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Of chickens and eggs: Exporting, innovation novelty and productivity

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ABSTRACT

While it is well-known that exporters are more productive than non-exporters it is less clear why. Is it simply that more productive firms export (the Learning to Export hypothesis)? Or, is it exporting which leads to higher productivity (the Learning by Exporting hypothesis)? The distinction is important as each hypothesis points to very different policy and strategic prescriptions. Here, we use GMM estimation and data on a large, unbalanced panel of UK firms to expose the complex interlinkages between exporting and export persistence, innovation and innovation novelty, and productivity. LTE and LBE effects prove important with export persistence playing a key moderating role in performance outcomes. Our results suggest that: i) in LTE, radical innovations increase export performance, but incremental innovations do not ii) In LBE, exports increase both radical and incremental innovation performance iii) LTE and LBE effects occur only for persistent exporters iv) Exporting has a direct positive impact on productivity, but innovation has only an indirect productivity effect via it's positive influence on exporting. Building on these linkages to increase productivity suggests targeting export support at non-exporters with a technological lead in the domestic market.

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Keywords: Productivity, exporting, innovation, persistence, novelty

CONTENTS

1. INTRODUCTION

It is well established that exporting firms are more productive than non-exporters (Cassiman et al., 2010). For example, the ONS estimated that in 2016, only about 5% of all UK firms were engaged in international trade. These firms were, however, around 20% more productive than non-trading firms, and they accounted for over 40% of employment. The question of why exporting firms are more productive remains less clear: Is it simply that more productive firms export, or is it exporting which leads to higher productivity?

Two complementary hypotheses have been suggested to explain the widely observed link between exporting and high productivity. The first, the Learning to Export (LTE) hypothesis posits that more productive firms self-select into exporting because they are better able to bear the sunk or irrecoverable costs associated with export market entry (Eliasson et al., 2012, De Loecker 2010, Gkypali et al., 2021). Thus, firms learn to export by ramping up productivity within their domestic market setting. Innovation plays a key role here - process innovation can enhance organisational processes that allow more effective export management, while product innovation can expand the organisation's potential market base to include international markets, making it profitable to export. The LTE export hypothesis has received considerable attention in the empirical literature, with a consensus that more innovative and more productive firms are indeed more likely to enter foreign markets, and that product innovation (as opposed to process innovation) stimulates export market entry (Alvarez and Lopez, 2005, Golovko and Valentini , 2014, Cassiman et al., 2010, Gkypali et al., 2021).

The second hypothesised link between exporting and productivity is the Learning by Exporting hypothesis (LBE). This suggests that subsequent to starting to export, firms gain access to new sources of knowledge for example from foreign clients, export intermediaries, and competitors (Saloman and Shaver, 2005). This is privileged knowledge unavailable to firms selling solely in their domestic market. Exporters can then integrate this new knowledge with their existing knowledge base, enabling the introduction of new or improved products and a subsequent increase in productivity. The empirical evidence on LBE is mixed (Love and Roper, 2015), with any positive impacts of exporting depending strongly on other factors including the technological capabilities of the firm (Salomon and Jin, 2010) and the nature of firms' engagement in international markets (Andersson and Loof, 2009). The mixed evidence for the LBE hypothesis partly reflects the tendency of empirical studies to use productivity itself as a proxy for learning, whereas innovation represents a more direct outcome of LBE (Silva et. al., 2012). Where studies examine LBE effects using innovation outcomes, insights into the LBE phenomena tend to be more consistently positive (Roper and Love, 2002, Ganotakis and Love, 2011, Harris and Li, 2009, Saloman and Shaver, 2005, Love and Ganotakis, 2013, Love et al., 2016, Salomon and Jin, 2018, Freixanet et al., 2018, Feixanet and Rialp, 2022).

Despite prior analysis of the links between exporting, innovation and productivity, there remain several gaps in our understanding. First, for both LTE and LBE, we know little about how the degree of innovation novelty – an indication of the extent of learning - stimulates exporting or ensues from exporting[1]. Radical innovations, or new to the market (NTM) innovations, represent products that 'incorporate a substantially different core technology and provide substantially higher customer benefit' relative to existing products within an industry (Chandy and Tellis, 2000, p.6). These innovations signify a significant departure from the firm's existing knowledge base, and are typically risky and costly (McDermott and O'Connor, 2002). On the other hand, incremental innovations, or new to the firm (NTF) innovations, represent product 'improvements, adaptations or extensions while maintaining the basic essence of the product' (Freixanet and Rialp, 2022, p.59). It is thus intuitive that radical innovations are more likely to incentivise firms to explore foreign markets to maximise the value they are able to derive from their novel product or service (LTE) (Saridakis et al., 2019, Silva et al., 2017). Once a firm exports, its learning from foreign markets may lead to further novel innovations, or may merely support more incremental product changes intended to customise and adapt products to the tastes of foreign customers (Salomon and Jin, 2010, Freixanet and Rialp, 2022). Despite the recognition that the literature provides limited information on the different types of innovation and their role in the exporting and productivity relationship (Love and Roper, 2015), the implications of innovation novelty in LBE and LTE remain largely unexplored.

Another gap in our understanding of LTE and LBE relates to the types of exporting behaviour and export strategies that could support learning (Ipek, 2019). In particular, a firm's commitment to exporting- i.e., whether it is a persistent or intermittent exporter - may determine the extent of LTE and LBE through its implications for the level of engagement with foreign markets (Andersson and Loof, 2009, Love and Manez, 2019). Third, there is a tendency in the literature to use either productivity or innovation as learning outcomes that lead to exporting or result from exporting. There is an increasing recognition that innovation

[1] The LTE export literature generally distinguishes between product and process innovations but not between different degrees of novelty. The LBE literature rarely distinguishes between any type of innovation or degree of novelty.

more directly measures learning outcomes, while productivity represents wider firm level performance (Saloman and Jin, 2010, D'Angelo et al., 2020). However, few (if any) studies provide a comprehensive investigation of the links between innovation, exporting and productivity in a way that distinguishes between the role of learning and the role of firm performance in both the LTE and LBE contexts. Finally, methodological gaps have consistently been identified in the literature, namely the dominance of cross-sectional studies that limit causal inference (Love and Roper, 2015, Ipek, 2019).

To address these gaps in the literature, we directly examine the causal impacts of innovation novelty on exporting (LTE), and the novelty of innovations that result from exporting (LBE) in a longitudinal context. We do this by distinguishing between innovations that are new to the firm (incremental innovations) and those that that are new to the market or industry (radical innovations). Both types of innovation we consider as embodying different types of learning by the firm. Second, we consider the role of persistent exporting in determining the extent of LTE and LBE in terms of innovation novelty. This again focuses attention on how firms learn to export and learn from exporting. Third, we undertake a comprehensive examination of the interplay between innovation, exporting and productivity over time, helping to distinguish between the role of learning and the role of firm performance in both the LTE and LBE contexts. In particular we are able to identify separate learning and self-selection effects in LTE with results suggesting that the self-selection mechanism is more important than the pure learning mechanism. Critical to this is the use of longitudinal data on a large sample of UK firms and an econometric approach that allow us to account for the temporal interconnectedness of innovation, exporting and productivity and so extract the causal mechanisms in these relationships.

In addressing these gaps, we make three primary contributions to the literature. We shed new light on the role of innovation novelty in LTE and LBE process, with potential implications for organisational strategies that may prioritise different degrees of innovation novelty depending on desired exporting outcomes. We also highlight the role of export persistence in enabling firms to learn from their exporting activities. Finally, by simultaneously examining the causal relationships between innovation, productivity and exporting, we identify the direct and indirect impacts of export-related learning on firm-level productivity. Our results suggest that an increase in NTM innovation performance leads to higher export performance after two years, and this LTE effect is independent of prior levels of productivity. Moreover, NTF innovation performance has little impact on subsequent export performance. This suggests that, within product innovation, radical innovation drive exports but incremental innovations do not. Second, we find that an increase in export performance leads to higher NTM and NTF innovation performance after two years, with the effect being slightly larger for NTF innovation performance. This suggests that exporting may lead to greater incremental innovation success, perhaps reflecting product customisations and adaptations to meet the tastes of foreign customers. Thus, while radical innovations drive exports, both radical and incremental innovations ensue from exports. Third, we find strong moderating effects of persistent exporting in these LTE and LBE processes. In particular, the effect of innovation performance (NTF or NTM) on subsequent export performance (LTE), and the effect of export performance on subsequent innovation performance (LBE), are positive only for persistent exporters. This result underlines the importance of consistent access to foreign markets both in enabling learning from exporting, and in providing consistently larger markets for firm's innovations.

In terms of productivity, we find that exporting has a direct positive effect on firm level productivity, independent of the learning channels. However, despite the positive implications of innovation for exporting, both NTM and NTF innovations generally have no direct impact on subsequent productivity, perhaps reflecting efficiency losses related to intensive use of resources for product innovation (Roper et al., 2008; Roper and Bourke, 2022). There are potential complementarities between innovation and exporting, however, because both NTM and NTF innovators gain higher subsequent productivity if they are also exporters, suggesting that exporting enables the expansion of revenues and the spreading of innovations costs over a larger market base. This, innovation has an indirect productivity effect through its positive influence with exporting. The positive links between innovation and exporting also tend to be generally larger for firms in manufacturing sector although firms in services gain slightly higher productivity from their exports. Finally, LTE effects tend to be stronger for larger firms, while LBE effects are slightly stronger for the smallest firms.

The rest of the paper is organised as follows. The next section provides a review of the evidence base on the links between innovation, exporting and productivity, and outlines our conceptual framework. Section 3 presents the data and methods used in the analysis, and Section 4 presents the results. Discussions, conclusions and recommendations are provided in Section 5.

2. THEORETICAL FRAMEWORK

2.1 From innovation to exporting: Learning to Export

There is a consensus in the theoretical and empirical literature that more productive firms are more likely to become exporters, i.e., firms Learn to Export (LTE) (Greenaway and Kneller, 2004; Love and Roper, 2015). One reason for higher productivity among exporting firms may therefore be that more productive firms self-select into exporting. This is because more productive firms are better able to bear the sunk costs associated with export market entry as well as more intense competition in export markets (Clerides et al., 1998, Bernard and Jensen 1999, Delgado et al., 2002). Indeed, exporting involves additional fixed costs associated with, for example, forming distribution or servicing networks, new market research, negotiating new partnerships, modifying products for foreign markets, etc. (Bernard and Jensen, 1999; Helpman et al., 2004). Firms with relatively high levels of productivity and low marginal costs will benefit from export market sales, whereas less productive firms may find that these irrecoverable entry costs erode profitability from exporting (Clerides et. al., 1998, Love and Roper, 2015).

Innovation plays a key role in the LTE process because it embodies the learning that facilitates productivity increases, which in turn can lead to exporting (Roper and Love, 2002, Alegre et al., 2012, Becker and Egger, 2013, Cassiman et al., 2010, Paul et. al., 2017, Henley and Song, 2020). Firms may make strategic investments in new technologies with the aim of producing higher quality, higher value products that are suitable for export markets, and this conscious self-selection may be reflected in greater productivity in the lead up to exporting (Alvarez and Lopez, 2005, Golovko and Valentini, 2014, Cassiman et al., 2010, Gkypali et al., 2021). The ability to create and sustain a competitive advantage in international markets depends on the resources and capabilities of the firm, particularly intangible technological resources that drive innovation and enable the type of product differentiation needed to succeed in international markets. Since technology gaps exist between countries, innovative firms have an incentive to export in order to maximise returns on their innovation investments, reap economies of scale, and sustain their competitive advantage (Posner, 1961, Teece, 1986, Roper and Love, 2002, Anwar and Nguyen, 2011).

2.1.1 The role of innovation novelty in LTE

Not all innovations are the same, however. The type of innovation a firm pursues can affect its likelihood of exporting, its returns from exporting, and its degree of export market participation. There is near consensus in the empirical literature that it is product or service innovations, not process innovations, which stimulate export market entry (Roper and Love, 2002; Nguyen et al., 2008, Cassiman et al., 2010, Caldera, 2010; Añón Higón and Driffield, 2011; Becker and Egger 2013; Saridakis et al., 2019; Gkypali et al., 2021). This is partly because product or service innovations tend to reflect demand variations, which in turn are important in determining performance differences among firms. By contrast, process innovations are associated more directly with technical efficiency (Cassiman et al 2010, Turner et al., 2020). Thus, product/service innovations have a greater potential to expand the firm's market reach to include international markets, making it profitable to export (Cassiman et al., 2010).

Within product/service innovations, however, relatively little is known about the role of innovation novelty in determining exports. When firms introduce a product/service that is new to their market or industry, taking advantage of potential foreign markets before competitors have a chance to imitate the new product/service should be an obvious strategy (McGuiness and Little, 1981). Theoretical contributions also suggest that radical NTM innovations are more suited to exporting than incremental NTF innovations. At the early stages of the product life cycle, new products embody new technologies (Vernon 1979; Hirsh 1975); they tend to be functionally superior to existing products and hence internationally competitive (McGuinness and Little, 1981). Superior product quality and distinctive features, for which there is no immediate competition, enables firms to expand market share and to access international markets (Roper and Love, 2002; Saridakis et al 2019). This is consistent with the Schumpeterian view of 'creative destruction' in which innovative entrepreneurial firms commercialize novel products and create new markets (Schumpeter, 1934).

The characteristics of novel products, and of the firms that produce them, may have implications for exporting. New products may reduce managerial perception of risks relating to export markets (McGuinness and Little, 1981). In particular, firms with new products are less likely to view exporting as a risky strategy; rather, they may recognise it as an opportunity for expansion (McGuinness and Little, 1981, Reid, 1981). New products also tend to have a higher relative cost of failure; large investments in the development of such products often mean large sales volumes are required to make them profitable, motivating firms to pursue foreign markets (McGuiness and Little, 1981). Indeed, exporting allows the firm to exploit its market power overseas and to maximise returns, especially since novel products may stimulate demand beyond the domestic market (Vernon, 1979; Hirsh and Bijaoui, 1985; Roper and Love, 2002). Since NTM innovations are costlier, more challenging, and riskier than NTF innovations, firms may even make the strategic decision to undertake radical innovations with the explicit aim of exporting to maximise returns, i.e., they may consciously self-select into exporting (Martin and Salomon, 2003, Alvarez and Lopez, 2005). This is especially likely in the context of globalisation and shorter product life cycles where firms with novel products have greater motivations to adopt internationalisation strategies (Castano et al., 2016).

The ability to create radical or NTM innovation may also be linked to above average levels of technological capability making firms more likely to internationalise (Dhanaraj and Beamish, 2003). Early empirical evidence suggests a consistent and positive relationship between firms' technological intensity (a measure of innovativeness) and its export intensity (McGuinness and Little, 1981; Gruber and Vernon, 1967), with new products from high technology firms having considerably higher export performance than new products from low technology firms (McGuiness and Little, 1981). This suggests that the degree of innovativeness of the firm, independent from the degree of novelty of its new products, enhances its engagement with foreign markets, perhaps reflecting an entrepreneurial orientation that favours an aggressive pursuit of opportunities (McGuiness and Little, 1981, Yeoh, 2004). Early research in organisational strategy also suggests that a pre-requisite for competitiveness in international markets is that firms have intangible assets and capabilities that confer competitive advantages in the domestic market (Buckley and Casson, 1976).

With a few exceptions, recent empirical research has tended to ignore the role of innovation novelty in determining exports. Saridakis et al. (2019) find that, among UK SMEs, introducing NTM innovations increased export propensity by 18%, while introducing incremental innovations increased export propensity by 6.5%. This suggests that NTM innovators are almost three times more likely to export than NTF innovators. Radical innovations also lead to more distant export markets (Love et al., 2016) and greater export performance (Silva et al., 2017). These innovations are more likely to be exported since their superior quality mean superior prices, and higher priced products are the main object of exports (Kugler and Verhoogen, 2008). Other research suggests that innovation novelty has differential impacts on export market entry and export intensity. Roper and Love (2002) find that in the UK and Germany, undertaking novel innovation increases the probability of exporting, but does not increase the scale of exporting. By contrast, Hagsten and Kotnick (2017) find that more advanced ICT technologies are associated with export intensity, whereas relatively basic technologies are associated with the decision to export.

In sum, the LTE literature is clear that the type of innovation matters for exporting outcomes, in that product innovations are more likely than process innovations to stimulate exporting. However, relatively little is known about whether and how the novelty of product innovations matters for exporting. The theoretical literature suggests that novel inventions are more likely to lead to exporting and export success, because they are functionally superior to existing products, and because exporting presents an opportunity for firms to increase sales volume and maximise returns on costly and risky innovations. Firms with these novel products are also more likely to pursue export markets in order to exploit their marker power before competitors have a chance to imitate their product. Empirical evidence suggests that firms with new-to-market innovations have a higher export propensity than firms with new to the firm innovations. This leads to our first hypothesis:

H1: Relative to NTF innovation, NTM innovation has a higher impact on subsequent export performance

2.1.2: The role of persistent exporting in LTE

There is very little in the LTE literature regarding the potential role of persistent exporting in enabling firms to turn their innovations into successful exports. We argue that, among exporters, the impact of innovation on subsequent export performance may depend on the firm's commitment to export markets. Persistent exporters have consistent access to the larger market base afforded by exporting. This provides them with a consistently larger market base in which to market their innovations, increasing the likelihood that their innovative products can help enhance their export performance. On the other hand, for intermittent exporters that export only some of the time, their innovation sales will be limited to the domestic market during non-exporting episodes, limiting the impact of their innovation on subsequent export market performance. This leads to our next hypothesis:

H2: Relative to intermittent exporters, the effect of NTM and NTF innovation on subsequent export performance is stronger for persistent exporters

2.2 From exporting to innovation: Learning by Exporting (LBE)

In addition to LTE, firms can also learn by exporting (LBE). Exporting can be viewed as a learning process through which firms accumulate timely and accurate information about the international environment (Kafouros et al., 2008, Ipek, 2019). LBE should occur through interactions with a greater variety of knowledge sources, exposure to knowledge and technology that is more distant, and exposure to more intense competition (Andersson and Loof, 2009). Organisational learning theories suggest that firms primarily learn through their interactions with the environment and through their experiences, which are then transformed into organisational routines (Ipek, 2019). LBE suggests firms may make a strategic decision to export with the aim of improving their products and services and as a means of increasing productivity (Salomon and Shaver, 2005).

Exporters have informational advantages over non-exporters due to their access to foreign knowledge spillovers to which non-exporters have no access (Salomon and Shaver, 2005, Grossman and Helpman, 1991). Interactions with foreign market actors enable exporters to accumulate market information relating to consumer preferences (Salomon and Shaver 2005), and to access technological expertise from their international clients who may suggest better processes, products, or product features to suit their own requirements (Zahra et al., 2000). The focal firm can then recombine this new knowledge with pre-existing knowledge, ideas, and technological capabilities to produce new or significantly improved products and services (Alegre et al., 2012).

Foreign customers and competitors represent important sources of new ideas that can drive innovation (Nicholls et al., 1999). Customer learning processes are crucial in exporting since cultural and geographical differences may determine customer preferences, and interactions with foreign customers can provide timely information, especially in the context of rapid changes in customer tastes. Such market related knowledge, which form the bulk of the information used by exporting firms (Cleridas et al., 1998), enables firms to tailor or customise their products to meet market trends (Salomon and Jin, 2010). Knowledge gained from foreign customers also helps set a clear innovation objective by helping overcome ambiguity in the early stages of new product development (Nicholls et al., 1999). If a firm serves as a supplier to a foreign client for example, the client may desire to increase its sourcing efficiency and may ask domestic suppliers to improve designs or adopt new technologies (Andersson and Loof, 2009).

Furthermore, competitor learning processes, which involve the acquisition, interpretation and integration of knowledge gained from foreign competitors, may also lead to innovation (Nicholls et al., 1999). Knowledge about the technologies and processes of foreign competitors allows a firm to benchmark its own competitiveness in foreign markets. This then allows firms to leverage their own strengths, imitate or improve upon competitor strengths, or nullify competitor strengths by differentiating their own products. Technological knowledge may also flow from foreign trade associations or international supply chains, or through insights gained by examining the technological advancements embedded in competitor products (Salomon and Jin, 2010).

Empirically, there is less consensus for LBE than there is for LTE; it is unclear which firms are more likely to learn from exporting (Salomon and Jin, 2010). Largely, it appears that LBE depends on contextual and firm specific factors, and on the extent of engagement in foreign markets (Greenaway and Kneller 2004, Love and Roper, 2015, Andersson and Loof, 2009). While some studies find direct effects of exporting on productivity (cf. Gkypali et al., 2021), others do not (Eliasson et al., 2012, Gatonakis and Love, 2011). The inconclusive evidence on LBE may reflect a widespread use of productivity, as opposed to innovation, as a measure of learning outcomes (Salomon and Jin, 2005; Love and Roper, 2015, Chang and Chung 2017). It is likely that direct productivity effects may take longer to detect, requiring efficiency gains to materialise from product modifications or inventions that often incur significant costs. It is therefore important that innovation, which embodies the new knowledge and technological spillovers from engagement with foreign market actors, is used to proxy any direct learning by exporting effects (Salomon and Shaver, 2005, Silva et al., 2012, D'Angelo et al., 2020, Love and Ganotakis, 2013). Indeed, the relatively smaller number of empirical studies that use innovation outcomes to proxy learning tend to find positive LBE effects (Roper and Love, 2002, Ganotakis and Love, 2011; Harris and Li, 2009, 2010, Saloman and Shaver, 2005, Love and Ganotakis, 2013, Love et al., 2016, Salomon and Jin, 2008, Freixanet et al 2018).

2.2.1 The role of innovation novelty in LBE

Organisations vary in the rate at which they learn from exporting, depending on their degree of technological capabilities, knowledge retention abilities and resources (Argote, 2012, García et al., 2012). An important source of variation in the extent of learning relates to a firm's absorptive capacity, i.e., the 'ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends' (Cohen and Levinthal, 1990, p.128). Since absorptive capacity is highly path dependent, relying crucially on a firm's prior related knowledge and expertise (Cohen and Levinthal, 1990), it follows that it is higher among technologically advanced firms that introduce new to the market, radical inventions (Salomon and Jin, 2010). These firms would have accumulated significant innovation capabilities that confer on them superior leaning capabilities, enabling them to better exploit new foreign knowledge. Indeed, prior studies have linked absorptive capacity to higher LBE effects (D'Angelo and Love, 2020). This resource view of the firm is in contrast to the strand of organisational learning literature that sees less technologically advanced firms, technological laggards, as having greater learning potential from internationalisation strategies (Blalock and Gertler, 2009). These firms are more likely to encounter knowledge that is new to them and to reap greater marginal returns from this knowledge (Yelle, 1979). This, in turn, may enable lagging firms to catch up to leading firms. The resource-based view departs from this premise and instead posits that superior technological capabilities are self-reinforcing, allowing technologically leading firms to shift the technological frontier outwards through innovation, widening the technological gap between leading and lagging firms (Salomon and Jin, 2010).

Empirically, Freixanet and Rialp (2022) find that, for a sample of Spanish firms, export intensity increases the likelihood of engaging in both radical and incremental innovation, but this effect becomes negative after an optimal level of export intensity is reached. Love and Ganotakis (2013) find that exporting leads to subsequent innovation among a sample of high technology UK SMEs. Examining Spanish firms, Salomon and Jin (2010) find that prior to exporting, both technologically leading firms and technologically lagging firms become more innovative (LTE), but it is only technologically leading firms that increase innovation performance subsequent to exporting (LBE). Freixanet et al. (2018) also find that technologically leading family firms become more innovative after export market entry, compared to their technologically lagging counterparts. Lisboa et al. (2011) find that firms with greater explorative capabilities in the domestic market and higher exploitative capabilities in export markets are more innovative. LBE effects may also be higher among high productivity firms who are better able to innovate in order to meet export demand (Aghion et al., 2018), and firms with greater technological capabilities receive higher productivity benefits from exporting (García et al., 2012).

The empirical evidence also suggests that exporting leads to greater *patenting* activities (Aghion et al., 2018, MacGarvie 2006, Salomon and Jin, 2010), suggesting that LBE is associated with more radical inventions. Indeed, interactions with foreign customers enable new product success because they facilitate a match between product attributes and target customers' tastes and preferences (Nicolls et al., 1999). These interactions not only provide information on current customer preferences but also on their potential needs and future market trends, making it a valuable source of new product ideas (Nicolls et al., 1999). Firms may also use foreign competitor development time and entry intentions as a benchmark to gain speedier innovations that can confer pioneering advantages (Nicholls et al., 1999). In addition, interactions with foreign competitors may provide technological knowledge that enables firms to identify opportunities for radically new products or services (Salomon and Jin, 2010). This leads us to our next hypothesis:

H3: The positive effect of export performance on subsequent innovation is stronger for NTM innovations than for NTF innovations.

2.2.2 The role of export persistence in LBE

The extent to which firms learn by exporting may also depend on the nature of their engagement with foreign markets. High levels of engagement and participation in export markets can affect the extent of knowledge inflows and the subsequent organisational learning that ensues (Freixanet and Rialp, 2022). This is in line with insights from learning-by-doing theory which suggests that learning from any activity is the product of experience (Arrow, 1962). In particular, firms that exhibit persistence in their exporting patterns have greater opportunities to learn because they have repeated and largely uninterrupted exposure to foreign knowledge sources (Andersson and Loof, 2009). Such constant and continuous exposure to foreign markets is more likely to support deep, routine-based learning, as opposed to punctuated learning that occurs with sporadic exporting patterns (Love and Manez, 2019). Persistent exporting patterns also signify a commitment and dependence on export markets, and such dependence can incentivise firms to be more attentive to the requirements and feedback from foreign customers and partners (Freixanet and Rialp, 2022). This will enable it to continuously innovate in order to provide better quality and differentiated product in an increasingly competitive export environment (D'Angelo et al., 2020). On the other hand, interruption or discontinuities in learning which may occur when activities are frequently changed or intermittently performed can lead to a loss of learning (Yelle, 1979). Still, the marginal benefit of each additional time period of exporting may decrease, since most learning occurs at the early stages of internationalisation (Love et al., 2016).

Some of the learning benefits of export persistence may stem from its relationship to the maturation of a firm's internationalisation strategy (Andersson and Loof, 2009). At the initial stages of internationalisation, a firm will likely have fewer destinations, perhaps not so distant. As internationalisation matures, a firm may access more distant markets (Andersson and Loof, 2009), enhance its interactions with foreign contacts, allowing it to exploit opportunities in export markets (Ogasavara et al., 2016). Experience in carrying out export activities also enable firms to increase their knowledge about institutions and stakeholders in the host country (Alegere et al., 2012). Persistent exporters may also be more willing to learn since they have an ongoing and uninterrupted commitment to exporting, as opposed to occasional exporters who may not have a clear exporting strategy and who may not therefore benefit from exporting (Silva et al., 2012). By persistently exporting, firms also learn how to organise and manage exporting activities more effectively (Andersson and Loof, 2009). In line with this, more experienced exporters have greater absorptive capacity and are better able to recombine foreign knowledge with their existing knowledge base (Lane et al., 2006). We therefore hypothesize that:

H4: Relative to intermittent exporters, the effect of export performance on subsequent NTM and NTF innovation performance is stronger for persistent exporters

2.3 Productivity implications of exporting and innovation novelty

2.3.1 From exporting to productivity

As previously discussed, the direct benefits of exporting for productivity are heterogeneous and depend on the degree of export market participation and firm level resources (Andersson and Loof, 2009, Greenaway and Kneller, 2004, D'Angelo a et al., 2020). Nevertheless, exporting is expected to increase productivity since selling in new markets enables firms to spread the cost of innovation over a larger market base, thereby expanding revenues per unit of input, (Gkypali et al., 2021). This should increase firm performance by increasing market share, profitability and growth (Dhanaraj and Beamish, 2003). Exposure to foreign markets also increases the competition firms face which may induce process improvements as firms seek to reduce costs and raise efficiency in competitive global markets. Requirements to comply with international standards can also drive similar improvements (Love and Roper, 2015).

The empirical evidence for the productivity effects of exporting is mixed, however. Some studies find no effect of exporting on productivity (Eliasson et al., 2012, Gatonakis and Love, 2011), perhaps reflecting the longer time it may take for learning effects to reflect in productivity outcomes (Salomon and Shaver, 2005). On the other hand, Andersson and Loof (2009) find that exporting improves productivity for more intensive and persistent exporters, suggesting the role of export market participation in driving these effects. Recent studies on UK small businesses also find direct positive effects of exporting on productivity (Gkypali et al., 2021, Henley and Song, 2020). This suggests:

H5: Higher export performance leads to higher subsequent productivity

2.3.2 From innovation (novelty) to productivity

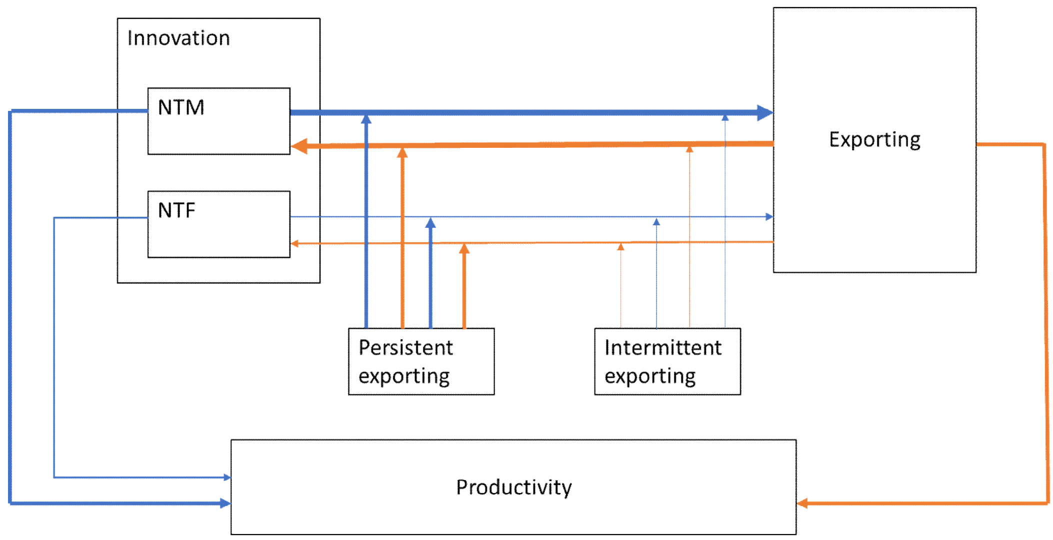
Theoretically, innovation should increase firm level productivity (Hall, 2011). Process innovations can enhance efficiency through lower production costs, and product innovations enable product differentiation, allowing firms to outperform the competition and gain higher market share (Crepon et al., 1998, Hall, 2011). These channels are however moderated by a number of internal and external enablers, including organisational factors, workforce and managerial skills, and internal finance, as well as external factors such as innovation collaborations, the intensity of industry competition, and links to export markets (Love and Roper, 2015).

Empirically, various studies have found positive impacts of innovation on productivity, (Hall et al., 2009, Cheng, 2018, Crowley and McCann, 2018) and on other measures of firm performance including sales and employment growth (Robson and Bennett, 2000, Ganotakis and Love, 2012, Cucculelli and Ermini 2013, Roper et, al., 2008). However, some studies that specifically examine product innovation have found negative productivity effects (Crowley and McCann, 2015), especially those utilising UK firm-level data (Roper et al., 2008, Ganotakis and Love 2012, Gkypali et al., 2021, Henley and Song 2020, Turner et al., 2021). This is perhaps because product innovations may first induce a ‘disruption effect’ since the firm incurs significant costs for new product development (Roper, et al., 2008), potentially leading to short-term efficiency losses (Mohnen and Hall, 2013). This is also consistent with the premise that complex learning processes, more typical of product innovations, represent complicated resources which may only improve competitive advantage in the longer term (Dickson, 1996) and may not be optimal for superior financial performance (Ipek, 2019). Based on the expected short-term efficiency losses associated with product innovations, and the empirical evidence of a negative impact of product innovation on productivity, we expect that NTM and NTF innovations will affect productivity negatively in the short term. Within product innovations, however, there is relatively little evidence on the links between different degrees of innovation novelty and productivity. It is expected that the aforementioned channels linking product innovation and productivity are even stronger for radical new to the market innovations since these enable greater product differentiation but also require greater investments. We thus hypothesize:

H6: NTM innovation performance has a stronger impact on subsequent productivity than NTF innovation performance

Figure 1 summarises our conceptual framework where stronger lines suggest stronger relationships.

Figure 1: Conceptual framework



3. DATA AND METHODS

3.1 Data sources

We use data from eight waves of the UK Innovation Survey (UKIS) – UKIS 4 to 11 – to examine the links between innovation, exporting and productivity. The UKIS is based upon a core questionnaire developed by the European Commission (Eurostat) and Member States, and forms part of a wider survey covering European countries – the European

Union Community Innovation Survey[2]. In the UK, the Office for National Statistics (ONS) – the UK official government statistical office – manages the administration and data collection for the UKIS. The UKIS is conducted every two years through a postal questionnaire and follow-up telephone interviews, and is the main source of innovation data in the UK. The survey provides information on the types on innovation that firms engage in (product or process for example), the degree of novelty of each type of innovation (i.e., new to the market or new to the firm innovation), and the percentage of sales from each type of innovation. It also provides information on the export status of firms and the share of total sales accounted for by exports. In addition, the survey provides information on employment and turnover for all firms, as well as other important control variables such as engagement with R&D and science and engineering skills within firms. Moreover, the UKIS is a large-scale survey with each wave covering around 14,000 firms across manufacturing and services sectors, although not all firms are consistently surveyed across waves. In total, the data covers the 2002 to 2018 period, enabling us to construct an unbalanced longitudinal dataset for those firms that are surveyed more than once. This allows a dynamic and intertemporal analysis of the causal links between innovation, exporting and productivity.

3.2 Model variables

3.2.1 Main dependent variables.

We estimate four baseline models for each of export performance, new-to-market innovation performance, new-to-firm innovation performance, and productivity; these form our main dependent variables. The survey asks respondents to estimate the proportion of their current turnover accounted for by exports and sales from various types of innovations. Export performance is measured as the logarithm of the business's total estimated value of exports as a share of its total turnover at the end of the survey period. New-to market innovation performance is measured as the logarithm of the share of the business's current turnover from sales of goods and services (at the time of the survey) that are new to the market during the preceding three years. New to the firm innovation performance is similarly defined, this time referring to the share of current turnover from sales of goods and services new to the business during the preceding three years. We define productivity

[2] The background and motivation for the innovation survey can be found in the Organisation for Economic Co-operation and Development's (OECD) Oslo manual (OECD 2005), along with a description of the type of questions and definitions used.

in terms of labour productivity, measured as the logarithm of the business's total turnover at the end of the survey period divided by the number of employees during the same period[3]. The survey questions used to construct our dependent variables are presented in Table A1 of Appendix A. On average, export sales represent around 6.4% to 7.2% of turnover depending on the estimation sample[4]. Average NTM innovation sales is around 1.5% to 1.8% of turnover, while average NTF innovation sales range from 2.5% to 3% of turnover. Average productivity (turnover per employee) is around £30,000 (Table A2 of the Appendix A)

3.2.2 Main independent variables

Given our interest in estimating the interrelationships between innovation, exporting and productivity, our main independent variables of interest continue to be new-to-market innovation performance, new-to-firm innovation performance, and export performance, as defined above. In our LTE models, both types of innovations are independent variables in the exporting equations. Conversely, in our LBE models, exporting is an independent variable in the NTM and NTF innovation equations. Exporting, NTM and NTF innovation are independent variables in the productivity equations. Since productivity can itself drive both exporting and innovation, we also include it as an independent variable in the exporting and innovation equations.

We classify a firm as a persistent exporter using an indicator variable equal to one if: i) the firm was surveyed in three or more waves; and, ii) in each wave, the firm reported that it exported it's goods and services. Conversely, a firm is classified as an intermittent exporter if it was surveyed three or more times but reported exporting in some waves but not in others. Our models relating to persistent exporting therefore limit the sample to exporting firms observed in at least three of the eight waves of the survey[5].

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[3] A better measure of productivity would be in terms of value added productivity. However, the UKIS has no data on value added. There is the possibility of matching the UKIS with other datasets, but this is likely to be of little value. Other datasets that contain data on value added, such as ABI, are not available for the population of UK firms so we lose sample size in matching to these. The Business Structures Database (BSD) which covers the population of UK firms also does not provide data on value added productivity.
[4] As will be discussed in later sections we rely on two estimation methods, SUR and system GMM models, that have different data requirements and hence use different estimation samples.
[5] Of course, our classification is based on the assumption that the firms we observe between three and seven times, and who exported each time they were surveyed, also exported in periods they were not surveyed.

3.2.3 Control variables

We include variables to control for factors affecting innovation, exporting and productivity[6]. Specifically, we control for firms' engagement with process innovation by including an indicator variable equal to one if the firm introduced any new or significantly improved processes for producing or supplying goods or services in the preceding three years, and equal to zero otherwise. We take account of the scale of firms' resources by controlling for firm size using three indicator variables relating to small firms (less than 49 employees) medium sized firms (between 50 and 249 employees) and large firms (250 or more employees). We also take account of the skills levels of firms' employees by including the proportion of employees who held a degree or higher qualification in science and engineering subjects, as well as the proportion of employees who held a similar qualification in other (non-science or engineering) subjects. We include the proportion of total expenditure accounted for by investments in design activities. Further, we control for other forms of innovation-related investment by including indicator variables relating to expenditure in training, the acquisition of external knowledge for innovation, expenditure on market introductions of innovations, and investments in internal and external Research and Development (R&D) activities. We control for time specific common effects, for example financial crises or leaving the European Union, by including a full set of wave dummy variables. Finally, we control for time invariant sector and region-specific effects by including sectoral dummies at the 2-digit SIC level as well as regional dummies for 12 UK regions as defined by the Office of National Statistics.

Descriptive statistics and correlation coefficients for all variables used in the analysis are presented in Appendix A.

3.3 Econometric approach

As previously discussed, innovation, exporting and productivity are highly inter-connected: more productive firms may self-select into exporting, and exporting may further enhance productivity. In the same way, innovation sales may enhance export performance, which in turn can drive future innovations. Indeed, theoretical models of innovation and exporting suggests that these firm-level strategic decisions are simultaneously determined with performance outcomes in mind (Hughes, 1986), and both depend on many of the same

[6] See for example factors identified in Love and Roper, (2015).

firm-level factors (Reid, 1981). Moreover, innovation, exporting and productivity are each persistent in that current levels of these outcome variables are likely to depend on their past values. Firms' previous export experience will also affect future export decisions (Love and Manez, 2019, Caldera, 2010), and the cumulative nature of knowledge means that past innovations reinforce future innovations (Love et al., 2014). Past levels of productivity also influence current productivity through enhancing the likelihood of investments in productivity enhancing strategies such as exporting and innovation (Aghion et al., 2018). It becomes important, therefore, to implement a dynamic model that allows each outcome of interest to depend on its past values, so that we do not inadvertently attribute its influence to other variables in the model. This is even more important in our context given the temporally intertwined nature of innovation, exporting and productivity. To model these relationships effectively, therefore, one must contend with various potential sources of endogeneity, including self-selection, simultaneity, reverse causality and dynamic panel bias.

First, we estimate the following four models:

$$\log\,(Export\ share)_t = \beta_1 \log(NTM\ innovation)_{t-1} + \beta_2 \log(NTF\ innovation)_{t-1} + \beta_3 \log(Productivity)_{t-1} + \beta_4 Controls_{t-1} + \varepsilon_{i,t},\ \ i = 1 \dots 4 \dots\dots\dots\ (1)$$

$$log\ (NTM\ innovation)_t = \beta_1\ log(Export\ share)_{t-1} + \beta_2\ log(NTF\ innovation)_{t-1} + \beta_3 log(Productivity)_{t-1} + \beta_4 Controls_{t-1} + \varepsilon_{i,t} \dots\dots\dots\ (2)$$

$$log\ (NTF\ innovation)_t = \beta_1\ log(Export\ share)_{t-1} + \beta_2\ log(NTM\ innovation)_{t-1} + \beta_3 log(Productivity)_{t-1} + \beta_4 Controls_{t-1} + \varepsilon_{i,t} \dots\dots\dots\ (3)$$

$$log\ (Productivity)_t = \beta_1\ log(Export\ share)_{t-1} + \beta_2\ log(NTM\ innovation)_{t-1} + \beta_3 log(NTF\ innovation)_{t-1} + \beta_4 Controls_{t-1} + \varepsilon_{i,t} \dots\dots\dots\ (4)$$

Equation (1) represents our LTE model, in which the firm's export share in wave *t* depends on its sales from NTM innovations and NTF innovations, as well as its productivity, in wave *t-1.* The introduction of lags in the independent variables not only allows for the passage of time required for exporting to respond to changes in innovation and productivity, but also reduces simultaneity by removing contemporaneous correlations[7]. Equations (2) and (3)

[7] Note again that the UKIS waves are two years apart. A t-1 – or one wave lag – here therefore indicates a two-year time lag in each variable.

present our LBE models, where NTM innovation performance (Equation (2)) and NTF innovation performance (Equation (3)) depend on previous export share and previous productivity. Finally, equation (4) represents our productivity equation, where current productivity depends on previous export share, NTM innovation performance and NTF innovation performance. In each of Equations (1) to (4), *Controls* is a vector of control variables, including time, sector and region dummies, as outlined in Section 3.2.3.

To estimate the moderating effect of export persistence on LTE and LBE, we limit the sample to include only firms that have been surveyed at least three times, and then only firms that have reported exporting at least once. This allows us to distinguish between persistent exporters and intermittent exporters as described in Section 3.3, while eliminating firms that have never exported during the sample period. We then estimate the following models:

$$\log(Export\ share)_t = \beta_1 \log(NTM\ innovation)_{persistent,t-1} + \beta_2\, log(NTM\ innovation)_{intermittent,t-1} + \beta_3\, log(NTF\ innovation)_{t-1} + \beta_4 \log(Productivity)_{t-1} + \beta_5 Controls_{t-1} + \varepsilon_{i,t},\ \ i = 1 \dots 4 \dots\dots\dots \text{(5)}$$

$$log\ (Export\ share)_t = \beta_1\, log(NTF\ innovation)_{persistent,t-1} + \beta_2\, log(NTF\ innovation)_{intermittent,t-1} + \beta_3\, log(NTM\ innovation)_{t-1} + \beta_4 log(Productivity)_{t-1} + \beta_5 Controls_{t-1} + \varepsilon_{i,t},\ \ i = 1 \dots 4 \dots\dots\dots \text{(6)}$$

$$log\ (NTM\ innovation)_t = \beta_1\, log(Export\ share)_{persistent,t-1} + \beta_2\, log(Export\ share)_{intermittent,t-1} + \beta_3\, log(NTF\ innovation)_{t-1} + \beta_4 log(Productivity)_{t-1} + \beta_5 Controls_{t-1} + \varepsilon_{i,t} \dots\dots\dots \text{(7)}$$

$$log\ (NTF\ innovation)_t = \beta_1\, log(Export\ share)_{persistent,t-1} + \beta_2\, log(Export\ share)_{intermittent,t-1} + \beta_3\, log(NTM\ innovation)_{t-1} + \beta_4 log(Productivity)_{t-1} + \beta_5 Controls_{t-1} + \varepsilon_{i,t} \dots\dots\dots \text{(8)}$$

As a baseline estimation approach, we first estimate Equations (1) to (8) using a Seemingly Unrelated Regression (SUR) model. This model estimates each equation separately but allows the errors, $\varepsilon_{i,t,\ \ i=1..4}$ to be correlated across the equations, with errors that are jointly normally distributed (Roodman, 2011). This property makes SUR a more efficient estimator than separate Ordinary Least Squares (OLS) estimators, especially where there exists correlation among disturbances as we expect in these equations.[8]. Since models are simultaneously estimated, Equation (5) and equation (6) which have the same dependent variable (Export share) are merged in the SUR models, so that we estimate the moderating effects of persistence for both NTM and NTF innovation performance in one exporting equation.

Although we include a full set of sector, time, and regional fixed effects, and we use lagged values of independent variables to limit simultaneity, the SUR model still does not account for other sources of endogeneity. For example, in the LTE models (Equation 1), lagged innovation is only predetermined, but not strictly exogenous, with respect to current exports; the decision to innovate in the previous period may be taken with the expectation of exporting in the current period. In this way, previous innovation becomes endogenous in the exporting equation. Moreover, we are unable to account for the aforementioned persistence in innovation, exporting and productivity through including lagged dependent variables; doing so here will introduce another source of endogeneity, i.e., dynamic panel bias[9].

To address these concerns, we estimate a system GMM estimator (Blundell and Bond, 1998). This estimator is designed for longitudinal data in which the number of firms in the data is considerably larger than the number of available time periods (Large *N*, small *T* panels). It is specifically designed for a data generating process subject to the following: i) it may be dynamic, with past values of the outcome variables influencing current values; ii) some covariates are endogenous; iii) there is the potential for firm-specific fixed effects; iv) the errors may be heteroskedastic and serially correlated. We therefore estimate each of Equations (1) to (8) separately within the GMM framework, this time including the lagged dependent variable in each equation and excluding regional and industry dummy variables. This is because the system GMM model already accounts for such group specific fixed effects by instrumenting the lagged dependent variable, and other similarly endogenous variables, with instruments assumed uncorrelated with time invariant fixed effects; explicitly including these may bias the estimates especially in samples with small T dimension (Roodman, 2009).

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[8] We use the CMP module within STATA (Roodman, 2011) to estimate these equations simultaneously

[9] Note that, without a large time dimension, a dynamic fixed effects estimator is similarly biased (Judson and Owen, 1999, Roodman 2009)

The system GMM estimator we employ handles the endogeneity of the lagged dependent variable (dynamic panel bias), and other similarly endogenous variables, by using internal instruments. In particular, the right-hand side variables in Equations (1) to (8) are instrumented with the first differences of their past levels. In the absence of second order serial correlation, these first differences are uncorrelated with current errors $\varepsilon_{i,t}$, but they should be highly correlated with the levels of covariates, making them potentially ideal instrumental variables. In our application, we use the first differences of second and deeper lags of the covariates as instruments, meaning our GMM estimation sample is limited to firms with at least four observations. The identification strategy in system GMM requires convergence (i.e., that the coefficient of the lagged dependent variable is less than unity), which is easily observable from the estimated models. It also requires the absence of second order serial correlation, which we test using the Arellano Bond test (Arellano and Bond, 1991). To test for the exogeneity of our instrument set, we use the Hansen's J statistic of overriding restrictions[10]. We also include the full set of time dummy variables to remove common time related shocks, reducing contemporaneous cross-section dependence. Finally, we employ the two-step system GMM estimator which is asymptotically more efficient than the one-step estimator (Roodman, 2009), and we use Windmeijer (2005) standard errors to correct for the downward bias of standard errors in two-step estimation.

4. RESULTS

Table 1 shows the results from our LTE models in Equations (1), estimated using the SUR and GMM models. Here and in subsequent tables, we omit covariates to save space but we include full regression tables in Appendix B. It is noteworthy that our dependent and independent variables are logarithmic, such that our coefficients represent elasticities, i.e., a percentage change in the dependent variable in response to a percentage change in the

[10] We prefer the system GMM estimator to the difference GMM estimator because the former allows us to include dummy variables as control variables in the model, such as indicators of firm size; these would be differenced out in a difference GMM estimator. The system GMM estimator is also less sensitive to a problem of weak instruments, although it requires a larger number of instruments. However, our large number of observations and the large individual (firm) dimension make this of limited concern.

independent variable. To facilitate comparison across the variables, we also report our results in terms of the standardised coefficients, presented in Appendix C[11].

In Table 1, results from the SUR model show that a 1% increase in NTM innovation performance is associated with a 0.07% increase in subsequent export performance. In standard deviation terms, a one Standard Deviation (SD) increase in NTM innovation performance is associated with a 0.03 standard deviation increase in export performance. Table 1 also shows, for the SUR model, that a 1% increase in NTF innovation performance is associated with a 0.03% increase in subsequent export performance (a one SD change is associated with a 0.02 SD increase in export performance). In the second column of Table 1, results from the GMM model show that a 1% increase in NTM innovation performance leads to a 0.03% increase in subsequent export performance; a one SD increase leads to a 0.02 SD increase in exports. NTF innovation performance has no causal impact on subsequent export performance. Taken together, the results lead to a similar qualitative conclusion: NTM innovation performance is a much stronger driver of export performance than is NTF innovation performance. In line with H1, this result shows that NTM innovation, not NTF innovation, matters most for LTE.

Although qualitatively similar, it is important to note the quantitative differences between the SUR and GMM estimation methods. In the GMM model, the magnitude of the effect of NTM innovation is about half that from the SUR models and NTF innovation performance loses economic and statistical significance. This partly reflects the fact that the GMM model accounts for the high persistence in export performance. For example, in column 2 of Table 1, a 1% increase in export performance leads to an 0.83% increase in subsequent export performance. The SUR model therefore overestimates the importance of both NTM and NTF innovation performance in determining exports; it does not account for previous export performance, thereby attributing its effects to other variables in the model. Differences between the two models also reflects the GMM model's use of strong instrumental variables that account for the potential endogeneity of innovation (and other similarly endogenous variables) in the export equations. This is best illustrated with the estimated coefficient of productivity on export performance: a 1% increase in productivity raises subsequent export performance by 0.21% in the SUR model, more than four times the

[11] Standardised coefficients are calculated as the coefficient estimate multiplied by the ratio of the standard deviation of the independent variable to that of the dependent variable. For each of the SUR and GMM models, we use the standard deviations of the corresponding sample (see Appendix A).

estimated impact from the GMM model (0.045%)[12]. This underlines the importance of adopting a dynamic specification with a strong identification strategy if we are to disentangle the causal relationships we seek to identify.

In our LTE models, it is also interesting to note the relative importance of productivity and innovation in driving subsequent export performance. Since we include both variables in our export equations, we are able to disentangle the 'learning' from the 'self-selection' hypotheses advanced in the literature. Our results suggest that the self-selection mechanism is more important than the pure learning mechanism, since the impact of productivity on subsequent export performance is stronger than the impact of both NTM and NTF innovations. This result, consistent across the SUR and GMM models, can help explain smaller effect sizes of the innovation measures.

The subsequent columns of Table 1 show the role of persistent exporting in moderating these LTE relationships (Equation (5) and (6)). Here, results from both the SUR model and the GMM model show strong moderating effects of export persistence. In particular, both NTM and NTF innovation performance exert a strong positive effect on subsequent export performance if the firm is a persistent exporter. Conversely, if a firm is an intermittent exporter, the effects of NTM and NTF innovations are negative and significant. Specifically, the SUR models (column 3 of Table 1) show that a 1% increase in NTM (NTF) innovation performance is associated with an increase in subsequent export performance of 0.1% (0.17%) for persistent exporters. In standard deviation terms, a one SD increase in NTM (NTF) innovation performance is associated with a 0.04(0.13) SD increase in export performance for persistent exporters. On the other hand, a 1% increase in NTF (NTM) innovation performance is associated with a reduction in export performance of 0.07% (0.12%) for intermittent exporters. This translates into a 0.03 (0.1) SD reduction in export performance in response to a one SD increase in NTM (NTF) innovation performance. The GMM models (columns 4 and 5 of Table 1) show a similar pattern with generally lower magnitudes of effects. Here, a 1% increase in NTM (NTF) innovation performance increases subsequent export performance by 0.078% (0.08%) for persistent exporters, but reduces it by 0.093% (0.085%) for intermittent exporters. In standard deviation terms, a one SD increase in NTM (NTF) innovation performance increases export performance by 0.043 (0.064) SD for persistent exporters, and reduces it by 0.051 (0.067) SD for intermittent exporters. Together, these results strongly support H2, and suggests that only

[12] Future work will consider long-run estimates of the GMM model which may be slightly larger.

persistent exporters are able to turn their innovations into higher subsequent export performance; intermittent exporters may instead focus on domestic markets for their innovations.

Table 2 shows results from our LBE models in Equations (2) and (3). Both SUR and GMM models suggest that the effect of export performance on subsequent innovation performance is positive and significant for both NTM and NTF innovations, but the effect is larger for NTF innovation performance. The first two columns of Table 2 show the results from the SUR models. Here, a 1% increase in export performance is associated with an increase of 0.03% (0.05%) in NTM (NTF) innovation performance; a one SD increase in export performance is associated with a 0.05 (0.06) SD increase in NTM (NTF) innovation performance. The GMM model (columns 3 and 4 of Table 2) shows that a 1% increase in export performance increases NTM (NTF) innovation performance by 0.04% (0.06%). A one SD increase in export performance increases NTM (NTF) innovation performance by 0.09 (0.07) SD. It is interesting to note here that, unlike the LTE models, the magnitude and significance of the effects of exporting on innovation are similar in both the SUR and GMM models. This reflects the fact that innovation performance is much less persistent than export performance in our models, with the GMM models showing that a 1% increase in NTM (NTF) innovation performance increases subsequent NTM (NTF) innovation performance by 0.25% (0.16%). For LBE, results from both models suggest that export performance has a higher impact on NTF innovation performance than on NTM innovation performance, although the differences in the magnitudes of the effects are smaller than those from the LTE models. Nevertheless, this result does not support H3, which states that the positive effect of export performance on subsequent innovation performance is stronger for NTM innovations. That LBE leads to more incremental innovations, as opposed to radical inventions, is in line with the argument that exporting firms may learn the most from their foreign clients and customers, and that such learning may result in product customisation and adaptation to suit the tastes and preferences of these clients rather than new radical innovations.

Table 2 also shows the role of persistent exporting in LBE (Equations (7) and (8)). Again, both SUR and GMM models show a strong and significant positive impact of export performance on NTM and NTF innovation performance for persistent exporters, but a negative effect (SUR models) or an insignificant effect (GMM model) for intermittent exporters. In particular, the SUR models (columns 5 and 6 of Table 2) show that for persistent exporters, a 1% increase in export performance is associated with a 0.05% (0.09%) increase in subsequent NTM (NTF) innovation performance. This translates to a

0.08 (0.11) SD increase in NTM (NTF) innovation performance in response to a one SD increase in export performance. Conversely, for intermittent exporters, a 1% increase in export performance is associated with a 0.02% (0.04%) reduction in subsequent NTM (NTF) innovation performance. In standard deviation terms, a one SD increase in export performance is associated with a 0.04 (0.05) reduction in NTM (NTF) innovation performance for intermittent exporters. The GMM models (Columns 7 and 8 of Table 2) show that for persistent exporters, a 1% increase in export performance leads to a 0.04% (0.05%) increase in subsequent NTM (NTF) innovation performance; a one SD increase in export performance increases NTM (NTF) innovation performance by 0.1 (0.07) SD. Conversely, export performance has no effect on intermittent exporters in the GMM model. Together, these results provide strong support for H4 and suggest that only persistent exporters learn by exporting; intermittent exporters that have interrupted access to foreign markets do not increase their innovation performance subsequent to exporting.

Table 3 shows the productivity effects of exporting and innovation. Both the SUR and GMM models show a strong and significant impact of export performance on subsequent productivity. The SUR models (column 1 of Table 3) shows that a 1% increase in export performance is associated with 0.17% increase in subsequent productivity. This corresponds to a 0.22 SD increase in productivity in response to a one SD increase in export performance. The GMM model (column 2 of Table 3) shows a much smaller causal impact: a 1% increase in export performance leads to a 0.03% increase in subsequent productivity, corresponding to a 0.03 SD increase in productivity resulting from a one SD increase in export performance. As with the LTE models, this discrepancy between the SUR and GMM models regarding the magnitude of the effects of exporting on productivity is most likely to reflect the dynamic specification of the GMM model since productivity, like export performance, is highly persistent in our data. Nevertheless, results from the SUR and GMM models both support H5 which states that higher export performance leads to higher subsequent productivity.

Table 3 also shows the effects of NTM and NTF innovation performance on productivity. The SUR model (column 1 of Table 3) shows that a 1% increase in NTM innovation performance is associated with a 0.04% decrease in productivity; this corresponds to a 0.03 SD reduction in productivity in response to a one SD increase in NTM innovation performance. NTF innovation performance has no significant impact in the SUR model. The GMM model (column 2 of Table 3) shows a negative but insignificant effect of both NTM innovation and NTF innovation on subsequent productivity. Taken together and prioritising the GMM estimates, the results indicate an absence of a strong relationship between both types of innovation and productivity[13]. This provides no support for H6, which states that NTM innovations have a stronger (negative) impact on subsequent productivity than NTF innovations. Nevertheless, the finding of an insignificant effect of innovation on productivity is in line with the 'disruption effect' of innovation leading to short term efficiency losses (Roper, et al., 2008; Turner et al. 2021).

4.1 Supplementary analysis

Given the contrasting effects of exporting and innovation on productivity, we explore potential complementarities between them. These complementarities may exist because innovation increases product quality, allowing firms to charge higher prices and sell higher quantities domestically and abroad (Golovko and Valentini, 2011). Exporting also allows access to international knowledge spillovers, which further enhance firms' innovation activities. This interdependence between innovation and exporting, generated through LTE and LBE, may produce a virtuous and reinforcing circle, implying that they are potentially complementary activities for firm performance (Golovko and Valentini, 2011). Indeed, Golovko and Valentini (2011) find empirical evidence for such complementarities. In their analysis only firms that innovate *and* export have high sales growth, but engaging in either exporting or innovation alone proves a suboptimal strategy.

To explore such complementarities, we estimate the influence of exporting status in moderating the effects of innovation propensity and innovation performance on productivity. We first estimate the productivity effect of NTM and NTF *innovation propensity*, conditional on firms' exporting status. NTM innovation propensity is measured using an indicator variable to equal to 1 if a firm answered "yes" to the survey question: "During the [preceding] 3-year period, were any of your goods or services innovations new to the market?", and zero otherwise. Similarly, NTF innovation propensity is measured using an indicator variable equal to 1 if the firm answered "yes" to the survey question: "During the [preceding] 3-year period, were any of your goods or services innovations only new to your business?", and zero otherwise. Innovation propensity therefore measures the probability that firms engaged in NTM or NTF innovation over the preceding three years.

We then estimate the productivity effect of NTM and NTF i*nnovation performance* (i.e. proportion of innovation sales) conditional on firms' exporting status. In columns 3 and 4 of

[13] This is corroborated by the insignificant of the productivity coefficients in innovation equations (Table 2)

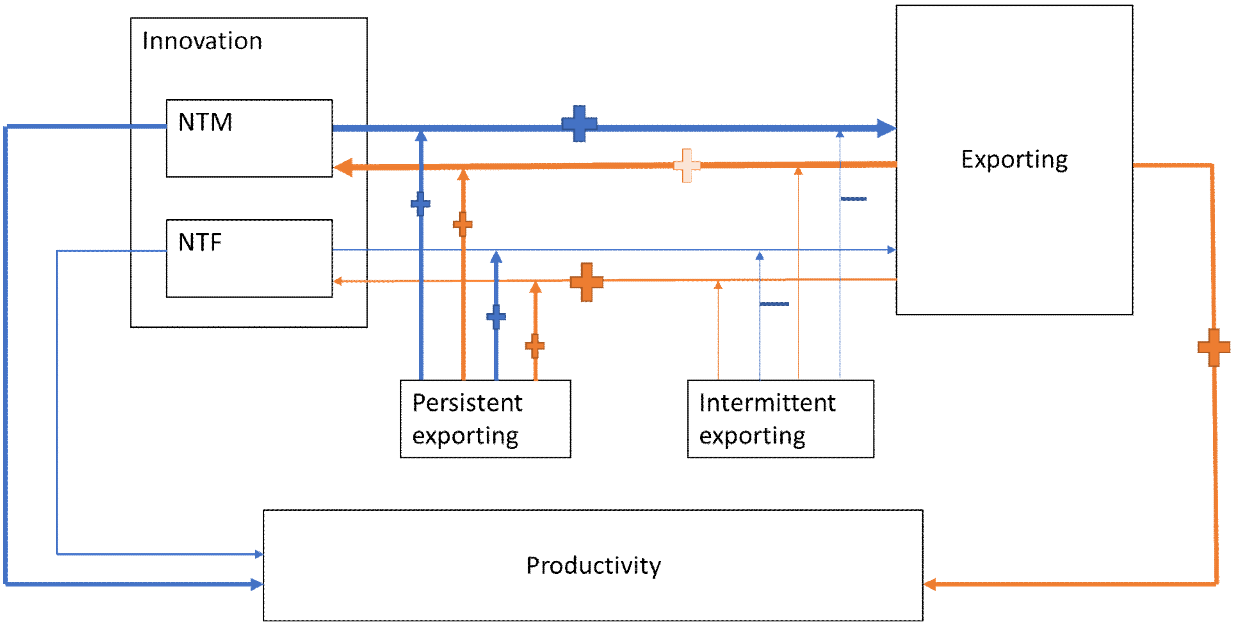
Table 3, both the GMM and SUR models show that being a NTM or NTF innovator has a positive productivity impact *if the firm is also an exporter* and a negative impact if the firm is not. Thus, export market participation appears to offset some of the disruption effects of engaging in product innovation since it provides a larger market base on which to spread innovation costs. However, subsequent columns of Table 3 show that this moderating effect of export status does not extend to innovation performance. That is, higher innovation performance (NTM or NTF) does not increase productivity even if the firm is an exporter. This suggests that complementarities between innovation and exporting are more important for innovation propensity than for innovation performance[14].

Given that firms in different industries may learn to export or learn by exporting at different rates, for example depending on their technological gap with trading partners (Salomon and Jin, 2008), we estimated our models for manufacturing and services firms and investigate differences. We also examine how the effects we identify differ for small, medium and larger firms, since smaller firms may be more agile and may therefore learn more efficiently from exporting (Andersson and Loof, 2009). Small firms may also be more likely to undertake radical innovations subsequent to exporting (Golovko and Valentini, 2014). Table 4a and Table 5a show the results from SUR models, Table 4b and Table 5b show those from GMM models. The results suggest that many of the effects we identify are stronger for manufacturing firms, except that the productivity effects of exporting is slightly larger for services firms. There is greater variation by firm size. The effects of NTM innovation on exporting (LTE) tends to be larger for medium and large firms, while the effects of exporting on both NTF and NTM innovation (LBE) tend to be slightly larger for small firms.

Figure 2 below depicts our main hypothesis as set out in our conceptual model in Figure 1, here including the direction and strength of effects we identify.

[14] In unreported regressions we also consider potential complementarities between innovation performance and persistent exporting, but we find no significant effects.

Figure 2: Results summary for the relationship between innovation novelty, exporting and productivity



5. DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

We set out to examine the causal links between exporting, innovation novelty and productivity while considering how export persistence may affect these relationships. We hypothesised that, compared to incremental innovations, radical innovations will lead to greater export performance, and export performance will in turn lead to greater radical innovation. We also hypothesised that both of these channels would be stronger for persistent exporters, as opposed to firms that export only intermittently. Moreover, we argued radical innovation would have a stronger impact on firm level productivity in the short-term, since cost implications may lead to short-term efficiency losses. We also hypothesized that export performance would lead to higher productivity even in the short-term, since it implies that firms have a wider market base in which to sell their products. Hypotheses and empirical outcomes are summarised in Table 6.

Our findings contribute to the literature on Learning to Export (LTE) and Learning by Exporting (LBE) in several ways. We found that, as hypothesised, radical innovations exert a strong positive impact on subsequent export performance, but incremental innovations do not (Table 6). This finding qualifies a long-standing consensus in the LTE literature, namely that product/service innovations, not process innovations, matter for export success (Cassiman et al., 2010, Gkypali et al., 2021). In particular, our findings indicate diversity even within product/service innovations: only radical, new to the market product innovations are linked to export performance, whereas incremental product modifications or new to the firm innovations are of little importance. This is intuitive since such breakthrough innovations are likely to elicit higher demand in foreign markets. Of course, here we consider the UK, which is a technologically advanced country whose export destinations consist mainly of similarly advanced nations. It is therefore intuitive that only technologically superior innovations will have a competitive advantage in these foreign markets, whereas minor product modifications may not be competitive. Now that the UK has left the European Union and has the ambition to engage with more diverse export markets, it will be interesting to see whether incremental innovations in the UK begin to drive export performance when less technologically advanced countries become important export destinations. In those countries, UK incremental innovations may provide substantially higher customer benefits than domestically produced goods.

We also found that higher export performance leads to greater innovation performance for both radical and incremental innovations, but that this effect is somewhat stronger for incremental innovations (Table 6). This finding contributes to the literature on Learning by Exporting (LBE). Here, again, previous studies have paid little attention to the degree of innovation novelty that may result from engagement with export markets, with a recent study finding that export performance affects radical and incremental innovations in similar ways (Freixanet and Rialp, 2022). Our finding suggests that exporting is more likely to induce product modifications, rather than more radical product innovations. This may partly reflect the type of information that firms access in foreign markets, which in turn informs their innovation activities. In particular, our findings suggest that firms gather information about tastes and preferences of foreign customers, and use this to adapt and customise their existing products to suit these preferences. Taken together with our previous finding, the implication is that firms need radical inventions to be successful exporters, and that successful exporting then allows them to continuously improve their products, enhancing incremental innovation performance. Nevertheless, exporting also allows more radical innovation, albeit to a lesser extent. This latter channel is most likely to work through exporting firms' access to advanced foreign technological knowledge that is conducive to radical innovations.

Our third main finding relates to the role of persistent exporting in determining whether innovation, radical or incremental, leads to higher export performance (LTE), and whether export performance leads to higher innovation performance (LBE). We find that only firms that export persistently are able to gain higher export performance from their innovations (LTE), and only these firms experience greater innovation performance because of their exports (LBE) (Table 6). For intermittent exporters that export only some of the time, innovations lead to lower subsequent export performance, and export performance has no impact on subsequent innovation performance. These findings contribute to our understanding of how different types of exporting behaviour and export strategies influence the learning processes associated with exporting (Ipek, 2019). In particular, our findings suggest that consistent access to foreign markets is important, because it allows a consistently larger market base in which to market innovations, and it provides uninterrupted interactions with foreign market actors, including foreign clients, which may better facilitate the knowledge gathering efforts necessary for innovation.

We further find differences by firm size and industry in the LTE and LBE effects. In particular, LTE effects tend to be stronger for larger firms, while LBE effects are slightly stronger for the smallest firms. This underlines the level of resources required for the type of radical inventions that support high export performance, which may put small firms at a disadvantage. On the other hand, the fact that exporting leads to slightly higher innovation performance for smaller firms reflects their agile nature that allows them to learn more efficiently from exporting (Andersson and Loof, 2009). In terms of industry, our findings suggest that the benefits of innovation and exporting tend to be generally larger for firms in the manufacturing sector relative to those in the services sector.

Our next finding relates to the implications of exporting and innovation for productivity. Here, we find that innovation, radical or incremental, has little impact on productivity at least in the short-term, but exporting has a positive productivity impact. These findings are generally in line with previous studies (for example Gkypali et al., 2021, Henley and Song 2020, Turner et al., 2021). We also find that engaging in both radical and incremental innovations increase productivity if the firms are also exporters, indicating strong complementarities between innovation status and exporting status.

Our study has a number of limitations. First, we do not consider the export destinations of firms, and this has been found to be an important determinant of the learning and innovation processes related to exporting (Freixanet and Rialp, 2022). Future research can seek to establish the role that innovation novelty and export persistence play in determining LTE and LBE while considering export markets with varying degrees of technological advancement. Second, data limitations mean that our measure of persistent exporting is imperfect, and makes out-of-sample assumptions about exporting behaviour of some firms based on their in-sample exporting behaviour. It will be useful if future research with a balanced longitudinal dataset can capture a more robust impact of export persistence on the LTE and LBE processes. Finally, our finding on the role of export persistence in LTE is particularly novel, and while it may reflect that persistent exporters have a larger market base for their innovation, it may also suggest that intermittent exporters are simply domestically focused in the periods following their innovations, so that their export performance falls. This finding therefore opens up future avenues for research, particularly on a conceptual level, on how and why persistent exporting may enhance the benefits of innovation for subsequent export performance.

Our paper suggests implications for policy. First, our findings suggest that the benefits of innovation support measures with the aim of stimulating exporting are greatest for firms that already have a technological advantage in the domestic market and are achieving greater sales from their radical innovations. This suggests that identifying companies which are domestic market leaders but not exporting, and targeting these firms for export support may create the greatest productivity improvements through greater and faster returns on their innovations. Second, to support the cultivation of a more innovative economy more generally, export support policies should explicitly incorporate the exploration of foreign knowledge sources as a deliberate policy objective, since exporting enhances both NTM and NTF innovations. Smaller firms may also be in a better position to translate the learning from export markets into innovations, or at least benefit more from that learning. Third, export promotion policies should also encourage sustained and committed engagements with export markets in order to maximise the value of learning. Finally, our findings suggest that such policies can be tailored to firms in both manufacturing and services sectors, and firms of all sizes.

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TABLES

Table 1: Learning to Export (LTE)

	LTE-SUR	LTE-GMM	LTE: persistence-SUR	LTE: persistence-GMM	
Y=log(exports)					
Log (exports), t-1		0.829***		0.732***	0.721***
		(0.00936)		(0.0149)	(0.0155)
Log (NTM sales), t-1	0.068***	0.0313**			0.00489
	(0.013)	(0.0152)			(0.0217)
Log (NTF sales), t-1	0.030***	0.00248		0.00364	
	(0.009)	(0.00912)		(0.0144)	
Log (productivity), t-1	0.209***	0.0451***		0.0639***	0.0585***
	(0.011)	(0.00712)		(0.0171)	(0.0188)
Log (NTM sales), t-1- persistent exporter			0.097***	0.0777***	
			(0.027)	(0.0233)	
Log (NTM sales), t-1- intermittent exporter			-0.070**	-0.093***	
			(0.031)	(0.031)	
Log (NTF sales), t-1- persistent exporter			0.174***		0.0796***
			(0.020)		(0.0195)
Log (NTF sales), t-1- intermittent exporter			-0.121***		-0.0845***
			(0.020)		(0.0208)
Observations	24,594	11,009	9,676	4,454	4,454
Number of firms		7,768		2,802	2,802
AR(2) test		1.336		1.271	1.305
AR(2) p-vale		0.182		0.204	0.192
Hansen test		260.9		276.1	271.5
Hansen p-value		0.274		0.277	0.362
p-value				0.00	0.000
Time dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	No	Yes	No	No

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Covariates omitted for brevity

Table 2: Learning by Exporting (LBE)

Table 2: Learning by Exporting (LBE)								
	LBE-SUR		LBE-GMM		LBE: persistence-SUR		LBE: persistence-GMM	
Y= NTM/NTF innovation sales	Log(NTM sales)	Log(NTF sales)	Log(NTM sales)	Log(NTF sales)	Log(NTM sales)	Log(NTF sales)	Log(NTM sales)	Log(NTF sales)
Log (NTM sales), t-1		-0.014*	0.248***	0.161***		-0.015	0.300***	0.180***
		(0.008)	(0.0236)	(0.0258)		(0.013)	(0.0363)	(0.0389)
Log (NTF sales), t-1	0.004		0.0343***	0.164***	0.008	-0.015	0.0494***	0.205***
	(0.004)		(0.00961)	(0.0161)	(0.007)	(0.028)	(0.0183)	(0.0257)
Log (exports), t-1	0.029***	0.047***	0.0392***	0.0563***				
	(0.007)	(0.010)	(0.00572)	(0.00805)				
Log (productivity), t-1	-0.015*	-0.009	-0.00357	0.00169	-0.031		-0.0109	-0.00430
	(0.008)	(0.013)	(0.00473)	(0.00607)	(0.020)		(0.0101)	(0.0136)
Log (exports), t-1- persistent exporter					0.046***	0.086***	0.0425***	0.0522**
					(0.010)	(0.015)	(0.00824)	(0.0232)
Log (exports), t-1- intermittent exporter					-0.024**	-0.041**	-0.0102	-0.00272
					(0.012)	(0.017)	(0.0101)	(0.0377)
Observations	24,594	24,594	14,974	15,102	9,676	9,676	5,722	5,746
Number of firms			11,220	11,353			3,798	3,830
AR(2) test			-0.329	1.189			-0.298	0.771
AR(2) p-vale			0.742	0.235			0.766	0.440
Hansen test			237.9	222.2			241.9	205.5
Hansen p-value			0.667	0.879			0.727	0.974
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	No	No	Yes	Yes	No	No

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Covariates omitted for brevity. Observations are significantly lower in the export persistence models as these are limited to the sample of exporters observed in three or more survey waves.

Table 3: Productivity -direct and complementary effects of exporting and innovation novelty

	Main models		Innovation status and exporting status		Innovation performance and exporting status	
Y=log(productivity)	SUR	GMM	SUR	GMM	SUR	GMM
Log (productivity)		0.784***		0.703***		0.787***
		(0.0127)		(0.0106)		(0.0129)
Log (exports)	0.169***	0.0262***			0.170***	0.0292***
	(0.010)	(0.00450)			(0.010)	(0.00467)
Log (NTM sales)	-0.042***	-0.00925				
	(0.012)	(0.00831)				
Log (NTF sales)	0.000	0.00680				
	(0.008)	(0.00572)				
NTM innovator-exporter			0.063**	0.0491***		
			(0.026)	(0.0174)		
NTM innovator-non-exporter			-0.083***	-0.0410**		
			(0.022)	(0.0171)		
NTF innovator-exporter			0.148***	0.0685***		
			(0.024)	(0.0160)		
NTF innovator-non-exporter			-0.072**	-0.0379		
			(0.030)	(0.0254)		
Log (NTM sales)-exporter					-0.050***	-0.0109
					(0.016)	(0.0108)
Log (NTM sales)-non exporter					-0.029	0.000928
					(0.019)	(0.0128)
Log (NTF sales)-exporter					0.001	-0.00341
					(0.011)	(0.00698)
Log (NTF sales)-non-exporter					-0.001	0.0179**
					(0.011)	(0.00821)
Observations	24,594	14,833	28,090	24,999	24,594	14,828
Number of firms		10,961		15,810		10,959
AR(2) test		1.070		1.577		1.073
AR(2) p-vale		0.285		0.115		0.283
Hansen test		264.1		371.2		295.6
Hansen p-value		0.231		0.117		0.249
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	No	Yes	No	Yes	No

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Covariates omitted for brevity.

Table 4a: LTE, LBE, and productivity effects by sector- GMM models

	LTE		LBE		Productivity		
VARIABLES	Log(exports)	Log(exports)	Log (NTM sales)	Log (NTF sales)	Log (Productivity)	Log (Productivity)	Log (Productivity)
Log(exports)-manufacturing			0.0648***	0.0821***			0.0221***
			(0.00864)	(0.0115)			(0.00487)
Log(exports)-services			0.00975	0.0228**			0.0311***
			(0.00737)	(0.00977)			(0.00663)
Log (NTM sales) manufacturing	0.0796***				-0.0250**		
	(0.0214)				(0.0114)		
Log (NTM sales) services	0.00509				-0.000865		
	(0.0188)				(0.00960)		
Log (NTF sales) manufacturing		0.0596***					
		(0.0153)					
Log (NTF sales) services		-0.0183**				0.0106	
		(0.00927)				(0.00669)	
Observations	11,009	11,009	14,974	15,102	14,833	14,833	14,833
Number of firms	7,768	7,768	11,220	11,353	10,961	10,961	10,961
AR(2) test	1.335	1.345	-0.331	1.161	1.071	1.072	1.070
AR(2) p-vale	0.182	0.179	0.740	0.246	0.284	0.284	0.285
Hansen test	279.7	270.9	246.6	233.4	276.5	285	278.2
Hansen p-value	0.242	0.372	0.701	0.872	0.286	0.179	0.197
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Covariates omitted for brevity.

Table 4b: LTE, LBE, and productivity effects by sector- SUR models

	LTE	LBE		Productivity
VARIABLES	Log(Export share)	Log(NTM sales)	Log(NTF sales)	Log(productivity)
Log (exports)-manufacturing		0.050***	0.066***	0.131***
		(0.009)	(0.013)	(0.012)
Log(exports)-services		0.015*	0.037***	0.194***
		(0.008)	(0.012)	(0.011)
Log (NTF sales)-manufacturing	0.080***	0.028***		-0.002
	(0.014)	(0.006)		(0.014)
Log(NTF sales)-services	0.004	-0.006		0.001
	(0.010)	(0.004)		(0.010)
Log(NTM sales, manufacturing)	0.087***		-0.020	-0.048**
	(0.020)		(0.013)	(0.020)
Log(NTM sales) services	0.053***		-0.008	-0.039***
	(0.016)		(0.010)	(0.015)
Log(productivity)	0.209***	-0.014*	-0.009	
	(0.011)	(0.008)	(0.013)	
Observations	24,594	24,594	24,594	24,594

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5a: LTE, LBE and Productivity effects by firm size- GMM models

	LTE		LBE		Productivity		
VARIABLES	Log (exports)	Log (exports)	Log (NTM sales)	Log (NTF sales)	Log (productivity)	Log (productivity	Log (productivity
Log (NTM sales)-small	0.00427					-0.00591	
	(0.0230)					(0.0119)	
Log (NTM sales)-medium	0.0664***					-0.0132	
	(0.0219)					(0.0117)	
Log (NTM sales)-large	0.0528**					0.0189	
	(0.0216)					(0.0138)	
Log (NTF sales)-small		0.0148					0.00139
		(0.0146)					(0.00803)
Log (NTF sales)-medium		0.0124					-0.000942
		(0.0130)					(0.00742)
Log (NTF sales)-large		0.0131					0.0202*
		(0.0148)					(0.0106)
Log (exports)-small			0.0560***	0.0517***	0.0222***		
			(0.0136)	(0.0150)	(0.00645)		
Log (exports)-medium			0.0289***	0.0470***	0.0172***		
			(0.00810)	(0.0122)	(0.00659)		
Log (exports)-large			0.0243**	0.0441***	0.0257***		
			(0.0120)	(0.0160)	(0.00819)		
Observations	11,127	11,040	15,015	15,143	14,877	14,954	15,051
Number of firms	7,825	7,736	11,242	11,376	10,985	11,015	11,070
AR(2) test	1.368	1.368	-0.299	1.196	1.384	1.122	1.199
AR(2) p-vale	0.171	0.171	0.765	0.232	0.167	0.262	0.231
Hansen test	287.3	274.6	260.2	256.5	310.2	291.7	281.4
Hansen p-value	0.339	0.579	0.638	0.697	0.0426	0.275	0.449
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Covariates omitted for brevity.

Table 5b: LTE, LBE and Productivity effects by firm size SUR models

VARIABLES	(1) Log(NTM sales)	(2) Log(NTF sales)	(3) Log(Export share)	(4) Log(productivity)
Log (NTM sales)-small			0.042**	-0.037*
			(0.020)	(0.021)
Log (NTM sales)-medium			0.069***	-0.075***
			(0.022)	(0.021)
Log (NTM sales)-large			0.100***	0.020
			(0.026)	(0.028)
Log (NTF sales)-small			0.032**	-0.007
			(0.013)	(0.014)
Log (NTF sales)-medium			0.032**	0.004
			(0.014)	(0.014)
Log (NTF sales)-large			-0.006	-0.003
			(0.017)	(0.017)
Log (Export share)-small	0.051***	0.065***		0.082***
	(0.009)	(0.013)		(0.012)
Log (Export share)-medium	0.024***	0.051***		0.077***
	(0.008)	(0.012)		(0.011)
Log (Export share)-large	0.021**	0.040***		0.094***
	(0.009)	(0.014)		(0.013)
Log(Productivity)	-0.015*	-0.002	0.141***	
	(0.008)	(0.012)	(0.011)	
Observations	25,116	25,116	25,116	25,116

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Hypotheses and overview of results: full sample

	Hypothesis	Outcome (SUR)	Outcome (GMM)
H1: LTE	Relative to NTF innovation, NTM innovation has a higher impact on subsequent export performance	Supported	Supported
H2: LTE - moderated	Relative to intermittent exporters, the effect of NTM and NTF innovation on subsequent export performance is stronger for persistent exporters	Supported	Supported
H3: LBE	The positive effect of export performance on subsequent innovation is stronger for NTM innovations than for NTF innovations.	Not supported	Not supported
H4: LBE - moderated	Relative to intermittent exporters, the effect of export performance on subsequent NTM and NTF innovation performance is stronger for persistent exporters	Supported	Supported
H5: Exporting to productivity	Higher export performance leads to higher subsequent productivity	Supported	Supported
H6: Innovation to productivity	NTM innovation performance has a stronger impact on subsequent productivity than NTF innovation performance	Not supported	Not supported

APPENDICES

Appendix A: Descriptive statistics and correlation coefficients

Table A1: Descriptive statistics

	SUR estimation sample			GMM estimation sample		
Variable	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Log (Export share)	18,768	0.857	1.449	9,776	0.804	1.416
Log (Productivity)	22,768	4.473	1.092	13,414	4.514	1.092
Log (NTM sales)	22,260	0.262	0.794	14,511	0.163	0.623
Log (NTF sales)	22,300	0.471	1.157	15,102	0.397	1.076
Process innovation	24,594	0.162	0.369	15,102	0.132	0.339
Small firm	24,594	0.431	0.495	15,102	0.448	0.497
Medium firm	24,594	0.300	0.458	15,102	0.304	0.460
% SCI & ENG grads	19,849	7.475	16.596	15,102	0.248	0.432
% other grads	20,583	10.426	19.120	11,773	7.054	16.156
Design investment	24,594	0.171	0.376	12,179	9.442	17.376
Training investment	24,594	0.247	0.431	15,102	0.132	0.338
Acquisition of existing knowledge	24,594	0.085	0.279	15,102	0.174	0.379
Market introduction of innovations	24,594	0.257	0.437	15,102	0.052	0.222
Acquisition of advanced machinery	24,594	0.439	0.496	15,102	0.178	0.383
Internal R&D	24,594	0.277	0.447	15,102	0.339	0.474
External R&D	24,594	0.097	0.296	15,102	0.217	0.412
East Midlands	24,594	0.080	0.272	15,102	0.077	0.266
Eastern	24,594	0.046	0.210	15,102	0.057	0.232
Eastern England	24,594	0.058	0.233	15,102	0.051	0.221
London	24,594	0.095	0.294	15,102	0.099	0.299
N Ireland	24,594	0.043	0.204	15,102	0.040	0.195
North East	24,594	0.060	0.237	15,102	0.059	0.236
North West	24,594	0.100	0.299	15,102	0.102	0.302
Northern Ireland	24,594	0.031	0.173	15,102	0.040	0.196
Scotland	24,594	0.084	0.277	15,102	0.085	0.279
South East	24,594	0.106	0.308	15,102	0.105	0.306
South West	24,594	0.088	0.283	15,102	0.091	0.287
Wales	24,594	0.058	0.233	15,102	0.053	0.223
West Midlands	24,594	0.076	0.266	15,102	0.070	0.255
Yorkshire and the Humber	24,594	0.075	0.206	15,102	0.071	0.189
Manufacturing	24,594	0.259	0.438	15,102	0.219	0.413

Table A2: Pairwise correlation coefficients from the SUR estimation sample

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Log (NTM sales)	1																	
2	Log (Export share)	0.26	1.00																
3	Log (NTF sales)	0.71	0.25	1.00															
4	Log (Productivity)	0.06	0.22	0.06	1.00														
5	Process innovation	0.36	0.17	0.44	0.07	1.00													
6	Small firm	-0.01	-0.08	-0.04	-0.07	-0.08	1.00												
7	Medium firm	0.01	0.09	0.02	0.06	0.03	-0.57	1.00											
8	Large firm	0.01	0.01	0.02	0.03	0.06	-0.53	-0.40	1.00										
9	% SCI & ENG grads	0.22	0.28	0.18	0.10	0.13	-0.01	0.03	-0.02	1.00									
10	% other grads	0.05	0.06	0.07	0.07	0.04	-0.03	0.02	0.01	0.19	1.00								
11	Design investment	0.38	0.25	0.42	0.06	0.31	-0.08	0.03	0.05	0.15	0.05	1.00							
12	Training investment	0.32	0.14	0.38	0.03	0.33	-0.05	0.01	0.05	0.16	0.10	0.39	1.00						
13	Acquisition of existing knowledge	0.23	0.13	0.29	0.03	0.22	-0.04	0.01	0.05	0.11	0.06	0.31	0.35	1.00					
14	Market introduction of innovations	0.36	0.16	0.42	0.04	0.28	-0.05	0.01	0.06	0.10	0.07	0.46	0.45	0.31	1.00				
15	Acquisition of advanced machinery	0.24	0.10	0.28	0.01	0.30	-0.02	0.01	0.02	0.10	0.05	0.30	0.43	0.26	0.40	1.00			
16	Internal R&D	0.41	0.34	0.48	0.08	0.36	-0.10	0.04	0.07	0.25	0.08	0.50	0.43	0.31	0.46	0.35	1.00		
17	External R&D	0.28	0.19	0.32	0.07	0.25	-0.08	0.01	0.08	0.14	0.06	0.35	0.31	0.41	0.32	0.24	0.43	1.00	
18	Manufacturing	0.18	0.38	0.19	0.07	0.16	0.01	0.03	-0.04	-0.06	-0.13	0.22	0.11	0.09	0.16	0.14	0.25	0.13	1

Table A3: Pairwise correlation coefficients from the GMM estimation sample

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Log (NTF sales)	1																	
2	Log (Export share)	0.231	1.000																
3	Log (Productivity)	0.049	0.229	1.000															
4	Log (NTM sales)	0.774	0.209	0.046	1.000														
5	Process innovation	0.404	0.172	0.062	0.332	1.000													
6	Small firm	-0.032	-0.085	-0.064	-0.013	-0.084	1.000												
7	Medium firm	0.031	0.091	0.064	0.014	0.045	-0.596	1.000											
8	Large	0.005	-0.001	0.005	-0.001	0.050	-0.517	-0.380	1.000										
9	% SCI & ENG grads	0.177	0.277	0.103	0.181	0.121	-0.029	0.043	-0.012	1.000									
10	% other grads	0.082	0.097	0.088	0.053	0.055	-0.033	0.032	0.003	0.214	1.000								
11	Design investment	0.418	0.233	0.054	0.369	0.306	-0.068	0.042	0.034	0.139	0.043	1.000							
12	Training investment	0.379	0.143	0.031	0.307	0.329	-0.052	0.019	0.040	0.162	0.088	0.380	1.000						
13	Acquisition of existing knowledge	0.258	0.120	0.023	0.216	0.209	-0.036	0.003	0.038	0.095	0.042	0.291	0.303	1.000					
14	Market introduction of innovations	0.411	0.146	0.032	0.342	0.270	-0.040	0.006	0.039	0.084	0.050	0.463	0.408	0.275	1.000				
15	Acquisition of advanced machinery	0.290	0.112	0.017	0.231	0.321	-0.019	0.008	0.013	0.094	0.029	0.307	0.408	0.224	0.394	1.000			
16	Internal R&D	0.473	0.329	0.073	0.394	0.369	-0.102	0.052	0.063	0.237	0.086	0.498	0.437	0.292	0.444	0.354	1.000		
17	External R&D	0.305	0.175	0.060	0.284	0.244	-0.075	0.025	0.060	0.124	0.054	0.334	0.293	0.352	0.298	0.232	0.419	1.000	
18	Manufacturing	0.173	0.357	0.062	0.158	0.142	0.002	0.030	-0.034	-0.058	-0.137	0.211	0.093	0.080	0.153	0.124	0.235	0.111	1

Appendix B: Full tables of results

Table B1: Learning to Export (LTE)

	SUR		GMM		
Y=Log(export share)	Main model	Export persistence	Main model	Export persistence	
Log (export share)t-1			0.829***	0.732***	0.721***
			(0.00936)	(0.0149)	(0.0155)
Log (NTM sales) t-1	0.068***		0.0313**		0.00489
	(0.013)		(0.0152)		(0.0217)
Log (NTF sales) t-1	0.030***		0.00248	0.00364	
	(0.009)		(0.00912)	(0.0144)	
Log (productivity)t-1	0.209***	0.217***	0.0451***	0.0639***	0.0585***
	(0.011)	(0.024)	(0.00712)	(0.0171)	(0.0188)
Log (NTM sales) t-1- persistent exporter		0.097***		0.0777***	
		(0.027)		(0.0233)	
Log (NTM sales) t-1- intermittent exporter		-0.070**		-0.0928***	
		(0.031)		(0.0308)	
Log (NTF sales) t-1- persistent exporter		0.174***			0.0796***
		(0.020)			(0.0195)
Log (NTF sales) t-1- intermittent exporter		-0.121***			-0.0845***
		(0.020)			(0.0208)
Process innovation, t-1	-0.016	0.000	-0.0287	-0.0221	-0.0199
	(0.025)	(0.043)	(0.0240)	(0.0436)	(0.0417)
Small firm, t-1	-0.133***	0.035	0.0336**	0.0953**	0.0948**
	(0.023)	(0.044)	(0.0170)	(0.0437)	(0.0437)
Medium firm, t-1	0.050**	0.089**	0.0570***	0.120***	0.107***
	(0.023)	(0.041)	(0.0183)	(0.0405)	(0.0404)
% SCI & ENG grads, t-1	0.012***	0.009***	0.00295***	0.00422***	0.00431***
	(0.001)	(0.001)	(0.000683)	(0.000946)	(0.000960)
% other grads, t-1	0.005***	0.004***	0.000880*	0.000208	8.02e-05
	(0.001)	(0.001)	(0.000510)	(0.000905)	(0.000920)
Design investment, t-1	0.144***	0.086*	0.0501*	0.0764	0.0698*
	(0.027)	(0.047)	(0.0263)	(0.0507)	(0.0402)
Training investment, t-1	-0.086***	-0.038	-0.0312	0.000637	-0.00665
	(0.024)	(0.044)	(0.0212)	(0.0357)	(0.0325)
Acquisition of existing knowledge, t-1	0.017	0.072	0.0317	0.0252	0.0626
	(0.033)	(0.056)	(0.0381)	(0.0620)	(0.0583)
Market introduction of innovations, t-1	0.026	-0.020	0.00100	-0.0177	-0.0207
	(0.025)	(0.044)	(0.0217)	(0.0396)	(0.0407)
Acquisition of advanced machinery, t-1	-0.070***	-0.103***	-0.0131	-0.0393	-0.0199
	(0.021)	(0.039)	(0.0170)	(0.0371)	(0.0352)
Internal R&D, t-1	0.347***	0.317***	0.147***	0.191***	0.187***
	(0.025)	(0.044)	(0.0259)	(0.0465)	(0.0459)
External R&D, t-1	-0.006	-0.024	0.0174	0.0459	0.00924
		(0.100)	(0.0363)	(0.0517)	(0.0600)
Observations	24,594	9,676	11,009	4,454	4,454
Number of firms			7,768	2,802	2,802
AR(2) test			1.336	1.271	1.305
AR(2) p-vale			0.182	0.204	0.192
Hansen test			260.9	276.1	271.5
Hansen p-value			0.274	0.277	0.362
Time dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	No	No	No

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B2: Learning by exporting (LBE)

	SUR				GMM			
	Main models		Export persistence		Main models		Export persistence	
Y=NTM/NTF innovation sales	Log(NTM sales)	Log(NTF sales)	Log(NTM sales)	Log(NTF sales)	Log(NTM sales)	Log(NTF sales)	Log(NTM sales)	Log(NTF sales)
Log (export share) t-1	0.029***	0.047***			0.0392***	0.0563***		
	(0.007)	(0.010)			(0.00572)	(0.00805)		
Log (NTM sales) t-1		-0.014*		-0.015	0.248***	0.161***	0.300***	0.180***
		(0.008)		(0.013)	(0.0236)	(0.0258)	(0.0363)	(0.0389)
Log (NTF sales) t-1	0.004		0.008		0.0343***	0.164***	0.0494***	0.205***
	(0.004)		(0.007)		(0.00961)	(0.0161)	(0.0183)	(0.0257)
Log (productivity) t-1	-0.015*	-0.009	-0.031	-0.015	-0.00357	0.00169	-0.0109	-0.00430
	(0.008)	(0.013)	(0.020)	(0.028)	(0.00473)	(0.00607)	(0.0101)	(0.0136)
Log (export share) t-1-persistent exporter			0.046***	0.086***			0.0425***	0.0522**
			(0.010)	(0.015)			(0.00824)	(0.0232)
Log (export share) t-1-intermittent exporter			-0.024**	-0.041**			-0.0102	-0.00272
			(0.012)	(0.017)			(0.0101)	(0.0377)
Process innovation, t-1	0.183***	0.334***	0.191***	0.038	0.0420*	0.124***	0.0513**	0.101**
	(0.018)	(0.027)	(0.031)	(0.031)	(0.0216)	(0.0336)	(0.0260)	(0.0437)
Small firm, t-1	0.071***	0.095***	0.108***	-0.181***	0.0488***	0.0478**	0.0567*	0.0797*
	(0.015)	(0.023)	(0.029)	(0.029)	(0.0131)	(0.0196)	(0.0307)	(0.0459)
Medium firm, t-1	0.048***	0.081***	0.053*	-0.099***	0.0279**	0.0482**	0.0268	0.0712*
	(0.016)	(0.024)	(0.028)	(0.028)	(0.0134)	(0.0206)	(0.0293)	(0.0415)
% SCI & ENG grads, t-1	0.003***	0.004***	0.004***	0.005***	0.00204***	0.000967	0.00242***	0.00153
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000573)	(0.000664)	(0.000775)	(0.000966)
% other grads, t-1	0.000	0.001	-0.001	0.004***	-0.000291	0.000460	-0.000895**	-0.000595
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000295)	(0.000441)	(0.000456)	(0.000576)
Design investment, t-1	0.160***	0.292***	0.196***	-0.001	0.0821***	0.183***	0.109***	0.194***
	(0.019)	(0.028)	(0.032)	(0.033)	(0.0249)	(0.0412)	(0.0389)	(0.0641)
Training investment, t-1	0.061***	0.100***	0.111***	0.053*	0.0193	0.0540**	0.0244	0.0602
	(0.016)	(0.024)	(0.030)	(0.030)	(0.0168)	(0.0255)	(0.0268)	(0.0482)
Acquisition of existing knowledge, t-1	0.019	0.062*	0.029	-0.004	0.0259	-0.0201	0.0280	-0.0472
	(0.023)	(0.035)	(0.040)	(0.040)	(0.0312)	(0.0448)	(0.0467)	(0.0786)
Market introduction of innovations, t-1	0.139***	0.221***	0.198***	-0.058*	0.0453***	0.107***	0.0526	0.147***
	(0.017)	(0.025)	(0.030)	(0.030)	(0.0172)	(0.0269)	(0.0329)	(0.0473)
Acquisition of advanced machinery, t-1	0.028**	0.050**	0.065**	-0.059**	0.00774	0.0158	0.0288	0.0291
	(0.014)	(0.021)	(0.026)	(0.026)	(0.0107)	(0.0174)	(0.0190)	(0.0249)
Internal R&D, t-1	0.187***	0.330***	0.164***	-0.054*	0.0975***	0.166***	0.0698**	0.158***
	(0.018)	(0.026)	(0.030)	(0.031)	(0.0207)	(0.0330)	(0.0340)	(0.0523)
External R&D, t-1	0.095***	0.036	0.088**	0.078**	0.0464*	-0.0255	0.0510	-0.0118
			(0.069)	(0.069)	(0.0268)	(0.0464)	(0.0482)	(0.0639)
Observations	24,594	24,594	9,676	9,676	14,974	15,102	5,722	5,746
Number of firms					11,220	11,353	3,798	3,830
AR(2) test					-0.329	1.189	-0.298	0.771
AR(2) p-vale					0.742	0.235	0.766	0.440
Hansen test					237.9	222.2	241.9	205.5
Hansen p-value					0.667	0.879	0.727	0.974
Industry dummies	Yes	Yes	Yes	Yes	No	No	No	No
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B3: Direct and complementary effects of innovation novelty and exporting on productivity

	SUR			GMM		
Y=log(Productivity)	Main models	Innovation and exporting status	Innovation performance and exporting status	Main models	Innovation and exporting status	Innovation performance and exporting status
Log (productivity)t-1				0.784***	0.703***	0.787***
				(0.0127)	(0.0106)	(0.0129)
Log (export share) t-1	0.169***		0.170***	0.0262***		0.0292***
	(0.010)		(0.010)	(0.00450)		(0.00467)
Log (NTM sales) t-1	-0.042***			-0.00925		
	(0.012)			(0.00831)		
Log (NTF sales) t-1	0.000			0.00680		
	(0.008)			(0.00572)		
(NTM innovator-exporter) t-1		0.063**			0.0491***	
		(0.026)			(0.0174)	
(NTM innovator-non-exporter) t-1		-0.083***			-0.0410**	
		(0.022)			(0.0171)	
(NTF innovator-exporter)t-1		0.148***			0.0685***	
		(0.024)			(0.0160)	
(NTF innovator-non-exporter)t-1		-0.072**			-0.0379	
		(0.030)			(0.0254)	
Log (NTM sales-exporter) t-1			-0.050***			-0.0109
			(0.016)			(0.0108)
Log (NTM sales-nonexporter) t-1			-0.029			0.000928
			(0.019)			(0.0128)
Log (NTF sales-exporter) t-1			0.001			-0.00341
			(0.011)			(0.00698)
Log (NTF sales-nonexporter) t-1			-0.001			0.0179**
			(0.011)			(0.00821)
Process innovation	0.060**	0.044**	0.060**	0.0212	0.0155	0.0192
	(0.024)	(0.017)	(0.024)	(0.0163)	(0.0127)	(0.0166)
Small firm	-0.113***	-0.167***	-0.113***	-0.0259*	-0.0307**	-0.0268*
	(0.020)	(0.015)	(0.020)	(0.0152)	(0.0131)	(0.0151)
Medium firm	-0.018	-0.037**	-0.017	-0.00424	-0.00777	-0.00701
	(0.021)	(0.016)	(0.021)	(0.0159)	(0.0133)	(0.0160)
% SCI & ENG grads	0.007***	0.008***	0.007***	0.000466	0.00164***	0.000542
	(0.001)	(0.000)	(0.001)	(0.000384)	(0.000331)	(0.000388)
% other grads	0.007***	0.007***	0.007***	0.000613*	0.00119***	0.000577*
	(0.000)	(0.000)	(0.000)	(0.000313)	(0.000300)	(0.000308)
Design investment	0.007	0.004	0.008	-0.00875	0.00639	0.000709
	(0.025)	(0.018)	(0.025)	(0.0184)	(0.0137)	(0.0178)
Training investment	-0.014	0.001	-0.014	-0.0281*	-0.0157	-0.0225
	(0.021)	(0.016)	(0.021)	(0.0152)	(0.0122)	(0.0151)
Acquisition of existing knowledge	0.035	0.010	0.035	0.0309	0.0111	0.0262
	(0.030)	(0.021)	(0.030)	(0.0231)	(0.0176)	(0.0234)
Market introduction of innovations	-0.021	0.006	-0.022	0.0148	-0.000657	0.00804
	(0.021)	(0.016)	(0.021)	(0.0144)	(0.0121)	(0.0141)
Acquisition of advanced machinery	-0.017	-0.013	-0.018	-0.0130	0.00267	-0.0168
	(0.018)	(0.014)	(0.018)	(0.0131)	(0.0115)	(0.0134)
Internal R&D	0.018	0.023	0.018	0.0113	0.00534	0.0114
	(0.023)	(0.017)	(0.023)	(0.0154)	(0.0127)	(0.0153)
External R&D	0.071**	0.045**	0.072**	0.0199	0.00608	0.0217

		(0.021)	(0.030)	(0.0193)	(0.0156)	(0.0193)
Observations	24,594	28,090	24,594	14,833	24,999	14,828
Number of firms				10,961	15,810	10,959
AR(2) test				1.070	1.577	1.073
AR(2) p-vale				0.285	0.115	0.283
Hansen test				264.1	371.2	295.6
Hansen p-value				0.231	0.117	0.249
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	yes	Yes	No	No	No

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Observations are larger using exporting and innovation dummies due to the higher number of firms that indicated exporting or innovating, but did not indicate the corresponding share of sales from each activity.

Table B4: The role of export persistence in the innovation-productivity relationship

Y= Log(productivity)	SUR	GMM	GMM
Log (productivity)		0.825***	0.832***
		(0.0205)	(0.0206)
Log (export share)		0.0114*	0.0104*
		(0.00633)	(0.00536)
Log (NTM sales)			-0.00590
			(0.0100)
Log (NTF sales)		0.00399	
		(0.00798)	
Log (NTM sales)- persistent exporter	-0.031	-0.00364	
	(0.020)	(0.0108)	
Log (NTM sales)-intermittent exporter	-0.045*	-0.0147	
	(0.024)	(0.0151)	
Log (NTF sales)- persistent exporter	-0.006		0.00431
	(0.014)		(0.00778)
Log (NTF sales)- intermittent exporter	0.018		-0.00500
	(0.016)		(0.0104)
Process innovation	0.038	0.00823	0.0214
	(0.031)	(0.0220)	(0.0204)
Small firm	-0.181***	-0.0501**	-0.0478**
	(0.029)	(0.0204)	(0.0203)
Medium firm	-0.099***	-0.0378**	-0.0423**
	(0.028)	(0.0184)	(0.0185)
% SCI & ENG grads	0.005***	-0.000206	-0.000268
	(0.001)	(0.000458)	(0.000452)
% other grads	0.004***	-0.000159	-0.000259
	(0.001)	(0.000364)	(0.000359)
Design investment	-0.001	-0.00364	-0.00917
	(0.033)	(0.0204)	(0.0187)
Training investment	0.053*	-0.00894	-0.00336
	(0.030)	(0.0176)	(0.0175)
Acquisition of existing knowledge	-0.004	0.00389	0.00383
	(0.040)	(0.0285)	(0.0293)
Market introduction of innovations	-0.058*	-0.00873	-0.00617
	(0.030)	(0.0183)	(0.0184)
Acquisition of advanced machinery	-0.059**	-0.0207	-0.0227
	(0.026)	(0.0184)	(0.0164)
Internal R&D	-0.054*	-0.0133	-0.0185
	(0.031)	(0.0205)	(0.0188)
External R&D	0.078**	0.00263	0.00763
	(0.069)	(0.0195)	(0.0191)
Observations	9,676	5,955	5,955
Number of firms		3,894	3,894
AR(2) test		0.108	0.152
AR(2) p-vale		0.914	0.879
Hansen test		237.9	242.2
Hansen p-value		0.865	0.828
Time dummies	Yes	Yes	Yes
Industry dummies	Yes	No	No

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B5: Relationships between error terms in SUR models (Rho-ρ)

	Main models	Persistence models	Dummy interactions	Interactions with innovation and export sales
Rho (NTM-NTF)	1.182	1.155	1.182	1.182
	(132.60)***	(79.68)***	(132.60)***	(132.60)***
Rho (NTM-Export share)	0.034	-0.026	0.034	0.033
	(2.38)**	(1.25)	(2.37)**	(2.37)**
Rho (NTM-Productivity)	0.008	0.011	0.009	0.000
	(0.68)	(0.54)	(0.79)	(0.03)
Rho (NTF-export share)	0.035	-0.029	0.035	0.034
	(2.49)**	(1.38)	(2.48)**	(2.45)**
Rho (NTF-productivity)	0.005	0.001	0.006	0.000
	(0.42)	(0.04)	(0.51)	(0.00)
Rho Export share-productivity)	-0.129	-0.090	-0.129	0.070
	(7.80)***	(3.67)***	(7.81)***	(7.10)***
N	24,594	9,676	24,594	28,090

Appendix C: Standardised coefficient estimates

Learning to Export (LTE)								
Y=log(exports)	SUR		GMM					
	Standardised coefficients	Elasticities	Standardised coefficients	Elasticities				
Log (exports), t-1			0.829	0.829				
Log (NTM sales), t-1	0.030	0.068	0.017	0.031				
Log (NTF sales), t-1	0.023	0.030	0.002	0.002				
Log (productivity), t-1	0.161	0.209	0.034	0.045				
Log (NTM sales), t-1- persistent exporter	0.043	0.097	0.043	0.078				
Log (NTM sales), t-1- intermittent exporter	-0.031	-0.070	-0.051	-0.093				
Log (NTF sales), t-1- persistent exporter	0.132	0.174	0.064	0.080				
Log (NTF sales), t-1- intermittent exporter	-0.092	-0.121	-0.067	-0.085				
Learning by Exporting (LBE)								
	SUR				GMM			
Y= NTM/NTF innovation sales	*Log(NTM sales)*		*Log(NTF sales)*		*Log(NTM sales)*		*Log(NTF sales)*	
	Standardised coefficients	Elasticities	Standardised coefficients	Elasticities	Standardised coefficients	Elasticities	Standardised coefficients	Elasticities
Log (NTM sales), t-1			-0.010	-0.014	0.248	0.248	0.093	0.161
Log (NTF sales), t-1	0.006	0.004			0.059	0.034	0.164	0.164
Log (exports), t-1	0.053	0.029	0.059	0.047	0.089	0.039	0.074	0.056
Log (productivity), t-1	-0.021	-0.015	-0.008	-0.009	-0.006	-0.004	0.002	0.002
Log (exports), t-1- persistent exporter	0.084	0.046	0.108	0.086	0.097	0.043	0.069	0.052
Log (exports), t-1- intermittent exporter	-0.044	-0.024	-0.051	-0.041	-0.023	-0.010	-0.004	-0.003
Productivity								
Y=log(productivity)	SUR		GMM					
	Standardised coefficients	Elasticities	Standardised coefficients	Elasticities				
Log (productivity)			0.784	0.784				
Log (exports)	0.224	0.169	0.034	0.026				
Log (NTM sales)	-0.031	-0.042	-0.005	-0.009				
Log (NTF sales)	0.000	0.000	0.007	0.007				

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