Full Paper

Innovation, internationalisation and the performance of microbusinesses

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Andrew Henley
Cardiff University, UK

Meng Song
Aston University, UK

Abstract

This article integrates internationalisation, and specifically exporting, into a conceptualisation of how innovation production leads to productivity performance in microbusinesses employing fewer than 10 people. Innovation production is reframed for the microbusiness context by focusing on knowledge acquisition and formalisation rather than on research and development (R&D) activity. Propensity score matching analysis is used to investigate British microbusiness survey data. It finds a causal process in which innovation promotes exporting activity. This in turn leads to improved productivity. In contrast to research on larger businesses, this study finds no direct link between innovation production and productivity. These findings are robust to various checks for potential endogeneity arising from feedback into innovation from internationalisation and from self-selection of high productivity firms into exporting.

Keywords

innovation, exporting, knowledge acquisition, microbusiness, productivity

Introduction

Microbusinesses form an economically significant element of the business population in all economies. They typically face two strategies for growth improving products to expand market share by innovation and expanding markets by entering foreign markets (i.e. internationalisation) (Golovko and Valentini, 2011). For the smallest businesses, the primary means of foreign market entry is through exporting (Lengler et al., 2016; Leonidou and Katsikeas, 1996). These strategies are likely to be complimentary and reinforcing, determined by the drivers of innovation activity and exporting

Corresponding author:
Andrew Henley, Cardiff Business School, Cardiff University, Aberconway Building, Colum Drive, Cardiff CF10 3EU, UK.
Email: HenleyA@cardiff.ac.uk

decisions. Whereas previous research has focused on larger organisations and larger small and medium enterprises (SMEs), little is known about the production of innovation in microbusinesses, and the extent to which it supports their exporting decisions. In this article, we shed light on the manner in which microbusinesses, defined as having fewer than 10 employees, generate innovation to understand the extent to which it supports improvements in microbusiness performance. A model of innovation production in the spirit of Crepon, Duguet and Mairesse (1998)[1] (CDM) but specific to the microbusiness context is proposed. We integrate this with the widely accepted hypothesis that SME innovation drives internationalisation (Vernon, 1966). We demonstrate how the interplay of developing and exploiting innovation explains the development paths of microbusinesses in the Britain. Using two waves of the UK Longitudinal Small Business Survey data, which contains an unusually large sub-sample of microbusinesses, we analyse how the production of innovation in turn contributes to improved performance, in terms of exporting activity and productivity, for this under-researched form of organisation.

This article makes three contributions to the literature. First, it reframes the understanding of the production of innovation to the microbusiness context, where explicit research and development (R&D) programmes are rare, by demonstrating the importance of knowledge acquisition from various sources as innovation inputs. Second, it integrates internationalisation theories in order to better understand the consequences of innovation for microbusiness performance. The literature on internationalisation compliments the CDM (Crepon et al., 1998) approach to innovation outputs by describing how innovation leads to internationalisation (specifically here exporting activity), which in turn contributes to productivity. Third, in the specific context of microbusinesses, this article assesses the extent to which internationalisation leads to, rather than is led by, productivity improvements. We find evidence, after controlling for any selection effect that more productive firms are more likely to export, of a significant 'learning-by-exporting' effect (Karami and Tang, 2019; Wagner, 2012). The discussion and evidence highlight potential complexity in microbusiness development paths (Assadinia et al., 2019), and particularly the role of internationalisation as the link between innovation and higher productivity.

The British context for this study is significant. Since the global financial crisis, the UK has seen a sharp growth in microbusiness numbers, with under 10 employees. Between 2008 and 2018 the number of microbusinesses grew by around 22%, from 4.6 million to 5.6 million. During this period, the number of employees working for microbusinesses also increased from four million to nine million, rising from 26% to 33% of total employment in the UK (Department for Business, Innovation and Skills (BIS), 2008; National Statistics, 2019). Nevertheless, public spending austerity has limited public resource to support business growth (Jorda and Taylor, 2016). Thus, the proportion who remain small, often as sole-traders, calls into question the performance of the sector and may contribute towards explaining poor productivity growth. The findings provide a new perspective on how microbusinesses produce innovation, and how the impact of that innovation on performance is channelled through exporting activity. In summary, by contrast with large manufacturers and larger SMEs, internal effort to acquire knowledge and formalise it into business plans does not directly lead to productivity gain. However, these activities endow an ability to obtain competitive advantage in the form of higher likelihood of innovation and exporting activity, potentially contributing to productivity improvement even after controlling for selection effects in innovation and exporting.

The remainder of this article is structured as follows. The next section provides the theoretical background from which key hypotheses are developed. This is followed by description of the data source and the methods. Further sections present findings and robustness analysis. The paper concludes with discussion and exploration of the limitations of the present analysis.

Theoretical background and hypothesis development

Innovation knowledge accumulation in microbusinesses

Innovation is recognised as a source of competitive advantage through which firms transform capabilities and resources into performance outcomes (Barney, 1991). How firms innovate and how innovation affects firm performance has attracted significant attention (Antonelli et al., 2015). While these questions have been widely investigated for manufacturing firms, typically large ones, the understanding of the development of microbusinesses remains limited (Love and Roper, 2015). Small firms can demonstrate motivation to innovate and capacity to translate innovation into improved performance (Exposito and Sanchis-Llopis, 2018). However, innovation and growth patterns may not follow the same patterns as larger counterparts (De Zubielqui et al., 2019; Spithoven et al., 2013). In large organisations, innovation can require significant threshold levels of R&D investment, and their scale allows innovation output to be exploited to achieve growth (Dey et al., 2019). In smaller firms, resources for formal R&D expenditure are less available, financing is more difficult to acquire and threshold levels of investment are more difficult to achieve (Ortega-Argiles et al., 2009). As a result, formal R&D often involves higher risk for smaller firms (Baumann and Kritikos, 2016; Freel, 2007). Nevertheless, smaller firms may have organisational and market flexibility that can be advantageous in boosting innovation (Lee et al., 2010). Consequently, innovation activities and market development strategies can be diverse, such that development paths may vary from those experienced by large firms (Fuentelsaz et al., 2018; Rosenbusch et al., 2011; Van de Vrande et al., 2009), and show limited research consensus (Booltink and Saka-Helmhout, 2018). In this respect, the smallest microbusinesses, in particular, remain under-researched (Wright et al., 2015).

Innovation can be multidimensional, but most studies employ a single R&D investment approach, rather than a range of variables to reflect both formal and informal technological activities (Higón and Driffield, 2011). Particularly for microbusinesses where knowledge acquisition activity can be very informal, R&D investment may not capture various in-house innovation efforts, leading to an underestimated effect of innovation on firm performance (Kleinknecht, 1987).

If microbusinesses face resource and skill deficiencies which restrict formal R&D, a range of external knowledge sources can be important in overcoming knowledge gaps (Bennett and Robson, 2003), and in the production of innovation (Roper and Hewitt-Dundas, 2017). Access to external advice can boost performance (Mole et al., 2017), by allowing small firms to fill gaps in expertise and to raise entrepreneurial orientation and attitude to risk (Van Doorn et al., 2017). In addition, it is increasingly accepted that knowledge spillovers enhance technological change and economic growth by raising alertness to opportunity (Acs et al., 2009). For individual businesses, peer-to-peer engagement (e.g. business networking) thus provides important inputs to innovation production by enhancing innovative capacity (Pittaway et al., 2004; Thorpe et al., 2005). Such knowledge exchange can be face-to-face, but is also increasingly facilitated by digital technology (Scuotto et al., 2017). Internal capacity to absorb and systematise information from this range of sources is also likely to support the innovation production process. Thus, business planning can formalise the process of learning from external sources and identifying business opportunities (Brinckmann et al., 2010; Brunswicker and Vanhaverbeke, 2015). Formal business planning may help microbusinesses in reducing resistance to change and implementing innovation plans (Terziovski, 2010). It can facilitate goal achievement, allowing faster decision-making and more cost-effective resource management (Delmar and Shane, 2003).

The influential work of Crepon et al. (1998) provides a helpful formalisation of the innovation performance nexus. This approach builds by focusing first, on how firms transform inputs into innovation output (i.e. the knowledge production function, Griliches, 1979) and then second, on the exploiting of innovation output to improve economic performance. Innovation brings new knowledge, processes and technologies that enter production as inputs to improve efficiency and decrease costs, thereby increasing productivity (Romer, 1990). The CDM model specifically concerns R&D expenditure and employs an innovation-augmented Cobb–Douglas production function to capture the effects of innovation output on productivity (Hall and Mairesse, 2006). Although microbusinesses may depend more on external knowledge to produce innovation, their ability to transform knowledge into innovation output is not necessarily weak compared with larger counterparts, and impacts of innovation on business revenue can be proportionately large (Spithoven et al., 2013). In this article, we adapt this approach to the microbusiness context by proposing that knowledge inputs, acquired through the range of means discussed above and supported by business planning activity, drive innovation activity (Roper and Hewitt-Dundas, 2017). Our interest in the microbusiness innovation production process is thus summarised in the following hypothesis:

> *H1*. Knowledge acquisition and capacity to exploit knowledge lead to increased likelihood of microbusiness innovation.

In our empirical analysis, we focus specifically on external and peer-to-peer knowledge acquisition and in the capacity of microbusinesses to systematise and exploit knowledge thus acquired through business planning activity.

In summary, microbusinesses face significant and often complex needs in the challenge of producing innovation to take advantage of emerging business opportunities. The ability to identify, acquire and process information is integral to this and may be supported by both the acquisition of appropriate knowledge and the capacity to support knowledge acquisition with business planning activity. In turn, these may translate into improved economic performance and outcomes across a range of domains.

Internationalisation as a channel for the impact of innovation on performance

The CDM model focuses on productivity as the single performance outcome resulting from innovation. In terms of method, this single outcome approach sidesteps concerns around the endogenous determination of different domains of business performance, and permits a recursive model structure. Thus, subsequent studies based on the CDM model also typically focus on only one domain, for example, growth (Ipinnaiye et al., 2017). However, this risks the over-simplification of small business development, and provides limited insight into the specific channels through which firms translate innovation into performance. This is because for various reasons innovation may not bring immediate productivity growth for microbusinesses (Rosenbusch et al., 2011). First, innovation impact may take time to work through to economic performance, especially for organisational innovation (Damanpour and Evan, 1984; Gunday et al., 2011). The positive contribution from innovation to productivity may not be easy to discern during a short period. Second, innovation may incur adjustment costs from lost prior experience, as well as costs of acquiring new capabilities required by new process or technology adoption (Lawless and Anderson, 1996). As a result, the impact of innovation on performance could vary across microbusinesses because of heterogeneity in ability to generate economic returns from innovation (Coad and Tamvada, 2012). Third, innovation may not directly lead to improved microbusiness performance, since other channels for market expansion may need to be developed to realise potential performance benefits.

We argue that internationalisation is an important channel for innovation benefits which ought to be integrated within the CDM framework. Without proper strategies, such as expansion into foreign markets, microbusinesses may not be well placed to realise economic benefits from innovation. There is abundant evidence for internationalisation-related benefits,[2] including the leveraging of overseas competitive advantage (Zahra et al., 2000) and diversifying market risks (Barkema and Vermeulen, 1998). Importantly, internationalisation can help smaller firms to obtain productivity benefits from innovative activities (Booltink and Saka-Helmhout, 2018; Karami and Tang, 2019).

Exporting has traditionally been the main route to internationalisation for the smallest firms (Lengler et al., 2016; Leonidou and Katsikeas, 1996). While levels of learning from market entry through exporting might be lower than for other ‘high-control’ modes (Zahra et al., 2000), exporting avoids the risks and sunk cost commitments of foreign direct investment or establishment of overseas subsidiaries (Lu and Beamish, 2006). Internationalisation theory stresses the importance of innovation for exporting. First, innovation confers market differentiation which in turn allows firms to better compete internationally (Krugman, 1979; Vernon, 1966). Second, as innovation is costly to produce, firms are motivated to enter foreign markets to increase sales volume to spread those costs (Rogers, 2004). Third, innovation allows firms to respond quickly to rapidly changing international market conditions (Azar and Ciabuschi, 2017).

A selection effect is an important consideration, since those who innovate might already be exporting. This is because access to foreign markets provides businesses with valuable knowledge and intelligence which in turn generates innovation potential, as well as necessitating innovation through a learning effect required to meet the competitive demands of foreign markets (Bratti and Felice, 2012; Fassio, 2018). Businesses which have already innovated may be more likely to innovate again. It is therefore important to control for whether innovation decisions are determined by exporting, even where a longitudinal survey design identifies prior-dated innovation decisions. We summarise this discussion on the innovation-exporting link in the following hypothesis:

H2. Microbusiness innovation decisions lead to increased exporting activity, after controlling for potential endogeneity of innovation.

Our final hypothesis predicts that exporting will boost productivity. First, strong international competition can incentivise firms to remain competitive by sustaining improved efficiency, technology absorption and productivity (Love and Roper, 2015). Second, serving wider markets will increase scale, allowing firms to lower unit production costs faster than non-exporting competitors (Greenaway and Kneller, 2007). Third, access to foreign knowledge may also bring in complementary knowledge that may not be easily accessible and therefore enhance performance (‘learning-by-exporting’) (Karami and Tang, 2019; Love and Ganotakis, 2013; Tse et al., 2017; Wagner, 2012). However, selection is also an important consideration (Greenaway and Kneller, 2007). As more productive firms may ‘learn to export’ and self-select into export markets (Coad and Tamvada, 2012; Love and Roper, 2015), empirical studies should control for this effect (Cassiman and Golovko, 2011). As the literature which adopts the CDM model demonstrates, innovation may be the source of this productivity advantage. For instance, Eliasson et al. (2012) find evidence for self-selection among Swedish firms, but no evidence for productivity-enhancing learning by exporting after market entry. We argue that for microbusinesses, exporting could be an important channel through which they could better benefit from innovation output in order to improve productivity. This is formally expressed as follows:

H3. Microbusiness exporting decisions lead to higher productivity, consistent with a learning-by-exporting effect.

In Figure 1, we provide a schematic representation of the overall conceptual framework, identifying the proposed causal channel from innovation inputs through to productivity. Each of the hypotheses developed above is shown. In addition, the figure highlights the potential endogeneity

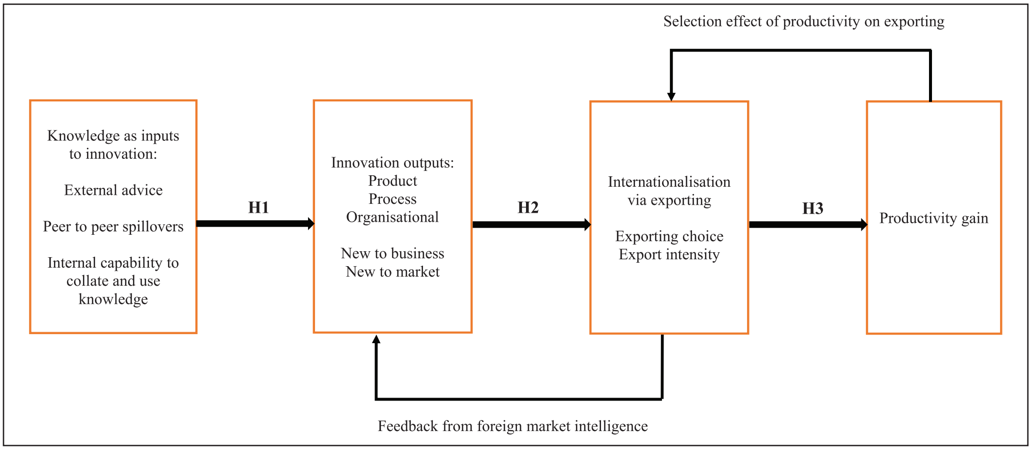

Figure 1. Conceptual model.

of innovation and exporting, and of exporting and productivity as discussed earlier, and as shown by the feedback relationships.

Data source

This analysis uses Waves 1 and 2 of the UK Longitudinal Small Business Survey (LSBS) commissioned by the Department for Business, Innovation and Skills (BIS) and conducted in 2015 and 2016. The survey was designed to provide a representative source of information on performance and a range of drivers of performance for the UK small business population. The longitudinal aspect, although limited to two annual waves, allows analysis to incorporate prior-dated covariates, although at the expense of some sample attrition. Technical details and full questionnaires are provided in BIS (2016) and Department for Business, Energy and Industrial Strategy (BEIS) (2017). The sampling method was stratified by firm size (measured by number of employees), region and industry sector. The UK administrative Inter-Departmental Business Register (IDBR) was used as the sample source for registered businesses, while Dun and Bradstreet's database was used for unregistered businesses. Wave 1 response rates were 19% (IDBR sample) and 9% (Dun and Bradstreet sample), providing an achieved sample of 15,501. Of these, 7279 were successfully re-contacted in Wave 2. Of these, 3882 microbusinesses employed below 10 in Wave 1 and remained in the survey in Wave 2. Only 161 of these had grown to 10 employees or over by 2016. Aside from those businesses not selected to remain in the panel, the most significant reason for sample attrition was refusal. A total of 6% of originally sampled businesses were uncontactable or were known to have ceased trading at Wave 2. Questionnaire instruments in each wave solicited information about turnover, employment, innovation and exporting activity. They also sought information on business capabilities and planning, access to knowledge and business networking. There is further sample reduction due to non-response or 'don't know' responses to particular questions. The business networking question was only asked of respondents in England and Wales, which leads to a sample loss of about 10% on the whole UK sample available.[3]

Summary statistics reported in Table 1 show that half of the firms in the microbusiness sample (50%) are sole proprietorships. Just under half of the microbusinesses (49.6%) had engaged in product, services or process innovation in the three years up to 2015, 17% had developed new-to-the-market products, services or process innovation. About 19% of firms engaged in exporting activity.

About 8.7% of microbusinesses had exported goods in the past year and 12.5% had exported services. For turnover per employee information, there is some loss of sample due to missing responses, even after incorporating some banded responses. The distribution is skewed – in 2015 mean turnover for microbusinesses was about £150,000 per employee, but the median was only £80,000. Therefore, for modelling purposes, turnover per employee is expressed in log form to remove skewness.[4] There is a slight fall in average (log) turnover per employee between 2015 and 2016, but this fall should be treated with caution given that panel attrition might be non-random.

Method and econometric model specification

Our preferred approach is to adopt the propensity score matching (PSM) method (Li, 2012) in order to assess the size and direction of causal effects between the key variables of interest: innovation, exporting and productivity. However, we also estimate structural regression models, as in previous literature adopting the CDM model, and use various approaches to test and control for endogeneity caused by selection or simultaneity effects. The clear conclusion from these methods is that our key findings are robust to choice of method.

PSM is used to investigate sequentially the treatments at each link in our hypothesised model (Figure 1). PSM addresses selection bias by eliminating systematic differences between the treated and control group.[5] After appropriate conditioning on observable pre-treatment covariates, any differences in the outcomes between treated and control groups unrelated to the treatment in question should be as good as random. The PSM method imputes missing selection-corrected outcomes for the treated group. Thus, if the quality of sample matching is high, PSM can control for the impact of any selection effects on the unadjusted differences between the two groups. The mean difference of the observable outcome and counterfactual outcome of the treated group is the average treatment effect on the treated (ATT), which can be expressed as

$$E(w^1 - w^0 | treatment = 1) = E(w^1 | treatment = 1) - E(w^0 \mid treatment = 1)$$

where w^1 is an observable outcome and w^0 is the unobservable counterfactual outcome of the treated group. ATT estimates are obtained to establish a counterfactual outcome for the treated group, in the event that they had not been treated. There are three steps in testing our conceptual model. The first step tests H1 by assessing three knowledge input treatment effects on various indicators of innovation as outcome: (1) acquiring external advice or information, (2) using business networks (either through a local chamber of commerce, other formal or informal networks, or via social media networking) and (3) using a formal business plan. The second step tests H2 by assessing the treatment effect of innovation on exporting, and the third step tests H3 by assessing the treatment effects of both exporting and innovation on productivity. Different measures of innovation and exporting are used to capture a more detailed and nuanced perspective of the relationships in the model. Relevant pre-treatment variables from Wave 1, as suggested by the literature, are used to achieve a matched balance between the treated and control group, and all outcomes are based on Wave 2 of the data to mitigate potential endogeneity.[6]

The following model is used to estimate propensity scores

$$\Pr(treatment_{it} = 1) = \Phi^*(h(X_{kit-1}))$$

Table 1. Summary statistics for LSBS microbusiness sample.

	Wave 1 (2015)					Wave 1 (2016)				
	Obs.	Mean	Std. dev.	Min.	Max.	Obs.	Mean	Std. dev.	Min.	Max.
Business performance:										
Has goods/services/process innovation (0/1)	3454	0.496	0.500	0	1	3574	0.370	0.483	0	1
Has new to the market innovation (products/services/processes)	3421	0.167	0.373	0	1	3553	0.110	0.313	0	1
Export goods and/or services (0/1)	3461	0.190	0.392	0	1	3585	0.173	0.378	0	1
Export goods (0/1)	3468	0.087	0.281	0	1	3588	0.080	0.271	0	1
Export services (0/1)	3463	0.125	0.331	0	1	3585	0.114	0.318	0	1
Export sales from goods	3102	2.104	10.898	0	100	3246	2.003	10.924	0	100
Export sales from services	3232	3.634	14.982	0	100	3366	3.678	15.423	0	100
Log turnover per employee	2653	11.158	1.241	7.388	14.221	2946	11.101	1.197	7.388	14.221
Self-assessed business capabilities:										
Capability for business plan/strategy (0/1)	3371	0.579	0.494	0	1	NA	NA	NA	NA	NA
Capability for new products/services (0/1)	3156	0.555	0.497	0	1	NA	NA	NA	NA	NA
Capability to acquire finance (0/1)	2468	0.391	0.488	0	1	NA	NA	NA	NA	NA
Capability for operational improvement (0/1)	3272	0.657	0.475	0	1	NA	NA	NA	NA	NA
Knowledge sources and planning:										
Use information or advice (0/1)	3460	0.316	0.465	0	1	3571	0.225	0.418	0	1
Has business networks (0/1)	3473	0.701	0.458	0	1	NA	NA	NA	NA	NA
Has a business plan (0/1)	3431	0.352	0.478	0	1	3560	0.459	0.498	0	1
Business characteristics and sector:										
Has multiple business sites (0/1)	3453	0.084	0.277	0	1	3569	0.093	0.291	0	1
Aware of business support (0/1)	3473	0.619	0.486	0	1	NA	NA	NA	NA	NA
Rural area (0/1)	3462	0.308	0.462	0	1	3589	0.303	0.460	0	1
Employees 0 (0/1) (base group: sole proprietorship)	3473	0.499	0.500	0	1	3589	0.422	0.494	0	1
Employees 1–4 (0/1)	3473	0.320	0.467	0	1	3589	0.366	0.482	0	1
Employees 5–9 (0/1)	3473	0.181	0.385	0	1	3589	0.212	0.409	0	1

(Continued)

Table 1. (Continued)

	Wave 1 (2015)					Wave 1 (2016)				
	Obs.	Mean	Std. dev.	Min.	Max.	Obs.	Mean	Std. dev.	Min.	Max.
Firm age 1–5 years (0/1) (base group)	3466	0.141	0.348	0	1	NA	NA	NA	NA	NA
Firm age 6–10 years(0/1)	3466	0.147	0.354	0	1	NA	NA	NA	NA	NA
Firm age 11–20 years (0/1)	3466	0.195	0.396	0	1	NA	NA	NA	NA	NA
Firm age > 20 years (0/1)	3466	0.518	0.500	0	1	NA	NA	NA	NA	NA
Business sector (UK SIC section):										
Non-service sectors:										
ABDE – Primary	3473	0.052	0.222	0	1	3589	0.051	0.219	0	1
C – Manufacturing	3473	0.066	0.248	0	1	3589	0.066	0.249	0	1
F – Construction	3473	0.115	0.320	0	1	3589	0.113	0.316	0	1
Service sectors:										
G – Wholesale/retail	3473	0.145	0.352	0	1	3589	0.142	0.349	0	1
H – Transport/storage	3473	0.033	0.177	0	1	3589	0.032	0.175	0	1
I – Accommodation/food	3473	0.041	0.197	0	1	3589	0.038	0.192	0	1
J – Information/communication	3473	0.073	0.261	0	1	3589	0.074	0.262	0	1
KL – Financial/real estate	3473	0.043	0.203	0	1	3589	0.044	0.205	0	1
M – Professional/scientific	3473	0.219	0.414	0	1	3589	0.217	0.412	0	1
N – Administrative/support	3473	0.057	0.231	0	1	3589	0.061	0.240	0	1
P – Education	3473	0.035	0.183	0	1	3589	0.037	0.188	0	1
Q – Health/social work	3473	0.039	0.195	0	1	3589	0.043	0.202	0	1
R – Arts/entertainment	3473	0.029	0.166	0	1	3589	0.029	0.167	0	1
S – Other service	3473	0.054	0.225	0	1	3589	0.054	0.226	0	1
Business location:										
England (0/1) (base group)	3473	0.965	0.183	0	1	3589	0.964	0.185	0	1
Wales (0/1)	3473	0.035	0.183	0	1	3589	0.036	0.185	0	1

Source: authors' tabulations from UK Longitudinal Small Business Survey.
LSBS: Longitudinal Small Business Survey; SIC: Standard Industrial Classification.
NA indicates not available, as some items are only asked in the first wave of the data.

where $\Phi(.)$ represents the cumulative density function of a normal distribution. X_{kit-1} refers to vectors of firm i's characteristics which affect both the treatment and outcome in innovation production ($k=1$), exporting behaviour ($k=2$) and productivity ($k=3$), all prior dated using information from the first panel wave. Table 1 lists all variables used and descriptive information on both treated and control groups. Correlation information is also provided in Table 4 of Appendix 1. In the model for innovation, X_{1it-1} includes a dummy variable indicating whether a firm has multiple business sites from which it may capture knowledge obtained via internal organisational networks (Zhou and Li, 2012). A dummy variable for awareness of business support programmes is included to capture orientation towards seeking support for business development. A dummy variable indicating whether a firm is located in a rural area is included to control for place effects. This is because firm characteristics, development barriers and business strategies may differ between rural and urban areas (Lee and Cowling, 2015). Firm age and size are also included since older and larger firms are on average more resourceful, innovative and have better economic performance than younger and smaller firms (Atkeson and Kehoe, 2005). Firm size is categorised into three bands: sole proprietorships (the base group in all estimations), those with between 1 and 4 employees and those with between 5 and 9 employees. Firm age is categorised into four bands: those less than 5 years old (the base group), those between 6 and 10 years old, those between 11 and 20 years old and those more than 20 years old. Regional and industry sector dummy variables (5 and 14 groups respectively) are included to control for time-invariant heterogeneity in performance related to common locational and sectoral characteristics.[7]

In addition to those variables in X_{1it-1}, the exporting behaviour function vector X_{2it-1} also includes innovation performance measures. Innovation has long been recognised as encouraging exporting (Golovko and Valentini, 2011). In addition, firms need superior capabilities to create new knowledge leading to better performance, especially in competitive or challenging environments such as international markets (Knight and Cavusgil, 2004). Four dummy variables are included to capture internal capabilities with potential to drive exporting. These capture whether a firm perceives itself to have strong or very strong capabilities for (1) developing and implementing a business plan and strategy, (2) developing and introducing new products or services, (3) accessing external finance and (4) operational improvement. In the productivity function, in further addition to those variables in X_{2it-1}, vector X_{3it-1} also includes lags of innovation, export performance and productivity, to further alleviate any potential endogeneity and persistence effects (Rosenbusch et al., 2011; Tse et al., 2017).

A kernel-based matching method is used because it incorporates information from all available controls. Unlike other matching methods, kernel matching uses more information than other estimation algorithms, down weighting more distant observations (Guo and Fraser, 2015). Kernel matching provided the best matching quality and variable balance between the treated and control groups.[8] Estimates of standard errors and confidence intervals for ATTs are obtained by bootstrapping. In order to test the robustness of the findings from the PSM method, a number of regression model-based specification tests, investigating the potential selection effects described in Figure 1, are undertaken. These are described in the robustness analysis section.

Findings

Sample matching success

Table 2 presents estimated ATTs for each of the three treatments in the first step (using external advice and information, using business networks, and having a business plan) on each of three

Table 2. Semi-parametric kernel matching: average treatment effect on innovation outcomes for the treated.

ATT estimate		(1)		(2)		(3)	
		Treatment: use external advice or information		Treatment: uses business networks		Treatment: has business plan	
Outcome: innovation							
Whether or not has product/service/process innovation	ATT (SE)	**0.107**	(0.020)	**0.101**	(0.024)	**0.110**	(0.020)
	Lower and upper confidence interval	*0.075*	*0.145*	*0.0534*	*0.149*	*0.069*	*0.148*
• Whether or not has product innovation	ATT (SE)	**0.062**	(0.017)	**0.049**	(0.016)	**0.039**	(0.015)
	Lower and upper confidence interval	*0.026*	*0.096*	*0.022*	*0.081*	*0.016*	*0.079*
• Whether or not has service innovation	ATT (SE)	**0.077**	(0.017)	**0.073**	(0.018)	**0.081**	(0.020)
	Lower and upper confidence interval	*0.049*	*0.122*	*0.042*	*0.122*	*0.030*	*0.113*
• Whether or not has process innovation	ATT (SE)	**0.062**	(0.015)	**0.059**	(0.019)	**0.072**	(0.016)
	Lower and upper confidence interval	*0.035*	*0.097*	*0.023*	*0.096*	*0.033*	*0.096*

Source: authors' computations from UK Longitudinal Small Business Survey.
ATT: average treatment effect on the treated; SE: standard error.
Semi-parametric kernel matching was used to estimate ATT. Bootstrapping standard errors and confident intervals are reported. Bold font indicates significant average treatment effect for the treated at 5% significance level.
Italics denotes confidence interval.

innovation outcomes (product, service and process). Table 3 presents estimated ATTs for the effects of those innovation outcomes on exporting and productivity. Those ATT estimates which are statistically significant at 5% level are in bold. For each ATT estimation, balancing indicators, comparing differences in the covariates between treated and control groups, were computed and are available on request. These all demonstrated a high level of matching success, suggesting that matching has controlled for any selection effects or that selection effects are not a feature of the data.

The key findings in Table 2 are that using external advice or information, using business networking and having a formal business plan are all associated with a significant increase in the likelihood that microbusinesses will innovate, thus confirming H1. In column (1), microbusinesses that obtain knowledge from external sources are 10.7% more likely to have product/service/process innovation output compared with matched comparators, with the 95% confidence interval here lying in the range 7.5%–14.5%. The size of ATT of obtaining external advice or information for specific forms of innovation varies between 6.2% and 7.7% and again in all cases is statistically significant. The biggest impact is on service innovation. Results in column (2) show the impact of engaging in business networking on innovation output. Overall, networked businesses are 10% more likely to produce innovation, with the impact from specific forms of innovation varying between 4.9% and 7.3%. Finally, in column (3) of Table 2, having a business plan increases the likelihood of innovation by 11%, with a very similar confidence interval to results in the other columns. The range of impact on specific forms of innovation varies between 3.9% and 8.1%.

ATT estimates for hypotheses 2 and 3

Table 3 shows the ATT effects of the treatment of innovation on export behaviour and productivity outcomes. Columns (1)–(4) first examine the ATT of having any type of innovation treatment and

Table 3. Semi-parametric kernel matching: average treatment effect on exporting and productivity for the treated.

		(1)		(2)		(3)		(4)		(5)	
		Treatment: whether or not has product/ service/process innovation		Treatment: whether or not has product innovation		Treatment: whether or not has service innovation		Treatment: whether or not has process innovation		Treatment: whether export goods and/or services	
Whether exports goods and/or services (all)	ATT (SE)	**0.110**	(0.020)	**0.140**	(0.022)	**0.070**	(0.017)	**0.054**	(0.019)		
	Lower and upper confidence interval	*0.069*	*0.149*	*0.110*	*0.182*	*0.034*	*0.095*	*0.023*	*0.089*		
• Whether exports goods (non-service sectors)	ATT (SE)	**0.034**	(0.016)	**0.110**	(0.020)	−0.016	(0.012)	0.007	(0.013)		
	Lower and upper confidence interval	*0.006*	*0.066*	*0.071*	*0.148*	*−0.044*	*0.005*	*−0.021*	*0.030*		
• Share of export sales from goods (non-service sectors)	ATT (SE)	1.329	(0.689)	**3.766**	(0.911)	−0.510	(0.660)	1.245	(0.915)		
	Lower and upper confidence interval	*−0.200*	*2.573*	*2.290*	*5.775*	*−2.205*	*0.712*	*−0.328*	*2.673*		
• Whether exports services (service sectors)	ATT (SE)	**0.082**	(0.016)	**0.066**	(0.019)	**0.082**	(0.016)	0.036	(0.020)		
	Lower and upper confidence interval	*0.048*	*0.113*	*0.037*	*0.104*	*0.057*	*0.111*	*−0.003*	*0.076*		
• Share of export sales from services (service sectors)	ATT (SE)	**3.187**	(0.907)	1.625	(0.990)	**3.026**	(0.919)	1.993	(1.047)		
	Confidence interval	*1.401*	*5.057*	*−0.173*	*3.606*	*1.347*	*4.897*	*−0.463*	*4.099*		
Turnover per employee	ATT (SE)	−0.034	(0.068)	−0.045	(0.062)	0.011	(0.052)	0.009	(0.050)	**0.109**	(0.054)
	Lower and upper confidence interval	*−0.159*	*0.119*	*−0.175*	*0.048*	*−0.085*	*−0.061*	*−0.080*	*0.103*	*0.002*	*0.219*

Source: authors' computations from UK Longitudinal Small Business Survey.
ATT: average treatment effect on the treated; SE: standard error.
Semi-parametric Kernel matching was used to estimate ATT. Bootstrapping standard errors and confident intervals are reported. Bold font indicates significant average treatment effect for the treated at 5% significance level.
ATT estimates for hypothesis 1.
Italics denote confidence interval.

then distinguish between product, service and process innovation as treatments, respectively (H2). Looking at any form of innovation in column (1), microbusinesses with innovation have around 11% higher likelihood of exporting than those without any innovation. This effect is significantly different from zero, with a 95% confidence interval in the range of 7%–15%. Also in column (1), having any type of innovation raises export share by 3.2% for service businesses. In column (2) for non-service sectors, having product innovation raises the likelihood of exporting by 11%, and increases export sales share (intensity) by 3.8%. As for service businesses in column (3), those with service innovation are 8.2% more likely to export and have 3% higher export intensity than those without service innovation. Column (4) shows that the ATT for process innovation is only statistically significantly different from zero for the widest exporting definition in the first row, pooling manufacturing and service sectors together. For completeness, the bottom row of Table 3 reports estimates of the treatment effects of the different forms on innovation directly on productivity. None of these treatments are statistically significant, providing further support for the model structure proposed in Figure 1.

Finally, column (5) reports the size and significance of the ATT for the impact of exporting on productivity (H3). Labour productivity is 11% higher in exporting businesses relative to matched comparators, although, because this estimate is only significant at just below the 5% level, the confidence interval is relatively wide. The results also demonstrate that for any type of innovation treatment, firms with innovation do not have higher productivity outcomes, confirming that there are no direct benefits of innovation on productivity, but the effect comes from exporting as an internationalisation strategy.

Robustness analysis

Testing for endogeneity and robustness checks

Although balancing indicator analysis supports the reliability of the PSM method in this case, our concern here is to further test for potential endogeneities in the relationships between innovation, exporting and productivity, as shown in Figure 1, which might lead to biased regression estimates in the event that unobserved factors are correlated with innovation or exporting. We adopt three approaches based on regression analysis. Modelling details and explanation for these checks are in the Appendix.

First, Wooldridge's modified correction function approach is adopted as it fits discrete choice models with multiple discrete endogenous variables (Wooldridge, 2010). The correction (or control) function explicitly models the relationship between the endogenous variable(s) in the regression and its error term. This two-step method has the advantage of allowing for multiple treatments and for various distributional characteristics over other approaches (Wooldridge, 2010), and has been shown to generate consistent, asymptotically normal estimation of the average treatment effects. It also provides a straightforward specification test. In the first step, first-stage Probit equations are estimated, respectively, for innovation and exporting outcomes using all the same explanatory variables as those used to generate propensity scores to keep models consistent. Then, correction functions are formed from the normal density of the predicted probabilities obtained through Probit models. In the second step, the baseline equations for exporting and for productivity are estimated with the additional inclusion of interaction terms of the correction functions with the mean differenced exogenous variables. In all cases (see Table 5 of the Appendix, columns (6) and (7)), we find no evidence for endogeneity, indicating that pooled Probit and ordinary least squares (OLS) regression model specifications for exporting and productivity are sufficient to provide consistent estimates (results presented in Table 5 of the Appendix, columns (2) and (5)). These models further confirm the size and significance of the ATTs obtained from the PSM method.[9]

Second, a two-step Rivers and Vuong (1988) test is adopted to test possible reverse causality running from productivity to exporting (i.e. self-selection effect). The test is designed for Probit models with potential continuous endogenous variables. The first stage estimates firm productivity with a full list of explanatory variables and generates a residual term. In a second stage, the residual from the first stage is included in the baseline model. An insignificant coefficient on this residual in the second stage indicates absence of endogeneity, which is the case for our data ($\chi^2 = 0.49$, p value $= 0.486$).

Third, conditional mixed-process (CMP) modelling is employed as this provides consistent estimation for recursive systems (Roodman, 2011). Unlike other simultaneous equation systems estimators, CMP has the flexibility of allowing for non-continuous dependent variables. It conducts a test of whether there are unobserved factors affecting any two equations in the recursive system. This is shown in the CMP correlation of unobserved factors statistics in Table 5 of the Appendix. The model in column (8) fails to find any correlation of unobserved factors that affect both innovation and exporting (statistic (a) $= 0.029$, p-value $= 0.750$), confirming innovation is not endogenous in determining exporting. The finding in column (8) confirms the results from PSM that having innovation indeed encourages exporting behaviour, after controlling for the potential endogeneity of innovation. Given the absence of endogeneity, a pooled Probit model would suffice to give consistent estimations, as reported in column (2) in Table 5 of the Appendix. Column (9) shows that there is a significant negative correlation between productivity and exporting (statistic (b) $= -0.445$, p-value $= 0.001$). This means that the unobserved characteristics that determine productivity are negatively correlated with the unobserved factors that explain exporting behaviour. Even allowing for this correlation, the main finding still holds that it is exporting rather than innovation that improves productivity of microbusinesses. Apart from this, there are no sign of any correlations between unobserved factors that affect any other outcomes, (a) and (c). In addition, to test whether or not there is reverse causality (i.e. self-selection effect) running from productivity to exporting, column (10) in Table 5 of the Appendix shows there is no correlation between unobserved factors that determine productivity and exporting (statistic (b) $= -0.116$, p-value $= 0.997$), and productivity is insignificant in shaping exporting decision. In summary, all these robustness checks confirm the findings obtained from PSM models.

Innovation novelty

Innovation novelty refers to the degree of change created in existing practice (Damanpour, 1988). In comparison with incremental innovation, radical innovation brings novel functionalities and customer value, which has high potential for growth in sales and market share (Sainio et al., 2012). Radical innovation is more difficult to imitate, thus enhancing innovators' competitive position (Lee et al., 2003). Radical innovation, captured in our data as an indicator of new-to-market innovation, is only a third as common among UK microbusinesses (Table 1). However, this form of innovation should be more strongly associated with exporting behaviour. This is because radically enhanced products help microbusinesses overcome the additional liability of 'foreignness' when serving multiple regions beyond the home market. Table 6 in the Appendix reports ATT estimates focusing on new-to-market versus new-to-business innovation as treatments on exporting. The results show that new-to-market innovation is associated with a 15.3% increase in likelihood of exporting (95% confidence interval 9.4–20.3%), a 3.3% uplift in goods export share and a 5.6% uplift in services export share. All of these effects are stronger than for the wider innovation definition used in Table 3. By clear contrast, ATTs for new-to-business innovation show no statistically significant impacts on exporting. This finding supports other UK research (Love et al., 2016). Finally, the results here show no direct relationship between novel innovation and productivity, and confirm the significant impact of exporting on productivity. Novel innovation activity therefore only indirectly impacts productivity via exporting.

Discussion and limitations

We find evidence to support each of the three proposed hypotheses. These findings demonstrate a causal chain linking the acquisition and formalisation of information to the production of innovation and through to microbusiness performance. Using a range of appropriate econometric methods to investigate and control for potential selection and endogeneity effects, these findings confirm that innovation indirectly impacts on productivity performance through stimulating exporting activity. This is consistent with a learning-by-exporting explanation of firm performance, and supports the view that innovation is an important driver of exporting behaviour. Innovation enables microbusinesses to expand internationally. In turn, the competitive discipline of selling overseas then focuses microbusinesses on the effective use of labour resources to generate turnover. In contrast to previous research (Baumann and Kritikos, 2016), these findings show that microbusinesses behave differently from larger firms in terms of transforming knowledge inputs to product and process innovation output, and in utilising innovation to increase labour productivity. In short, microbusiness innovation does not contribute directly to productivity, but any effect is channelled through exporting activity. This is in line with previous work (Azar and Ciabuschi, 2017), but contrasts with other findings (Harris and Li, 2009), and supports the integration of internationalisation into the CDM approach.

Innovation in microbusinesses, where explicit resourcing of R&D activity is much less common than in larger counterparts, is an informal process. These findings show that access to external information sources, via both advisory and support services and peer-to-peer business networking activities, are associated with increased propensity to innovate. Knowledge exploration and acquisition contribute to innovation, but neither has a direct impact on exporting or productivity performance. Formal business planning supports the process of innovation production by enabling microbusinesses to integrate and systematise knowledge from this range of sources. However, these findings contrast with other literature which finds that formal planning has a direct impact on economic performance (as measured by turnover per employee) (Brunswicker and Vanhaverbeke, 2015). Thus, we are able to extend previous work on microbusiness (Love and Roper, 2015), by filling in gaps between knowledge acquisition and planning, innovation and exporting success. Microbusinesses may be better at acquiring and internalising advice to close gaps in expertise, but may not be as effective as larger firms in directly commercialising such knowledge to generate turnover.

Previous research tends to rely on a single innovation measure (Booltink and Saka-Helmhout, 2018), with studies tending to focus solely on manufacturing, ignoring the importance of and potential differences in the service sector (Mina et al., 2014). In this study, we have examined the impacts of different types of innovation in service as well as non-service sectors. In non-service sectors, it is only product innovation that leads microbusinesses to export, whereas the results show that across the full sample of businesses service and process innovation also contributes to exporting decisions and intensity. This contrasts with prior research which suggests that process and service innovation can support exporting of manufactures (Higón and Driffield, 2011). However, whereas large manufacturers may exploit process innovation to achieve cost reductions (Dey et al., 2019), such innovation may be of less benefit to manufacturing microbusinesses. However, for service-based microbusinesses process innovation is innate to improved service delivery. Innovation novelty is also important. In both non-service and service sectors, it is more radical (i.e. new to the market) innovation that contributes in particular to microbusiness exporting. This reinforces other research which concludes that radicalness embedded in new-to-market innovation helps microbusinesses to overcome ‘foreignness’, brings value to international customers and achieves exporting success (Silva et al., 2017).

Therefore, why does microbusiness innovation not appear to lead directly to productivity gain as suggested elsewhere (Baumann and Kritikos, 2016)? Innovation activity can bring short-term interruptions to business operation that arrests turnover growth (Gunday et al., 2011). Innovation gestation periods can be longer than captured in the data structure in this study (Damanpour and Evan, 1984). Alternatively, microbusinesses could face other unmeasured absorptive capacity constraints in translating innovation into turnover. However, the findings do suggest, at least in the short term, that microbusinesses productivity is best promoted by channelling the benefits of innovation through export promotion to achieve learning-by-exporting exposure (Booltink and Saka-Helmhout, 2018).

Although our purpose here is not to evaluate R&D support policy, there are clear implications in these findings for the potential value of external business support. Other research shows that demand for formal business support and advice is correlated with growth motivation, and that business advisory programmes can be an important conduit for the dissemination of knowledge (Mole et al., 2017). External advice can increase strategic knowledge and improve competitiveness (Bennett and Robson, 2003). However, research often highlights low levels of take-up by the smallest businesses, for a range of reasons concerning awareness, cost and poor fit between professional advisors and recipients (Bennett, 2008; Mole et al., 2017). In terms of specific support for R&D, research highlights the importance of policy focus and mix, and the potential limitations of using binary treatment indicators to capture complex intervention effects or quantitative variation in the scale of intervention (Dumont, 2017; Mulligan et al., 2019). These findings do suggest that policy mix and balance is likely to be important. If policy intervention focuses exclusively on one link in the causal chain identified here, then it may achieve limited traction overall. It might be argued here that microbusinesses need support at a number of levels (Wright et al., 2015), such as to access knowledge from external and peer-to-peer sources (Robson and Bennett, 2000; Thorpe et al., 2005), to translate knowledge into appropriate innovation activity, and support to access international markets where smaller businesses are disadvantaged by absence of scale economies (Lu and Beamish, 2006). Furthermore, since only a minority of microbusinesses demonstrate an ability to innovate and export, policy design needs to target those businesses most likely to achieve this development path towards growth and productivity. The challenges of achieving good policy design and implementation are not issues which our dataset allows us to address, although they all merit ongoing research, in the context of microbusiness performance.

We have faced a number of limitations in this study. In common with much research which undertakes secondary analysis of small business survey data, we are constrained by questionnaire design and spread. The absence of information in the LSBS data source on microbusiness attributes and characteristics is one limitation preventing further detailed exploration of the issues addressed here, for example, in the potential moderating effects of management skills. Furthermore, other sources of knowledge, not captured by questionnaire items available, may also support the innovation production process. Although we refer to previous literature which highlights the informal nature of R&D in the smallest business, our data source does not allow us to test any potential role for formal R&D activity and expenditure in the production of innovation. Our analysis has used just two waves of data, and this highlights a compromise facing research on microbusinesses where sample attrition rates are high due to business death rates which are much higher than for larger businesses. There is a trade-off between the problem that results might be influenced by survivor bias, ability to model fully business heterogeneity and concerns that full causal effects might arise over intervals longer than one year. A longer panel structure would also allow for a full structural investigation of the dynamics implied by the model conceptualisation. Finally, our sample is for England and Wales, and so there is the inevitable question concerning the generalisation of findings to other contexts. This must be the subject of further research.

Conclusion

This article has addressed important issues in the production and impact of innovation in the context of microbusinesses in services and production, under-researched segments of the business population. This has been undertaken using UK longitudinal business survey data, well-suited to the deployment of PSM and treatment analysis appropriate to analysing the recursive structure which underpins the CDM framework, and to addressing endogeneity problems faced in early research. The analysis has uncovered important conclusions about the channels through which knowledge acquisition and capacity to exploit knowledge facilitates the production of innovation in microbusinesses, which in turn stimulates exporting activity leading on to improved business productivity. The key finding, which stands in contrast to previous work, is that these channels are indirect rather than direct – there is no direct link, in the case of microbusinesses, between knowledge production or innovation output and productivity. The role that innovation plays in stimulating and supporting exporting behaviour appears to be a critical mediating link. Both the type and novelty level of innovation are also found to be important. Innovation indirectly benefits microbusinesses via a learning-to-export effect through which improvements in productivity are achieved. From this it is concluded that support for microbusinesses requires careful targeting and balance, with particular focus on innovation as a route to business growth. The policy support case depends on two particular issues – first that overall the proportion of innovative microbusinesses is small, and second that the quantitative impact of business planning or use of external advice as 'treatments' are also small in absolute size, perhaps raising the likelihood of innovating by between 4% and 13% points. Nevertheless, careful targeting of support could see quantitatively significant indirect effects through to higher business productivity performances in particular microbusinesses.

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ORCID iD

Andrew Henley https://orcid.org/0000-0003-4057-1679

Notes

1. Hereafter, through this article, we abbreviate references to the influential Crepon et al. (1998) model as 'CDM'.
2. Recent small business examples include Golovko and Valentini (2011) who find that novel product innovation leads to exporting success in Spain, and D'Angelo et al. (2013) who report that innovation investment as well as product innovation significantly boosts export intensity in Italy. However, other studies fail to observe any relationship between innovation and exporting (Damijian et al., 2010).
3. Business support activity is devolved across the individual nations of the UK. For some reason, the networking question was appended to business support questions asked only in England and Wales.
4. Log transformation significantly reduces the skewness of turnover per employee, with transformed median value being very similar to mean value. In subsequent analysis, results were found to be consistent after winsorising the top and bottom 1% of the productivity distribution to eliminate potential outlier influence, and these results are reported where log productivity is the dependent or outcome variable.
5. For instance, when generating the treatment effect of having innovation on exporting, the effect of self-selection into innovation is already accounted for when generating propensity scores to balance the treated and control group.
6. The availability of only two survey waves is a limitation since it precludes modelling innovation production at t-2, exporting behaviour at t-1, and productivity at t. Subsequent to our initial analysis, a further

wave of data has been released. However, high attrition between Waves 2 and 3 would have forced a very large reduction in sample size if a three-period modelling strategy had been adopted.
7. Although we might wish to include some measure of past innovation experience in the specification, such a measure is not available. However, the data reveal significant variation in levels of innovation across sectors, and so sector controls ought to capture a significant element of variation in past innovation history and persistence.
8. A bias-corrected matching estimator developed by Abadie and Imbens (2002) was adopted as an alternative matching technique. It does not require consistent estimation of unknown functions to predict propensity scores. Consistent results are found and available upon request.
9. Detailed descriptions of methods and results are provided in Table 5 of the Appendix.

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Author biographies

Andrew Henley is professor of entrepreneurship and economics at Cardiff Business School, Cardiff University, UK. His research interests include entrepreneurship choice, small business growth and performance and regional development.

Meng Song is lecturer in entrepreneurship at Aston Business School, Aston University, UK. Her research interests include firm innovation and growth, internationalisation and the interplay between firm behaviour, industry and institutions.

Appendix

Correlation analysis

Table 4. Correlation matrix.

Correlation coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1) Has goods/services/process innovation (0/1)	1.00																							
(2) Has new to the market innovation (products/services/processes)	**0.46**	1.00																						
(3) Export goods (0/1)	**0.11**	**0.14**	1.00																					
(4) Export services (0/1)	**0.17**	**0.16**	**0.14**	1.00																				
(5) Export sales from goods	**0.10**	**0.15**	**0.60**	**0.34**	1.00																			
(6) Export sales from services	**0.10**	**0.14**	**0.23**	**0.63**	**0.66**	1.00																		
(7) Log turnover per employee	**0.05**	*0.02*	**0.12**	**0.10**	**0.11**	**0.09**	1.00																	
(8) Capability for business plan/strategy (0/1)	**0.06**	**0.07**	−0.02	0.00	−0.01	**0.03**	**0.04**	1.00																
(9) Capability for new products/ services (0/1)	**0.19**	**0.18**	**0.08**	0.00	**0.06**	0.02	0.00	**0.30**	1.00															
(10) Capability to acquire finance (0/1)	−0.02	**−0.05**	**−0.04**	**−0.08**	**−0.05**	**−0.06**	**0.08**	**0.25**	**0.12**	1.00														
(11) Capability for operational improvement (0/1)	**0.07**	**0.06**	**−0.07**	−0.01	**−0.04**	−0.02	*0.03*	**0.27**	**0.18**	**0.21**	1.00													
(12) Use information or advice (0/1)	**0.20**	**0.13**	**0.06**	**0.09**	**0.05**	**0.05**	**0.05**	**0.07**	0.03	0.02	*0.03*	1.00												
(13) Has business networks	**0.22**	**0.13**	**0.06**	**0.13**	**0.05**	**0.10**	0.02	**0.07**	**0.07**	−0.03	**0.06**	**0.18**	1.00											
(14) Has a business plan (0/1)	**0.16**	**0.12**	**0.03**	**0.04**	**0.04**	0.02	**0.03**	**0.23**	**0.11**	**0.07**	**0.14**	**0.16**	**0.20**	1.00										
(15) Has multiple business sites (0/1)	**0.05**	**0.05**	0.01	**0.05**	0.01	**0.03**	**0.05**	*0.03*	**0.04**	0.01	**0.04**	**0.05**	**0.04**	**0.07**	1.00									
(16) Aware of business support (0/1)	**0.11**	**0.08**	**0.06**	**0.10**	**0.06**	**0.05**	−0.01	**0.10**	**0.04**	**0.05**	*0.03*	**0.13**	**0.18**	**0.15**	0.00	1.00								
(17) Rural area (0/1)	*−0.02*	0.00	**0.03**	**−0.03**	**0.03**	**−0.04**	**0.08**	0.00	0.00	**0.06**	0.01	**0.03**	−0.02	**−0.02**	0.00	0.00	1.00							
(18) Employees 0 (0/1) (base group: sole proprietorship)	**−0.05**	−0.01	**−0.08**	−0.02	**−0.06**	**0.02**	**−0.11**	**−0.05**	**−0.07**	**−0.06**	−0.03	**−0.11**	*−0.03*	**−0.20**	**−0.08**	**−0.06**	0.02	1.00						
(19) Employees 1–4 (0/1)	**0.02**	0.01	*0.02*	**0.03**	**0.03**	0.00	**0.10**	0.02	**0.05**	−0.02	−0.01	**0.04**	0.00	**0.07**	0.01	**0.04**	0.02	**−0.66**	1.00					
(20) Employees 5–9 (0/1)	**0.03**	−0.01	**0.07**	−0.01	**0.03**	**−0.03**	*0.02*	*0.03*	*0.03*	**0.10**	**0.05**	**0.09**	**0.04**	**0.16**	**0.09**	0.03	**−0.04**	**−0.45**	**−0.37**	1.00				
(21) Firm age 1–5 years (0/1) (base group)	**0.05**	**0.07**	−0.01	0.02	0.02	0.02	**−0.08**	**0.04**	**0.06**	**−0.06**	0.00	**0.04**	**0.06**	**0.13**	0.02	**0.04**	**−0.06**	**0.03**	0.02	**−0.06**	1.00			
(22) Firm age 6–10 years (0/1)	**0.03**	0.02	0.01	0.02	**0.04**	0.01	−0.03	0.01	−0.01	**−0.07**	**0.03**	0.00	**0.06**	**0.05**	0.01	0.01	*−0.03*	**0.07**	−0.01	**−0.07**	**−0.17**	1.00		
(23) Firm age 11–20 (0/1)	**0.04**	**0.06**	0.01	0.03	−0.02	**0.04**	−0.02	−0.01	0.01	−0.01	0.01	0.00	0.00	**−0.06**	0.00	0.01	−0.02	**0.05**	**−0.05**	−0.01	**−0.20**	**−0.20**	1.00	
(24) Firm age > 20 (0/1)	**−0.09**	**−0.12**	−0.01	**−0.05**	−0.02	**−0.05**	**0.09**	−0.02	**−0.04**	**0.10**	**−0.03**	−0.02	**−0.08**	**−0.08**	−0.02	**−0.04**	**0.07**	**−0.11**	*0.03*	**0.11**	**−0.42**	**−0.43**	**−0.51**	1.00

Source: authors' computations from UK Longitudinal Small Business Survey.
Italics denote correlation significant at $p < 0.10$; bold at $p < 0.05$.

Regression models and exogeneity tests

Table 5 reports the findings from a series of tests for exogeneity. The tests focus on (1) whether or not innovation is endogenous in determining exporting behaviour, (2) whether or not productivity is endogenous in determining exporting behaviour, and (3) whether or not both innovation and exporting are endogenous in determining productivity. As described in the robustness analysis section we adopt three approaches. First, we employ Wooldridge's (2010) modified correction function approach, to test cases (1) and (3). Details of implementation as follows.

In case (1), a Probit model is used to estimate the probability of a firm being an exporter based on pre-exporting characteristics. The Probit equation takes the following form

$$Export_{it}^{*} = \alpha_0 + \alpha_1 Innovation_{it-1} + \alpha_2 X_{it-1} + \varepsilon_{i1t}, Export_{it} = 1\left[Export_{it}^{*} > 0 \right] \quad (1)$$

In case (3), productivity is determined by a regression of the following form

$$Productivity_{it} = \beta_0 + \beta_1 Innovation_{it-1} + \beta_2 Export_{it-1} + \beta_3 X_{it-1} + \varepsilon_{i2t} \quad (2)$$

where $Export_{it}^{*}$ is a latent variable taking value greater than zero for firm *i* at time *t*. $Productivity_{it}$ is a continuous variable measured by turnover per employ in logarithm form. ε_{i1t} and ε_{i2t} are idiosyncratic error terms. Firm-level control variables are included in the vector X= {*Self-assessed business capabilities, business planning and networking, firm characteristics, sectors and locations*}.

$Innovation_{it-1}$ is potentially endogenous in (1) and both $Innovation_{it-1}$ and $Export_{it-1}$ are potentially endogenous in (2). Lagging all the explanatory variable by one year may not suffice to address endogeneity, and we, therefore, adopt Wooldridge's (2010) modified correction function approach to test the robustness of our PSM findings. Wooldridge proposes a two-step test where the baseline models (1) and (2) can be augmented with correction functions. The first-stage estimates a Probit equation for each firm's innovation decision and exporting decision, respectively, on all explanatory variables. This will generate correction functions from the normal density of the predicted probabilities obtained through Probit models. In the second stage, the interaction terms of the correction functions with the mean differenced exogenous variables are added in the baseline equation. The second-stage models are then estimated by Probit model when the dependent variable is the binary exporting variable, and by OLS when the dependent variable is log productivity.

More specifically, let $Endogenous_{ikt}(k = 1\, for\, innovation, 2\, for\, exporting)$ be the two potentially endogenous variables. These censored endogenous variables take standard Probit reduced forms

$$Endogenous_{ikt} = 1 \mid [\theta_0 + \theta_1 X_{it1} + u_i \geq 0]$$

where $\left[u \middle| X \right] \sim Normal(0,1)$ and X is the vector of covariates in the model specified in equation (1). Let $r = (1, X)$, so that $r\theta = \theta_0 + X\theta_1$, then the correction function, $h(X,\theta)$ is $h_{ijt}(X,\theta) = \phi(r\theta)$, where $\phi(.)$ is the standard normal density. Equations (1) and (2) can be modified as

$$Export_{it}^{*} = \gamma_0 + \gamma_1 Innovation_{it-1} + \gamma_2 Innovation_{it-1} * (X_{it-1} - \overline{X_t}) + \chi_1' \ X_{it-1} + \rho_1 \widehat{\phi_1} + \epsilon_{i1t} \tag{3}$$

$$\begin{aligned} &Productivity_{it} = \beta + \sum\nolimits_k \beta_k' \ Endogenous_{ikt-1} + \\ &\sum\nolimits_k \delta_k' \ Endogenous_{ikt-1} * (X_{it-1} - \overline{X_t}) + \chi_2' \ X_{it-1} + \sum\nolimits_k \rho_k \widehat{\phi_{k2}} + \epsilon_{i2t} \end{aligned} \tag{4}$$

Equations (3) and (4) are then respectively estimated by Probit and OLS with bootstrapped standard errors to account for the fact that the control functions are generated regressors as denoted by the ^ symbol. Results are presented in columns (6) and (7) in Table 5. Joint significance of the control functions provides a test of exogeneity of the potential endogenous variable. There is no sign that innovation is endogenous in the innovation leading to exporting relationship in column (6), or innovation and exporting being endogenous in determining productivity in column (7).

For case (2), we test endogeneity using a two-step Rivers and Vuong (1988) test. Statistical significance of the predicted residual indicates the presence of likely endogeneity, as described in section 'Robustness analysis'. There is no sign of productivity being endogenous to exporting, and productivity does not significantly affect the likelihood of exporting.

The CMP modelling is employed as this provides consistent estimation for recursive systems (Roodman, 2011). The same explanatory variables employed in the PSM model and the other robustness checks are used in the model to ensure consistency. In addition, two instruments have been included as exclusion restrictions. In the innovation outcome equation, an indicator of whether or not workforce receives labour training is included, as enhanced human capital is important for innovative activities of microbusinesses. In the exporting outcome equation, an indicator of whether or not a firm uses a third-party website (e.g. Amazon or Ebay) to promote sales, as such platforms could provide an easy initiation into serving overseas customers and therefore facilitate exporting behaviour.

Finally, as a comparison to the discrete exporting decision modelled in column (2), columns (3) and (4) report Tobit estimates for export sales share (intensity) in goods and in services, measured as percentage of sales accounted for by exports in each case. These regressions correspond with the treatment effects estimated in Table 3 where in the third and fifth rows the outcome is export intensity. A Tobit (censored regression) estimator is used because of distributional skewness and the significant proportion of firms where export intensity is zero. These further reinforce findings of impact from innovation on exporting, and show that lagged innovation is associated with between 3% and 4% points increase in export intensity, corresponding very closely to the results reported in Table 3.

Table 5. Alternative estimates by multiple regression and exogeneity tests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimation method:	Probit	Probit	Tobit	Tobit	OLS	Wooldridge	Wooldridge	CMP	CMP	CMP
Dependent variable:	Innovation: has product/ service/process innovation (0/1)	Exporting: (goods and/ or services) (0/1)	Export intensity, goods	Export intensity, services	Productivity	Exporting: goods and/or services (0/1) (innovation potentially endogenous)	Productivity (innovation and exporting potentially endogenous)	Exporting: goods and/ or services (0/1)	Productivity	Exporting: goods and/or services (0/1) (productivity potentially endogenous)
Has goods/services/process innovation (0/1)		0.090***	2.814**	3.988***	0.002	0.091***	0.112	0.104***	−0.089*	
		0.015	1.246	0.740	0.036	0.017	0.077	0.024	0.054	
Exporting goods/services (0/1)					0.099**		0.519***		0.590***	
					0.044		0.094		0.157	
Uses external information or advice (0/1)	0.106***	0.017	1.386	0.252	0.049	0.038*	0.137	0.026	−0.0004	0.032
	0.017	0.015	1.162	0.706	0.042	0.021	0.124	0.017	0.039	1.549
Uses business networks (0/1)	0.111***	0.056***	1.090	1.963**	0.018	0.060***	−0.035	0.062***	−0.007	0.054
	0.019	0.019	1.262	0.971	0.043	0.020	0.149	0.021	0.044	0.657
Has business plan (0/1)	0.092***	0.012	1.848	−0.396	0.007	0.005	−0.010	0.017	−0.035	0.011
	0.017	0.016	1.145	0.718	0.040	0.019	0.089	0.017	0.04	0.561
Capability for business plan/ strategy (0/1)		0.023	0.678	0.626	0.048	−6.22e–06	0.104	0.020	0.063	0.002
		0.016	1.172	0.750	0.038	0.016	0.073	0.018	0.039	1.130
Capability for new products/ services (0/1)		0.008	1.664	0.0815	0.052	0.006	−0.117	0.005	0.034	0.013
		0.016	1.245	0.699	0.037	0.017	0.076	0.017	0.038	0.444
Capability to acquire finance (0/1)		−0.042***	−1.641	−2.458***	−0.006	−0.051***	0.273**	−0.041**	0.021	−0.052
		0.016	1.145	0.746	0.040	0.017	0.126	0.017	0.039	1.116
Capability for operational improvement (0/1)		−0.036**	0.712	−1.022	0.032	−0.028*	0.127	−0.043**	0.041	−0.043
		0.016	1.139	0.725	0.039	0.017	0.095	0.017	0.039	0.622
Lagged productivity					0.743***				0.750***	0.067
					0.022				0.015	6.296
Has multiple business sites (0/1)	0.024	0.014	5.523***	−0.702	0.103	0.020	0.118	0.018	0.047	0.01
	0.027	0.025	1.508	1.157	0.075	0.029	0.206	0.028	0.064	2.189

(Continued)

Table 5. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimation method:	Probit	Probit	Tobit	Tobit	OLS	Wooldridge	Wooldridge	CMP	CMP	CMP
Dependent variable:	Innovation: has product/ service/process innovation (0/1)	Exporting: (goods and/ or services) (0/1)	Export intensity, goods	Export intensity, services	Productivity	Exporting: goods and/or services (0/1) (innovation potentially endogenous)	Productivity (innovation and exporting potentially endogenous)	Exporting: goods and/ or services (0/1)	Productivity	Exporting: goods and/or services (0/1) (productivity potentially endogenous)
Aware of business support (0/1)	0.014	0.033**	−0.024	1.613**	0.01	0.070***	−0.171	0.037**	−0.026	0.051
	0.017	0.016	1.184	0.747	0.040	0.017	0.152	0.017	0.039	0.045
Rural area (0/1)	−0.014	−0.024	0.343	−2.201***	0.072*	−0.0001	0.224***	−0.024	0.061	−0.042
	0.018	0.016	1.144	0.802	0.038	0.017	0.083	0.018	0.040	0.492
Employees 1–4 (0/1) (base group: sole proprietorship)	0.065***	0.016	−1.019	0.359	0.034	−0.042*	−0.130	−0.031	−0.205***	−0.039
	0.018	0.016	1.209	0.728	0.04	0.022	0.111	0.023	0.052	0.24
Employees 5–9 (0/1)	0.045*	0.014	0.694	−1.034	0.235***	−0.027	0.209**	−0.010	−0.127**	−0.029
	0.024	0.022	1.401	1.160	0.049	0.023	0.088	0.023	0.053	1.192
Firm age 6–10 years (0/1) (base group: 1–5 years)	0.007	0.047*	−0.846	2.822**	−0.023	0.015	0.133	−0.021	0.136***	0.014
	0.028	0.024	2.130	1.098	0.064	0.028	0.134	0.024	0.053	2.160
Firm age 11–20 (0/1)	0.025	0.024	0.492	1.514	−0.021	0.003	0.103	0.030	0.105**	0.048
	0.027	0.024	1.913	1.105	0.058	0.025	0.140	0.022	0.052	2.160
Firm age > 20 (0/1)	−0.059**	0.027	0.437	1.636*	−0.072	0.011	0.401***	0.010	0.056	0.029
	0.024	0.021	1.725	0.968	0.055	0.023	0.132	0.021	0.048	1.800
Constant					2.856***		10.062***			
					−0.259		0.500			
Location and industry dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Joint significance of the control functions (*p*-value in brackets)						$\chi^2(4) = 1.14$ (0.888)	$\chi^2(8) = 12.13$ (0.146)			

(Continued)

Table 5. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Estimation method:	Probit	Probit	Tobit	Tobit	OLS	Wooldridge	Wooldridge	CMP	CMP	CMP
Dependent variable:	Innovation: has product/ service/process innovation (0/1)	Exporting: (goods and/ or services) (0/1)	Export intensity, goods	Export intensity, services	Productivity	Exporting: goods and/or services (0/1) (innovation potentially endogenous)	Productivity (innovation and exporting potentially endogenous)	Exporting: goods and/ or services (0/1)	Productivity	Exporting: goods and/or services (0/1) (productivity potentially endogenous)
CMP correlation of unobserved factors that affect:										
(a) exporting and innovation								−0.029 (0.750)	−0.011 (0.904)	
(b) productivity and exporting									−0.445 (0.001)	−0.116 (0.997)
(c) productivity and innovation									0.101 (0.136)	
Log likelihood	−2118.641	−883.720	−372.345	−1297.219						
R-squared					0.585					
Observations	3486	2332	538	1692	1709	2254	1811	2790	2785	1802

Source: authors' computations from UK Longitudinal Small Business Survey.
OLS: ordinary least squares; CMP: conditional mixed process.
All explanatory variables are one-year lagged except for the industry and location dummies. In columns (3) and (4), the DV is the percentage of sales (goods or services) accounted for by exports. In columns (5), (7) and (9), the dependent variable is log turnover per employee.
Standard errors reported below each coefficient estimate are clustered by firms.
Average marginal effects are reported in columns (1)–(4). Column (6) reports marginal effects after estimating column (2) using Wooldridge (2010) two-step method, treating innovation as potentially endogenous. Similarly, column (7) shows marginal effects after estimating column (5) using Wooldridge (2010) two-step method, treating both innovation and exporting as potentially endogenous. The columns (6) and (7) use bootstrapped standard errors to account for the fact that the control functions are generated regressors. Tests for joint significance of the control functions reject endogeneity in columns (6) and (7). Reduced sample size is due to loss of observations when introducing instruments in the estimation second stage.
Columns (8), (9) and (10) report continuous mixed process estimates. Column (8) confirms results of the same specification reported in column (6), with insignificantly related unobserved factors determining innovation and exporting (i.e. innovation is not endogenous in shaping exporting). The absence of endogeneity is also observed in column (9) apart from the significantly negative correlations between unobserved factors that affect productivity and exporting. Even allowing this correlation, main results still hold that it is exporting rather than innovation that directly improve productivity. Column (9) confirms that in column (7). Column (10) tests whether there is self-selection of more productive firms become exporters. There is no sign of endogeneity, and productivity is insignificant in determining the likelihood of exporting.
In columns (5), (7) and (9) the top and bottom 1% of the productivity distribution are trimmed from the sample.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Innovation novelty

Table 6. Semi-parametric kernel matching: ATT estimates by innovation novelty.

		(1) Treatment: whether or not has new to the market innovation (products/services/processes)		(2) Treatment: whether or not has new to the business innovation (products/services/processes)		(3) Treatment: whether export goods and/or services	
Outcome:							
Whether exports goods and/or services (all)	ATT (SE)	**0.153**	0.030	0.011	0.019		
	Confidence interval	*0.094*	*0.203*	*−0.023*	*0.046*		
• Whether exports goods (non-service sectors)	ATT (SE)	**0.103**	0.020	−0.016	0.013		
	Confidence interval	*0.061*	*0.142*	*−0.038*	*0.010*		
• Share of export sales from goods (non-service sectors)	ATT (SE)	**3.308**	0.943	−0.691	0.634		
	Confidence interval	*1.388*	*5.456*	*−1.565*	*0.627*		
• Whether exports services (service sectors)	ATT (SE)	**0.094**	0.023	0.012	0.016		
	Confidence interval	*0.056*	*0.154*	*−0.016*	*0.043*		
• Share of export sales from services (service sectors)	ATT (SE)	**5.575**	1.378	−0.260	0.841		
	Confidence interval	2.978	*8.149*	*−1.786*	*2.121*		
Turnover per employee	ATT (SE)	−0.003	0.061	−0.003	0.032	**0.109**	0.054
	Confidence interval	*−0.132*	*0.126*	*−0.071*	*0.065*	*0.002*	*0.219*

Source: authors' computations from UK Longitudinal Small Business Survey.
ATT: average treatment effect on the treated; SE: standard error.
Semi-parametric Kernel matching was used to estimate ATT. Bootstrapping standard errors and confident intervals are reported. Bold font indicates significant average treatment effect for the treated at 5% significance level.
Confidence intervals are in italics.