is generated to compare the characteristics of firms that innovate against those that do not. Although there are 477 innovators in the sample, and 864 non-innovators, not all have full data on the other variables in 2002, thus the corresponding number of observations for each variable is reported in the table.

Based on the mean values a clear pattern emerges; that innovators have larger values, across the board, than those that do not undertake innovation activities. Innovators are typically larger than non-innovators, with 124 employees on average compared to 68 for non-innovators; they have slightly higher employment costs per employee, at £15,000 on average compared to £12,000; and their GVA per employee is also marginally higher at £25,000 compared to £23,000. As evidenced in the above exports section, whereby a relationship between exports and R&D spending was reported (in the quantile regression model), it is interesting to note that firms that innovate have larger export sales than those who don't; with mean exports of £7m compared to £2m. As would also be expected, R&D spending is higher for

CIS 4 the ownership of the CIS data has moved from DETI to the ONS and as such was unable to be provided for use in this study under the same conditions.

innovators, with a mean value of £56,000 compared to just £7,000 for those that do not innovate. The mean value for the share of employees with science and engineering degrees is 9 per cent for innovators and just 3 per cent for the non-innovating group of firms[52]. T-tests are performed on the variables to test whether the differences in the means between the innovator and non-innovator firms are statistically significant. The results show that the differences are statistically significant for each variable.

Table 6.15: Descriptive Statistics for CIS Respondents 2002-04

	Employment	Employment Costs per employee (£000s)	Labour Productivity (£000s)	Exports (£000s)	R&D Spending (£000s)	Sci & Eng share Of Employment
			Innovator (n=477)			
N	**437**	**437**	**437**	**243**	**468**	**468**
Mean	124.24	14.88	25.44	6,556.22	55.83	8.91
Median	41.00	13.13	20.24	386.79	0.00	0.00
Std. dev.	412.61	10.50	23.49	35,049.70	255.29	19.33
			Non-innovator (n=864)			
N	**804**	**803**	**801**	**217**	**856**	**856**
Mean	67.79	12.01	22.58	1,598.64	7.07	2.73
Median	29.60	10.86	18.65	148.00	0.00	0.00
Std. dev.	152.30	7.46	18.09	4,494.69	107.11	9.91
T-tests	3.47***	5.59***	2.38**	2.07**	4.86***	7.69***

Note: Sales, exports, R&D spending, employment costs and Labour Productivity (GVA per employee) are in £000s at 1995 prices.
*** p<0.01, ** p<0.05, * p<0.10
Source: Authors own estimates of DETI data

The sectoral composition of those that undertake innovation is shown in Table 6.16; three sectors together constitute three quarters of the sample, manufacturing at 28 per cent; wholesale and retail at 25 per cent and other services at 24 per cent. The propensity to innovate varies greatly between the sectors; firms in the business services sector have the highest propensity to innovate, with around three fifths of firms doing so; those in the Construction sector least likely, at 16 per cent. Separating innovation into its two components; product and process, reveals that

[52] The same tables are re-created for the product and process innovators separately. The results are displayed in Appendix 1, Tables A1.7 – A1.8; they show that both product and process innovators have larger mean values for all variables than those that do not partake in either activity. T-tests reveal significant differences for all variables for product innovators. The results for process innovators indicate significant differences again for most of the variables with the notable exception of GVA per employee, for which no significant difference between process innovators and non-process innovators is found.

manufacturing firms have the highest propensity to undertake product innovation, with 41 per cent of firms doing so, with those in business services most likely to be involved in process innovation, with 46 per cent of firms engaging in the activity.

Table 6.16: Propensity to Innovate by Sectoral Composition 2002-04

	Innovator		***Product Innovator***		***Process Innovator***		
	0	**1**	**0**	**1**	**0**	**1**	**Total**
Manufacturing	195	184	225	154	277	102	379
	(52%)	*(49%)*	*(59%)*	*(41%)*	*(73%)*	*(27%)*	*(28%)*
Construction	124	23	127	20	136	11	147
	(84%)	*(16%)*	*(86%)*	*(14%)*	*(93%)*	*(7%)*	*(11%)*
Wholesale & Retail	264	76	290	50	292	48	340
	(78%)	*(22%)*	*(85%)*	*(15%)*	*(86%)*	*(14%)*	*(25%)*
Business Services	59	90	103	46	81	68	149
	(40%)	*(60%)*	*(69%)*	*(31%)*	*(54%)*	*(46%)*	*(11%)*
Other Services	222	104	255	71	257	69	326
	(68%)	*(32%)*	*(78%)*	*(22%)*	*(79%)*	*(21%)*	*(24%)*
Total	864	477	1,000	341	1,043	298	1,341
	(64%)	*(36%)*	*(75%)*	*(25%)*	*(78%)*	*(22%)*	

Source: Authors own estimates of DETI data

6.9.1 Missing Data

As discussed above, not all the firms with innovation data had complete data for the other variables, with the export variable in particular only available for 460 firms, or 34 per cent of the sample. Dropping those with missing data from the subsequent regressions risked losing a considerable number of observations, particularly amongst the non-innovating group, for whom there are exports data for just one quarter of firms. Two approaches could be taken to deal with this; either estimate the missing observations by imputation or drop them and proceed using the reduced sample. The problem with imputation is that, considering the degree of missingness on the exports variable, imputation for this would have to be undertaken for two thirds of the non-innovators and one half of the innovators, these large shares potentially impacting on the interpretation[53].

[53] Acuna and Rodriguez (2004) state that “Rates of less than 1% missing data are generally considered trivial, 1-5% manageable. However, 5-15% require sophisticated methods to handle, and more than 15% may severely impact any kind of interpretation” (pg.2)

Given that innovation activity and its subsequent effects are the focus of the analysis and that the regressions are run primarily on innovative firms only, casewise deletion would largely only impact the first stage, due to the inclusion of both innovators and non-innovators (and the extent of missing export data is greatest for the latter group). Proceeding with the casewise deletion of those with missing observations would not cause any bias if they are MCAR, as discussed in Chapter 5.

In order to determine the type of missingness, and how it would impact on the results the data was tested using the ‘misstable’ and logit commands in Stata. The ‘misstable’ command is used to generate a new indicator variable for each existing variable which is equal to 1 if a given observation is missing and 0 if it is not. Logit models are then run to test if any of the other variables predict whether a given variable is missing. If they do, then the data is MAR rather than MCAR. Considering that the exports variable is the main one of concern, a logit was run on this using, as the regressors, size, sector, R&D, innovator, GVA and employment costs. The results (Appendix 1, Table A1.9) indicated that the other variables did indeed predict the missingness, and thus the data are MAR; their deletion would cause bias. Given that both imputation and deletion may cause problems with interpretation, there is no obvious best solution. The imputation method is more challenging to undertake and would produce no better results; casewise deletion was thus selected with the results qualified that they may be subject to bias.

6.10 Methodology

The methodology, as first developed by Crépon, Duguet and Mairesse (1998) and augmented by Griffith et al. (2006), is referred to as the augmented-CDM model. It appears to be the most appropriate with which to model the R&D-innovation-productivity growth equation in that it corrects for endogeneity issues surrounding the effects of selectivity and simultaneity bias that arise in such scenarios where firms in the sample are not randomly drawn from the population.

The augmented-CDM approach is thus used here; a basic structural model is formed, which can be formalised in four equations:

1. The firm’s decision to engage in effort to result in observable R&D investment;
2. the intensity with which the firm undertakes R&D;

3. the innovation or knowledge production function, where knowledge is allowed to take two different forms – product and process innovations;
4. the output production function, where knowledge is an input.

This four stage model helps to solve selectivity bias as it takes into account that not all firms are engaged in innovative activity. A Heckman model is estimated for all firms with steps 1 and 2 based on reported R&D figures, the predicted values for all firms are then used to proxy innovation effort in the knowledge production function. This model reflects the fact that all firms exert some innovative effort but not all firms report this effort. The estimates from this step form the Inverse Mills Ratio which is then used as an explanatory variable in the following two steps, to control for selection bias.

The model also solves the potential simultaneity bias which arises in the latter stages, that is, that innovation may improve productivity growth but productivity growth can encourage innovation (Knell and Nas, 2006). This endogeneity problem can be overcome by the use of a simultaneous equation system incorporating instrumental variables. Typically a two-stage least squares (2SLS) or other GMM estimator is utilised. The main problem with this is finding variable(s) that can serve as suitable instrument(s) i.e. the instrument must be correlated with the endogenous innovation variable but have no effect on the dependent productivity variable, the validity of which can be tested with a Sargan-Hansen test. Due to the difficulty in finding a suitable instrument for this stage, based on the available variables, the predicted values of product and process innovation will be used to identify the model. These predicted values satisfy the properties of an instrument as they are clearly correlated with innovation activity but because they represent average values of exogenous variables, they are uncorrelated with the residual.

The model works by estimating a reduced-form coefficient in each of the equations separately and from these infers the structural form parameters of the model. The first equation, the firm's decision to invest in R&D, is given as:

$$rd_i = \begin{Bmatrix} 1 \text{ if } rd_i^* = w_i'a + \varepsilon_i > c, \\ 0 \text{ if } rd_i^* = w_i'a + \varepsilon_i \leq c \end{Bmatrix} \qquad (6.20)$$

where rd_i is the observed binary endogenous variable equal to zero for those firms not undertaking R&D and equal to one for those firms that report R&D expenditure; rd^*_i is a corresponding latent variable indicating that firms decide to do (spend on) R&D if it is above a certain threshold level *c*; *w* is a vector of variables which explain the R&D decision; α a vector of parameters of interest which impact on the probability of being engaged in R&D and ε_i an error term.

Conditional on firm i undertaking (spending on) R&D, the amount spent, as a share of turnover, (stage 2 of the equations), can be estimated by:

$$r_i = \begin{Bmatrix} r_i^* = z_i^{'}\beta + e_i \text{ if } rd_i = 0 \\ 0 \text{ if } rd_i = 0 \end{Bmatrix} \qquad (6.21)$$

The first two equations are estimated using a two-step method with maximum likelihood; the Heckman procedure in Stata is used. Observations on those spending on R&D and those with no R&D expenditure are included.

The third equation in the model constitutes the knowledge / innovation production function:

$$g_i = r_i^* \gamma + \chi_i^{'}\delta + u_i \qquad (6.22)$$

Where g_i is knowledge as measured by the product innovation indicator (the equation is also run separately for the process innovation indicator); r^*_i is the latent innovation effort from equation 2 and enters as an explanatory variable; x_i is a vector of other determinants of knowledge production; γ,δ a vector of parameters of interest and u_i an error term.

The third equation is estimated in Stata as a probit, using maximum likelihood. The predicted value r^*_i is drawn from the Heckman equation, in stages 1 and 2, and thus allows us to instrument innovative effort. Using the predicted value also means that equation 6.22 can be estimated for all firms, and not just those who spend on R&D.

The final stage of the system of equations, the output production function, is modelled as a conventional Cobb-Douglas, in which real output is driven by inputs of physical capital and knowledge capital, estimated as:

$$y_i = \pi_1 k_i + \pi_2 g_i + v_i \qquad (6.23)$$

Where, output y_i is growth of labour productivity, k_i is the log of physical capital per employee; and g_i is knowledge input as proxied by the product (or process) innovation indicator as derived from equation 6.22. Using the predicted values from the knowledge production function thus takes care of the endogeneity of g_i in this equation.

6.11 Model specification

The model for the decision to undertake R&D is given by the following equation, where R&D effort is the outcome of a combination of factors that condition the demand for and supply of R&D resources:

$$Y_{it} = \beta_0 + \beta_1 \text{lgvaperemp}_{it-1} + \beta_2 \text{ltotalemp}_{it} + \beta_3 \text{shscien}_{it} + \beta_4 \text{ exporter}_{it} + \beta_5 \text{lempcostsperemp}_{it-1} + \beta_6 Z_{it} + \varepsilon_t \quad (6.24)$$

Where Y is a dummy variable for spending on R&D; equal to one if the firm has R&D spending>0 and zero otherwise. Intramural R&D, which is R&D that is performed internally within the firm, is preferred over total R&D expenditure (which includes extramural R&D) as it reflects activities undertaken within the firm itself.

Lgvaperemp refers to the log of labour productivity and is included as an explanatory variable to control for the existing productivity level within the firm. We would anticipate that firms with higher levels of productivity are more likely to do R&D, as the higher productivity may be a function of past investment in innovative activity.

Ltotalemp refers to the log of firm size and is included as an explanatory variable to take account of a number of theories which postulate a positive relationship between size and R&D. Size is expected to be positively related to R&D, based on to the Schumpeterian argument surrounding the resources of larger firms; the idea that larger firms have greater access to finance and are more willing to undertake the risks associated with R&D (Hall, 2002); the ability of larger firms to internalise R&D spillovers due to greater diversification (Klette, 1996); the likelihood that larger firms have complementary capabilities, such as marketing, to exploit the innovations; and the notion that larger firms have a greater level of output over which it can spread the average costs of R&D (Nelson et al., 1967; Cohen and Klepper, 1996).

Exporter is a dummy variable equal to one if a firm exports, and is included in the model to take account of the theoretical literature which suggests that firms engaged in global business activity are more likely to undertake innovative behaviour due to exposure to foreign technologies, and access to a higher diversity of knowledge and information (Salomon and Shaver, 2005). The literature suggests that the causality can run either from exports to R&D or vice-versa, or both. Given the potential endogeneity the model is tested using both a lagged and a simultaneous exporter variable; the a priori expectation is a positive coefficient on the exporter variable.

Shscien relates to the share of science and engineering graduates in the firm's total workforce and reflects the level of human capital and absorptive capacity within the firm. We would expect that firms with higher shares of such employees are engaged in more technologically advanced activities and would be more likely to do R&D; hence we expect a positive finding between the two variables.

Lempcostsperemp refers to employment costs per employee and is used to proxy the quality of the product/service produced by the firm. We would expect that firms with higher employment costs are working at higher levels of the value chain and hence we would expect the relationship between employment costs and R&D to be positive.

Sectoral variables are included to control for the fact that the likelihood of undertaking R&D will vary by sector, due to costs and barriers to entry. We would anticipate positive values for Manufacturing and Business Services (against the base case of other services) and possibly negative values for Construction and Wholesale and Retail activities, which are generally not considered to be sectors associated with high levels of R&D activity.

The second equation within the model relates to R&D intensity i.e., R&D investment as a share of turnover, and is conditional on undertaking R&D. The model is given as:

$$Y_{it} = \beta_0 + \beta_1 \text{lgvaperemp}_{it-1} + \beta_2 \text{ltotalemp}_{it} + \beta_3 \text{ exportint}_{it} + \beta_5 Z_{it} \qquad (6.25)$$

Where Y is R&D intensity and ranges from zero to one. Again those with higher productivity levels and larger firms are expected to spend a greater proportion of turnover on R&D as they both are more likely to have greater capacity, resources and expertise to do so. Exporting in this stage is captured as export intensity (**exportint**) that is, exports as a share of sales. We would expect the coefficient to be positive, suggesting that the higher the share of exports the higher the share of R&D spending. This is explained by the supposition that where firms already export, they have a greater need to undertake R&D in order to remain competitive or gain advantage in existing export markets.

Table 6.17 presents descriptive statistics for the variables included in the first two stages. The data indicates that 48 per cent of the sample undertakes intramural R&D, whilst the average amount spent is 26 per cent of turnover. The majority of firms in the sample export, at 79 per cent, however export intensity is just 24 per cent. On average, just 7 per cent of the average firm's workforce is composed of science and engineering graduates. This reduced sample (due to missing data) is more skewed towards manufacturing than was previously the case, with 79 per cent of all firms in the sector.

Table 6.17: Descriptive Statistics for R&D Equations

stats	*N*	*mean*	*Median*	*sd*	*Min*	*Max*
Intramural R&D (1/0 dummy)	435	0.48	0.00	0.50	0.00	1.00
Intramural R&D intensity *(Intramural R&D spend / turnover)*	403	0.26	0.00	0.08	0.00	0.68
Exporter (1/0 dummy)	435	0.79	1.00	0.41	0.00	1.00
Export intensity *(Exports value / sales)*	435	0.24	0.12	0.27	0.00	1.00
Labour Productivity *(GVA per employee)*	435	23.6	19.4	20.2	6.99	221.77
Size *(total employment)*	435	87.7	32.7	275.0	0.00	6,524.0
Science and Engineering Share *(Science & Eng grads as a share of employees)*	435	0.07	0.01	0.17	0.00	1.00
Employment Costs *(employment costs per employee)*	435	13.02	11.81	8.76	2.32	94.20
Manufacturing (1/0 dummy)	435	0.79	1.00	0.41	0.00	1.00
Construction (1/0 dummy)	435	0.04	0.00	0.20	0.00	1.00
Wholesale & Retail (1/0 dummy)	435	0.06	0.00	0.23	0.00	1.00
Business Services (1/0 dummy)	435	0.08	0.00	0.27	0.00	1.00
Other Services (1/0 dummy)	435	0.03	0.00	0.18	0.00	1.00

Note: Employment costs and Labour Productivity are in £000s at 1995 prices.
Source: Authors own estimates of DETI data

The third stage of the model is the knowledge production function; separate models are run for product innovation and process innovation as these activities are not always undertaken by the same firms (as shown in Table 6.16).

The basic model is given as:

$$\begin{aligned} Y_{it} &= \beta_0 + \hat{\beta}_1 \text{RDintensity}_{it} + \beta_2 \text{ltotalemp}_{it} + \beta_3 \text{info}_{it} + \\ &\beta_4 \text{coop}_{it} + \beta_5 \text{support}_{it} + \beta_6 \text{protect}_{it} + \varepsilon_i \end{aligned} \tag{6.26}$$

where Y is a dummy variable representing engagement in product innovation (or process innovation).

The first explanatory variable included in the model is R&D intensity (**RDintensity**) which is derived from the previous stage; we expect firms that spend a higher proportion of turnover on R&D to be more likely to undertake innovation as R&D is an input into the innovation process, the resulting new product or process representing the output.

Given that innovation can result, not only from R&D but also from knowledge sourced externally due to the technological opportunities it provides to firms (Roper and Love, 2004; Corrocher et al., 2007), the various sources of information, and co-operation partners are included as explanatory variables in the knowledge production function to capture these ‘network’ effects. In the model the information variables (**info**) are included as three separate variables for information sourced from the market, institutions and other sources. The co-operation variables (**coop**) again include three separate variables to account for co-operation partners in the UK, Europe and other areas. We would anticipate positive relationships between both these categories of variables and innovation activities.

The nature of innovation means that it is not always easy for a firm to appropriate the returns. Knowledge spillovers and the likelihood of imitation mean that firms can underinvest in R&D, thus providing a rationale for government intervention. As a result support variables which capture support from central and local government (**support**) are included in the model; and variables which relate to the formal and strategic protection of the innovation (**protect**). We expect positive findings for both sets of variables on the likelihood of engaging in innovation. The descriptive statistics for this stage of the modelling are given in Table 6.18.

The table shows that overall, a higher share of firms undertake product innovation than process innovation, at 42 per cent compared to 31 per cent. More than half of firms utilise information from outside sources, with market sources proving most popular with 76 per cent of firms making use of such sources. Firms generally do not co-operate with outside bodies, with on average around one tenth of firms, or less, having co-operation partners. Support from government is also relatively low, which is not as expected, with around one fifth of firms receiving support from either local or national government. Around two fifths of firms seek some sort of protection for their innovations, with a slightly higher share opting for strategic protection than formal.

Table 6.18: Descriptive Statistics for the Knowledge Production Function

Stats	*N*	*mean*	*median*	*sd*	*min*	*Max*
Product Innovation	435	0.42	0.00	0.49	0.00	1.00
Process Innovation	435	0.31	0.00	0.47	0.00	1.00
Market Sources of Info	435	0.76	1.00	0.43	0.00	1.00
Institutional Sources of Info	435	0.20	0.00	0.40	0.00	1.00
Other Sources of Info	435	0.55	1.00	0.50	0.00	1.00
Local Co-operation	435	0.14	0.00	0.35	0.00	1.00
UK Co-operation	435	0.11	0.00	0.32	0.00	1.00
EU Co-operation	435	0.10	0.00	0.30	0.00	1.00
Other Co-operation	435	0.05	0.00	0.21	0.00	1.00
Local Govt Support	435	0.21	0.00	0.41	0.00	1.00
National Govt Support	435	0.20	0.00	0.40	0.00	1.00
EU Support	435	0.03	0.00	0.17	0.00	1.00
Formal Protection	435	0.38	0.00	0.49	0.00	1.00
Strategic Protection	435	0.42	0.00	0.49	0.00	1.00

Source: Authors own estimates of DETI data

The final stage of the model is the output production function; productivity growth is used as the dependent variable. A variable to capture productivity growth over the 2004-08 period, rather than 2002-08, is constructed as the innovation variables relate to activities undertaken in the 2002-04 period. The model is run separately for the predicted values of product innovation and process innovation. The equation for the final stage of the model is given as:

$$\Delta \ln Y_{it} = \beta_0 + \hat{\beta}_1 \text{Prinnov}_{it} + \beta_2 \text{exportint}_{it} + \beta_3 \text{ltotalemp}_{it} + \beta_4 \text{lempcostsperemp}_{it} + \beta_5 \text{stockperemp}_{it} + \beta_6 \text{labprod}_{it} + \beta_7 Z_{it} + \varepsilon_i \quad (6.27)$$

where ΔlnY is the log difference in labour productivity between 2004 and 2008.

Prinnov is the predicted value of either product or process innovation; the central hypothesis of the model is that innovation activity results in increased productivity growth, thus we would anticipate a positive coefficient on the predicted innovation variables.

Amongst the other explanatory variables, export intensity (**exportint**) is included to control for the foreign trading activities of firms. Given the learning-by-exporting hypothesis, and its associated positive effect from exporting to productivity growth, the anticipation would be a positive sign on the export intensity variable.

The size variable (**ltotalemp**) is the log of total employment; the creative destruction argument would suggest that new entrants into the market embody newer technology, and as such have higher productivity growth. Given that such firms are more likely to be small, we would anticipate a negative relationship between size and productivity growth. Employment costs per employee (**lempcostsperemp**) are included again to proxy human capital, whereby higher costs suggest higher skill levels and a higher value product or service. The anticipated sign on the employment costs variable would be positive. A variable to control for the existing level of labour productivity is included (**labprod**); we might anticipate that firms with existing high productivity levels are less likely to grow faster than those with a lower base level, and thus expect a negative coefficient. Finally a variable to capture the physical capital within the firm is included; we would anticipate that, as for human capital, higher levels of physical capital would be associated with higher investment (and perhaps more modern equipment) and thus higher productivity growth.

Table 6.19 displays the descriptive statistics for this stage of the model; productivity growth increased by 9 per cent on average over the period. The average size of firms is 117 employees, with mean employment costs of £18,000. Average labour productivity for the sample of firms is £28,000 whilst the value of physical stocks per employee is around £8,000. In total firms exported an average of 24 per cent of turnover; as before manufacturing firms constitute around 80 per cent of the sample.

Table 6.19: Descriptive Statistics for the Output Production Function

stats	*N*	*mean*	*median*	*sd*	*min*	*max*
Productivity Growth 2004-08 *(% growth in GVA per employee)*	284	9.61	8.62	7.02	-4.28	56.40
Size *(total employment)*	284	116.53	55.00	273.18	7.46	2,783.00
Export Intensity *(export value / sales)*	284	0.24	0.13	0.27	0.00	1.00
Employment Costs *(emp costs per employee)*	284	17.87	16.54	8.80	4.77	94.20
Labour productivity *(GVA per employee)*	284	28.07	24.05	18.96	-7.80	137.60
Physical Stocks *(end year stocks per employee)*	284	8.45	5.18	12.75	0.00	161.52
Manufacturing (1/0 dummy)	284	0.80	1.00	0.40	0.00	1.00
Construction (1/0 dummy)	284	0.05	0.00	0.22	0.00	1.00
Wholesale & Retail (1/0 dummy)	284	0.04	0.00	0.20	0.00	1.00
Business Services (1/0 dummy)	284	0.07	0.00	0.26	0.00	1.00

Note: Employment costs and labour productivity and physical stocks are measured in £000s at 1995 prices.
Source: Authors own estimates of DETI data

6.12 Results

Table 6.20 shows the results of the Heckman model for R&D intensity. The probit stage models the determinants of engaging in R&D (that is, spending on intramural R&D) whilst the second stage reports the tobit results on R&D intensity[54]. The Chi Square value of the model is significant at the 5 per cent level suggesting that the model is a reasonably good fit in predicting R&D intensity.

The results suggest that all but the productivity level variable are significant in the selection model for R&D engagement. Larger firms are found to be more likely to engage in R&D, with the probability of R&D increasing by 0.06 units for a 1 per cent increase in size. Exporting firms are found to be more likely to engage in R&D than non-exporters, with probability of undertaking R&D 0.27 times greater for exporters than non-exporters. Those with higher shares of science and engineering graduates;

[54] In recognition of the fact that R&D expenditure is only a partial measure of spend on innovative activity; the models have been re-run using total innovative spend in the first-stage Heckman; this includes spending on R&D, machinery, knowledge, training, design and marketing; the variable drawn from the CIS. The results are recorded in Appendix 1, Tables A1.10 – A1.12. The probit for spending on innovation activities is similar to the original model for R&D spend, except the exporter variable is no longer significant. Predicted total innovation spending is found to have no significant impact on product or process innovation, differing from the R&D spend model in that the latter was found to significantly impact process innovation. The results for the subsequent impact on productivity are unchanged.

and those with lower employment costs are also more likely to engage in R&D; the latter associated with a 0.15 unit decrease in the probability of undertaking R&D for a 1 per cent increase in employment costs per employee.

These results are largely as expected *a priori* and are also consistent with theory and empirics; the size finding is widely reported in the literature and is consistent with Schumpeter's latter work which suggested that larger firms are more likely to engage in R&D due to finance and resource capabilities. The positive finding for exports is consistent with endogenous growth theories which postulate a positive link between engaging in international trade and with technological progress within the firm[55]; again this is also consistent with the literature both for NI (Love et al. 2010) and elsewhere (Janz et al., 2004; Harris and Li, 2005; Aw, Roberts and Winston, 2007; Lin and Lin, 2010; Bogliacino et al., 2010; Castellacci, 2011). The result on the share of science and engineering graduates confirms findings that that higher levels of human capital result in a greater likelihood of R&D activity, reflecting a greater ability for absorptive capacity within the firm. The employment costs result is the only one which did not meet *a priori* expectations; the negative coefficient suggesting that the lower the employment costs the more likely the firm is to undertake R&D. This could indicate that firms at the lower end of the value chain may need to invest in R&D to a greater extent than firms higher up the chain in order to become more competitive and remain in the marketplace.

The right hand side column of Table 6.20 shows the estimates of the determinants of how much firms spend on R&D (as a share of turnover), conditional upon undertaking R&D. Again firm size is important, however unlike the R&D dummy equation, the sign on employment size is negative. The results suggest that a 1 per cent increase in size is associated with a 0.02 per cent decrease in R&D intensity. These results are interesting, and suggest that whilst larger firms are more likely to engage in R&D, smaller firms spend a greater proportion (of sales) in doing so. This finding is consistent with elements within the literature whereby it is suggested that the relationship between R&D intensity and size differs from that for undertaking R&D (Janz et al., 2004).

The only other significant variable in the model is sectoral and relates to business services, suggesting that firms in this sector are more likely to undertake R&D than

[55] To test for the direction of causality the model was re-run with a lagged exporter value but it was found to be insignificant.

those in the remainder of the service sector. The lambda term in the model is significant and negative, suggesting the presence of selection bias, and indicating that there are unobserved variables which have a negative effect on the R&D intensity of firms.

Table 6.20: Heckman Selection Model for R&D Intensity conditional on Investing in R&D 2002-04

Dependent Variable	**Engage in R&D (1/0 dummy)**	**R&D Intensity**
Log Labour Productivity $_{(t-1)}$	0.063	-0.00185
	(0.061)	(0.0107)
Log Size	0.060**	-0.0151***
	(0.023)	(0.00527)
Share of Science and Engineering Employees	1.065***	-
	(0.212)	-
Exporter	0.273***	-
	(0.056)	-
Log Employment Costs	-0.154*	-
	(0.080)	-
Export Intensity$_{(t-1)}$	-	-0.00917
	-	(0.0185)
Lambda	-	-0.103***
	-	(0.0241)
Manufacturing	-	0.0203
	-	(0.0253)
Construction	-	-0.00472
	-	(0.0351)
Wholesale	-	0.0165
	-	(0.0353)
Business Services	-	0.0592**
	-	(0.0297)
N Obs	429	429
Chi-Sq (7)		18.13**

Marginal effects are reported
Standard errors in parentheses
Model estimated using Heckman (in Stata)
*** p<0.01, ** p<0.05, * p<0.10

The results of the knowledge production function are shown in Table 6.21; with separate results for product and process innovation. The predicted R&D intensity variable (drawn from the Tobit model) is insignificant for product innovation, indicating that spending on R&D (as a share of sales) has no impact on the probability of introducing new or significantly improved goods. This does not conform to the wider literature, although it is consistent with Benevente (2006) and Alvarez et al. (2010) who also reported no impact. It is likely that this result is due to the fact that both the R&D and innovation variables are measured over the same time frame; it could be expected that there would be a time lag between the R&D of a new product and the actual introduction of it, which the data does not allow to be tested.

Variables to indicate the degree of ‘network’ activity point to an impact on product innovation; information derived from market sources, for example suppliers, clients or competitors are significant in terms of introducing new products (compared to the base of using information from internal sources); the predicted probability of doing product innovation 69.1 percentage points greater for those using market sources of information than those using internal sources. The result confirms the conclusions of Bogliacino et al. (2010) who report that clients and suppliers are important sources of information for innovation activity; and the results here represent an important finding in that it suggests that outside influences have a greater impact on a firm’s product innovation activity than does the amount spent on R&D.

Strategic protection of innovations, such as through secrecy, complexity of design and/or lead time advantage on competitors is also important in the likelihood of undertaking product innovation; the predicted probability of innovation for those using such strategic appropriability methods 59.3 percentage points greater than those not using the methods, which is consistent with that reported for Norway (Castellacci, 2011). Importantly, there is no such impact from formal protection methods; it is likely that this reflects cost reasons, with informal strategic methods less likely to incur large monetary costs to the firm, than for example applying for a patent.

The model for process innovation differs in some important respects from that for product innovation. Firstly, and importantly, the predicted R&D intensity variable is positive and significant; the estimated marginal effect of 4.82 indicating that a small increase in the amount spent on R&D substantially increases the likelihood that the firm will introduce new or significantly improved processes. The size of the coefficient is within the range as reported in the literature, where elasticities up to and including more than 40 per cent were reported (OECD, 2009). The finding also suggests that the time lag between R&D and the introduction of a process innovation may be shorter than that for product innovation, hence the significant result only for the former.

Information sources are again important, particularly those from market sources as before, with the probability of doing process innovation 103 percentage points greater for those using market sources compared to those just using internal sources of information. Co-operation from external partners, particularly from the UK, is also found to be important for process innovation; the probability 47 percentage points higher for those with UK co-operation partners compared to those with local partners. Strategic protection is again positive and significant in this model, the probability of undertaking process innovation 49 percentage points greater for those using strategic appropriability methods compared to those not using any. Again this finding reinforces the likelihood of such protection methods being at a lower cost to the firm. Interestingly, there is no evidence of an impact on innovation activity from support received from local or central/devolved government; this is a surprising finding particularly given the market failure arguments surrounding innovation activities. Again the finding could reflect a timing issue with the simultaneous nature of the data providing an insufficient time lag with which to measure the result. Alternatively, it could be argued that government support is targeted more towards R&D than innovation per se, and thus the inclusion of the government support variables may have been better to have been modelled in the first stage equation on the likelihood or intensity of R&D.

Table 6.21: Multivariate Probit Model for Product and Process Innovation 2002 - 2004

Dependent Variable	Product Innovation	Process Innovation
Predicted R&D intensity	3.475	4.818**
	(2.200)	(2.243)
Log Size	0.0333	0.0147
	(0.0614)	(0.0616)
Information from market sources	0.691***	1.030***
	(0.212)	(0.240)
Information from institutional sources	0.0256	-0.0730
	(0.178)	(0.178)
Information from other sources	0.247	-0.123
	(0.160)	(0.165)
Co-operation from UK partners	0.424	0.465*
	(0.301)	(0.278)
Co-operation from European partners	0.0946	0.484
	(0.322)	(0.310)
Co-operation from other partners	0.206	-0.315
	(0.471)	(0.400)
Support from local authorities	0.216	-0.0518
	(0.177)	(0.173)
Support from central/devolved govt	0.173	0.271
	(0.191)	(0.186)
Formal protection	0.189	0.0181
	(0.168)	(0.171)
Strategic protection	0.593***	0.488***
	(0.166)	(0.171)
Constant	-1.573***	-1.764***
	(0.286)	(0.306)
N Obs	435	435
Chi-Sq (12)	108.64***	77.42***
Log-likelihood	-227.814	-221.778

Marginal effects are reported
Model estimated using mvprobit (in Stata)
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

The results of the final estimation stage, the output production function for productivity growth, are shown in Table 6.22. The dependent variable is the log growth of GVA per employee between 2004-2008; again separate models are run for product and process innovation. Importantly, the estimated coefficient on the predicted product innovation variable shows no impact on productivity growth whilst for process innovation the impact is significant but negative, implying that as firms move from not innovating to introducing new or significantly improved processes their productivity growth decreases by 0.33 per cent.

The only other significant variable, in both models, is labour productivity which suggests a 1 per cent increase in productivity levels is associated with a 0.3 per cent decrease in productivity growth; the negative relationship as previously predicted. The only sectoral variable of significance relates to the Construction sector which is negative in comparison to the base case (Other Services), implying that productivity growth in the Construction sector is lower than for the other service sectors.

The lack of an impact on productivity growth from product innovation can be explained by the fact that unless accompanied by economies of scale, the introduction of a new product may not necessarily increase productivity growth. Rather the resulting increase in demand arising from the introduction of a new product could result in increased labour, at the (temporary) expense of productivity increases. The results on the process innovation equation, although unfavourable and at odds with *a priori* expectations, are similar to other studies within the wider literature; those reporting negative process innovation effects typically measuring the impact only over a 2 year period. Where negative coefficients have been reported the estimates with regards to log of value added (or sales per employee) range from -0.02 (Mairesse and Robin, 2010) to -0.14 (Janz et al., 2004). The OECD (2009) report suggests that such a negative relationship could be due to adjustment costs and the associated learning involved with a new process, with a resultant temporary reduction in labour productivity. Alternatively Hall (2011) and Mohnen and Hall (2013) surmise that in the short-run, efficiency improvements from process innovations may not be revealed in the revenue figures if they result in lower prices without corresponding increases in output.

Table 6.22: Regression on Productivity Growth 2004-08

Dependent Variable	**Productivity Growth 2004-08** (with product innovation)	**Productivity Growth 2004-08** (with process innovation)
Predicted Prod Innov	-0.167	-
	(0.138)	-
Predicted Proc Innov	-	-0.329*
	-	(0.174)
Export Intensity	0.0108	0.0138
	(0.0343)	(0.0337)
Log Size	0.165	0.185
	(0.130)	(0.129)
Log Employment Costs	0.0412	0.0328
	(0.109)	(0.109)
Log Physical Capital	-0.0278	-0.0248
	(0.0304)	(0.0302)
Log Labour Productivity	-0.304***	-0.303***
	(0.0783)	(0.0780)
Manufacturing	-0.196	-0.190
	(0.211)	(0.210)
Construction	-0.503**	-0.516**
	(0.249)	(0.248)
Wholesale & Retail	-0.215	-0.227
	(0.253)	(0.252)
Business Services	-0.531	-0.559
	(0.569)	(0.567)
Constant	1.138***	1.162***
	(0.367)	(0.366)
Observations	257	257
Chi-Sq (9)	28.4***	30.50***
Log-likelihood	-198.998	-197.946

Model estimated using xtreg mle (in Stata)
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

6.13 Summary and Discussion

The purpose of this element of the analysis was to ultimately discover whether there is any evidence that innovation activities increase the labour productivity growth of firms in NI. The rationale for the hypothesis was based on concepts put forward by endogenous growth theories which suggest that through R&D; investments in human capital, and innovative behaviour firms learn to increase the efficiency of their productive efforts and thus speed up their rate of productivity growth. Previous evidence for NI had found there to be no productivity impact from process innovation and a negative impact from product innovation; the wider empirical literature also reported mixed evidence with regards to process innovation. Government policies in the innovation sphere have implied that there is a causal relationship between the two, particularly in the UK, where innovation is considered as one of the five drivers of productivity growth and in NI where successive strategies have sought to increase levels of innovation in order to improve the regions productivity position. Given the somewhat conflicting empirical evidence, the issue warranted a further examination.

In order to establish the evidence modelling was undertaken in a four stage equation framework, the first part of which sought to identify the determinants of engaging in R&D, and from this model the relationship between R&D and innovation behaviour. Innovation and R&D activities, although two separate concepts, are often used interchangeably to refer to the overall innovative effort thus it was important to make the distinction between the two. The results indicated that R&D was more likely to be undertaken by larger firms, those that export, and those with higher shares of science and engineering graduates, all of which were consistent both with theoretical notions and with similar empirical studies. Importantly the sign on the size variable was found to differ depending on the R&D measure, with larger firms more likely to undertake R&D but smaller firms spending a higher proportion of turnover doing so, which is likely to reflect the costs of R&D personnel to the firm.

The knowledge production function which examined the relationship between R&D and innovation behaviour only found evidence that R&D expenditure increased the likelihood of doing process innovation, with no effect found for product innovation. It may be the case that the lack of data on previous R&D expenditure was responsible for this apparent lack of impact (the data not providing enough of a time lag), particularly as it has been argued that persistence in innovative activity cannot be assumed (Raymond et al., 2010). In this case, the significant result on process innovation may indicate a shorter time lag between R&D investment and a resulting new or improved process. Intuitively this makes sense as one could imagine that new processes in a firm could be adopted within a quicker timescale than the introduction of new products, which would have to be designed, tested and brought to market.

Other results of the knowledge production function suggest there was no impact on innovation from government support; however other types of external linkages or 'network' effects, as termed by Roper and Love (2004) were found to be important determinants of innovative activity. These included, for product and process innovation, obtaining information from market sources. Co-operation with UK partners was also found to be important for process innovation only. These results highlight the fact that innovation does not solely result from investment in R&D, but indeed can come from other sources, and reaffirmed the notion that not all innovators are R&D performers (Eurostat, 2004).

The firm's ability to appropriate the benefits of innovation was associated with higher rates of innovation, but importantly only strategic protection measures, which are less costly to the firm in monetary terms, were significant. Again this finding is consistent with market failure concepts in which firms are less likely to undertake innovative activities if they cannot appropriate the spillovers; the finding suggests that firms opt for the least costly form of protection.

The final stage of the modelling process which examined how innovation affects productivity growth found no impact from product innovation and a negative impact from process innovation. This was in contrast to previous work for NI, where generally the opposite was found, with negative product innovation effects and no effect from process innovation (Roper et al., 2007, 2008; Love et al., 2010). Process innovation refers to novel or new to the firm techniques and ways of doing business, and allows firms to gain a cost advantage over their competitors. It is expected to have an obvious positive effect on productivity as new processes are typically introduced to reduce the costs involved with the production process, particularly with regards to labour. As a result, the negative finding was unexpected, and also relatively rare in the literature, with any negative impacts usually reported when product and process innovation are combined (Hall, 2011). However, as with other studies reporting a negative impact (on innovation in general), the time period of analysis was relatively short, therefore it is likely that the results could reflect a temporary drop in productivity whilst there is learning about the new process until it can be run efficiently. A similar 'disruption effect' was reported by Roper et al. (2008) in NI for product innovation; whereby the introduction of the new product temporarily affected production. Although referring to two different types of innovation, they both potentially suggest a disruptive learning effect when a new activity, process or good is introduced.

The results here are important from a policy perspective and bring into play the issue of timing. The nature of the relationship between innovation and productivity growth is typically implied or assumed, by policy makers, to be positive and of a direct nature. Here the results do not imply that innovation is not associated with higher productivity growth, nor do they suggest that it is not a good thing for firms to do, but rather they suggest that care should be taken when making bold statements about how innovation and productivity growth are correlated as the effect may actually be negative or have no impact, at least in the short-run. This is particularly important if innovation activity is associated with targets with regards to productivity growth, set within a certain time frame. Rather, it should be recognised that the relationship between innovation and productivity growth is long-term in nature, and is likely to be punctuated with negative blips, where firms take time to learn about and adjust to new productive processes, machinery or methods.

The reported lack of impact from government support further highlights that rather than narrowly focusing on measures to increase R&D that, given the importance of market sources and of co-operation partners as innovation drivers, policy should also concentrate on enabling firms to become more innovation active through these wider channels, thus making them more adaptable to customer needs. If firms are reluctant to invest in innovation through formal R&D channels due to the risk, costs involved and lack of protection, it seems sensible to open up other potential innovation channels, whereby the costs and risks are either shared or are minimised. This can be achieved through networking and collaborative events which, due to reasons associated with information asymmetry, may not naturally occur in the marketplace. Policies to help firms make these external linkages may be less costly to the public purse than the provision of subsidies and, as the results suggest, may have a greater impact.

6.13.1 Limitations and Recommendations

Despite reporting consistent results with other empirical studies of a similar nature and time frame, the study here is subject to a number of limitations. The findings are caveated with the fact that there is only one observation from the CIS upon which to base the evidence, which reduces the dynamic element of the estimation process. In addition the degree of missing data on key variables such as exporting excluded the possibility of undertaking imputation with any degree of validity, with the resulting reduced sample subject to biased results due to the casewise deletion of observations.

The use of dummy variables to represent product and process innovation, in the output production function, are also somewhat restrictive in that they signify the incidence of undertaking the activity rather than the intensity. It could be the case that productivity growth is associated with a certain amount of innovation, much like the ‘threshold of internationalisation’ as reported in the exporting literature and whilst the share of sales attributed to new products is recorded on the CIS, there is currently no such equivalent recorded for process innovation. The inability to measure this other than through a dummy variable may be potentially clouding any result.

A final restriction is that due to limited data availability the effect of innovation on productivity growth was only able to be measured over a four year period. Given the likelihood that a positive relationship between the two is long-term in nature, a longer time period would have been preferred. This suggests potential for a re-visit to the analysis in the future. In this case the data requirements will be more substantial as a longer time period opens up the possibility for there to be other confounding factors that influence growth including those at the firm level, the wider economy and the policy context.

Sub-section C Relationship between Public Financial Assistance and Productivity Growth

6.14 Introduction

The previous two sections have sought to analyse the relationship between productivity growth and the strategic activities firms undertake, namely exporting and innovation. Although both used firm-level characteristics to model the relationship, government intervention variables were also included in the models to capture the fact the NI firms are heavily assisted, as detailed in Chapter 1, and to control for the fact that assistance is offered for these strategic activities. A variable to reflect assistance from Invest NI was significant in the exporter logistic regression but variables capturing support from central and local government were insignificant in the probit models for innovation activity. Given the mixed impacts previously reported this part of the analysis seeks to put such policy interventions under the microscope, focusing on the direct effect of public grant assistance on the productivity growth of firms.

The provision of grant assistance to firms has been a feature of most industrialised countries' economic policies over the post-war era. The rationale for such intervention is to counteract situations arising from market failure, whereby there is a disincentive for firms to engage in certain behaviour, or a failure of the market to provide adequate resources to enable them to do so (Stiglitz, 1988). In these cases public financial assistance should be of benefit to firms and thus aid their performance however, rather than acting as a remedy, it is also possible that assistance can lead to inefficiencies in the market if it is targeted incorrectly or where it leads to deadweight or displacement effects (Harris and Trainor, 2005b). Testing for the impact of grant assistance is a difficult and relatively uncommon practice due to the data requirements needed by the exercise (Criscuolo et al. 2012), and the necessity to find out what would have happened in the absence of assistance; however when it can be done, it provides an invaluable resource to policymakers in the evaluation of their policies and programmes.

There have been a number of evaluations of the various types of business grant support offered in NI, although many of these looked at the employment impacts only (Gudgin et al., 1989; Hamilton, 1990; Sheehan, 1993; Hart and Scott, 1994; Hart and

Hanvey, 1995) or focussed on output or turnover (Harris, 1991; Harris et al., 2002; Harris and Trainor, 2005; SQW, 2013). Studies which specifically covered the impacts on productivity growth found there to be little or no effect (Hart et al., 2000, 2007; Hart and McGuinness, 2003; Roper and Hewitt-Dundas, 1998) and in fact positive effects where only detected when specific targeted grant types were assessed, although the impacts were found to be short-lived (McGuinness and Hart, 2004).

The remainder of this section presents the key hypothesis, as developed from the literature review in Chapter 4, with respect to the public financial assistance and productivity growth relationship being tested here. The methodologies which are used to examine the relationship are reviewed together with a discussion of the data and descriptive statistics. The results of the regression analyses are presented, and are set in context with other relevant empirical and theoretical literature. The section concludes with a discussion of the limitations and options for further work.

6.15 Testable Hypotheses

The hypothesis being tested in this section is based on market failure theories that provide a rationale for government intervention in the economy. Within the NI context there are several reasons for offering public assistance to private sector companies, which generally differs by ownership. For externally-owned firms the chief reason is to attract new investments to the region, particularly in a global marketplace. For NI-owned companies, or existing externally-owned firms, the rationale is usually different; typically being provided for viable projects that require financial assistance to bring them to fruition, where the firm has been unable to source this finance from elsewhere. Indeed Hart et al. (2008), in providing the rationale for RSA, suggest that such assistance is necessitated due to a combination of incomplete markets for private sector sources of external finance; positive externalities associated with firms being co-located; and information asymmetries from lack of awareness about sources of external finance

SFA, which is the NI equivalent to RSA, was historically offered as a means of generating long-term high quality employment, although this later altered to also include productivity improvements, in response to the general policy move towards increased business competitiveness (SQW, 2013). In order to qualify for the discretionary payments awarded under SFA, projects had to meet strict criteria which would be assessed by the agency administering the scheme. The project had to be located in NI; it had to be shown that without assistance the project would not have gone ahead, or that it would have been smaller in scale or completed over a longer timeframe. The expenditure on fixed assets had to be used in either setting up or expanding a new establishment; for modernising, rationalising or diversifying products or the production process; or for buying an establishment that had closed or would close without the investment. The jobs created or safeguarded had to be sustainable long-term jobs which would not displace those from elsewhere, likewise both the firm and project had to be viable and eventually be self-sustaining, after three years; and finally the project had to provide national and regional benefits (Industrial Development Order, 1982).

An important aspect of the legislation was the stipulation that projects must be additional to what would have occurred in the absence of assistance. Hence assistance was to be given to firms to bring projects forward in time or to expand the size of a project, in cases where the firm was unable to do this themselves due to failures in sourcing finance from the market. The resulting hypothesis is thus based on the notion that that such financial assistance generates additionality and hence, where it is given to expand productive capacity or promote efficiency, it raises the productivity growth of firms, thus:

> **H1: Controlling for firm effects, public financial assistance payments increase the productivity growth of recipient firms.**

6.16 Data and Descriptive Statistics

The data for this section is again drawn from the pooled dataset; the financial assistance data is sourced from Invest NI and relates to grant payments made to firms from 1983/84 to 2008/09. Invest NI provided a dataset of 2,937 client companies, for which grant payment data was available for just a sub-sample of 640 firms.[56] As discussed in Chapter 5 the client data was merged onto the dataset via the unique reference number, in total 75 per cent of the companies merged, whilst of the 640 with grant data 436 (68 per cent) merged onto the dataset.

[56] Whilst the grant data is comprehensive for this group of firms it reflects only a subset of all firms in receipt of assistance over the period i.e. those for which computerised payments data was recorded and accessible.

In order to keep the payments data consistent with the time period for the other variables on the dataset the payments prior to 1998/99 were amalgamated, thus the 1998/99 data point contains all payments made in that year and the years preceding it. Table 6.23 displays the descriptive statistics relating to the payment data. Notwithstanding the first year, which contains the amalgamated data, it is clear that the number of firms receiving payments generally declines over the period, as does the maximum value of the payments; between 1999 and 2008 the number of firms in receipt of payments falls from 340 to 57 annually whilst the maximum grant payment falls from £13m to just under £5m. The mean payment remains around the same value over the period while the median value increases, suggesting that by 2008, although fewer firms received assistance, the actual amount paid out to each firm was more consistent in size. The decline in the maximum size of the grants is consistent with the policy change that took place in the 1990s in which support for capital projects was run down to make way for support for more softer forms of assistance, as detailed in Chapter 3.

Table 6.23: Invest NI Grant Payment Data 1983-2008

	N	**Mean £000s**	**Median £000s**	**Min £000s**	**Max £000s**
1983 – 1998	340	2,136	574	6	41,120
1999	163	529	142	1	13,095
2000	121	602	122	3	15,875
2001	131	497	104	2	14,818
2002	108	373	105	5	4,307
2003	85	345	101	5	3,910
2004	81	401	99	4	6,543
2005	62	740	194	3	8,386
2006	62	638	152	7	7,185
2007	47	689	298	4	5,606
2008	57	503	248	7	4,927

Payment data is in £000's and deflated using 1995=100
Source: Invest NI

As stated above the SFA payments data was available for just 640 firms, which did not represent all firms in receipt of assistance over the period. The missing payment data potentially posed a number of problems; firstly, it was not feasible to impute the grant payment data that was missing, as, by its nature, grant assistance is very firm specific thus making it difficult to estimate accurately on a case by case basis. Secondly, although a wider list of client companies was provided, this was at a point in time (2006-08) and invariably did not include every company that had received assistance over the prior period making the wider population of assisted firms difficult to establish.

The difficulty in pinning down a specific SFA grant assisted group lies in the fact that unlike a particular programme with a specific start and end date for whom the recipients can be detected, the SFA grant recipients represent an ever-changing group of firms. This meant that it could not be assumed that every company that was not on the client list had not been given SFA assistance at any point over the period. Generating a dummy variable to indicate receipt of grant assistance, equal to one if the firm was a client and zero otherwise, risked incorrectly labelling all other firms on the dataset as non-assisted firms thus potentially biasing any model, if some had indeed received SFA assistance[57].

In order to try and remedy this and generate a more accurate non-assisted group of firms, additional data was sourced from Invest NI. This additional data comprised lists of firms who had either been approached by the agency, or who they had approached, in order to potentially access grant assistance (SFA or otherwise). This list indicated which firms subsequently became clients and which didn't as they were not 'willing to engage' with the agency[58]. Use of this additional data allowed other firms in the dataset to be classified as non-assisted if they had been in contact with Invest NI and a) had identified that they were not 'willing to engage' with the agency; or b) were 'willing to engage' but did not become Invest NI clients over the period. This filtering provided a suitably adequate control group of firms, 1,406 in total, for whom we can be reasonably confident were not assisted at all during the period in question.

Given that the hypothesis focuses on the impact of payments rather than simply on being an assisted firm, the reduced sample of 436 firms with payments data (that merged onto the dataset) and the 1,406 non-assisted firms were used in the models. It is acknowledged that both groups represent small subsets of their wider populations however given the difficulties in estimating the missing grant data and the difficulties in establishing the wider non-assisted group of firms this appears to be

[57] A further problem was that firms can apply for a range of financial assistance products; thus even if they could be identified as not having received SFA it is possible they could have received other types of public assistance. The inability to detect and control for this potentially biasing the results.

[58] One of the conditions for receiving grant assistance from the Agency is that firms have to agree to 'engage' with them on a regular basis, to include providing regular updates on the financial position of the company and on the associated outcomes of the grant provision.

the only viable option, as such any inferences made from subsequent modelling work relate to the sample only.

The data were pooled over time (1998-2008) and the characteristics of the assisted and non-assisted compared; the pooling resulted in 1,229 observations for the assisted group and 4,531 for the non-assisted. Table 6.24 displays key descriptive statistics; as perhaps would be expected, those that were assisted are larger both in employment and turnover terms, with average employment around four times higher in assisted firms; and average turnover three times higher, with these differences statistically significant. Interestingly there is little difference in mean labour productivity between the two sets of firms, and the difference is also not statistically significant. The dummy variable for exporter indicates that the assisted are more likely to export than the non-assisted whilst the average export intensity is also double, with assisted firms on average exporting 42 per cent of sales and non-assisted exporting half this, at 21 per cent. A similar story is found for R&D intensity with assisted firms spending on average around 6 per cent on R&D compared to 2 per cent for the non-assisted. All differences between the two groups of firms, except those for labour productivity, are statistically significant.

Table 6.24: Descriptive Statistics for SFA Assisted versus Non-Assisted Firms

Stats	*Size*	*Turnover*	*Labour Productivity*	*Employment Costs per Employee*	*Exporter*	*Export Intensity*	*R&D Intensity*
				SFA Assisted (n=1,229)			
Mean	392.76	42,188.36	29.84	17.82	0.93	0.42	0.06
Median	157.00	9,074.43	23.00	16.53	1.00	0.33	0.00
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	7,320.00	2,970,241.00	322.91	114.08	1.00	1.00	1.00
				Non-assisted (n=4,531)			
Mean	99.14	14,051.41	30.18	16.72	0.75	0.21	0.02
Median	40.00	2,448.74	23.95	15.49	1.00	0.10	0.00
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	5,562.00	3,510,733.00	683.65	140.96	1.00	1.00	1.00
t-test	*21.29****	*6.19****	*0.24*	*3.32****	*-*	*21.58****	*2.32***
Chi sq	-	-	-	-	*155.88****	-	-

Note: Turnover, Labour Productivity, and Employee Costs are in £000's in 1995 prices; Export Intensity defined as exports as a share of sales; R&D Intensity defined as R&D spending as a share of turnover
Source: Author's estimates of DETI data

Given that the sample of firms is distinct from the wider population, the size and sectoral distributions are examined in more detail. The sectoral distribution of the two groups is shown in Table 6.25; firms are overwhelmingly involved in manufacturing, particularly the non-assisted of which 86 per cent are manufacturing firms. The SFA assisted firms are also mostly in the manufacturing sector however there are also sizeable shares in business services (9 per cent of firms) and in other services (16 per cent) reflecting the focus of Invest NI, on manufacturing and tradeable service sectors. Due to its dominance, the manufacturing sector is disaggregated into its component sub-sectors for the estimation.

Table 6.25: The Sectoral Distribution of SFA-Assisted and Non-Assisted Firms

	Non-assisted	*SFA-Assisted*	*Total*
Manufacturing	3,880	868	4,748
	(86%)	*(71%)*	*(82%)*
Construction	153	5	158
	(4%)	*(0%)*	*(3%)*
Wholesale and Retail	169	45	214
	(4%)	*(4%)*	*(4%)*
Business Services	198	115	313
	(4%)	*(9%)*	*(5%)*
Other Services	131	196	327
	(3%)	*(16%)*	*(6%)*
Total	4,531	1,229	5,670

Source: Author's estimates of Invest NI and DETI data

The size distribution of firms (Table 6.26) reveals distinct differences between the two groups of firms; the majority of the non-assisted are small firms; more than half have fewer than 50 employees whilst just 8 per cent have more than 250 employees. In contrast, the SFA assisted are more skewed towards the larger end; with more than two fifths having 250 or more employees and just 13 per cent having fewer than 50.

Table 6.26: The Size Distribution of SFA Assisted and Non-Assisted Firms

	Non-assisted	*SFA Assisted*	*Total*
<50	2,615	163	2,778
	(58%)	*(13%)*	*(48%)*
50-249	1,548	523	2,071
	(34%)	*(43%)*	*(36%)*
250+	368	543	911
	(8%)	*(44%)*	*(16%)*
Total	4,531	1,229	5,760

Source: Author's estimates of Invest NI and DETI data

6.17 Methodology

The methodology for estimating the effect of financial assistance payments on productivity growth reflects the fundamental problem in dealing with measuring the effects of programmes or treatments, in that the counterfactual outcome for individual firms had they not received the treatment, is unobservable. The same problem arose when estimating the effect of exporting on productivity growth, and also when measuring the impact of R&D intensity on innovation behaviour. There are a number of techniques available, which can be used to detect the true effect of a programme/treatment on an outcome variable when the treated users differ (in other ways than treatment) from the non-users; Bartik (2002) suggests five methods:

1. Statistically controlling for observed variables that affect the economic outcome and might be correlated with treatment, by including these observed variables in the estimation equation that is used to predict the outcome variable. A problem with this approach is that it cannot correct for biases that might be caused by unobserved variables that are correlated with both economic outcomes and treatment. It is also assumed that the functional form by which the observed variables affect economic outcomes is known.
2. Using difference-in-differences estimation (DID). Under this approach the difference before and after the treatment, of the differences between users and non-users, is compared. The limitation of this approach is that there may be many other variables, observed and unobserved, that also affect economic outcomes and are correlated with the treatment.
3. Matching treated users with non-users that are similar in observed characteristics. This can be done with propensity score matching, where the

propensity score is an estimated probability given observed variables, that a given entity will be treated.

4. Explicitly modelling selection into the treatment and how it is correlated with unobserved variables affecting economic outcomes. This requires three equations: one equation explaining economic outcomes for treated users; a second explaining economic outcomes for non-users and a third explaining whether a given entity is treated. The estimation of the third equation allows a selection bias correction term to be added to each of the first two equations, which in theory corrects for the bias cause by unobserved variables that affect economic outcomes and are correlated with treatment. This approach assumes that the variables and functional form that should enter all three equations are adequately specified. It also assumes a particular statistical distribution for the error terms of all three equations.
5. Using an instrumental variable that predicts treatment and is uncorrelated with unobservable variables that affect economic outcomes. The effects on economic outcomes of the instrument-induced shifts in treatment show the true effects because the shifts are uncorrelated with unobservable variables predicting economic outcomes. The problem with this technique is finding such instruments – they must do a good job of explaining treatment but have zero correlation with unobservable variables affecting economic outcomes. It is difficult however to test assumptions about the correlation of a proposed instrument with unobservable variables.

The main techniques which have thus far been used in this type of analysis include Heckman selection type models (Gabe and Kraybill, 2002); instrumental variables (Gual and Jodar-Rosell., 2006; Criscuolo et al., 2012); propensity score matching (Moffat, 2013) and difference-in-differences (Bronzini and de Blasio, 2006). Indeed, a combination of the approaches, such as matching combined with difference-in difference has also been used (Girma et al., 2003; Pellegrini & Centra, 2006; Ankarhem et al., 2010; Bernini and Pellegrini, 2011). The validity of the various different approaches to test the above hypothesis is discussed below, along with the subsequent methods selected. It is proposed to undertake at least two approaches to model the relationship in order to sensitivity test the results.

6.17.1 Difference-in-Difference (DID) Approach

The DID approach works by estimating a difference over time (before-after treatment) and a difference across subjects (between beneficiaries and non-beneficiaries) and produces an estimate of the impact of the treatment. Simply measuring the difference in outcomes between beneficiaries and non-beneficiaries after the intervention has taken place may leave it open to selection bias, in that the beneficiaries may have been better performing to begin with. However by incorporating data on the outcome variable for beneficiaries and non-beneficiaries observed before the intervention takes place the pre-intervention difference in outcomes can be subtracted from the post-intervention difference to eliminate selection bias related to time-invariant individual characteristics.

The DID estimator thus works on the principle that if what differentiates beneficiaries and non-beneficiaries is fixed in time, subtracting the pre-intervention differences eliminates selection bias and produces a plausible estimate of the impact of the intervention. Whilst this appears a reasonable solution to the problem of estimation of the counterfactual, the method is not without its drawbacks. Users of this method tend to use several years of serially-correlated data but neglect the resulting inconsistency of standard errors (Bertrand et al., 2004). This method can also yield a biased estimator if the treatment and control groups do not share the same trend in the outcome variable. The method further relies on the assumption that the treatment is truly random, and rules out general equilibrium effects i.e. that the treatment does not affect the control group. The latter is particularly difficult to assess as firms within the control group may well indirectly benefit if they are part of the supply-chain of the assisted firms.

The purpose of the estimation here is to identify the effects of SFA payments on the performance measure labour productivity growth. In order to undertake this using the DID model the change in labour productivity for assisted firms would be estimated across two periods (pre- and post-assistance) and compared to the change in the same periods for the non-assisted. The resulting DID estimator would provide an unbiased estimate of the effect of the assistance if, without the assistance, the average change in labour productivity would have been the same for the assisted and non-assisted. Obviously the key element of DID estimation is this latter assumption, known as the 'parallel trend' i.e. that the counterfactual trend is the same for treated and non-treated units. This, along with other elements suggest that

DID estimation may be limited in terms of its usage here. A pre-condition of the validity of the DID assumption is that the programme is not implemented based on the pre-existing differences in outcomes and therefore it is only appropriate to use when the interventions are as good as random; conditional on time and group fixed effects (Bertrandet al., 2004). This method therefore would not be suitable to use here as Invest NI provides assistance to firms on the basis of them meeting certain criteria, which include, amongst others, targets for future growth and pre-existing performance measures. In addition, unlike programmes that have a specific start and end point, SFA assistance can be given repeatedly or as a one off payment. It is therefore difficult to construct a pre- and post-assistance period that is consistent for all firms and that contains a large enough sample. As a result of these issues the DID method is not suitable for use here.

6.17.2 Propensity Score Matching

Propensity Score Matching provides an alternative option to deal with the selection issue; it employs a predicted probability of group membership, for example treatment versus control group, based on observed predictors usually obtained from logistic regression, to create a counterfactual group. The method has been discussed in the section on exporting and productivity growth and has been successfully employed in the learning-by-exporting analysis. The technique involves strict criteria for successful matching outcomes, namely that variables used for treatment and control groups have substantial overlap; that matching is conducted on variables that are precisely measured and stable (to avoid extreme baseline scores that will regress toward the mean) and that a composite variable that minimizes group differences across many scores is used. Of course, the technique also has its drawbacks in that large samples are required; the group overlap must be substantial and that hidden bias may remain because matching only controls for observed variables (to the extent that they are perfectly measured) (Shadish, Cook, & Campbell, 2002). The technique appears valid for use here, conditional on the ability to balance the selected covariates, in that the sample is large enough to draw a control group; post-estimation testing for hidden bias can also be undertaken using Rosenbaum bounds[59] to rule out the effect being caused by unobserved confounders.

[59] Refer to Chapter 6.4.4 for details.

6.17.3 Instrumental Variable Approach

To be able to make a valid causal claim about a relationship, the explanatory variable needs to be truly exogenous. However many evaluation type studies are faced with problems of endogeneity such as omitted variable bias; measurement error and simultaneity or reverse causality; the latter of which reflects the notion that two or more variables are jointly determined in the model. The latter is a particular problem in analysis such as this whereby firms with higher productivity growth may be more likely to receive SFA assistance (in a scenario where they are typically pro-active and self-select into receipt of assistance) and likewise SFA assisted firms may have higher productivity growth.

In order to eradicate this problem the instrumental variables approach can be used however the model needs to be properly identified; this means that an instrument is needed for each regressor that is contemporaneously correlated with the error. The instrument itself must be contemporaneously uncorrelated with the error but must be highly correlated with the regressor for which it is serving as an instrument. The reasoning is as follows, the basic relationship is given as:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i \tag{6.28}$$

However x_i may be endogenous, thus we cannot trust the estimate of β_1. We can instead derive an instrumental variable estimate of β_1 as:

$$\beta_1^{IV} = \frac{Cov(y,z)}{Cov(x,z)} = \frac{Cov(\beta_0 + \beta_1 x + \varepsilon, z)}{Cov(x,z)} = \frac{Cov(x,z)\beta_1 + Cov(\varepsilon, z)}{Cov(x,z)} \tag{6.29}$$

If we are correct regarding the instrument z then $Cov(e,z) = 0$ and therefore:

$$\beta_1^{IV} = \frac{Cov(x,z)\beta_1 + Cov(\varepsilon, z)}{Cov(x,z)} = \frac{Cov(x,z)\beta_1}{Cov(x,z)} = \beta \tag{6.30}$$

The instrumental variable estimator is thus an unbiased estimator of β_1.

In this instance SFA assistance is likely to be endogenous in the productivity growth equation. An instrument would thus need to be found which would be highly correlated with receipt of assistance but which would be uncorrelated with productivity growth. Economic theory should guide the selection of the instrument however in this type of evaluation work instrumental variables are typically not readily available due to data limitations and the fact that traditional variables incorporated in the model such as size, age and sector can directly impact the likelihood of receiving assistance as well as impacting on the continuous growth or performance variable.

Given this, an attempt will be made to undertake instrumental variable modelling, conditional on being correctly identified. Any instruments will be tested using the ivreg2 (with endog) command in Stata (Baum et al., 2010); this performs a two-stage regression, and tests for under-, over- and weak identification of the instrumented variables, and also tests whether the instrumented variable is endogenous.

The test for under-identification using the ivreg2 command uses the Anderson (1951) canonical correlation Lagrange multiplier (LM) statistic. It tests whether the excluded instruments are correlated with the endogenous regressors. Under the null hypothesis that the equation is under-identified, the matrix of reduced form coefficients on the L1 excluded instruments has rank=K1-1 where K1=number of endogenous regressors. Under the null, the statistic is distributed as chi-squared with degrees of freedom= (L1-K1+1). A rejection of the null indicates that the matrix is full column rank, i.e., the model is identified (Baum et al., 2007).

The test for over-identification is the Sargan-Hansen test; the joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared in the number of (L-K) over-identifying restrictions. A rejection casts doubt on the validity of the instruments (Baum et al., 2007).

The test for weak identification is an F-test of the Cragg-Donald Wald statistic, (N-L)/L1*CDEV, where L is the number of instruments; L1 is the number of excluded instruments and CDEV is the Cragg-Donald Wald statistic. Weak identification occurs when the instrument(s) are only weakly correlated with the endogenous regressor for which they are acting as an instrument, in such cases estimators can perform poorly. Stock and Yogo (2005) have compiled critical values for the Cragg-Donald F statistic for several different estimators, several different definitions of "perform poorly" (based on bias and test size), and a range of configurations (up to 100 excluded instruments and up to 2 or 3 endogenous regressors, depending on the estimator) (Stock and Yogo, 2002, 2005).

Given the potential for the instrumental variables approach to be incorrectly identified, and/or a lack of suitable instruments to be available, alternative approaches are also adopted, namely the Treatment model approach and the Propensity Score matching approach, following Guo and Fraser (2010) who suggest:

> *"..although the IV approach sounds attractive, it is often confounded by a fundamental problem: in practice, it is difficult to find an instrument that is both highly correlated with the treatment condition and independent of the error term of the outcome regression. On balance, we recommend that whenever users find a problem for which the IV approach appears appealing, they can use the Heckit treatment effect model (Guo and Fraser, 2010, pg. 101).*

6.17.4 Treatment and Selection Models

Treatment and selection models, although different, are both used in a similar way to counteract the effects of selection, or omitted variable bias in this type of analysis. Selection is known to occur in a wide range of applications in econometrics (Puhani, 2000), and was originally devised for the estimation of wage equations in which there are non-random components and/or incomplete information. The problem was identified by Heckman (1979) who argued that in estimating an earnings model one has the problem that information on working hours and wages is only available for individuals who have chosen to work (i.e. for those for whom their wage exceeds the reservation wage), which causes the sample to be non-random, drawn from a subpopulation of a wider population. The problem then arises in that the results of any earnings model will not equate to the population, as it will not contain any information on the wages and hours of those non-working individuals, had they chosen to work. Thus the problem, as Heckman portrayed it, was one of missing observations deriving from the *self-selecting* choices made by economic agents. Kennedy (2003) further elaborates, stating that there are two basic categories of selection mechanisms, one in which a selection mechanism determines which observations enter the sample and the other in which, although all observations are in the sample, a selection mechanism determines how an observation is categorised within that sample. He states that for each of these categories selection can occur because of decisions taken by the researcher in gathering the data, because of administration procedures or because of decisions taken by the individual (Heckman's self-selection).

Heckman proposed a practical solution for such situations, which treats the selection problem as an omitted variable problem. He developed a two stage model, known as the two-step or limited information maximum likelihood method (LIML); the regression equation considering mechanisms determining the outcome variable and the selection equation considering a portion of the sample whose outcome is observed and mechanisms determining the selection process (Heckman, 1978, 1979). The model is based around the following equations:

$$y_1^* i = x'_{1i}\beta_1 + u_{1i} \qquad (6.31)$$

$$y_2^* i = x'_{2i}\beta_2 + u_{2i} \qquad (6.32)$$

$$\begin{aligned} y_{1i} &= y_{1i}^* \quad if\ y_{2i}^* > 0 \\ y_{1i} &= 0 \quad\ \ if\ y_{2i}^* \leq 0 \end{aligned} \qquad (6.33)$$

Equation 6.31 represents Heckman's wage equation, with 6.32 representing a probit-type equation that describes an individual's propensity to work i.e. earn a wage. The variables y_1^* and y_2^* are unobserved, whereas y_1 is observed. x_1 and x_2 are vectors of explanatory variables, for example wage could be a function of education, whereas the probability of working (i.e. the wage being observed) could be a function of marital status. The underlying question could relate to how an additional year of education affects wages however the problem is that wages are not observed for individuals that do not work (shown in equations 6.33). Sample selection is then a problem in this case because the error terms of the two equations are likely to be positively correlated, in that individuals with higher wages are more likely to work, suggesting that the sample of observed individuals does not represent the underlying population. The Heckman approach to dealing with the problem is to estimate likelihood by way of a two-step method. For the subsample with a positive y_1^* the conditional expectation of y_1^* is given by:

$$E(y_{1i}^* | x_{1i}, y_{2i}^* > 0) = x'_{1i}\beta_1 + E(u_{1i} | u_{2i} > -x'_{2\,i}\beta_2) \qquad (6.34)$$

It is commonly assumed that u_1 and u_2 have a bivariate normal distribution, therefore given this, the conditional expectation of the error term is:

$$E(u_{1i} \mid u_{2i} > -x'_{2\,i}\beta_2) = \frac{\sigma_{12}}{\sigma_2} \frac{\phi(-(x'_{2i}\beta_2 / \sigma_2))}{1 - \Phi(-(x'_{2i}\beta_2 / \sigma_2))} \qquad (6.35)$$

where $\phi(.)$ and $\Phi(.)$ denote the density and cumulative density functions of the standard normal distribution respectively. The conditional expectation of y_1^* can therefore be rewritten as:

$$E(y_{1\,i}^* \mid x'_{1i}, y_{2i}^* > 0) = x_{1i}\beta_1 + \frac{\sigma_{12}}{\sigma_2} \frac{\phi(-(x'_{2i}\beta_2 / \sigma_2))}{1 - \Phi(-(x'_{2i}\beta_2 / \sigma_2))} \qquad (6.36)$$

Heckman’s two-step proposal is to estimate the Inverse Mills Ratio (IMR):

$$\lambda(x'_{2i}\beta_2 / \sigma_2) = \frac{\phi(-(x'_{2i}\beta_2 / \sigma_2))}{1 - \Phi(-(x'_{2i}\beta_2 / \sigma_2))} \qquad (6.37)$$

by way of a probit model and then estimate equation 6.34 in the second step:

$$y_{1i} = x'_{1i}\beta_1 + \frac{\sigma_{12}}{\sigma_2} \lambda(x'_{2i}\beta \hat{/} \sigma_2) + \varepsilon_1 \qquad (6.38)$$

Hence, Heckman characterised the sample selection problem as a special case of the omitted variable problem with λ being the omitted variable if OLS were used on the subsample for which $y_1^* > 0$.

A key aspect of the model is that because the IMR is a nonlinear function of the variables included in the first-stage probit model, call these Z, then the second-stage equation is identified, because of this nonlinearity, even if Z=X. However, it has been noted that it is highly questionable as to whether this assumption should be used as the sole source of identification[60]. Indeed Smith (2003) suggests that practical experience with the classical selection bias estimator as well as several Monte Carlo studies suggests that it performs very poorly when Z=X , with the estimates typically exhibiting marked instability. Thus, it is recommended to include a variable in Z that is not also included in X, as this makes the source of identification clear.

The selection model, as proposed by Heckman, can thus be used here for the financial assistance – productivity growth relationship whereby the problem is similar to the wage equation in that the value of assistance cannot be observed for those firms that were not SFA-assisted. In this case the selection equation predicts the propensity to be SFA-assisted while the regression equation predicts the effect of the actual grant payment on productivity growth.

The treatment model is somewhat different from the selection model in that a dummy variable indicating the treatment condition is directly entered into the regression equation and thus the outcome variable of the regression equation is observed for both the treated and untreated, in this case the SFA-assisted and the non-assisted. The treatment model is expressed by the following two equations:

The regression equation:

$$y_i = x_i\beta + w_i\delta + \varepsilon_i \qquad (6.39)$$

The selection equation:

$$w_i^* = z_i\gamma + u_i \qquad (6.40)$$

$$\text{where } w_i = 1 \text{ if } w_i^* > 0, \text{ and } w_i = 0 \text{ otherwise}$$

$$\text{Prob}(w_i = 1|z_i) = \Phi(z,\gamma)$$

and

$$\text{Prob}(w_i = 0|z_i) = 1 - \Phi(z,\gamma)$$

where ε_j and u_j are bivariate normal with mean zero and covariance matrix $\begin{bmatrix} \sigma_\varepsilon & \rho \\ \rho & 1 \end{bmatrix}$

Given sample selection, and that w is an endogenous dummy variable, the

[60] http://www.stata.com/support/faqs/statistics/endogeneity-versus-sample-selection-bias/

evaluation task is to use the observed variables to estimate the regression coefficients β while controlling for selection bias induced by the non-ignorable treatment assignment (Guo and Fraser, 2010). The treatment effect is estimated in a two-step procedure similar to that described for the sample selection model and can be used here to test for the impact of the dummy endogenous variable, receipt of SFA grant assistance, on productivity growth.

6.18 Model Specification

The general model for estimating productivity growth is given as:

$$\begin{aligned}\Delta \ln Y_i = \beta_0 + \beta_1 \mathrm{SFAassist}_{it} + \beta_2 \mathrm{ltotalemp}_{it} + \beta_3 \mathrm{totalempsq}_{it} + \\ \beta_4 \mathrm{lempcostsperemp}_{it} + \beta_5 \mathrm{labprod}_{it} + \beta_6 \exp\mathrm{ortint}_{it-1} + \\ \beta_7 \mathrm{rdint}_{it-2} + \beta_8 Z_{it} + \varepsilon_i\end{aligned} \quad (6.41)$$

Where $\Delta \ln Y_{it}$ represents the productivity growth rate between t and t+1; and separately t and t+3. The two different time periods used to account for the immediate impact on productivity growth and separately, the 3 year period to reflect medium term impacts.

The **SFAassist** variable takes two different forms depending on the model; it is used in log form in the selection model to test for the impact of the financial assistance variable, and is used in dummy form in the treatment, instrumental variables and propensity score matching models to test for the impact of being assisted. The central hypothesis is that assistance has a positive impact on productivity growth and thus we would anticipate a positive coefficient from both the dummy and continuous variables.

The firm size variable, **ltotalemp**, is recorded in log form and is included to control for size effects in the productivity equation. It is assumed that smaller firms will have higher productivity growth rates as they will include new firms who typically utilise more modern techniques, as per the creative destruction theory. For this reason the anticipated sign on the size variable is negative. The square of size is also included to take account of the quadratic relationship.

The log of employment costs per employee, **lempcostsperemp**, is included to act as a proxy for the wages and hence the value of the product or service offered by the firm. Employment costs are likely to be higher where the skill levels of the workforce are higher, suggesting a higher value added good or service. In this case we may expect those at the higher end of the value chain to have higher productivity growth, and thus anticipate a positive coefficient.

The existing labour productivity levels in the firm are controlled for in the model with the **labprod** variable. The anticipated sign could be either positive or negative; those with lower productivity levels may have the need to catch up with competitors and hence have faster growth, alternatively those with higher productivity levels may be more efficient and more pro-active in terms of seeking better ways to work.

The export intensity variable, **exportint**, is included to take account of the degree of foreign trade. It is expected that those selling a higher proportion of sales into export markets are faced with greater competition and also can reap the benefits of knowledge spillovers in markets where competitors are more technologically advanced (the learning-by-exporting hypothesis). In this case we would expect a positive coefficient on the export intensity variable.

As discussed in the section on innovation, there was only one observation available for innovation activity (2002-04); as a result it was not possible to include it within the estimation here due to the reduction in observations that would have occurred. Instead R&D intensity, **rdint**, is used as a proxy for innovative behaviour, and although it is acknowledged that R&D is an input into the innovation process rather than an output, the previous statistically significant finding that a higher R&D intensity was associated with a greater propensity to undertake process innovation, suggests that its use can be justified. Given the potential endogeneity between R&D and exporting, the R&D intensity variable is included with two lags, and the exporting intensity variable with one lag.

A vector of time and sectoral dummies are also included in the model; the latter used to control for differences in the expected productivity growth of the various sectors.

6.19 Results

An attempt was made to run an instrumental variables model to test whether SFA-assisted firms had higher productivity growth than non-assisted firms. As the grant assistance variable was likely to be endogenous the model had to incorporate suitable instruments which would impact on the likelihood of receiving assistance but have no impact on productivity growth. Given the limited variables within the dataset there were few obvious contenders. As a test, a variable relating to the value of stocks was used to instrument grant assistance. This was selected to account for the fact that assistance, particularly in the form of loans, is more likely to be given to firms with adequate tangible assets; these assets in themselves not necessarily a pre-requisite to higher productivity growth.

The identification tests in the lower half of Table 6.27 below suggest, as suspected, that this was in fact a poor instrument. The three year model is neither under- nor over- identified, as seen by a failure to reject the respective null hypotheses of valid instruments. However, the endogeneity test indicates that the variable 'SFA assisted' is still endogenous, as seen by the failure to reject the null hypothesis that the specified endogenous regressor can actually be treated as exogenous. In addition, the test for weak identification indicates that the instrument used is weak, as seen by the failure of the low Cragg-Donald statistic to exceed the Stock-Yogo critical value. Such weak identification means that the excluded instruments are only weakly correlated with the endogenous regressor and as such the asymptotic identification status of the equation is called into question, which can mean that the resulting model is a poor estimator. According to Baum (2009), in the worst case, the bias of the IV estimator under weak identification is the same as that of OLS.

The one year model suffers from the same problems; given the endogeneity and weak instrument problem, and the resulting strong potential for bias the results of the IV model cannot used to produce evidence of a causal relationship. As a result they are not treated as valid models with which to test the financial assistance – productivity growth relationship[61].

[61] Lagged values of the excluded instrument were also tested to try and improve the identification of the model however none produced a satisfactory result.

Table 6.27: Instrumental Variables Model for Productivity Growth 2000-08

	Productivity Growth 1 year	*Productivity Growth 3 year*
SFA Assist	0.226	-0.883
	(1.790)	-1.256
Size	-0.0516	-0.042
	(0.150)	-0.074
Size Squared	1.99e-08	0.000
	(1.24e-08)	0.000
Employment Costs	-0.128**	0.000
	(0.0603)	-0.053
Labour Productivity	0.941***	1.084***
	(0.0260)	-0.030
Export Intensity (t-1)	-0.0292	
	(0.0433)	
R&D Intensity (t-2)	0.00335	
	(0.0176)	-0.111
Export Intensity (t)		-0.126
		-0.009
R&D Intensity (t-1)		-0.019
Year	Yes	Yes
Sector	Yes	Yes
Observations	3,402	2,396
R Squared	0.616	0.517
F Statistic	165.34***	99.32***
Excluded instruments: lstock		
Under-identification test		
Anderson canon. Corr. LM statistic	0.743	1.915
Chi-sq(3) P-value	0.863	0.590
Over-identification test		
Sargan statistic	0.00	0.000
Chi-sq(2) P-value	-	-
Weak-identification test		
Cragg-Donald Wald F statistic	0.245	0.630
Stock-Yogo critical value, 5%	13.91	13.91
Endogeneity test		
Test statistic	0.016	0.695
Chi-sq(1) P-value	0.901	0.405

Note that sector dummies are included in the model; they are not displayed for space reasons.
Model estimated using xtivreg (in Stata)
Standard errors reported in parentheses
*** p<0.01, ** p<0.05, * p<0.10

6.19.1 Treatment and Selection Models

As suggested by Guo and Fraser (2010) treatment models were run as alternatives to the IV regression; as before two sets of models were included to estimate the immediate and medium term impacts, the first modelling the annual change in labour productivity (after receipt of last payment); the second modelling the change in labour productivity over a three year growth period. The treatment model is a two stage model with the first stage probit run on the determinants of receiving an SFA payment. The second stage takes this payment dummy and includes it as one of the explanatory variables in the productivity growth model. The nature of this model means that the outcomes for both those who did and did not receive assistance can be observed.

A second set of models, two-step Heckman Selection models, were then used with the same dependent variables. The selection model is somewhat similar to the treatment model however in this model only the outcomes for those who received assistance are observed. This model thus allows the actual payment variable, as opposed to the dummy, to be used as one of the explanatory variables. When used in log form the payment variable can thus provide an estimate of the elasticity of productivity growth with respect to grant assistance received, which forms part of the key hypothesis being tested.

The results for the one and three year treatment models are given in Table 6.28; the highly significant Wald Chi-squared tests indicate that both models have a good fit, and indeed both models produce almost similar results in terms of the size, sign and significance of all the coefficients. Examining the first stage probit results for the one year model (Model 1) shows that larger firms, exporters; and those with a higher value of stock all have a higher probability of being grant assisted, all of which confirm the *a priori* expectations that assistance is targeted towards larger, more resourceful and external-oriented firms. Interestingly, those with lower turnover were found to be more likely to be grant assisted; this finding goes against prior expectations, particularly given that a specific turnover threshold is one of the current criteria for receipt of assistance. Re-examining the descriptive statistics from Table 6.24 indicates that the mean turnover for both sets of firms is relatively high (£42m for assisted and £14m for non-assisted) implying that both sets of firms are on average larger than the wider population, and hence the lower turnover result actually refers to the lower end of a relatively high turnover range.

The key result in the model is that of the second stage, predicting productivity growth; whereby the grant assisted variable was found to be insignificant, suggesting that grant assisted firms do not have higher productivity growth than non-assisted firms over a one year growth period. Lambda is also insignificant in the model suggesting that running an OLS to test for the effect would not have produced biased results. The results are consistent with earlier studies on RSA (Harris and Robinson, 2004, 2005; Crisculolo et al., 2012) and SFA (Hart et al., 2007), in which no productivity impacts were found, even though, in these other studies, the effects were modelled over longer time frames.

In terms of the other impacts, size was negative and significant in the model, which was similar to previous findings for NI firms regarding the effects of size on employment growth and turnover growth (McGuinness and Hart, 2004). Those with lower employment costs were found to have higher productivity growth which diverged from prior expectations. The finding could suggest that those with lower employment costs are involved in the production of lower value-added products for which the production process is easier to streamline and make more efficient. If this is the case productivity growth for such firms would be likely to increase at a faster rate, plateauing at the point at which production was at its most efficient given existing resources.

The variable capturing the labour productivity level was significant and positive suggesting, as expected, that those with higher productivity levels had higher growth; this was anticipated as being due to such firms being pro-active regarding their productivity improvements, although it contrasted with results for Spain as reported in Duch et al. (2009). Importantly there was found to be no effect from either the export intensity or R&D intensity variables; the former is consistent with previous findings whereby there was no evidence of a relationship from starting to export on productivity growth. The latter finding is also consistent with the results from the previous product innovation equations, whereby a higher R&D intensity was not found to have any bearing on product innovation and this in turn had no impact on productivity growth.

The results of the second model predicting productivity growth over a three year period (Model 2) suggests the same story. For the first stage probit the only change in the results was that employment costs were now also positive and significant (previously they were insignificant) suggesting that assistance was more likely to be paid to those firms who pay higher wages, and are further up the value chain (proxied by higher employment costs). This appears to be intuitively valid, as more technologically advanced firms may be more likely to seek out public funding opportunities due to the uncertainty and risks associated with their activities which would limit the available funds accessible from risk-averse private credit agencies.

The second stage of the model, predicting productivity growth, again found neither the lambda term nor the assistance dummy to be significant, suggesting no significant difference in the productivity growth, over a three year period, between those who did and did not receive assistance. Other significant variables in this model included size and employment costs, both of which again were negative. The results imply that after controlling for the fact that larger firms and those with higher employment costs were more likely to be assisted, smaller firms had higher productivity growth, as did those with lower employment costs. In addition to the arguments already made regarding those with lower employment costs, the results also suggest that it may be easier to increase productivity growth if starting from a smaller scale, with smaller firms who are perhaps producing a limited number of products or services able to more easily focus on cost-reducing processes than larger firms who may be involved in multiple activities.

Regarding the sectoral variables of interest, firms in the textiles sector were found to have higher productivity growth than those in Other Services (the base case). During the period in question the number of textiles firms in NI had been reducing due to cheaper worldwide competition; as a result the remaining firms targeted more niche markets or retained higher value added activities (Intertrade Ireland, 2005, pg. 6), which it appears, led to faster productivity growth. Wholesale and retail also had a positive and significant effect on growth whilst other manufacturing n.e.c had a negative impact, both of which are consistent with the economic climate of the early to mid-2000s.

Table 6.28: Treatment models for Productivity Growth 2000-2008

	Model 1		***Model 2***	
	Prod Growth 1 year	**SFA Assisted**	**Prod Growth 3 year**	**SFA Assisted**
SFA Assist	0.037		0.117	
	(-0.086)		(-0.113)	
Size	-0.0324***	0.811***	-0.0596***	0.942***
	(-0.012)	(-0.066)	(-0.015)	(-0.087)
Size Squared	0.000		0.000	
	(0.000)		(0.000)	
Employment Costs	-0.276***	0.120	-0.183***	0.345***
	(-0.023)	(-0.085)	(-0.030)	(-0.125)
Labour Productivity	0.466***		0.557***	
	(-0.016)		(-0.020)	
Export Intensity (t-1)	0.007			
	(-0.028)			
R&D Intensity (t-2)	0.008			
	(-0.015)			
Export Intensity (t)			-0.058	
			(-0.039)	
R&D Intensity (t-1)			0.009	
			(-0.015)	
Exporter		0.706***		0.863***
		(-0.141)		(-0.210)
Turnover		-0.323***		-0.409***
		(-0.063)		(-0.080)
Value of Stock		0.192***		0.180***
		(-0.033)		(-0.041)
Lambda	-0.007		-0.036	
	(-0.049)		(-0.064)	
Year	Yes		Yes	
Sector	Yes		Yes	
Constant	-0.712***		-1.215***	
	(-0.066)		(-0.080)	
Observations	3,706		2,647	
Wald Chi Sq	2743.77***		1923.77***	

Note: that sector dummies are included in the model; they are not displayed for space reasons.
Model estimated using treatreg (in Stata)
Standard errors reported in parentheses
*** p<0.01, ** p<0.05, * p<0.10

The results from the selection models are shown in Table 6.29; again there appears to be no effect from SFA assistance, suggesting the amount of the assistance paid out has no impact on the productivity growth of firms. The main difference between these and the treatment models is that the lambda term is significant and negative indicating that the error terms in the selection (probit) and main equations are negatively correlated. Selection bias is thus an issue, with unobserved factors that make receipt of assistance more likely, inclined to be associated with lower productivity growth; when this is controlled for assistance has no impact on productivity growth.

Interestingly, the R&D intensity and export intensity variables are significant in the model; R&D intensity with one lag is positively associated with productivity growth for SFA assisted firms, whilst export intensity has a negative impact. The negative relationship for the latter is consistent with the idea that firms starting to export, with a low intensity, may be exposed to more rapid learning, resulting in a relatively quick improvement in capacity-use (Damijan and Kostevc, 2006); more experienced exporters who may already have experienced this may find that their subsequent productivity growth increases more incrementally. The fact that both R&D intensity and export intensity are significant in the three year model rather than the annual growth model suggests that the effects arise only after a certain period of time has elapsed, which is important from a policy perspective where the timeliness of impacts is often an issue.

Table 6.29: Selection Models for Productivity Growth 2000-2008

	Model 1		***Model 2***	
	Prod Growth 1 year	**SFA Assisted**	**Prod Growth 3 year**	**SFA Assisted**
SFA Payment	0.000		0.003	
	(-0.017)		(-0.026)	
Size	-0.117*	0.764***	-0.224**	0.789***
	(-0.068)	(-0.061)	(-0.096)	(-0.075)
Size Squared	0.000		0.000	
	(0.000)		(0.000)	
Employment Costs	-0.699***	0.104	-0.272	0.697***
	(-0.089)	(-0.0800	(-0.170)	(-0.103)
Labour Productivity	0.666***		0.662***	
	(-0.045)		(-0.070)	
Export Intensity (t-1)	0.031			
	(-0.069)			
R&D Intensity (t-2)	0.045			
	(-0.061)			
Export Intensity (t)			-0.217*	
			(-0.113)	
R&D Intensity (t-1)			0.569**	
			(-0.222)	
Exporter		0.752***		0.881***
		(-0.137)		(-0.193)
Turnover		-0.272***		-0.336***
		(-0.057)		(-0.070)
Value of Stock		0.165***		0.169***
		(-0.030)		(-0.037)
Lambda	-0.223*		-0.453**	
	-0.133		(-0.194)	
Year	Yes		Yes	
Sector	Yes		Yes	
Constant	0.651		0.338	
	(-0.536)		(-1.001)	
Observations	4,440		4,263	
Wald Chi Sq	581.02***		269.41	

Note: that sector dummies are included in the model; they are not displayed for space reasons.
Model estimated using Heckman (in Stata)
Standard errors reported in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Both the treatment and selection models failed to find a productivity impact from either the incidence of receiving grant assistance or the amount received. The result is consistent with previous findings on the same type of assistance; however the lack of impact over the one year period is at odds with those reported by McGuinness and Hart (2004) who found immediate one year impacts from certain types of assistance on productivity growth, albeit using a different dataset covering small firms only. In order to test the robustness of the results a further methodological approach was used.

6.19.2 Propensity Score Matching

Given the inefficiency of the instrumental variables approach and the lack of any positive causal findings from the treatment and selection models, a third method to test for the impact of grant assistance on productivity growth was run to act as a sensitivity test. Propensity score matching was performed as the alternative method due to the limitations in the ability to perform difference-in-differences, as described in the introductory paragraphs of the methodology.

Propensity score matching was performed using productivity growth as the dependent variable for the one and three year models, as before. Given that the variables selected as explanatory variables must be balanced in order to produce reliable effect estimates trial and error attempts using a combination of variables was undertaken and the resulting selected variables, as shown in Table 6.30, chosen as the covariates to compute the propensity score. They were estimated using one time lag to help to deal with the potential endogeneity between the variables and the likelihood of receiving assistance.

Table 6.30 displays the differences in the explanatory variables across the two groups of firms both before and after matching for the one year growth model[62]. For most of the chosen covariates the t-test results after matching show no significant differences, whilst the percentage bias is also below 5 per cent indicating that they are well balanced. However in the nearest-neighbour with replacement model; the kernel matching and the caliper matching models the exporter variable breaks both these conditions, whilst the employment costs variable is just over the 5 per cent bias level in two of the models. To test if these impact on the overall standardised bias of the models, the mean percentage bias is estimated (Table 6.31); the results show that all four methods have a mean bias of 4 per cent or less, giving confidence that the matching techniques are based on similar firms. This implies that any impact on productivity growth, arising from these matching techniques, is not due to any

[62] The comparator table for the three year model is shown in Appendix One Table A1.13.

observed differences between the two groups of firms and thus truly reflects the impact of the assistance[63].

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[63] The results for the three year model shown in Appendix One Table A1.14 are also consistent

Table 6.30: Pre and Post-matching differences for Assisted and Non-Assisted Firms

		N-N with replacement				N-N without Replacement				Kernel				Caliper			
Variable	**Sample**	**Treat**	**Control**	**t-test**	**% bias**	**Treat**	**Control**	**t-test**	**% bias**	**Treat**	**Control**	**t-test**	**% bias**	**Treat**	**Control**	**t-test**	**% bias**
Size (t-1)	Unmatched	5.2	3.8	27.3***	107.4	5.2	3.8	27.3***	107.4	5.2	3.8	27.3***	107.4	5.2	3.8	27.3***	107.4
	Matched	5.3	5.3	0.2	0.8	5.3	5.2	1.2	5.8	5.3	5.3	0.5	2.3	5.3	5.3	0.2	0.8
Turnover (t-1)	Unmatched	9.4	7.9	22.7***	89.2	9.4	7.9	22.7***	89.2	9.4	7.9	22.7***	89.2	9.4	7.9	22.7***	89.2
	Matched	9.6	9.5	0.5	2.7	9.6	9.5	0.7	3.3	9.6	9.5	0.7	3.8	9.6	9.5	0.5	2.7
Value of Stock (t-1)	Unmatched	7.2	5.6	20.3***	91.1	7.2	5.6	20.3***	91.1	7.2	5.6	20.3***	91.1	7.2	5.6	20.3***	91.1
	Matched	7.4	7.4	-0.3	-1.2	7.4	7.4	0.3	1.4	7.4	7.4	0.1	0.4	7.4	7.4	-0.3	-1.2
Exporter (t-1)	Unmatched	0.9	0.8	10.0***	46.4	0.9	0.8	10.0***	46.4	0.9	0.8	10.0***	46.4	0.9	0.8	10.0***	46.4
	Matched	1.0	0.9	2.2***	9.1	1.0	1.0	-0.5	-1.6	1.0	0.9	1.9	7.5	1.0	0.9	2.2	9.1
Emp Costs (t-1)	Unmatched	7.9	6.4	26.1***	103.3	7.9	6.4	26.1***	103.3	7.9	6.4	26.1***	103.3	7.9	6.4	26.1***	103.3
	Matched	8.1	8.0	0.4	1.9	8.1	8.0	1.2	5.7	8.0	8.0	1.0	5.0	8.1	8.0	0.4	1.9
Labour Prod (t-1)	Unmatched	3.2	3.1	0.6	2.2	3.2	3.1	0.6	2.2	3.2	3.1	0.6	2.2	3.2	3.1	0.6	2.2
	Matched	3.2	3.1	0.5	3.1	3.2	3.2	0.3	1.9	3.2	3.1	0.9	5.5	3.2	3.1	0.5	3.1
Sector	Unmatched	31.4	28.6	5.4***	17.2	31.4	28.6	5.4***	17.2	31.4	28.6	5.4***	17.2	31.4	28.6	5.4***	17.2
	Matched	25.3	25.0	0.41	1.4	25.3	25.5	-0.4	-1.5	25.2	25.4	-0.2	-0.7	25.3	25.0	0.4	1.4

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 6.31: Pre- and Post-matching differences in standardised bias

Matching Method	Sample	Mean Bias %	Median Bias %
N-N with replacement	Raw	65.3	89.2
	Matched	2.9	1.9
N-N without replacement	Raw	65.3	89.2
	Matched	3.0	1.9
N-N with kernel	Raw	65.3	89.2
	Matched	3.6	3.8
N-N with caliper	Raw	65.3	89.2
	Matched	2.9	1.9

The matching techniques for the one year productivity growth model indicate that there is common support for 3,213 observations; 530 treated firm observations are matched to 2,683 untreated firm observations. For the three year productivity growth model there is common support for 2,141 firms; 311 treated firm observations matched to 1,830 untreated. Table 6.32 displays the resulting ATT effects; the coefficient on the 'treated' shows the impact on the outcome for the treatment group whilst the 'control' shows the counterfactual, the impact for the matched control group; the 'difference' thus indicating the impact of the treatment on the treated. In this case the treated are those that were SFA assisted; 'control' are the non-assisted; the treatment is the SFA assistance payment dummy and the outcome is productivity growth. The null hypothesis is that there is no difference in the outcome (productivity growth) between the two groups of firms.

In each of the one year models the coefficient on 'difference' is statistically significant, and is negative, suggesting that the payment of SFA assistance has a negative impact on the one year (post payment) productivity growth of firms. The coefficient estimates range from -0.075 to -0.090 suggesting that productivity growth is between 7.5 and 9.0 per cent lower for assisted firms than non-assisted firms. The three year models show no impact on productivity growth. The fact that the one year model is negative may indicate that once in receipt of payments firms utilise the grant to either implement new practices, processes or undertake new staff, the result of which is a temporary reduction in the efficiency of production. A similar temporary 'disruption' or learning effect was also found in the previous section on innovation.

Table 6.32: The Impact of SFA Assistance on Productivity Growth

Technique	Sample	Treated	Controls	Difference	S.E.	T-stat
			Productivity Growth 1 Year			
Technique	**Sample**	**Treated**	**Controls**	**Difference**	**S.E.**	**T-stat**
N-N replace	ATT	0.023	0.102	-0.079	0.048	-1.650*
N-N without	ATT	0.023	0.114	-0.090	0.038	-2.400**
Kernel matching	ATT	0.017	0.092	-0.075	0.036	-2.09**
Caliper matching	ATT	0.023	0.102	-0.079	0.048	-1.650*
			Productivity Growth 3 Year			
Technique	**Sample**	**Treated**	**Controls**	**Difference**	**S.E.**	**T-stat**
N-N replace	ATT	0.218	0.195	0.023	0.065	0.350
N-N without	ATT	0.218	0.151	0.067	0.052	1.290
Kernel matching	ATT	0.225	0.148	0.077	0.048	1.610
Caliper matching	ATT	0.218	0.195	0.023	0.065	0.350

Model estimated using psmatch2 (in Stata)
*** p<0.01, ** p<0.05, * p<0.10

The negative finding contrasts with that of the treatment model, in which no such significant effect was found on productivity growth; however the treatment model allows for selection on unobservables, which the propensity score matching technique does not. To examine whether these unobservables influence the results, the PSM model is tested for robustness using the Rosenbaum bounds approach. This allows for an identification of the extent to which unobserved confounding variables would have to bias the results to jeopardise their robustness. At a level of Γ equal to 1 there would be no hidden bias, however as this increases, the likelihood of hidden bias affecting the robustness of the ATT also increases. The significance levels allow for a rejection or not of the hypothesis that the ATT may result completely from hidden bias at each Γ level; the higher the level of Γ without violating the robustness the less sensitive to hidden bias are the results.

Table 6.33 displays the resulting upper and lower bounds for the one year growth model. As the coefficient on the ATT was negative the lower bounds are assessed; they indicate that at a level of 1.2 the results would no longer be robust at the 5 per cent significance level, and at a Γ level of 1.4 no longer significant at the 10 per cent level. Given that these levels are relatively low the conclusion to be drawn is that the ATT results are highly sensitive to unobserved variables, as a result we cannot be confident of the negative causal result of SFA assistance on productivity growth due to other unconsidered confounding factors. The test is not performed on the three year model as no such significant impacts were detected.

Table 6.33: Rosenbaum bounds for ATT estimates (p-values)

Γ	*sig+*	*sig-*
1	0.014602	0.019485
1.1	-0.00961	0.043384
1.2	-0.03193	0.065208
1.3	-0.05263	0.085403
1.4	-0.07177	0.10396
1.5	-0.08986	0.121436
1.6	-0.10669	0.137854
1.7	-0.12278	0.153375
1.8	-0.13804	0.168022
1.9	-0.15259	0.181949
2	-0.16654	0.19545

6.20 Summary and Discussion

The aim of this element of the analysis was to estimate the relationship between public financial assistance and firm productivity growth. Grant assistance has been a feature of the NI economy for most of the post-war era and in fact the region is one of the most heavily subsidised in the UK (Harris and Trainor, 2005b). If the arguments for market failure are correct, that public assistance to industry provides finance to firms in cases where the market fails to act, so the assumption that follows is that the assistance is intended to have a visible positive impact. Empirical evidence has suggested that in fact the intended outcome is not always guaranteed, and assistance can have deadweight effects, whereby the same outcome would have occurred anyway; displacement effects, whereby the outcome is not additional but has simply displaced something else; or can have negative effects where the assistance has been wrongly targeted (Beaston and Weinstein, 1996; Lee, 1996; Bergstrom, 2000; Harris and Trainor, 2005b; Martin et al., 2011; Criscuolo et al., 2012; Koski et al., 2013). In the case of the latter this can have negative economy impacts, whereby unproductive firms are propped up and prevented from naturally exiting the market, thus reducing the reallocative distribution of less productive to more productive firms in the economy.

Previous literature on NI has found little evidence of a positive productivity impact, except in cases where the assistance is targeted (McGuinness and Hart, 2004). This has also been reported in the wider literature, where the evidence overwhelmingly suggests that government subsidies have no impact on productivity growth, except when targeted (Girma et al., 2007; Colombo et al.,2011 and Grilli and Murtinu, 2012); where it does the effects appear to be short lived (Bergstrom, 2000). The rationale for examining the subject in this context was to revisit the issue, using a range of methods to estimate the impact of public assistance to firms and making use of the actual payments variable, rather than just dummies, to quantify the size of any impact.

The estimation of such impacts is not straightforward, most notably due to the fact that the counterfactual is not observable but also due to issues with endogeneity and selection. In such cases a number of methodologies are available however their use is dependent largely on data availability and sample size. Here a few different methodologies were utilised to varying degrees of success. The instrumental variables approach was deemed unsuitable and subject to bias due to the inability to properly identify the model and correctly instrument the endogenous grant assistance variable. The propensity score matching approach was also biased by the failure to account for other confounding factors impacting on productivity growth. The difficulty in modelling the problem without bias indicates the complexity associated with the estimation, and perhaps explains the relatively limited empirical literature. The selection and treatment models appeared to be the only valid models with which to estimate the impact and both these found no effect in the short term (one or three year period) either from receipt of grant assistance or from the actual value of assistance.

The estimated results thus reject the null hypothesis that SFA assistance has a direct positive impact on the productivity growth of firms. The finding is inconsistent with theoretical justifications for government intervention and is not encouraging from a policy perspective. SFA is supposed to act as a “funder of last resorts”, implying that the firm has been unable to source the finance from the market. A necessary condition of SFA is that the project has to be scrutinised and the finance evaluated as bringing additional benefits to the firm; the lack of these benefits on productivity growth is thus worrying. It could imply that assistance is being targeted wrongly and rather than improving firm performance, the use of grants, particularly repeat grants, is having the opposite effect, with firms unwilling to or unable to stand on their own two feet. In this case the assistance may not be used efficiently, a likelihood proposed by Hoekman and Javorcik (2004), and a finding which Bergstrom (2000) reported for Sweden; resulting in the prevention of such firms from exiting the market, disrupting the natural creative destruction process. This has also been reported widely in the literature, where evidence of the support of unproductive, declining firms is widespread.

In NI there is evidence of repeat assistance[64] and a targeting of historical sectors of importance which may reflect other underlying arguments for supporting projects, such as their strategic importance. This argument can certainly be applied to the textiles sector in the past where, despite the low productivity in the sector and the declining employment, grant aid continued to be given:

> *"In designing strategic industrial policy in Northern Ireland, the clothing and textiles sector poses a major challenge. Although in continual decline, its rate of decline has undoubtedly been slowed by the use of large-scale grant aid to prop up ailing firms whose collapse would have destabilized an economy that was already under siege as a result of civil unrest" (Bradley, 2006, pg. 6).*

Certainly the fact that almost one fifth of firms in NI that had received assistance were multiple recipients (SQW, 2013) suggests a certain dependence on grant aid. This could imply that there is a huge market failure argument with regards to the sourcing of external finance within NI, however in such a case we would expect that, if the projects are viable, then returns to public assistance would be positive in the absence of other forthcoming types of external finance. It thus leads to the conclusion that firms are potentially engaging in rent-seeking behaviour with regards to applying for grant assistance that they don't actually need or submitting projects with low or zero additionality; the natural implication that the government agency is too compliant with its existing clients and not rigorous enough in its vetting for the grant funding process. Certainly when this evidence is considered along with recent previous evaluations in which 9-15 per cent of firms in receipt of SFA reported full non-additionality or deadweight (Hart et al. 2007; SQW, 2013); it does suggest a degree of unnecessary grant provision; a detail highlighted by the SQW report:

> "*The selectivity of SFA was less pronounced than it could have been, and it was not consistently, and evidentially, the 'funder of last resort'"* (SQW, 2013, pg. iii).

The fact that the rate of deadweight had increased between the two most recent evaluations also supports the assumption that the agency was becoming less adequate at assessing the degree of market failure for the project, thus in such a scenario, the lack of impact on productivity growth can be understood.

An alternative, or additional, conclusion is that, as shown above for the textiles sector, that there are specific firms and sectors in NI that are or were too strategically important to be allowed to either shrink or die. As these are likely to have been important from an

[64] In a recent evaluation of SFA it was reported that 19 per cent of firms received multiple offers of SFA assistance over the 2004-11 period (SQW, 2013, pg. 39).

employment perspective (for historic and cultural reasons) assistance to grow employment, or at least safeguard it would have taken priority over other economic outcome concerns. Given the obvious trade-off between productivity growth and employment growth, this strategy would at least partly explain the observed lack of impact of assistance on productivity growth in NI, particularly in the case here where the assistance instrument, SFA, was targeted towards both employment and productivity improvements.

6.20.1 Limitations and Recommendations

Despite the apparent lack of impact on productivity growth, and the arguments as to why this may be the case, there are several caveats which may also have an influence on the results. The main limitation is, as discussed above, that the type of assistance considered here was not directly targeted at improving productivity growth over the period in question, but was instead a flexible form of assistance which could also be utilised to target either employment or productivity growth. Without more information on the nature of each individual project and the associated aim of the grant payments, it is difficult to pinpoint which of these it was targeted towards. Such additional data may have allowed for the categorisation of grant payments into those that were aimed at increasing productivity and those that were targeted at other outcomes, as undertaken by Girma et al. (2007); Colombo et al. (2011) and Grilli and Murtinu (2012) and may have shed more light into the nature of the relationship. Without a more detailed dataset providing information on the specific purpose of the assistance it is thus difficult to reject outright that the SFA payments had no effect on productivity growth; the possibility of obtaining this information offering a potential future extension to the analysis.

A further limitation is that, as has been stated earlier, the market failure rationale for the provision of SFA assistance to improve efficiency and productive capacity was aimed at indigenous firms more so than externally-owned firms in NI. Without access to the ownership details the two types of firm could not be separated and thus again the model was run on the entire group of firms, as a whole, thus potentially clouding any specific effects on locally-owned firms. Indeed, Hart et al. (2008) were able to show that there were differing effects of RSA on the employment growth of UK-owned and MNE firms in England; thus it would be likely that a similar result would hold for NI. The ability to examine these separately may indeed have resulted in more favourable productivity impacts; the inclusion of ownership variables providing a possible future extension to the existing analysis.

7 SUMMARY AND CONCLUSION

7.1 Introduction

Motivated by the historically poor productivity performance of NI firms, the aim of this thesis was to examine productivity growth at the firm level, looking specifically at how exporting, innovation and public financial assistance impact on firm productivity growth. NI represented an interesting case study to assess these issues, as despite being one of the most heavily assisted regions of the UK since the 1960s (Roper, 1996) and the only UK region to border a euro-zone country (which itself had experienced huge economic growth in the mid to late 2000s), the region performed poorly on a number of key micro and macroeconomic variables, such as productivity, value of export goods, R&D expenditure and introduction of new products. The productivity measure in particular was a concern as it had steadfastly remained at around 80 per cent of the UK's value since the 1980s (DETI 2005a, 2007).

This poor productivity performance became a focus of economic policy in NI during the 1990s, with the policy response seeking to make firms more competitive through the promotion of exports and innovation amongst the manufacturing and tradeable service sectors (DED, 1990, 1995, 1999; DETI 2005a, 2007). Public sector assistance was reoriented from focusing solely on employment enhancing projects, to also include 'high-quality knowledge-based' projects which would promote efficiency and modernisation (Wren, 2005). A specific target of reducing NI's productivity gap with the rest of the UK by 2015 was also set out (NI Executive, 2008).

Despite a decade of such policies, the productivity position of NI in 2010 in relation to the UK was worse than it had been in 2000 (ONS, 2011), yet there was little evidence sought or brought to light to indicate why such policies had failed to improve productivity growth, indeed the majority of strategy and policy documents had little reference to any supporting theoretical or empirical evidence in support of the productivity-enhancing arguments of such strategic activities. There was also a distinct lack of post-strategy evaluation (NIEC, 1999a, 1999b; IREP, 2009); the gap in the evidence base for NI providing the opportunity for exploration here.

In an attempt then to understand the problem of the long-standing productivity gap in NI, by focusing on the drivers of productivity at the firm level, the thesis was thus designed to make several important contributions; firstly it sought to add to the empirical literature by providing new evidence for NI with regards to the productivity impacts from exporting; provide updated findings with regards to the innovation impact and offer new evidence on the productivity growth impact of the amount of public financial assistance given to firms. A second contribution was to use the results as derived from the newly linked dataset, to drive the discussion regarding productivity growth in the region, and thus aid in the development of evidence-based policy making. The linked dataset was designed as a starting point through which firm-level analysis could be undertaken, with the expectation that it could be enhanced in the future with annual updates and fleshed out with a more comprehensive set of variables in order to carry out more rigorous and robust analyses in a cost-efficient manner.

7.2 Discussion of Empirical Findings

7.2.1 Exporting and Productivity Growth

The relationship between exporting and productivity growth was the first to be examined; this presented new evidence for NI with regards to whether exporting was the cause or effect of better productivity performance. The findings initially confirmed that the likelihood of being an exporter was found to increase with firm size; with higher employee costs; and with higher labour productivity, as per the stylized facts in the wider literature (Bernard et al, 2007). R&D was also found to be positively associated with exporting but only when the heterogeneous nature of exporters was taken into account, that is, the model run on different quantiles of export intensity.

The self-selection of more productive firms into exporting was confirmed through the use of Kolmogorov-Smirnov tests; with the previous finding that size was positively related to exporting also appearing to corroborate the sunk costs argument (Melitz, 2003). However, there was no evidence to support the learning-by-exporting hypothesis. The overall conclusion to be drawn that in NI an increase in productivity happens before firms export, rather than exporting leading to any immediate productivity growth gains.

Although such findings are common across the literature (Wagner, 2007; Singh, 2010), a caveat is that limitations in the dataset used here may have contributed to these results. Developments in the wider empirical literature suggest that learning-by-exporting is most evident when the export markets can be categorised into higher and lower income economies; the learning most apparent when the export market is more developed and technologically advanced than the home market (DeLoecker, 2004). Additionally, it has been shown that prior exporting experience needs to be considered when examining the impact on productivity growth; with new entrants to exporting, continuing exporters, and exiters all likely to experience different productivity impacts (DeLoecker, 2010; Harris and Li, 2012). The dataset, as it stands, did not permit sufficient detailed analysis of the destination export market in order to test the former hypothesis whilst the unbalanced nature made it difficult to distinguish each of the separate types of exporting firm.

As with other studies testing the learning-by-exporting hypothesis the analysis here was unable to drill down to this level of detail as required to properly evaluate the impact of exporting on productivity growth thus reducing the strength of the conclusions. However, this in itself helps to provide an explanation as to the inconsistency within the wider literature; those studies focussed on market location and stage of development, and/or stage of exporting providing a more compelling case for the hypothesis than those simply looking at exporting as a homogeneous activity.

Despite the potential limitations with regards to the wider applications of the findings, the over-riding lesson from this element of the analysis is that exporting firms are heterogeneous. This has been recognised in the literature (Wagner, 2007) and has important implications for this type of analysis. In short, it requires that any modelling needs to include as much detail as possible on the firm; so rather than dummy variables which categorise firms into exporters and non-exporters; continuous variables which take account of the wide ranging type of exporters need to be considered as it is unlikely that those firms that export a small amount are similar to companies who export virtually all of their produce. Likewise there needs to be detail on the status of exporting; whether firms are new to the activity, whether they are prior exporters or whether they are intermittent exporters. Similarly, the markets to which they sell need to be considered. One would expect that those selling regularly to more developed markets would be more exposed to learning from exporting than either intermittent sellers or those who export little or to few markets.

This in particular highlights the continued need for access to detailed export data to provide an avenue for continued work in the area, and in doing so raises the current problem of access to HMRC data in the UK. Despite the widening of access to government business datasets for research purposes in the UK[65], detailed export data remains virtually impossible to access. Likewise in NI export data is collected but, again, it is difficult to access the full

[65] The Virtual Micro-Laboratory (VML) and UK Data Service (UKDS) have both been set up to provide access to government business datasets to those undertaking research in the public, private and academic sectors in the UK. Currently there is no access to HMRC export data under this agreement; users wishing to access HMRC data must currently produce evidence as to how their research will be of benefit to HMRC.

micro-level dataset[66]. Without access to these datasets trying to establish the nature of markets that firms export to is problematic thus making policy recommendations challenging. If one sees exporting as a means of directly raising the productivity level of firms or increasing their productivity growth through a learning process then understanding the export markets, the type of exports and the nature of exporters is imperative, and again feeds into the notion of evidence-based policymaking. As access to government survey data is widened it is imperative that the next step in the UK should be the provision of HMRC export data on a similar basis as to other datasets. If such export data were made available it could be linked together with other business datasets providing a powerful tool for analysis covering for example, continuing exporters and new exporters at different export intensities; such analyses better able to substantiate the type of hypotheses as tested here.

7.2.2 Innovation and Productivity Growth

The second major relationship to be tested was that for innovation and productivity growth. This was estimated using a three step model as pioneered by Crépon, Duguet and Mairesse (1998). The first stage of the model examined the decision to undertake R&D; it was found that firms involved in R&D were larger, were more likely to be exporters and had a higher share of employees with science and engineering degrees, all of which were consistent with *a priori* expectations as per the underlying theoretical notions. Conditional on undertaking R&D the model examined the determinants of R&D intensity, that is R&D spending as a share of sales, notably, the results revealed that smaller firms spend a higher share of turnover on investing in R&D than their larger counterparts. These results confirmed Schumpeterian arguments surrounding the resource capabilities for larger firms to undertake R&D (Schumpeter, 1942), whilst the skilled staff finding substantiated arguments with regards to the role of human capital and absorptive capacity (Cohen and Levinthal, 1990). The exports result indicated the degree to which innovation and exporting are interlinked at the firm level, as postulated by Grossman and Helpman (1994).

The second stage of the modelling process, the innovation production function, was run separately for product and process innovation. The R&D intensity variable, as drawn from the first stage, was found to be positive and significant for process innovation but insignificant for product innovation suggesting that R&D is a good predictor of process innovation only; a similar finding to Alvarez et al. (2010). However, the results also highlighted that R&D is not the only source of innovative activity for firms, a fact that is often

[66] Most of the datasets in the VML and UKDS cover Great Britain only as the NI datasets are collected under the NI Statistics Order and are not subject to the same access agreements.

naturally assumed (Eurostat, 2004). External linkages in the form of information from market sources were found to impact the likelihood of undertaking both types of innovation, and for process innovation, co-operation from sources in the UK were also positively correlated. The positive impact from such ‘network effects’, as coined by Love and Roper (2001), also relatively common across the literature (Criscuolo and Haskel, 2003; Griffith et al., 2006; Bogliacino et al., 2010; Lin and Lin, 2010). Strategic protection of the innovation, which is generally less costly than formal protection methods, was also found to be important for NI firms, confirming the concept of appropriability with regards to innovation activities (Arrow, 1962, Spence, 1984).

The final stage, the impact on productivity growth, was again estimated separately for the product and process innovation variables. Interestingly, and in contrast with earlier work for NI, product innovation was found to have no impact on productivity growth whilst process innovation was found to have a negative effect; previous results for NI recorded the opposite (Roper et al., 2007, 2008). The wider empirical literature also reports inconsistent results for process innovation (Hall, 2011); where it has been found to be negative it has been suggested that this may be a temporary effect due to the adjustment costs and associated learning with regards to the new process (Criscuolo, 2009). Given the relatively short timescale over which the effects were measured here, it is likely that this negative finding could well reflect such a temporary adjustment. The lack of impact from product innovation found here is at odds with the empirical literature (Criscuolo, 2009), and may also reflect the limited time frame for the analysis, although the finding could also be justified in cases where the product innovation has led to increased demand and the need for additional labour within the firm. In such a case the lack of impact on productivity in the short-term is not surprising given the trade-off between employment growth and productivity growth.

This element of the analysis again highlighted the need for detailed data requirements to properly model the effects of innovation on productivity growth. Here, as in other similar studies, a major limitation was that only one wave of the CIS was available, a problem emphasised by Knell and Nas (2006). Thus given the simultaneous variables on innovation expenditure and output (over the 2002-04 period) assumptions had to be made that expenditure on R&D represented previous behaviour. Arguments against persistence in innovation have been made (Raymond et al., 2010) and could explain the lack of effect from R&D expenditure to product innovation; the significant effect on process innovation potentially suggesting a relatively quick turnaround from R&D to process innovation but a longer time-lag for product innovation.

The results here also highlight that timing of effects is key in the estimation process. It has been noted in the literature review, that where negative process innovation effects have been found on productivity growth the effects have generally been measured over a short (often two year) period. Given that the very practice of introducing a new way of working; new machinery, or indeed the introduction of a new product is likely to disrupt the existing methods of production, and incur adjustment costs, then it seems defensible that there would be a short term negative effect on productivity, as found here. Indeed Criscuolo and Haskel (2003) make this point when they find that novel innovations initially reduce TFP growth whereas non-novel innovations have the opposite effect. As a potential future extension to the analysis, it would be interesting to categorise the innovations in this way. In addition it would be helpful to compare the short and long term effects of innovation on productivity growth. This could be undertaken by incorporating further waves of the CIS into the dataset to introduce lagged variables into the earlier stages of the analysis and thus measure the effects over a longer time period.

7.2.3 Public Financial Assistance and Productivity Growth

The final strand of the empirical analysis was to estimate the effect of public financial assistance on productivity growth. There were a number of alternative methods through which this could be estimated all of which encountering the fundamental problem in addressing the fact that the counterfactual outcome is unobservable. Methods available to deal with this included selection models, difference-in-difference estimation, propensity score matching and instrumental variables approach; although only the former, the selection models, appeared to provide an unbiased result here.

As perhaps would be expected, the results showed that assisted firms were larger, more likely to export and more likely to innovate. However the model failed to support the hypothesis that SFA assistance positively impacted productivity growth, and in fact found no impact from either being in receipt of assistance, or from the amount received. This lack of impact on productivity was generally consistent with the wider literature; typically public subsidies, when considered as an aggregate measure, have been found to either have no impact or a negative impact on productivity growth due to the targeting of inefficient or declining sectors (Beason and Weinstein, 1996, Lee, 1996; Harris and Trainor, 2005b; Criscuolo et al., 2012; Koski et al., 2013). Such a scenario was evident in NI through previous analysis (Bradley, 2006) and given the extent of repeat SFA grant awards (SQW, 2013) seems likely that the assistance is not being used efficiently by the recipient firms, as suggested by Harris and Trainor (2005b). In fact the SQW report specifically mentioned that there were selectivity issues with regards to the provision of SFA and suggested widespread evidence that it had not been used as a funder of last resort (SQW, 2013, pg. iii).

A major limitation of this area of the analysis was the inability to separate the objectives of the SFA assistance into those which were aimed at employment creation or safeguarding, and those aimed at productivity enhancements. In light of recent studies which have found the categorisation of subsidies to result in the difference between finding an effect and not (Girma et al., 2007; Colombo et al, 2011; Grilli and Murtinu et al., 2012) it represents a crucial drawback.

As with the earlier limitations, the lack of detail provides a rationale for seeking to update the current dataset with a wider range of variables with regards to assistance. It is obvious that when a subsidy can be provided for two competing outcomes, employment growth and productivity growth, that the effects will be muddied when considered as a combined variable[67]. Rather it can only be said with some degree of confidence, that the assistance has had an effect or not, when the objective and outcome can both be identified and separated from other effects. In the case of SFA assistance this is further complicated by the likelihood of firms being in receipt of other additional forms of public assistance. Having access to a more complete range of variables, encompassing other forms of assistance would enable a more robust conclusion to be drawn.

A final by-product of the analysis is linked to the importance of undertaking more than one type of modelling technique to measure the effects of assistance on growth. By its very nature the provision of assistance to firms is characterised by issues of selection and endogeneity; here it was shown that, as with most studies in the field, the difficulty lies in sourcing variables to instrument the endogenous assistance. Using a single alternative methodology is insufficient as it may be open to bias which can only be detected when sensitivity tests are performed; the recommendation is thus to use a range of techniques, as the data permits, to achieve a consistent conclusion.

7.3 Policy Implications

Notwithstanding the aforementioned limitations; the results of this study have some wider implications with regards to policy. The reported lack of impact on productivity growth from

[67] In a recent study of the impact of SFA, it was reported that 28 per cent of recipient firms believed job creation to be the most important objective of SFA and just 18 per cent stated productivity improvements (SQW, 2013).

exporting, innovation and public financial assistance could explain why NI has failed to close the gap with the remainder of the UK. It could be that firms in the region are exporting to countries at the same or lower levels of development, and hence there is a restricted opportunity to learn. Likewise, if the innovative activities are being undertaken by firms to increase profits or expand employment opportunities, at least in the short term, then it would explain why productivity growth is being hindered. As per government failure arguments, the lack of impact from the public assistance to firms may be due to an over-reliance on subsidies, and/or the targeting of unproductive sectors, resulting in further inefficiencies and an overall dampening of productivity in the economy. Certainly the results here coupled with evidence of repeated subsidisation of firms and relatively low levels of additionality (SQW, 2013) would suggest that this indeed the case. Whilst this study has provided a first step into examining these issues, further work utilising more detailed data could help substantiate this.

Regardless of the need for further investigation, the other findings within each of the analyses have important policy repercussions. The evidence for sunk costs, as reported in the exporting analysis, suggests that there are certain entry barriers to exporting which not all firms are willing to or able to overcome. If the problem with the latter is due to unfavourable characteristics of the owner/manager or of the product, then intervention may have no effect (Greenaway and Kneller, 2004). However if the problem is due to lack of finance or resources, then this suggests an opportunity for market intervention. Indeed, government policies to induce firms to start exporting are to be encouraged, not least because it reduces their subsequent reliance on the home market, increasing their chances of survival, and reducing any negative effects on the wider economy during domestic downturns.

The reported evidence for self-selection amongst new exporters is also encouraging from a policy perspective in that firms become more productive before exporting begins. In the literature this has been reported to be a deliberate action by firms, in recognition of the need to be highly competitive in the face of wider competition and to provide goods of a higher quality than those made for the domestic market (Alvarez and Lopez, 2005). The self-improving actions of firms through their investment in physical and human capital prior to exporting increases their productivity, and if exporting allows such companies to survive longer than non-exporters, there will be a general increase in productivity levels in the economy, as less productive firms exit the market and resources are reallocated to the more productive firms. This finding is encouraging and the potential for greater numbers of high productivity firms in the economy somewhat offsets the general lack of effects from learning-by-exporting, in which productivity growth is not further enhanced by starting to export.

The literature reports that learning-by-exporting is more apparent when the export destination is one of a higher income, more advanced economy (De Loecker, 2010). The implication for policy from this is that there should be a separation of exporting strategies; a general plan to increase the number of firms in the economy exporting, as detailed above; and a more specific plan to help existing exporters to sell to more advanced economies. The latter of these could be targeted at sectors in NI whose firms are below the sector technology frontier, for whom the exposure and learning would reap the most benefits. The potential for knock-on effects on innovation within the firm and for knowledge spillovers would then be increased, and help move the economy up the value chain.

The results from the innovation analysis inferred that outside influences, particularly from market sources, were likely to encourage firms to undertake innovative behaviour. From a policy point of view this suggests a role for government in providing the context and environment for the encouragement of such externally-sourced innovation, confirming the notions proposed within the 'systems of innovation' literature (Soete et al., 2010). Firms need to have easy access to market information and to external linkages in order to find the right co-operation partners; this is particularly important in a peripheral region such as NI where firms may be somewhat isolated from their clients, suppliers or competitors, as suggested by Porter and Stern (1999)

> *"Innovation tends to be facilitated by the presence of a cluster, particularly where the cluster is concentrated geographically (pg. 19)"*

A final observation from the innovation study was the notion that there was potentially a longer time lag between investment in R&D and the resulting product innovation, than was the case for process innovation, whose effects appeared to be more immediate. Whilst this may have been a construct of the simultaneous nature of the dataset, if in any way representative, it suggests greater time and cost pressures with regards to product innovation in that firms may be more risk averse to undertake this type of innovation if the time between the initial investment and the time to market is unduly lengthy. If this is due to compliance or other regulations it suggests a potential role for policy in reducing the structural burden.

The lack of impact of public financial assistance on firm-level productivity growth perhaps has the most wide-reaching policy implications, particularly in NI, where the degree of firm subsidy is higher than in other UK regions (Harris and Trainor, 2005b). Innovation and exporting are activities undertaken by firms for a variety of reasons, and thus the activities could not be considered to solely affect productivity; the lack of any impact therefore not unduly alarming if there are other positive effects for the firm and the economy. On the contrary, government financial assistance is provided for a specific purpose, which in certain cases is for productivity enhancing purposes. Although the results here were hampered by a failure to pin down these specific objectives; the wider literature suggests that public subsidies are not always targeted effectively. In fact, it has been found, more often than not, that declining and unproductive firms are typically supported, restricting the creative destruction process from naturally occurring in the economy and dampening overall productivity levels. Evidence has also been found in the literature for repeat subsidisation of firms, which further reduces the likelihood that the assistance will be used efficiently (Bergstrom, 2000). In NI, there is widespread use of repeat applications for public financial assistance (SQW, 2013) which suggests that government may be 'artificially' keeping firms in existence, which would otherwise not be the case if the market was operating independently. Government may therefore be preventing the exit of unproductive firms and thus inhibiting the natural growth in productivity. If policy seeks to close the productivity gap with the UK by raising individual firm-level, and overall productivity in the economy, it needs to ensure that its actions are not having the opposite effect, points made effectively by Hoekman and Javorcik (2004):

> *"…the issue (of a subsidy) is to address the externality, not to prop up uncompetitive firms or industries" (pg. 467).*

> *"Overall, it has been argued that effective policy-making in these areas should not hinder market processes that result in intra-firm reallocations and/or market entry and exit" (Harris and Li, 2012, pg. 650, summarising Hoekman and Javorcik, 2004.).*

Given that the findings here with regards to the lack of impact from public financial assistance corroborate that from other countries then it must be accepted, at least for a certain number of firms, that the assistance is having no additional impact on productivity growth. In such a scenario, particularly where there are accountability issues with regards to public funding, a bold conclusion would be to stop the provision of such funding in its current form. Rather, if financial assistance is to be provided with government truly acting as a funder of last resort then it should be in the form of loans rather than grants, and the extent of repeat assistance should also be capped. The former of these would incentivise the firm to regard the assistance as akin to a traditional loan with its accompanying interest rate and repayment schedule, whilst the latter would ensure that assistance is only sought in essential circumstances, both of which would help eradicate any rent-seeking behaviour currently associated with 'free' grant money and reduce levels of deadweight. This would also dampen the over-reliance of firms on public money and thus jointly reduce the likelihood of the government propping up unproductive sectors or firms whilst increasing demand (and potentially supply) of other forms of private finance.

7.4 Overall Conclusion

The aim of the thesis was to provide new and updated evidence with regards to the impact of government financial assistance, and the strategic activities undertaken by firms, on productivity growth in NI. Using current econometric techniques the analysis sought to substantiate the claims made in the various NI economic strategy documents about how these activities would make firms more competitive and hence raise productivity growth sufficiently to narrow the gap with the UK. The limitations of the study, as discussed above, mean that while the evidence partially fills the knowledge gap with regards to these issues the dataset is perhaps not detailed enough to corroborate or challenge the proposition that such activities directly increase productivity growth. Indeed over the short-term that has been analysed here, the results would imply that there is no such direct positive impact. Rather the study highlights the need for access to comprehensive data so that the diverse nature of firms and the activities they undertake can be accounted for. It is thought that the current inconsistencies in the literature are the exact result of a failure to look at these micro details, instead relying on combined or incomplete variables to try and capture, what are essentially diverse underlying entities and activities. As has been suggested in NI best practice for economic strategy is to consider it as a long-term process (IREP, 2009), this notion should also be carried into the evaluation field, the implication being that access to longitudinal datasets be made available to establish the medium and long-term impacts of policy targets.

The overall recommendation to arise from the study then is the need to have access to comprehensive data in order to incorporate this heterogeneity into the techniques and the variables. National statistical agencies are gradually becoming more amenable to widening access to their data, and combined with advances in linking methodologies, this opens up the possibility for more in-depth rigorous research, at a relatively low cost. Together these enable advances to be made with regards to micro-economic research and contribute better to evidence-based policy making. Indeed the Enterprise Research Centre (ERC) has taken the lead in this area with regards to accessing government business datasets to understand small firm growth.

Making use of the techniques explored here in terms of data-linking, one of the central goals of the ERC has been to use existing micro-level datasets to undertake such detailed analyses. These datasets have been made available via the UK Data Service's Secure Lab and include the Business Structure Database (BSD), the Annual Business Survey (ABS), the CIS and BERD surveys. Linking these data-sets together and cross tabulating them has enabled an exploration of a wider variety of indices on firm characteristics than was previously available, and has permitted longitudinal analyses to produce a more detailed view of the complexities of SME growth (Anyadike-Danes et al., 2013a, 2013b).

The data-linking has been particularly useful with regards to generating statistics at a more detailed regional level than was previously available, enabling for example analyses at the Local Enterprise Partnership (LEP) level (Anyadike-Danes et al., 2013c; Roper et al., 2014; ERC 2014). The fact that such analyses can be undertaken within a relatively short time-frame with no additional survey costs means than it can be responsive to changing government plans and priorities, such as the development of the LEP areas.

Working on these datasets through the ERC has also enabled further insights into the innovation behaviour of firms and on the effects of public assistance to be established; moving on from the initial results presented here. Following on from the findings that other sources of information and collaboration have an effect on firms' innovation activity, a recent paper has considered how firms' innovation objectives influence their choice of these interactive and/or non-interactive connections (Roper et al., 2015).

Work that is currently underway seeks to further utilise some of the findings here with regards to public assistance to firms, specifically analysing the impact of the various BIS support schemes for business on employment, turnover and productivity growth. A novel element of the analysis is to look explicitly at the extent of multiple-scheme take-up of assistance as well as repeat assistance within the same scheme. The study intends to shed light on some of the issues raised here with respect to the repeat subsidisation of firms and whether this helps or hinders the various performance outcomes.

Despite the strides forward with regards to access to government-owned datasets, and their use for detailed analyses there remain some short-comings in the sphere. In particular, as previously mentioned, access to detailed exports data through HMRC is still restricted which represents a major source of omitted variables when examining growth at the firm level. The results here have shown that exporters are a heterogeneous group of firms, thus having detailed information on export markets, the type of exports and the nature of exporters is imperative. If the UK, and NI, want to show best practice in economic policy development then existing evidence needs to be brought to the fore; widening access to datasets is the first step in this process and combined with robust analytical methods can provide a relatively cost-efficient way of evaluating past and current policy goals across the economic development platform.

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Appendix One

Table A1.1: Quantile Regression on External Sales Intensity

Dependent Variable	**External Sales Intensity**			
	Qreg (0.25)	**Qreg (0.5)**	**Qreg (0.75)**	**Qreg (0.9)**
Explanatory Variables				
Log total employment	0.0217***	0.0806***	0.0563***	0.00999***
	(0.000776)	(0.00360)	(0.00358)	(0.00172)
Total employment squared	1.84e-08***	-5.60e-10	-4.80e-09	-8.33e-10
	(1.12e-09)	(5.65e-09)	(5.65e-09)	(1.13e-09)
Log employment costs per employee	0.0174***	0.0732***	0.0875***	0.0331***
	(0.00245)	(0.0107)	(0.0104)	(0.00460)
Log gva per employee (t-1)	0.0134***	0.0671***	0.0459***	0.0150***
	(0.00200)	(0.00855)	(0.00847)	(0.00408)
R&D spending as percentage of turnover (t-1)	0.000699***	-0.000166	0.00836***	0.00981***
	(9.37e-05)	(0.000327)	(0.000854)	(0.000218)
Assist	.0689791***	.1316673***	.0772006***	.0213986*
	.0084734	.0167674	.0190695	.0126404
Food Manufacturing	-0.0102**	-0.0901***	-0.0698***	0.0304***
	(0.00507)	(0.0206)	(0.0188)	(0.00816)
Textiles Manufacturing	0.136***	0.446***	0.200***	0.0678***
	(0.00673)	(0.0272)	(0.0250)	(0.0108)
Paper & Printing	-0.0212***	-0.167***	-0.356***	-0.0699***
	(0.00589)	(0.0239)	(0.0219)	(0.00943)
Rubber Manufacturing	-0.00229	0.0246	-0.0437*	-0.00363
	(0.00622)	(0.0251)	(0.0229)	(0.00981)
Metal Manufacturing	-0.0176***	-0.152***	-0.264***	-0.149***
	(0.00482)	(0.0196)	(0.0179)	(0.00771)
Machinery Manufacturing	0.0278***	0.0998***	0.0904***	0.0352***
	(0.00592)	(0.0241)	(0.0222)	(0.00954)
Electrical & Optical Manufacturing	0.0442***	0.197***	0.107***	0.0440***
	(0.00689)	(0.0278)	(0.0256)	(0.0113)
Transport Manufacturing	0.0306***	0.164***	0.0524*	0.0274**
	(0.00783)	(0.0317)	(0.0291)	(0.0125)
Other Manufacturing	0.0380***	0.0605***	-0.0122	0.00252
	(0.00543)	(0.0220)	(0.0202)	(0.00875)
Construction	0.0140*	-0.0571*	-0.194***	-0.116***
	(0.00718)	(0.0292)	(0.0268)	(0.0115)
Wholesale & Retail	0.0363***	0.0883***	0.0250	0.0401***
	(0.00597)	(0.0242)	(0.0222)	(0.00958)
Business Services	0.0773***	0.253***	0.146***	0.0622***
	(0.00550)	(0.0224)	(0.0204)	(0.00882)
Constant	-0.110***	-0.339***	0.163***	0.755***
	(0.00761)	(0.0319)	(0.0304)	(0.0138)
Observations	12,374	12,374	12,374	12,374
Pseudo R2	0.0275	0.1174	0.1299	0.0459

Standard errors in parentheses
Model estimated using qreg (in Stata)
*** p<0.01, ** p<0.05, * p<0.10

Table A1.2: Quantile Regression on Overseas Sales Intensity

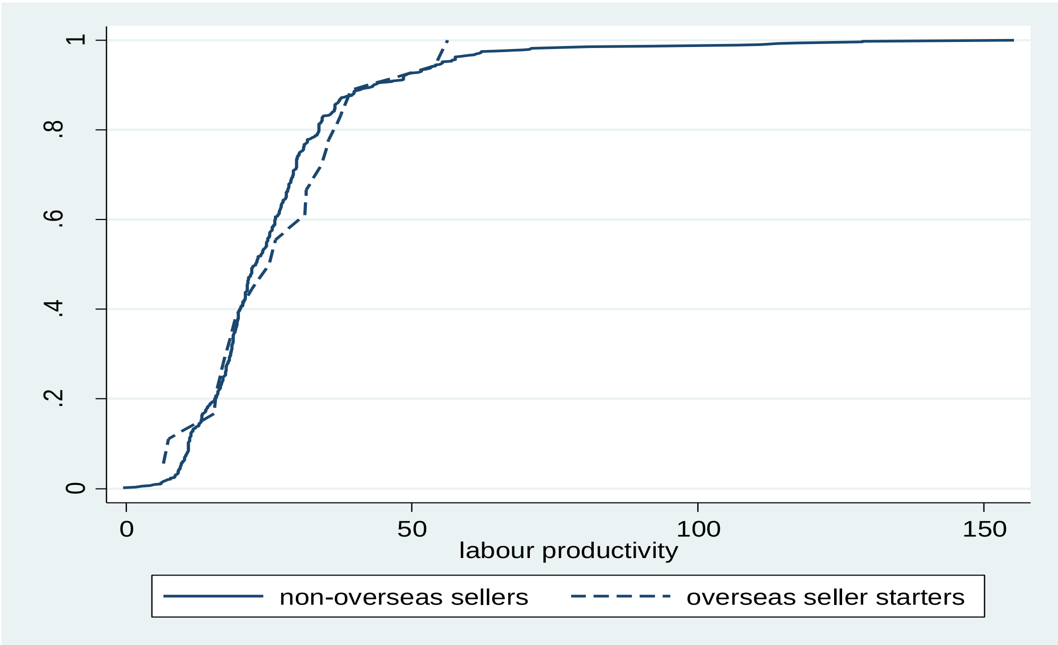
Dependent Variable	**Overseas Sales Intensity**			
	Qreg (0.25)	**Qreg (0.5)**	**Qreg (0.75)**	**Qreg (0.9)**
Explanatory Variables				
Log total employment	0	-7.94e-06***	-4.83e-07***	0.0145***
	(0)	(3.63e-08)	(3.88e-08)	(0.00221)
Total employment squared	0	3.06e-08***	3.99e-08***	6.80e-08***
	(0)	(0)	(0)	(1.20e-09)
Log employment costs per employee	0	4.12e-07***	5.31e-07***	0.0264***
	(0)	(1.08e-07)	(1.16e-07)	(0.00697)
Log gva per employee (t-1)	0	-1.25e-07	5.54e-07***	0.0239***
	(0)	(8.62e-08)	(9.21e-08)	(0.00577)
R&D spending as percentage of turnover (t-1)	0	8.03e-09**	0.000140***	0.0650***
	(0)	(3.30e-09)	(9.15e-09)	(0.000251)
Assist	(0)	2.05e-07	1.90e-06	.0221119
	(0)	.0001309	.0062752	.0246718
Food Manufacturing	0	-1.81e-06***	-8.97e-08	-0.0425***
	(0)	(2.07e-07)	(2.00e-07)	(0.00946)
Textiles Manufacturing	0	1.37e-06***	0.140***	0.277***
	(0)	(2.75e-07)	(2.64e-07)	(0.0123)
Paper & Printing	0	-1.65e-06***	-5.10e-07**	-0.0688***
	(0)	(2.41e-07)	(2.34e-07)	(0.0110)
Rubber Manufacturing	0	7.65e-07***	0.00825***	0.153***
	(0)	(2.53e-07)	(2.41e-07)	(0.0112)
Metal Manufacturing	0	-1.03e-06***	-9.57e-07***	-0.0856***
	(0)	(1.97e-07)	(1.91e-07)	(0.00919)
Machinery Manufacturing	0	2.61e-07	0.0600***	0.424***
	(0)	(2.43e-07)	(2.33e-07)	(0.0109)
Electrical & Optical Manufacturing	0	1.35e-06***	0.450***	0.655***
	(0)	(2.80e-07)	(2.69e-07)	(0.0129)
Transport Manufacturing	0	4.93e-07	0.0146***	0.292***
	(0)	(3.19e-07)	(3.08e-07)	(0.0144)
Other Manufacturing	0	-1.74e-07	2.57e-08	0.117***
	(0)	(2.22e-07)	(2.15e-07)	(0.0102)
Construction	0	-4.99e-06***	-8.07e-07***	-0.0632***
	(0)	(2.94e-07)	(2.86e-07)	(0.0134)
Wholesale & Retail	0	-1.22e-06***	3.49e-07	0.0249**
	(0)	(2.44e-07)	(2.36e-07)	(0.0111)
Business Services	0	-2.47e-07	0.0800***	0.539***
	(0)	(2.25e-07)	(2.18e-07)	(0.0102)
Constant	0	1.32e-05***	-2.77e-06***	-0.0680***
	(0)	(3.22e-07)	(3.45e-07)	(0.0202)
Observations	12,374	12,374	12,374	12,374
Pseudo R2	0.000	0.0047	0.0601	0.2279

Standard errors in parentheses
Model estimated using qreg (in Stata)
*** p<0.01, ** p<0.05, * p<0.10

Figure A1.3: Ex-ante Labour Productivity Distribution of External Seller Starters and Non-external Sellers

Note: Labour productivity defined as GVA per employee
Source: Authors own estimates of DETI data

Figure A1.4: Ex-ante Labour Productivity Distribution of Overseas Seller Starters and Non-overseas Sellers



Note: Labour productivity defined as GVA per employee
Source: Authors own estimates of DETI data

Table A1.5: Kolmogorov-Smirnov Test for Ex-ante Labour Productivity Differences between External Seller Starters and Non-external Sellers

	N		Two-sided Test		One-sided Test	
	External Seller Starters	**Non-external Sellers**	**Statistic**	**P-value**	**Statistic**	**P-value**
Non-external Sellers vs External Seller Starters	88	396	0.1279	0.185	-0.0360	0.828

Notes: The two-sided test is a test of the null that the two cumulative distribution functions are equal against the alternative that they differ. The one-sided test is a test of the null that the cumulative distribution function of the second group lies below (or is equal to) the cumulative distribution function of the first group against the alternative that it lies above.

Table A1.6: Kolmogorov-Smirnov Test for Ex-ante Labour Productivity Differences between Overseas Seller Starters and Non-overseas Sellers

	N		Two-sided Test		One-sided Test	
	Overseas Seller Starters	**Non-overseas Sellers**	**Statistic**	**P-value**	**Statistic**	**P-value**
Non-overseas Sellers vs Overseas Seller Starters	88	2,468	0.0904	0.470	-0.0904	0.238

Notes: The two-sided test is a test of the null that the two cumulative distribution functions are equal against the alternative that they differ. The one-sided test is a test of the null that the cumulative distribution function of the second group lies below (or is equal to) the cumulative distribution function of the first group against the alternative that it lies above.

Table A1.7: Descriptive Statistics for CIS Product Innovators 2002

	Employment	Employment costs per employee (£000s)	GVA per employee (£000s)	Exports (£000s)	R&D Spending (£000s)	Sci & Eng share Of Employment
			Product Innovator			
N	**313**	**313**	**313**	**196**	**333**	**333**
Mean	127.34	15.42	26.23	7,760.18	60.67	7.98
Median	46.46	14.17	20.34	473.80	1.00	0.00
Std. dev	435.42	9.62	24.20	38,910.35	258.69	17.95
			Non-Product Innovator			
N	**928**	**927**	**925**	**264**	**991**	**991**
Mean	74.29	12.21	22.69	1,587.40	12.08	3.88
Median	28.70	10.96	18.86	159.89	0	0
Std. dev	191.36	8.29	18.58	4,340.27	135.43	12.67
T-Test	*2.96****	*5.68****	*2.69****	*2.56***	*4.39****	*4.56****

Note: Sales, exports, R&D spending, employment costs and GVA per employee are in £000s at 1995 prices.
*** p<0.01, ** p<0.05, * p<0.10
Source: Authors own estimates of DETI data

Table A1.8: Descriptive Statistics for CIS Process Innovators 2002

	Employment	Employment costs per employee (£000s)	GVA per employee (£000s)	Exports (£000s)	R&D Spending (£000s)	Sci & Eng share Of Employment
			Process Innovator			
N	**270**	**270**	**270**	**147**	**293**	**293**
Mean	148.46	14.32	24.74	7,971.90	55.23	9.41
Median	36.00	12.83	19.43	259.11	0.00	0.00
Std. dev	515.03	10.43	23.09	42,957.31	252.32	20.35
			Non-Process Innovator			
N	**971**	**970**	**968**	**313**	**1,031**	**1031**
Mean	70.76	12.66	23.267	2,454.31	15.51	3.63
Median	32.42	11.48	19.40	264.86	0	0
Std. dev	147.58	8.20	19.31	10,129	146.19	11.72
T-Test	*4.13****	*2.75***	*1.06*	*2.15***	*3.42****	*6.19****

Note: Sales, exports, R&D spending, employment costs and GVA per employee are in £000s at 1995 prices.
*** p<0.01, ** p<0.05, * p<0.10
Source: Authors own estimates of DETI data

Table A1.9: Logit Regression on Missing Export Observations

Dependent Variable	**Missing Export Values**
Explanatory Variables	
Total Employment	0.00540***
	(0.00135)
Sector	0.0987***
	(0.00594)
R&D spending	-0.00140**
	(0.000552)
Innovator	-1.488***
	(0.180)
GVA	0.000204**
	(8.12e-05)
Employment Costs	-0.00110***
	(0.000203)
Constant	-2.844***
	(0.260)
Observations	1,225

Model estimated using logit (in Stata)
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table A1.10: Heckman Selection Model for Innovation Expenditure Intensity conditional on Investing in all types of Innovation 2002-04

Dependent Variable	**Engage in Innov Spending (1/0 dummy)**	**Innov Spend Intensity**
Log Labour Productivity $_{(t-1)}$	0.143	-0.0213
	(0.155)	(0.0260)
Log Size	0.141**	-0.0363***
	(0.0598)	(0.0139)
Share of Science and Engineering Employees	2.075***	-
	(0.583)	-
Exporter	0.227	-
	(0.158)	-
Log Employment Costs	-0.274	-
	(0.205)	-
Export Intensity$_{(t-1)}$	-	-0.00395
	-	(0.0470)
Lambda	-	-0.269**
	-	(0.118)
Manufacturing	-	0.00261
	-	(0.0656)
Construction	-	-0.00785
	-	(0.0862)
Wholesale	-	-0.0302
	-	(0.0836)
Business Services	-	0.00690
	-	(0.0772)
N Obs	431	431
Chi-Sq (7)		8.50

Standard errors in parentheses
Model estimated using Heckman (in Stata)
*** p<0.01, ** p<0.05, * p<0.10

Table A1.11: Multivariate Probit Model for Product and Process Innovation 2002 - 2004

Dependent Variable	**Product Innovation**	**Process Innovation**
Predicted Innov Spend intensity	2.221	2.808
	(2.039)	(2.043)
Log Size	0.0556	0.0384
	(0.0742)	(0.0748)
Information from market sources	0.675***	1.006***
	(0.211)	(0.238)
Information from institutional sources	0.0197	-0.0744
	(0.178)	(0.178)
Information from other sources	0.260	-0.104
	(0.160)	(0.164)
Co-operation from UK partners	0.423	0.461*
	(0.300)	(0.278)
Co-operation from European partners	0.119	0.514*
	(0.321)	(0.308)
Co-operation from other partners	0.196	-0.317
	(0.471)	(0.400)
Support from local authorities	0.219	-0.0440
	(0.178)	(0.173)
Support from central/devolved govt	0.181	0.282
	(0.192)	(0.187)
Formal protection	0.200	0.0356
	(0.167)	(0.170)
Strategic protection	0.597***	0.490***
	(0.166)	(0.170)
Constant	-1.753***	-1.967***
	(0.392)	(0.407)
N Obs	435	435
Chi-Sq (12)	108.5***	76.38***
Log-likelihood	-228.476	-223.177

Model estimated using mvprobit (in Stata)
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table A1.12: Regression on Productivity Growth 2004-08

Dependent Variable	**Productivity Growth 2004-08** (with product innovation)	**Productivity Growth 2004-08** (with process innovation)
Predicted Prod Innov	-0.158	-
	(0.141)	-
Predicted Proc Innov	-	-0.311*
	-	(0.173)
Export Intensity	0.162	0.179
	(0.132)	(0.129)
Log Size	0.0103	0.0133
	(0.0350)	(0.0337)
Log Employment Costs	0.0416	0.0337
	(0.111)	(0.109)
Log Physical Capital	-0.0282	-0.0256
	(0.0310)	(0.0302)
Log Labour Productivity	-0.305***	-0.306***
	(0.0801)	(0.0781)
Manufacturing	-0.200	-0.198
	(0.216)	(0.210)
Construction	-0.504**	-0.518**
	(0.255)	(0.248)
Wholesale & Retail	-0.220	-0.238
	(0.259)	(0.253)
Business Services	-0.535	-0.570
	(0.582)	(0.568)
Constant	1.145***	1.179***
	(0.375)	(0.367)
Observations	257	257
Chi-Sq (9)	28.3***	30.2***
Log-likelihood	-199.060	-198.103

Model estimated using xtreg mle (in Stata)
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table A1.13: Pre and Post-matching differences for Assisted and Non-Assisted Firms

		N-N with replacement				N-N without Replacement				Kernel				Caliper			
Variable	**Sample**	**Treat**	**Control**	**t-test**	**% bias**	**Treat**	**Control**	**t-test**	**% bias**	**Treat**	**Control**	**t-test**	**% bias**	**Treat**	**Control**	**t-test**	**% bias**
Size (t-1)	Unmatched	5.2	3.8	27.3***	107.4	5.2	3.8	27.3***	107.4	5.2	3.8	27.3***	107.4	5.2	3.8	27.3***	107.4
	Matched	5.4	5.4	0.3	1.9	5.4	5.3	1.3	7.7	5.3	5.3	0.5	2.7	5.4	5.4	0.3	1.9
Turnover (t-1)	Unmatched	9.4	7.9	22.7***	89.2	9.4	7.9	22.7***	89.2	9.4	7.9	22.7***	89.2	9.4	7.9	22.7***	89.2
	Matched	9.9	9.9	0.2	0.9	9.9	9.9	0.3	1.9	9.8	9.8	0.1	0.9	9.9	9.9	0.2	0.9
Value of Stock (t-1)	Unmatched	7.2	5.6	20.3***	91.1	7.2	5.6	20.3***	91.1	7.2	5.6	20.3***	91.1	7.2	5.6	20.3***	91.1
	Matched	7.6	7.7	-1.0	-5.9	7.6	7.6	0.2	1.2	7.5	7.6	-0.5	-3.3	7.6	7.7	-1.0	-5.9
Exporter (t-1)	Unmatched	0.9	0.8	10.0***	46.4	0.9	0.8	10.0***	46.4	0.9	0.8	10.0***	46.4	0.9	0.8	10.0***	46.4
	Matched	1.0	1.0	0.5	1.8	1.0	1.0	-0.5	-1.8	1.0	1.0	0.3	1.1	1.0	1.0	0.5	1.8
Emp Costs (t-1)	Unmatched	7.9	6.4	26.1***	103.3	7.9	6.4	26.1***	103.3	7.9	6.4	26.1***	103.3	7.9	6.4	26.1***	103.3
	Matched	8.4	8.3	0.7	4.1	8.4	8.3	1.2	6.8	8.3	8.2	0.5	3.1	8.4	8.3	0.7	4.1
Labour Prod (t-1)	Unmatched	3.2	3.1	0.6	2.2	3.2	3.1	0.6	2.2	3.2	3.1	0.6	2.2	3.2	3.1	0.6	2.2
	Matched	3.4	3.3	1.0	7.5	3.4	3.4	-0.6	-4.7	3.4	3.4	0.4	3.1	3.4	3.3	1.0	7.5
Sector	Unmatched	31.4	28.6	5.4***	17.2	31.4	28.6	5.4***	17.2	31.4	28.6	5.4***	17.2	31.4	28.6	5.4***	17.2
	Matched	24.8	25.3	-0.7	-3.2	24.8	25.2	-0.5	-2.3	24.9	25.2	-0.4	-1.9	24.8	25.3	-0.7	-3.2

*** p<0.01, ** p<0.05, * p<0.10

Table A1.14: Pre- and Post-matching differences in standardised bias

Matching Method	***Sample***	***Mean Bias %***	***Median Bias %***
N-N with replacement	Raw	65.3	89.2
	Matched	3.6	3.2
N-N without replacement	Raw	65.3	89.2
	Matched	3.8	2.3
N-N with kernel	Raw	65.3	89.2
	Matched	2.3	2.7
N-N with caliper	Raw	65.3	89.2
	Matched	3.6	3.2

Table A1.15: Sectoral Classifications

Sector	*Sic92 Classification*
Food	15-17
Textiles	18-19
Paper	21-22
Rubber	25
Metal	26-28
Machinery	29
Electrical	30-33
Transport	34-35
Other Manufacturing	23, 36-37
Construction	45
Wholesale & Retail	50-52
Business Services	70-74
Other Services	40, 55, 65-67, 75-86, 90-93