The Role of Technology Standards in Product Innovation: Theory and Evidence from UK Manufacturing Firms

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Abstract

This paper studies the role of technology standards in firms' product innovation in terms of both incremental innovation (within a technology life cycle) and radical innovation (beyond the present technology cycle). We first develop a theoretical model which predicts that technology standards can be used by firms as an "insurance" hedging against the risky process of developing new products. This insurance mechanism fosters incremental innovation and product growth especially for those further away from the technological frontier. Using data from a weighted panel of UK manufacturing firms over seven years, we find that the use of technology standards over past years significantly enables a firm's incremental innovation while also reducing its incentive to deliver radical innovation. Additionally, we show that this relationship is contingent on a firm's R&D intensity in line with predictions of our theoretical model.

JEL classification: L25; L84; M21

Keywords: technology standards; incremental innovation; radical innovation; R&D intensity

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1 Introduction

How does the use of technology standards influence manufacturing firms' innovation in terms of growth in new products and product variety? In this paper, we develop a theoretical model to examine the multifaceted role of standards in incremental versus radical product innovation and empirically test its predictions using data from UK manufacturers.

We apply a novel perspective to understand the enabling effect of technology standards on incremental innovation by facilitating firms to catch up with the technological frontier while reducing their incentive for radical innovation by delaying investment in the next generation technology platform. We emphasise the intrinsic technological and market risks associated with commercialising new products. We then test this conjecture by formalising the hypothesis that a firm may use standards to hedge against these risks while facilitating incremental innovation sales, in case of a failure to deliver the radical type. Since we are interested in standards' role in the process of bringing new products to market, we set our focus on product instead of process innovation. Incremental innovation occurs at the technological frontier (Ettlie et al., 1984; Nooteboom, 1999), as the firm develops a product or service that is new to the focal *firm*, but not to the market. This corresponds to an improvement within a life cycle. Radical innovation, by contrast, is defined as introducing a new product or service to the *market* for the first time. This typically corresponds to the beginning of a new technology life cycle.

Standards can emerge in various ways and our study focuses on technology standards which are prevalently and voluntarily used in manufacturing innovation. In contrast to management or quality standards that specify performance metrics or minimum quality, these technology standards aim to achieve interoperability for various components in technology-based systems, encompassing *de jure* (technical) standards that are officially developed and/or endorsed by standards organisations (e.g., Internet Protocol, 5G standard) as well as *de facto* standards (Farrell and Saloner, 1988) that emerge from market-based competition such as a standards battle (e.g., Sony's Betamax vs JVC's VHS video format; Apple's iOS vs Google's Android mobile operating system).[1]

In a variety of industrial sectors, technology development is characterised by a high degree of modularity that defines clear division of tasks required for the functioning of increasingly integrated techno-

[1] Here we only consider a firm's use of technology standards as a knowledge source for innovation instead of standards adoption as our empirical data do not capture the extent to which such standards have been implemented.

logical systems (Baldwin and Clark, 2000). Due to a high level of technological complexity and market uncertainty, converting technological input into commercially viable new products is an intrinsically risky process which necessitates the extensive use of technology standards. Prevalent in technology-based industries, these standards encompass an industry's technological base and thus can provide a non-proprietary and critical technological infrastructure – the "infratechnology" – upon which more advanced, complex and system-level products can be developed and marketed (see Justman and Teubal, 1995; Tassey, 2000; Roper et al., 2004 for further discussion on the importance of technological infrastructure).

While macroeconomic and industry studies generally point to a positive link between standardisation and economic growth (Tassey, 2000; Blind and Jungmittag, 2008; Baron and Schmidt, 2014), the link between standards and innovation at the firm level is less clear-cut with mixed evidence documented in the literature (Allen and Sriram, 2000; Narayanan and Chen, 2012). Aside the infratechnology embodied in many standards, recent burgeoning research also highlights significant learning benefits for innovation stemming from using standards as a source of codified knowledge and industry best practices (Swann, 2000; Blind and Gauch, 2009; Blind, 2012; Spulber, 2013; Baron et al., 2014). Standards or standardisation, nevertheless, can be perceived to impede product varieties especially in new products by creating monopolies, restricting technological variety and reducing consumer choices (Salop and Scheffman, 1983, 1987; Scheffman and Higgins, 2003).

Our focus on the role of standards in firm-level innovation outcome is primarily motivated by the nexus between standardisation and technology life cycles (e.g., Suarez, 2004; Murmann and Frenken, 2006; Tassey, 2017). One of the central tenets of this argument is that while standards often increase efficiency of technology development and subsequent commercialisation by accelerating technology diffusion within a life cycle,[2] standardisation can, at the same time, prolong existing life cycles to an excessive degree by inhibiting investment in the technological innovation that creates the next cycle (Tassey, 2000, p.587).[3] A better understanding of this trade-off is thus a key strategic concern for businesses since the demand for standardisation tends to occur earlier in the technology life cycle nowadays (Tassey, 2017, p.253).

[2]Blind et al. (2017), for instance, find that the use of standards enhances innovation efficiency especially in markets with high uncertainty.

[3]See also Manders et al. (2016) for a specific review of this trade-off in the case of ISO9001 quality management principles.

Our analysis begins by theoretically modelling the conjecture on the self-selection of firms into the use of standards to leverage the foundational technologies contained herewithin for developing their innovative products. Building on the notion of infratechnology, we assume that a firm makes a decision to invest in radical product development and leverage existing standards to convert its innovation effort into market success. Drawing on the perspective of technology life cycle, the success of radical innovation is expected to lead to a new technological cycle. It follows that existing standards are likely to become less relevant if the firm expects its investment in radical innovation to be successful (Tassey, 2017, p.267). The firms who have greater incentive to invest in the use of standards are, therefore, the least likely to deliver radical innovation. Hence, if the use of standards is associated with more incremental and less radical innovation, it is partly due to the self-selection by those firms who benefit the most from using standards.

We derive three testable predictions from this conjecture using a stylised model of firms investment choice in the presence of voluntary use of standards and risky investment in radical innovation. First, controlling for firm characteristics, the use of technology standards should be negatively associated with the incentive to invest in radical innovation. This is partly because by hedging against the risk of a failed radical innovation, the use of standards decreases the gain from investing (an incentive effect), and because a firm benefits more from having that insurance if its cost of investing in radical innovation is high (a selection effect). Second, the use of technology standards should be positively associated with incremental innovation. The importance of this relationship is decreasing with a firm's investment in internal R&D, as the more a firm invests the more likely it is to deliver a radical innovation. This is a direct consequence of standards being an insurance policy: you only use it when you need it. Third, unless the probability of delivering radical innovation is very high, as the level of R&D investment increases, the *difference* in the probability of radical innovation success should also increase between firms using standards and those not doing so, controlling for firm characteristics. A firm investing substantially in R&D is, ex ante, more likely to deliver radical innovation. However, if it receives information that a potentially radical innovation is unlikely to be successful, it can choose to use existing technology standards and still deliver incremental innovation.

We subsequently test these predictions using a weighted longitudinal dataset of 1,143 firms in the UK manufacturing sector spanning the period 2006-2012. We find evidence consistent with standards being used as an insurance in a firm's effort to generate product innovation. Overall, our findings suggest that technology standards are used to bring a firm closer to the frontier within a technology life cycle (incremental innovation) while being negatively associated with radical innovation that facilitates the transition to a new cycle, controlling for firm characteristics and R&D investment. We also find support for the assumption that the firm's decision to use standards is influenced by non-observable information on the likelihood of success of radical innovation. Finally, at least part of this information comes after the decision on how much to invest in R&D. Indeed, the marginal gain in the success of radical innovation from not using a standard increases with the level of investment in R&D.

The remainder of the paper is organised as follows. Section 2 reviews the related literature and Section 3 presents our theoretical model. Section 4 describes our data and empirical strategy before discussing estimation results from our model of the relationship between standards use and innovation performance. The last section concludes.

2 Related literature

We discuss the ways in which our paper is related to several strands of the literature on standards and innovation, before presenting our unique contributions. Above all, our study adds to the growing body of research on technical transition, technology transfer and the diffusion of new technology (Swann, 2000; Amable et al., 2009; Blind and Gauch, 2009). Prior literature has considered the economic impact of technical change and technology adoption using a variety of empirical proxies such as new book titles in the field of technology (Alexopoulos, 2011) and the number of technology standards released that are developed by standards setting organisations (Baron and Schmidt, 2014). While these studies offer important insight into the effect of technological change on industry and macroeconomic dynamics, our understanding of the microeconomic mechanism underlying how the use of foundational technology affects firm-level performance remains limited. Based on a survey of the use of nanotechnology-related standards, for instance, Blind and Gauch (2009) argue that the role of standards in informing innovation in emerging technologies is largely neglected by research organisations and businesses, vis-a-vis other information sources such as patents and scientific publications. Our study thus offers a direct response to the call in this literature to investigate the role of standards beyond the oft-studied management and performance fields but as a source of knowledge for innovation and as a channel for technology transfer to expedite the catching-up to the technology frontier (Blind and Gauch, 2009; De Vries et al., 2018).

Furthermore, innovators and financiers alike routinely claim that a chasm or the so-called "valley of death" exists between basic research and commercialisation of new products (Frank et al., 1996; Chandy et al., 2006). Our argument centres on the risk-reduction role of standards by levelling the playing field, enabling compatibility and opening up new market opportunities (Allen and Sriram, 2000; Tassey, 2014). Innovators are thus able to exploit standards to minimise risks arising from complex technologies and market uncertainty and avoid the "valley of death" so as to introduce products with new features. This is largely thanks to the intrinsic characteristics of standards in containing scientific and technological know-how as well as representing industry best practices and global consensus of stakeholders (ranging from private firms, research institutions, governments to consumers). In doing so, our research underlines the critical role of the standards as yet another (under-explored) channel for enabling the transition from basic research to commercialisation stage through diffusing knowledge in new products and between players in the innovation ecosystem (Teece, 2018).

Our paper differs from prior work and contributes to the literature on innovation and standards in several important ways. First, we offer a novel perspective centring on risks to better understand the micro mechanism whereby the use of technology standards influences innovation outcome. As Tassey (2014) states, the "risk spike" affiliated with commercialising new products is typically larger for radical innovation as opposed to incremental innovation. We provide a first theoretical model and micro-level empirical examination of firm incentives in this context. Our findings highlight the trade-off in firm innovation decisions and provide fine-grained insight into the nuanced role of standards being contingent on the distance to technological frontier and the probability of innovation success.

Second, our theoretical model better accounts for the dynamic effect of standards use by incorporating a firm's timing decision which is oft-neglected in the literature. Despite Farrell and Saloner (1985)'s conjecture that early adoption may confer a first-mover advantage in innovation, prior literature has not explicitly tested the dynamics of standards use.[4] We show that a firm's timing of standards use is endogenously determined with the level of R&D input to exert influence on its innovation outcome.

[4] The significance of timing was echoed by Tassey (2017) in his argument on the benefits from earlier standardisation in the technology life cycle as modern technologies become more complex.

Finally, most studies on the standards-innovation linkage investigate standards use on the basis of specific standards (e.g., management standards), case studies of specific industries or small-sample cross-sectional surveys (David and Steinmueller, 1994; Metcalfe and Miles, 1994; Blind and Gauch, 2009; Manders et al., 2016; De Vries et al., 2018). Our empirical analysis draws on a large-scale longitudinal sample of UK manufacturers, weighted to be representative of business population, which allows us to overcome sampling bias and produce generalisable findings.

3 Theory

The objective of this stylised theoretical model is to provide testable implications of our conjecture that firms use technology standards as an insurance allowing them to deliver incremental innovation in developing new products in case of a failure to deliver the radical type. In particular, we generate predictions regarding the relationship between standards use and product innovation within a technology life cycle and beyond the existing cycle, controlling for all other firm characteristics, which are subsequently empirically tested.

Consider a simple model in which firms make investment decisions in order to maximise their expected profit. A firm is characterised by two parameters: α, representing its current level of productivity, and β, scaling the cost of investing in radical innovation.

For the model to be as parsimonious as possible, we assume the level of productivity α acts as a multiplier of the profit when the firm is at the technological frontier, θ_s. It thus directly determines the current profit, $\alpha\theta_s$, with $\alpha \in [0,1]$ drawn from a continuous random distribution with full support. The parameter β characterises how costly it is for a firm to deliver radical innovation. We represent it using a simple quadratic form: conditional on a level of investment $I = \frac{\beta x^2}{2}$, the probability that the firm delivers radical innovation is equal to x. Thus, the higher β is, the more costly it is for a firm to deliver radical product innovation with probability x. The level of profit in case of successful radical innovation is $\bar{\theta} > \theta_s$. As x is a probability, by definition $x \leq 1$.[5]

We call the pair $\{\alpha, \beta\}$ a firm's "individual characteristics." We do not make any assumption about the link between the two parameters, even though it is realistic to think that they may be negatively corre-

[5] We thus limit our attention to parameter values such that there is an interior solution to the optimal x for all values of α, by assuming $\beta \geq \bar{\theta}$.

lated: those firms that are closer to the technological frontier have a lower cost of developing radical innovation.

The choice of whether to use a technology standard (s) or not (ns) is discrete. Using the standard has a cost, c_s, but guarantees that the firm will reach at least the current technological frontier, θ_s. This corresponds to the conventional wisdom that, within a life cycle, standards offer a crucial channel of technology transfer (Blind and Gauch, 2009). We show in the next section that, controlling for firm characteristics, the use of standards to inform innovation is indeed correlated with incremental innovation. Note that the use of a single cost c_s is again a simplification aiming at representing the idea that the use of standards involves financial and other economic costs.

If it does not use the standard and fails to deliver radical innovation, the firm stays at its current level of productivity, $\alpha\theta_s$. In this setup, the use of technology standards is therefore an insurance policy: it guarantees a certain level of "catching up" incremental innovation if the firm fails to achieve radical innovation.[6]

In order to capture the different possibilities in terms of timing and information, we assume that, after choosing its level of investment but before choosing whether or not to use the standard, the firm observes a signal, $\sigma \in \{g, b\}$, of whether the investment in radical innovation will be successful ($\sigma = g$) or not ($\sigma = b$). The probability of that signal being accurate is $p \in [1/2, 1]$.[7] Hence, $p = 1/2$ corresponds to the case in which the signal is not informative. In that case, the firm decides on its level of investment in circumstances that are identical to those it would face if the decision were simultaneous, or if the decision to use a standard was made before the decision on the level of investment. The other polar case, $p = 1$, corresponds to a fully sequential choice: the firm decides whether or not to use the standard only after perfectly observing the result of the investment in radical innovation. Finally, $p \in (1/2, 1)$ corresponds to the intermediary cases in which some information is revealed, and in which our insurance perspective applies.

[6] This also implies that the set of standards that are used within a technology life cycle do not immediately fully migrate to the next one. The extent to which such migration happens depends on how radically different the new technology is.

[7] We denote successful radical innovation by $R = G$ and failed radical innovation by $R = B$, so that

$$Pr(R = G \mid \sigma = g) = \frac{px}{px + (1-x)(1-p)}, \tag{1}$$

$$Pr(R = B \mid \sigma = b) = \frac{p(1-x)}{p(1-x) + (1-p)x}. \tag{2}$$

To summarize the timing, the firm:

1. Decides on its level of investment in radical innovation I ;
2. Receives a signal, with probability p of being correct, of whether the investment will be successful ;
3. Decides whether or not to use a technology standard.

Thus the firm has to make two decisions: whether to invest in radical innovation, and whether to pay the cost of using a standard, $\{x, i(\sigma)\}$, with $x \in [0,1]$ and $i \in \{s, ns\}$. As the signal is informative ($p \geq 1/2$), it is trivial that if a firm chooses to use the standard when the signal indicates that the investment in radical innovation will prove a success, $\sigma = g$; it also prefers doing so when the signal is that it won't, $\sigma = b$. Similarly, if a firm does not use the standard when the signal is $\sigma = b$, it prefers not to do so when the signal is $\sigma = g$. There are thus only three choices to consider in terms of standards use: always using them, never using them, or using them only when the signal conveys bad news, $\sigma = b$.
We first establish the following preliminary result:

Lemma 1 *For a given distance to the frontier α, the firms for which delivering radical innovation is more costly (high β) use the standard more often.*

The formal proof is provided in Appendix A. As the cost of using the standard is the same for everyone, it follows that - for a given distance to the frontier - the firms which are the most able to invest in radical innovation are less willing to bear it. Moreover, for a given choice of whether or not to use the standards, it is easy to see that the most able firms have a higher probability of delivering radical innovation, as the marginal cost of delivering it is lower.
We illustrate in Figure 1 the discrete choice of firms. To the left are firms that are further away from the technological frontier. Those firms invest - ceteris paribus - more in R&D when they do not use a standard. They nevertheless have more to gain from using one, as the cost of failing to deliver radical innovation is higher to them. To the top of the figure are the firms that are least efficient in delivering radical innovation. Those have a stronger incentive to use a standard because it is less costly for them to do so than to invest in delivering radical innovation.

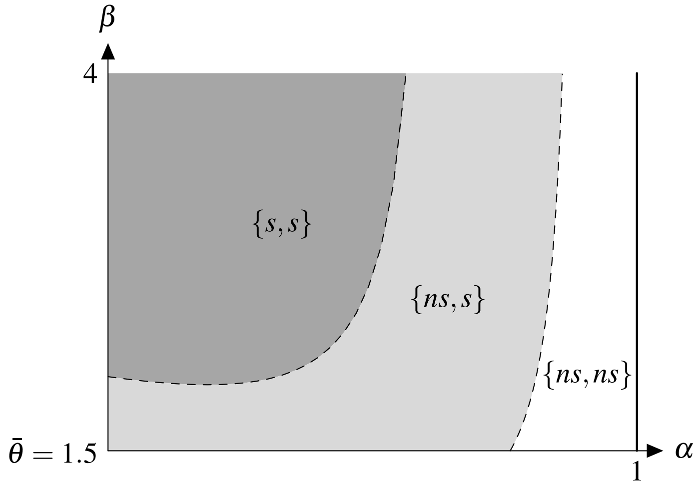

Figure 1: Radical innovation and investment in standards. With $\theta_s = 1$, $\bar{\theta} = 1.5$, $c_s = 0.2$, $p = 0.65$. The first element in the curly bracket corresponds to the decision on the use of standards in the signal is good, and the second if the signal is bad.

In our setup, the use of a technology standard reduces radical innovation, in the sense that it lowers the marginal benefit of investing in it. This corresponds to the path-dependency in technological evolution. This is also consistent with the intuition described in the introduction that technology standards may have the effect of prolonging existing life cycle of a technology to an excessive degree by inhibiting investment in the technological innovation that creates the next cycle (Tassey, 2000). Note that we take the quality of standards as exogenous. It is however easy to see that in our setting, improving the quality of standards would increase productivity within a life cycle but reduce the marginal benefit of investing in radical innovation thus prolonging the cycle. [8]

If the main hypothesis of our model - that firms use technology standards as an insurance - is correct, this explains partly why we should expect to see a lower rate of radical innovation among firms using a standard. Another explanation lies in a self-selection effect: the firms that do not use any standard will be those that have the highest ability to deliver radical innovation, all other things held equal.

The following proposition thus summarises the testable implications of our hypothesis that technology standards may be used as an insurance by firms undertaking product innovation.

Proposition 1 *1. For a given set of firm characteristics $\{\alpha, \beta\}$, a firm using standards delivers rad-*

[8] We thank a reviewer for this suggestion.

ical innovation less often, unless $p = 1/2$.

2. *For a given set of firm characteristics and decision on whether or not to use standards, if the signal conveys some information but is not perfectly informative $p \in (1/2, 1)$:*

   (a) *for all investment levels such that the probability of delivering radical innovation is not too high ($x \leq 1/2$), the difference in the probability of delivering radical innovation between a firm not using a standard and a firm doing so increases with the investment in R&D ;*

   (b) *else, the difference decreases with the investment in R&D.*

The formal proof is in the Appendix A. This proposition, together with the hypothesis that the use of standards fosters incremental innovation, corresponds to the testable predictions of our model of standards as an insurance. If the use of a standard is simultaneous with or precedes the investment in R&D, we should not observe any difference between firms using standards or not, after controlling for firm characteristics. If the use of standards depends on a firm's estimation of how likely its investment in radical innovation will be successful, we should observe that firms using a standard actually deliver less innovation, even after controlling for R&D. And unless the decision to use a standard is taken at the very end, as a plan B after radical innovation fails (i.e. a perfect signal in our setting), we should see this difference varying with the level of investment in R&D. If the probability of success is lower than 50%, the more a firm invests in R&D, the higher the difference will be between standards users and the others, for a given set of firm characteristics.

The logic of the proof is as follows. If firms with similar characteristics are observed to take different decisions, it must be that they have learned something different about their probability of delivering radical innovation. This is only possible if the signal is informative ($p > \frac{1}{2}$) and imperfect ($p < 1$). We show that this difference has a unique maximum when the probability of delivering a radical innovation is $x = 1/2$, and is equal to zero when $x = 0$ and $x = 1$. This result corresponds to the idea that there is more to be learned from the additional information if there was a high uncertainty in the first place. A very low or very high value of x indeed correspond to situations with little uncertainty.

4 Empirical analysis

In this section, we test our main hypothesis that standards help firms reach the technological frontier, as well as other testable predictions in Proposition 1 regarding the relationship between standards use and product innovation.

4.1 Data

Our empirical analysis employs longitudinal data drawing on the linked *UK Innovation Survey* (*UKIS*, commonly known as the *Community Innovation Survey*) and the *Annual Business Survey* (*ABS*) – both collected by the UK's Office for National Statistics (ONS)[9] – to test the above predictions. The *UKIS* (ONS, 2018) provides a wide-ranging survey of innovation activities of UK establishments ranging from innovation input to outcomes and has been extensively used in innovation studies (Harris and Li, 2008; Frenz and Ietto-Gillies, 2009; Battisti and Stoneman, 2010; Lambert and Temple, 2015). The *ABS* (ONS, 2020) provides the most comprehensive information on structure and performance of UK businesses using an annual compulsory questionnaire sent to some 70,000 business units and covers around two-thirds of the total business population.[10] To model product innovation of firms and its determinants, we construct most of our variables using data from three waves of the *UKIS* (*UKIS* 2009, 2011 and 2013) spanning a seven-year period (2006-2012). The *UKIS*, however, does not collect information on some important firm-specific characteristics such as age, domestic or foreign ownership, corporate structure or geographical configuration, nor does it adequately covers the industry environments in which these firms operate. To account for these further aspects which are expected to influence innovation outcome, we therefore merge in additional variables using the larger sample of *ABS* data at the establishment level - the business unit of analysis used in the *UKIS* surveys.

In total, 14,281 firms provided valid responses to the *UKIS* 2009 survey (covering the 2006-2008 period), 14,342 to the *UKIS* 2011 (covering the 2008-2010 period) and 14,487 to the *UKIS* 2013 (covering the 2010-2012 period), at a response rate of 49%, 50% and 51% respectively. There was a non-response problem associated with the 2011 wave of the *UKIS*: only 9,111 firms (out of 14,342 responses

[9]Data access is facilitated by the Secure Lab of UK Data Service - see Acknowledgements for further details.

[10]Data collected by the *ABS* are used for calculating national accounts. Its sampling frame includes all large businesses and a stratified sample of small and medium-sized enterprises. A detailed discussion of this data source can be found in Griffith (1999) and Harris and Li (2008).

received) provided valid information on innovation-related activities.[11] With an attrition rate of 36.5%, there is a potential nonresponse bias - a form of selection bias - due to missing information. We thus estimate an attrition probit model to determine whether attrition is random, and whether the final usable sample is unbiased in retaining the characteristics of the original *UKIS* 2011 sample, especially in terms of the key variables of interest. Our findings reveal some weak evidence of non-random attrition.[12] Thus, to calibrate non-response adjusted weights for the 2011 sample, we re-calculate population weights based on similar stratification criteria to those used by the ONS in compiling the *UKIS* data (i.e. industry division, region and employment size band). A weighting procedure is thus employed in all ensuing analyses to allow valid inferences of the UK business population.

Respondents were asked to report innovation outcome at the end of the survey period in relation to innovation activities taking place during the preceding three years (e.g. the 2009 *UKIS* survey covers activities over the 2006-2008 period). Since the underlying innovation activities may have been conducted anytime within the three-year window, despite such built-in time lag in *UKIS* survey, any analysis using a single cross-sectional *UKIS* wave may thus still be affected by reverse causality and simultaneity bias. Therefore, in order to address endogeneity problems arising from these sources, all explanatory variables are lagged by one period (i.e. going back up to four years in time). As each *UKIS* is drawn on a stratified random sample, only a small fraction of establishments were repeatedly sampled between 2006 and 2012 to allow us to construct a panel. After taking lags, our final estimation sample is much reduced in size compared with the pooled cross sections, consisting of an (unbalanced) panel of 1,143 manufacturing firms (1,384 firm-period observations), vis-a-vis 3,284 manufacturing firms in *UKIS* 2009, 1,731 in *UKIS* 2011 and 2,882 in *UKIS* 2013. Due to this further attrition in our estimation panel, we have re-calibrated panel weights using the same aforementioned strata and used adjusted weights in ensuing regression analysis.[13]

[11]This was largely due to changes in sampling design (e.g. a larger proportion of respondents new to the survey) and the collection procedures used (e.g. around half of survey responses were collected by telephone interview).

[12]Results are not reported here but available upon request. According to Outes-Leon and Dercon (2008), the pseudo R-squared from the estimated attrition probit model can be interpreted as the proportion of attrition that is non-random. In this instance, less than 2% of attrition is non-random and thus there is little evidence of substantial bias.

[13]Table 4 in Appendix B shows key statistics of all variables which are found to be broadly comparable between the full *UKIS* manufacturing sample (weighted) and this smaller estimation panel (weighted), for instance, across each size band. We also undertake further checks by estimating various regression models with and without adjusted weighting (see robustness checks). There is thus a reasonable degree of external validity of our results which can be generalised.

4.2 Variables

Dependent variables Following the definitions used in our theoretical model, we operationalise the notions of product innovation within a technology life cycle and that beyond the present cycle. More specifically, we consider performance in product innovation as the extent to which a firm generates commercially successful new products in terms of revenue from new product sales. Here we follow established measures in the literature by defining incremental innovation performance as the percentage of sales generated from “new to the enterprise but not new to the market” product portfolio and radical innovation performance as the percentage of current sales originating from “new to the market” products (Laursen and Salter, 2006; Laursen et al., 2013; Klingebiel and Rammer, 2014).[14]

Independent variables We first create a dummy variable, *technology standards*, to proxy for a firm’s use of technology standards to inform its innovation activities. This variable is based on the firm’s response to the question "how important to this business’s innovation activities was information from technical, industry or service standards" (with response options being of low, medium or high importance).[15] We thus construct a binary variable that takes the value of one if standards were regarded as of medium-high level of importance and zero if not used or deemed as of low importance. We subsequently calculate *R&D intensity* as the sales-weighted measure of a firm’s R&D effort based on both internal R&D expenditure and its acquisition of externally conducted R&D.

Control variables We derive three dummy variables indicating a firm’s appropriability strategies deployed to protect its intellectual property and to capture value from innovation: patents (*IP_patent*), trademarks (*IP_trademark*) and copyrights (*IP_copyright*). To capture the firm’s ability to implement organisational changes and/or new strategies, we create an index of *organisational change* based on a factor analysis of four aspects of changes made to: business practices, management techniques, organisational structures, and marketing strategies (Cronbach’s alpha for internal consistency = 0.71). We also control for the network effect of innovation by considering various types of innovation partners a firm may have - including suppliers, clients/customers, competitors, consultants/commercial labs/private re-

[14]For technology-intensive manufacturers in our sample, radical innovation can indicate a new technology platform.

[15]In a recent study by Lambert and Temple (2015), information on the stock of standards from PERINORM database has been linked to *UKIS*. Although this approach may offer a more accurate measure of firms’ exposure to standardisation across industries, this type of industry variation will not assist with our investigation into firm-level heterogeneity. Blind et al. (2017) also used the German version of the *Community Innovation Survey* to study the impact of standards on innovation costs. Unfortunately, this type of innovation surveys does not collect precise information pertaining to the nature of standards to allow us to disentangle the effects of distinct standard types.

search institutes, universities/other higher education institutes, and government research organisations - at both national and international levels (Cronbach's alpha = 0.82). Applying a factor analysis, two principal components are identified (with eigenvalues > 1) and interpreted as *national collaboration* and *international collaboration*. These two retained factors jointly explain 56% of all the variance (Kaiser-Meyer-Olkin measure of sampling adequacy = 0.85).

We next follow the convention of including firm *age* and *size* to proxy for the resource effect on innovation performance, arising from better access to knowledge, networks, management standards and financial assets. More specifically, five size bands are used to capture potential non-linear effects (Cohen, 1995). We also incorporate *labour productivity* to control for heterogeneity in firm-level efficiency and performance, *percentage of graduates* within a firm's workforce as a measure of human capital endowment (Harris et al., 2013), and, lastly, a binary variable *exporter*, to indicate whether a firm has sold product or services outside the UK (Cassiman and Veugelers, 2006; Harris and Li, 2008).

The *ABS* data provide reliable estimates of industry-wide characteristics covering about two thirds of the UK economy. Thus we include additional measures of domestic industry environment by calculating a *Herfindahl-Hirschman index (HHI) of industry concentration*[16] and an industry *agglomeration index* (as the percentage of industry output located in the travel-to-work area[17] in which the business is located), both at the disaggregated 5-digit SIC level. Given that the innovation performance of foreign subsidiaries may differ from that of indigenous firms, we also control for foreign ownership by including dummies for *USA-owned* and *other foreign-owned*. Additionally, the influence of organisational structure and its geographical configuration are considered using the binary variable *multi-industry*, which indicates if a firm belongs to an enterprise group operating in more than one (5-digit SIC) industry, and the binary variable *multi-region*, which indicates if a firm belongs to a multi-plant enterprise operating in more than one UK region. Finally, we control for industry, region and time effects to account for the impact of external influences and competitive environments on innovation outcome (Malerba et al., 1997; Peters, 2009; Woerter, 2014). Table 1 provides descriptive statistics of variables

[16]The HHI index is a simple measure of domestic market concentration which may not account for the nuances and complexities of certain industries especially those that face more intensive foreign competition. We thus also control for exporting and detailed foreign ownership in our regressions to account for some aspects of foreign competition.

[17]This geographical unit is used so that the bulk of the resident population also work within the same area. Specifically, the ONS uses the following criterion: of the resident economically active population, at least 75 per cent actually work in the area, and also, that of everyone working in the area, at least 75 per cent actually live in the area.

and a correlation matrix while definitions and sources of these variables can be found in Table 3 in the data Appendix B.

Table 1: Descriptive statistics and correlations of variables

Variables		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Radical innovation	1	0.02	0.09	1																							
Incremental innovation	2	0.03	0.11	0.11	1																						
Technological standards	3	0.40	0.82	0.24	0.24	1																					
R&D intensity	4	19.48	1270.39	0.06	0	0.03	1																				
IP_patent	5	0.24	0.43	0.08	0.03	0.15	0.01	1																			
IP_trademark	6	0.25	0.43	0.09	0.05	0.16	0	0.89	1																		
IP_copyright	7	0.26	0.44	0.1	0.07	0.17	0.01	0.87	0.87	1																	
Organisational change	8	0.17	0.28	0.22	0.26	0.47	0.02	0.19	0.22	0.24	1																
Intl collaboration	9	0.02	0.10	0.15	0.12	0.23	0.03	0.07	0.07	0.08	0.17	1															
Natl collaboration	10	0.16	0.15	0.23	0.23	0.56	0.02	0.14	0.14	0.16	0.42	0.26	1														
Export	11	0.27	0.45	0.13	0.12	0.25	0.02	0.1	0.1	0.11	0.2	0.18	0.2	1													
Industry concentration	12	0.07	0.09	0.01	0	0.02	-0.01	-0.05	-0.04	-0.06	-0.01	0.01	0.01	0.06	1												
Industry agglomeration	13	107.23	89.84	-0.01	-0.01	-0.01	-0.01	-0.05	-0.06	-0.06	-0.04	-0.02	-0.01	-0.04	0.02	1											
Size band(0-9)	14	0.20	0.40	-0.02	-0.03	-0.09	0	0.15	0.15	0.14	-0.07	-0.04	-0.07	-0.14	-0.04	-0.01	1										
Size band(10-19)	15	0.32	0.47	0.01	0.01	-0.05	0	-0.08	-0.08	-0.07	-0.05	-0.01	-0.04	-0.07	-0.01	0.01	-0.35	1									
Size band(20-49)	16	0.30	0.46	0	0.01	0.04	-0.01	-0.02	-0.03	-0.02	0.04	0	0.03	0.06	0.02	0	-0.33	-0.46	1								
Size band(50-199)	17	0.13	0.33	0.01	0.01	0.09	0.02	-0.04	-0.04	-0.05	0.07	0.03	0.07	0.13	0.02	-0.01	-0.19	-0.27	-0.25	1							
Size band(200+)	18	0.04	0.19	-0.01	0	0.07	0	0.01	0.01	-0.01	0.05	0.05	0.07	0.08	0.03	-0.01	-0.1	-0.14	-0.14	-0.08	1						
Age	19	11.03	8.09	-0.04	-0.07	0.02	-0.01	0.07	0.06	0.06	-0.04	0.02	0	0.14	0.09	0.06	-0.09	-0.08	0.02	0.1	0.16	1					
Labour productivity	20	178.41	3958.69	0	0	0	0	0	0	0	-0.01	0	0	0.02	0.01	-0.01	0.02	0	-0.01	-0.01	0	-0.01	1				
% graduates	21	13.70	25.59	0.16	0.13	0.24	0.04	0.14	0.16	0.2	0.26	0.15	0.2	0.26	-0.08	-0.11	-0.02	-0.01	0.01	0.02	0	-0.08	0	1			
Multi-region	22	0.10	0.30	0.01	-0.01	0.06	0	0.09	0.08	0.07	0.04	0.04	0.04	0.13	0.02	-0.03	-0.1	-0.13	-0.01	0.16	0.28	0.16	0.01	0.04	1		
Multi-industry	23	0.15	0.36	0	-0.02	0.05	0	0.09	0.08	0.07	0.03	0.02	0.05	0.1	0.05	0	-0.11	-0.13	0.01	0.15	0.23	0.15	0	0.01	0.53	1	
USA-owned	24	0.02	0.13	0.02	0	0.04	0	0.01	0	0	0.02	0.05	0.03	0.13	0.01	-0.03	-0.05	-0.04	-0.01	0.07	0.11	0.06	0.01	0.06	0.13	0.11	1
Other foreign-owned	25	0.04	0.19	0.02	0	0.06	0	0.02	0.02	0.02	0.02	0.07	0.02	0.16	0.05	-0.05	-0.07	-0.07	0	0.09	0.15	0.1	0	0.06	0.19	0.14	-0.03

Note: weighted UKIS-ABS data 2006-2012. Pearson correlation coefficients (Bonferroni-adjusted)

4.3 Estimation results

Since our dependent variables are censored and bounded between zero and one (i.e. the percentage of total sales attributed to innovation), we use a fractional response estimator for our econometric models (Papke and Wooldridge, 2008). More specifically, this utilises a quasi-likelihood estimator, using a probit model for the conditional mean, to estimate a fractional probit model of innovative performance in conjunction with weighting. This means that no assumptions need to be made regarding the true distribution of the entire model to obtain consistent parameter estimates. Continuous variables are specified in natural log form. To alleviate endogeneity concerns arising from reverse causality and simultaneity, all explanatory variables are lagged by one period (i.e. up to four years) (Hamilton and Nickerson, 2003).

Table 2 presents estimated parameters associated with all explanatory variables for incremental and radical innovation performance separately. Above all, our baseline model (Model 1) indicates that a firm's use of technology standards in the previous period has a statistically significant and positive association with its incremental innovation in the subsequent period. This is in support of our theoretical conjecture that standards help firms get closer to the technological frontier by being a catalyst for incremental innovation. Alongside the role of technology standards, other determinants of incremental innovation by UK manufacturers are found to be the previous level of R&D intensity, implementation of organisational change, collaboration with national partners, percentage of graduates employed and geographical diversification in UK regions. By contrast, a few factors in the past period are found to be negatively associated with the current incremental innovation such as patent ownership, labour productivity and industry diversification.

In the case of the most novel new-to-market innovation, a rather different picture emerges. Results of Model 3 show that a firm's previous use of technology standards is negatively associated with its radical product innovation. This overall finding is consistent with the predictions from the first part of Proposition 1 generated by our theoretical model. That is, holding other firm characteristics constant, a firm using standards in its innovation delivers radical innovation less often, which is beyond the current technology life cycle. In addition to technology standards, other drivers of radical innovation are found to include R&D intensity, patenting, implementation of organisational change, national collaboration in innovation, being more productive as well as industry diversification in the previous period.

Lastly, foreign subsidiaries owned by multinationals outside US are found to deliver less radical innovation compared with firms owned by UK or US groups.

To explore factors that moderate the standards-innovation relationship, we next turn to the role of a firm's R&D capability (proxied by its past R&D intensity) by introducing additional interaction terms to extend our baseline models and these interaction models are reported in Models 2 and 4. Overall, previous R&D intensity not only has a direct effect on both incremental and radical innovation, it is also found to significantly moderate the standards-innovation relationship. In particular, as shown in Model 2, R&D intensity is a significant moderator of the positive link between the use of technology standards and incremental innovation. Due to the inherent difficulty in interpreting interaction terms in non-linear models, we plot these interactions to better visualise how the effect of standards use on innovation is contingent on a firm's R&D intensity.

Figure 2 shows that the complementarity between standards use and incremental innovation seems to be most prominent among manufacturers with low-medium levels of R&D intensity. At very high levels of R&D intensity (equivalent to the top 15 percentile of manufacturers), the firms not using standards are actually associated with marginally better incremental innovation, although the marginal effect is less statistically significant. Put differently, the enabling role of technology standards in firms' incremental innovation is moderated by their R&D capabilities, such that the firms most capable of undertaking R&D (both internally and through external acquisition) benefit less from using standards in their product innovation. This finding resonates with the prediction of our theoretical model that the use of technology standards allows a firm to deliver incremental innovation to reach the technological frontier if the firm fails to achieve radical innovation. The empirical result that this effect is more important for the firms investing the least in R&D is consistent with our Lemma 1. As the more efficient firms invest more in R&D (relative to their size), R&D intensity is positively correlated with the probability of delivering radical innovation. Hence, conditional on having used a standard, the more a firm has invested in R&D, the less likely it will actually use this standard to reach the frontier.

Table 2: Fractional probit models of innovation performance in UK manufacturing: 2006-2012

	Incremental innovations				Radical innovations			
	Baseline (Model 1)		Interaction (Model 2)		Baseline (Model 3)		Interaction (Model 4)	
Independent variables	Coef	Robust SE	Coef	Robust SE	Coef	Robust SE	Coef	Robust SE
Technology standards(t-1)	0.090*	0.049	-0.059	0.086	-0.511***	0.128	-0.584***	0.159
ln R&D intensity(t-1)	0.054***	0.016	0.076***	0.014	0.087***	0.014	0.090***	0.014
Standards X ln R&D intensity(t-1)			-0.056**	0.023			-0.065**	0.031
IP_patent (t-1)	-0.115**	0.054	-0.108*	0.059	0.276***	0.070	0.270***	0.069
IP_trademark (t-1)	0.031	0.110	0.019	0.111	-0.096	0.107	-0.101	0.107
IP_copyright (t-1)	-0.089	0.071	-0.049	0.083	-0.144	0.172	-0.136	0.167
ln Organisational change (t-1)	0.021**	0.008	0.019**	0.008	0.029***	0.009	0.028***	0.008
ln Intl collaboration(t-1)	0.028	0.039	0.029	0.038	-0.002	0.025	-0.001	0.024
ln Natl collaboration(t-1)	0.162*	0.092	0.143	0.091	0.182**	0.074	0.180**	0.074
Size band(10-19) (t-1)	-0.262	0.228	-0.274	0.232	-0.047	0.212	-0.077	0.236
Size band(20-49) (t-1)	-0.187	0.218	-0.207	0.210	-0.164	0.208	-0.194	0.241
Size band(50-199) (t-1)	-0.270	0.233	-0.260	0.228	-0.442	0.270	-0.470	0.298
Size band(200+)(t-1)	-0.155	0.285	-0.140	0.280	-0.477	0.291	-0.498	0.316
ln Age(t-1)	-0.040	0.049	-0.043	0.050	-0.082	0.075	-0.086	0.073
ln Labour productivity(t-1)	-0.174***	0.051	-0.174***	0.048	0.302**	0.153	0.304**	0.153
ln % graduates(t-1)	0.016*	0.008	0.014*	0.008	0.013	0.014	0.013	0.014
Multi-region(t-1)	0.145*	0.079	0.155**	0.074	-0.123	0.105	-0.134	0.110
Multi-industry(t-1)	-0.306***	0.080	-0.299***	0.080	0.232***	0.072	0.228***	0.074
Export(t-1)	-0.176	0.109	-0.177	0.112	0.067	0.132	0.066	0.131
USA-owned(t-1)	0.053	0.180	0.044	0.176	-0.249	0.234	-0.250	0.236
Other foreign-owned(t-1)	0.103	0.127	0.091	0.123	-0.400***	0.088	-0.407***	0.086
ln Industry concentration(t-1)	-0.081	0.061	-0.081	0.063	0.037	0.049	0.038	0.049
ln Industrial agglomeration(t-1)	-0.036	0.027	-0.028	0.029	-0.069	0.052	-0.068	0.053
Industry effect	Yes		Yes		Yes		Yes	
Region effect	Yes		Yes		Yes		Yes	
Time effect	Yes		Yes		Yes		Yes	
Constant	Yes		Yes		Yes		Yes	
Observations	1,384		1,384		1,384		1,384	
Firms nos (unweighted)	1,143		1,143		1,143		1,143	
Log pseudo-likelihood	-85.51		-85.15		-68.21		-67.67	

Note: weighted *UKIS-ABS* data 2006-2012, manufacturing sample. Fractional probit models estimated, based on the pooled quasi-maximum likelihood estimation (QMLE) with a probit link function. Incremental innovation performance refers to % of sales based on innovation new to the firm; radical innovation performance refers to % of sales based on innovations new to the market. Clustered and robust standard errors in parentheses. One-tailed tests: $*p < 0.10$; $** p < 0.05$; $*** p < 0.01$. For variable definitions, see Table 3 Appendix B

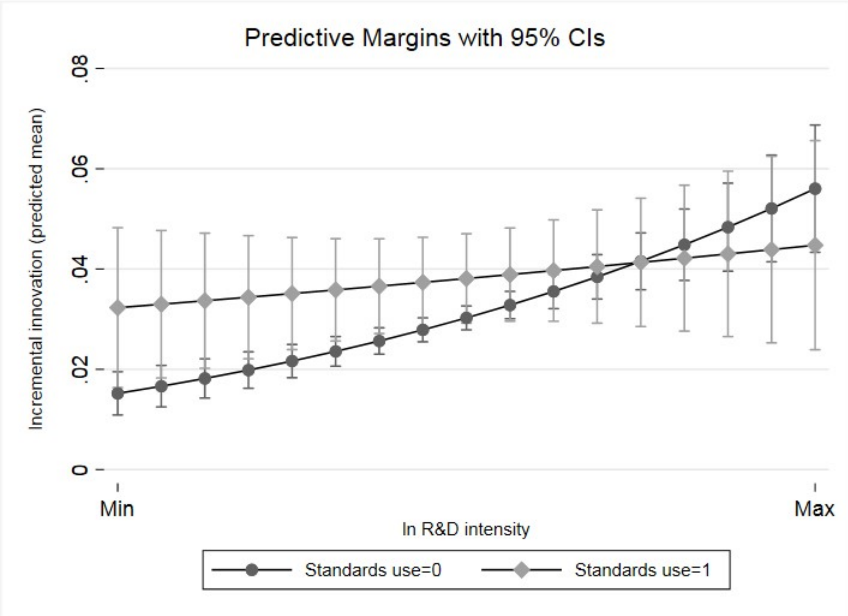

Figure 2: Marginal effects of technology standards on incremental innovation: interaction with R&D intensity (Model 2, Table 2)

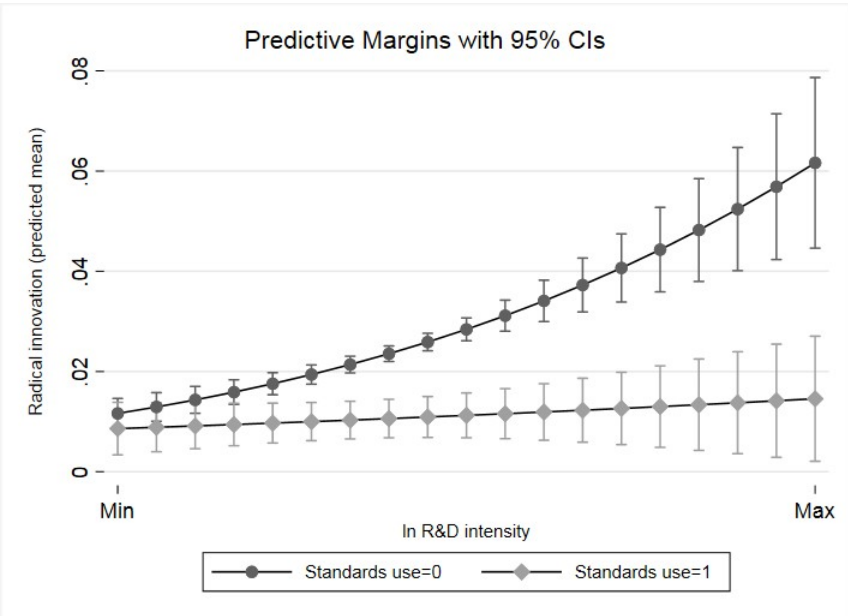

Figure 3: Marginal effects of technology standards on radical innovation: interaction with R&D intensity (Model 4, Table 2)

In a similar vein, pre-existing R&D capability is also found to be a significant moderator of the negative relationship between technology standards and radical innovation. Examining this interaction in more detail, Figure 3 plots the marginal effects of technology standards on radical innovation performance at different levels of R&D intensity. It indicates that the reduced incentive for undertaking new-to-the-market product innovation is most pronounced among manufacturers with high levels of R&D intensity. That is, the marginal gain in the performance of radical innovation from not using a standard increases with a firm's pre-existing R&D capability. This result corresponds to our prediction in the second part of Proposition 1 where the probability of delivering radical innovation remains below 50%. This is also in line with the stylised facts documented by these three *UKIS* waves that, on average, only some 40% firms were found to be product innovators and, out of these innovation-active firms, around 45% reported sales that were new to the market. However, only an average of 2% of product sales in manufacturing were attributable to products reported as new to the market (see Table 1).

Lastly, we report further robustness checks undertaken. Given the built-in time lags between innovation input and output variables collected by the *UKIS* survey, we have estimated our baseline models using a cross-section of manufacturers from each of the *UKIS* waves (see Tables 5 and 6 in Appendix B). This has the benefit of utilising the full manufacturing sample as opposed to a smaller longitudinal panel used in Table 2 due to a lag structure. Estimation results from these cross-section models are broadly consistent with our main results reported in Table 2 except for the *UKIS* 2011 sample where technology standard is not found to be significantly associated with either incremental or radical innovation. Moreover, to ensure that our re-calibration of weights for non-response and panel attrition is appropriate, we also run estimation models with and without adjustment for panel weights. Weights adjustment changes the point estimate very marginally but variance estimates become notably smaller indicating a more efficient mean estimate.[18]

5 Conclusion

The (voluntary) use of technology standards is widely perceived to accelerate the diffusion of innovative technologies. Despite the economic and policy significance of standardisation, it is still underexplored as to how technology standards influence product innovation both within the life cycle of a technology and between life cycles. Our study theoretically models this relationship and empirically

[18]For the sake of brevity, modelling results are not reported here but available upon request.

tests our predictions using a linked dataset for UK manufacturing firms over a seven-year period. We propose a new perspective treating standards as an insurance against the failure to achieve radical innovation. Such an insurance allows catch-up to the technology frontier within an existing life cycle but may delay the transition to the next technology platform. This allows us to shed fresh light on the complexities and nuances in the standards-innovation linkage arising from the distinct nature of innovation being undertaken (within vs. beyond the current technology life cycle) as well as being contingent on the focal firm's R&D capability.

Since the most dominant and prevalent form of innovation is incremental by nature, our results resonate with the widely recognised importance of infratechnology for evolving industrial structure. That is, technical standards constitute an instrumental component of an industry's technological infrastructure and ensure a firm's innovation effort read onto the right technological trajectory. At the same time, following the use of standards set at the present technological frontier, our empirical finding also indicates that there is a reduced incentive for future radical innovation that broadens product varieties and aims to push the frontier outwards. This echoes our theoretical insight that for a given distance to the technology frontier, the firms for which delivering radical innovation is more costly will benefit more from using technology standards in their innovation. The difference in the probability of delivering radical innovation between those using the standard and those not doing so is contingent on firms' R&D investment.

The negative correlation between technology standards and radical innovation can also be partially explained by insight from studies on dominant designs. According to this discourse, market-based competition can eventually result in a single standard or a limited set of standards accepted as the technology platform in the product category or industry (Abernathy and Utterback, 1978; Anderson and Tushman, 1990; Suarez and Utterback, 1995; Suarez, 2004; Murmann and Frenken, 2006). Higher levels of market concentration and competitors' costs following the emergence of dominant designs may lead to a lower probability of radically new products or product variety by other players in the industry. This nexus between technology standards and radical innovation is also in line with path-dependency in technology and the "lock-in" effect. On the one hand, in the case of technical standards, the variety of new products brought to market can be limited by the underlying standardised technology platforms (Metcalfe and Miles, 1994). As a result of this path-dependence in technology growth trajectory (Dosi, 1982; Krafft et al., 2014), which can be reinforced by technical standards, the scope and range of product expansion paths can thus become more limited, prolonging the transition to the next technology life cycle. The initially established industry or product standards, on the other hand, could put a "lock" on the industry and slowing down the transition to a new (optimal) technology life cycle due to an installed user base, network effects and the industry's resistance to obsolete sub-optimal technological assets (Katz and Shapiro, 1986; Arthur, 1989; David and Greenstein, 1990).

It is worth emphasising that only the extensive margin of product growth (product variety) becomes bounded following the use of technology standards. We should still expect more considerable growth potential overall – particularly for the industry collectively – stemming from the intensive margin of growth (products new to the firm) due to the scale and scope economies as well as efficiency gains from standards use. This in turn provides an incentive for early innovators to accelerate the adoption of standards in order to collectively scale-up the product market.[19] In the context of advanced manufacturing sector, for example, Tassey (2014) outlines that standards can facilitate the translation of basic science into complex modern technologies to achieve commercial viability in the marketplace. Since a firm's use of standards forms a key element of its innovation and competitive strategy (Farrell and Saloner, 1986; Besen and Farrell, 1994; Teece, 2018), our findings thus have useful managerial implications especially among catch-up firms whose innovation outcome can be significantly bolstered by using technology standards.

Our analysis underscores the importance of infratechnology as well as the potential market failure arising from path-dependency in technology and lock-in which can slow the effort to transition to the next technology life cycle. Given the public good characteristics that standards encompass, this study thus has important policy implications particularly in emerging technologies and their application to high-tech manufacturing sectors. Our research calls for a more proactive and direct role of governance bodies, industry associations and other standards development organisations (SDOs) in the development of an optimal set of standards and the promotion of the openness of technical standards especially early in the life cycle of complex industrial technologies. An enhanced public-private investment in technological infrastructure can help accelerate the effective and timely diffusion of infratechnology so as to achieve attendant innovation-enabled growth and international competitiveness (Tassey, 2017).

[19] We thank a reviewer for suggesting this point.

Our study is subject to several limitations, which provide promising opportunities for future research. First, we only consider two broad categories of technology-based standards, viz. technical and industry standards as the *UKIS* questionnaire does not identify the specific standards with which firms operate (e.g., ranging from management, measurement and testing, compatibility and interface, to quality and safety standards - see Tassey, 2000 for a typology). The different nature, vintage and dynamics of standards will also likely interact with industry and market environments (e.g., uncertainties) to condition the standards-innovation nexus throughout the technology life cycle (David and Steinmueller, 1994; Blind and Gauch, 2009; Lambert and Temple, 2015; Blind et al., 2017; Teece, 2018). Second, despite controlling for reverse causation by using lagged values, our empirical models do not allow us to identify a causal impact of standards for lack of truly exogenous sources of variations or valid instrument variables that only relate to a firm's standards use without a direct effect on its innovation outcome. Finally, our empirical analysis exclusively focuses on the effect of standards on product innovation. Future research should also employ firm-level data to examine the impact of standards use on process innovation and directly test the theoretical insights in this literature regarding efficiency gains, cost reduction and scale economies (Allen and Sriram, 2000). These caveats thus leave open questions for future research.

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Appendix A

Proof of lemma 1

Before moving to the proof, we need to establish the following result.

Lemma 2 1. *For a given choice to use a technology standard or not, a firm invests more in R&D when it is further away from the technological frontier (low α) and more efficient in R&D (low β).*

2. *For a given firm with characteristics $\{\alpha, \beta\}$, never using the standard yields higher (conditionally) optimal R&D investment than always using it. Using the standard only if $\sigma = b$ yields higher (conditionally) optimal investment in R&D than always using it, but it may yield more or less investment than never using it.*

Proof. The expected profit of a firm $\pi_{i(g),i(b)}$ is given by:

$$\pi_{s,s} = x\bar{\theta} + (1-x)\theta_s - \beta\frac{x^2}{2} - c_s, \tag{3}$$

$$\pi_{ns,ns} = x\bar{\theta} + (1-x)\alpha\theta_s - \beta\frac{x^2}{2}, \tag{4}$$

$$\pi_{ns,s} = x\bar{\theta} + (1-x)p\theta_s + (1-x)(1-p)\alpha\theta_s - \beta\frac{x^2}{2} - (x(1-p) + (1-x)p)\, c_s. \tag{5}$$

In the above expressions, we take the level of investment of a firm, $I = \beta\frac{x^2}{2}$, as given. If a firm always uses the technology standard (equation 3), radical innovation is successful with probability x, but even when it fails, with probability $1-x$, the firm still reaches the technological frontier, θ_s, because it has used the standard. The cost of using the standard c_s is paid with probability one. If a firm never uses the standard (equation 4), radical innovation is still successful with probability x but when it fails, with probability $1-x$, the firm stays at its original technological level, $\alpha\theta_s$. The cost of using the standard, c_s, is never paid, however. If a firm uses the standard only when the signal conveys bad news (equation 5), radical innovation is still successful with probability x. If the investment in radical innovation fails, with probability $1-x$, we need to consider whether or not the signal was correct. With probability p, it was correct in indicating bad news, but because the firm has paid the cost of using the standard, c_s, it still reaches the technological frontier, θ_s. With probability $1-p$, the signal was incorrect in indicating good news, and because the firm did not use the standard (on the basis of that news) it stays at its original technological level, $\alpha\theta_s$. Moreover, with probability $x(1-p)$, the standard was used because the signal was incorrectly $\sigma = b$, and yet the firm delivers radical innovation that makes the standard it uses obsolete.

We start by maximizing equations (3), (4) and (5) with respect to the probability of delivering radical innovation x

$$x^*_{ns,ns} = \frac{\bar{\theta} - \alpha\theta_s}{\beta} \tag{6}$$

$$x^*_{s,s} = \frac{\bar{\theta} - \theta_s}{\beta}, \tag{7}$$

$$x^*_{ns,s} = \frac{c_s(2p-1) + \bar{\theta} - (1-\alpha)\theta_s p - \alpha\theta_s}{\beta}. \tag{8}$$

The first item of the lemma follows from a simple inspection of the first-order condition, as x^* is always decreasing in β and (weakly) decreasing in α.

For the second item, recall that $\alpha < 1$ and $p \in [1/2, 1]$. It follows immediately that $x^*_{s,s} < x^*_{ns,ns}$ and $x^*_{s,s} < x^*_{ns,s}$. It holds that $x^*_{ns,ns} < x^*_{ns,s}$ if and only if the precision of the signal is high enough,

$$p > \frac{c_s}{2c_s - (1-\alpha)\theta_s}. \tag{9}$$

■

We can now provide the proof of lemma 1

Proof. Replacing the investment level, x, in equations (3), (4) and (5) by the values found in equations (6), (7) and (8) and rearranging the terms, we find

$$\pi^*_{ns,ns} = \alpha\theta_s + \frac{(\bar{\theta} - \alpha\theta_s)^2}{2\beta}, \tag{10}$$

$$\pi^*_{s,s} = \theta_s - c_s + \frac{(\bar{\theta} - \theta_s)^2}{2\beta}, \tag{11}$$

$$\pi^*_{ns,s} = (1-p)\alpha\theta_s + p(\theta_s - c_s) + \frac{\big((1-p)(\bar{\theta} - \alpha\theta_s) + p(\bar{\theta} - \theta_s) + c_s(2p-1)\big)^2}{2\beta}. \tag{12}$$

Denote $A = \bar{\theta} - \alpha\theta_s$ and $B = \bar{\theta} - \theta_s$, where it is straightforward that $A \geq B$ for $\alpha \leq 1$. We rewrite

$$\pi^*_{ns,ns} = \alpha\theta_s + \frac{A^2}{2\beta} \tag{13}$$

$$\pi^*_{s,s} = \theta_s - c_s + \frac{B^2}{2\beta}, \tag{14}$$

$$\pi^*_{ns,s} = (1-p)\alpha\theta_s + p(\theta_s - c_s) + \frac{((1-p)A + pB + c_s(2p-1))^2}{2\beta}, \tag{15}$$

First, observe that the three functions are linear with respect to $1/\beta$, so that they cross at most once for a given set of firm characteristics $\{\alpha, \beta\}$ and given parameters p, c_s, θ_s and $\bar{\theta}$. As $A > B$, $\pi^*_{ns,ns} - \pi^*_{s,s}$ is increasing in $1/\beta$: if some firms prefer to use a standard all the time over never using it, it must hold that those with the highest β use the standard, $\pi_{s,s} > \pi_{ns,ns}$ for $\frac{1}{\beta} \to 0$. This rewrites as $c_s < \theta_s - \alpha\theta_s$. As $p \in (1/2, 1)$ it follows directly that $(1-p)A + pB + c_s(2p-1) > B$. Thus, $\pi^*_{ns,s} - \pi^*_{s,s}$ is increasing in $1/\beta$: if some firms prefer to use the standard all the time, and some only when they receive a piece of bad news, the firms with the highest β use the standard all the time, $\pi_{s,s} > \pi_{ns,s}$ for $\frac{1}{\beta} \to 0$. This rewrites again as $c_s < \theta_s - \alpha\theta_s$.

Finally, we want to show that if some firms want to use the standard when the signal indicates bad news (investment in radical innovation will not be successful), then the least efficient firms will indeed want to do so. The most favourable condition for using a standard is where it is known with certainty that $R = B$. In that case, a standard is preferred if $c_s < \theta_s - \alpha\theta_s$. Hence, if this condition is not fulfilled, no firm will ever want to use the standard. The least efficient firm will want to use the standard, $\pi_{s,s} > \pi_{ns,s}$ for $\frac{1}{\beta} \to 0$, if $(1-p)\alpha\theta_s + p(\theta_s - c_s) > \alpha\theta_s$, which simplifies to $c_s < \theta_s - \alpha\theta_s$. Hence, unless the least efficient firm prefers to use the standard when $\sigma = b$, no firm ever does. ■

Proof of Proposition 1

Proof. It is straightforward that firms always using a standard are less successful than those that never do so. Propositions 1 and 2 set this out. However, controlling for firm characteristics, this effect should disappear, as firms' characteristics entirely determine their behaviour. The only firms with a different outcome and similar characteristics are those using the standard conditional on their signal, σ. For those firms, the probability of success given that they used a standard anyway is $Pr(R = G \mid \sigma = g)$

and $Pr(R = G \mid \sigma = b) = 1 - Pr(R = B \mid \sigma = b)$ as defined in equations (1) and (2). It is straightforward that $Pr(R = G \mid \sigma = g) \geq Pr(R = G \mid \sigma = b)$ and the difference

$$Pr(R = G \mid \sigma = g) - Pr(R = G \mid \sigma = b) = \frac{(2p-1)(x-1)x}{(p+x-1-2px)(p+x-2px)} \tag{16}$$

is increasing in x if and only if

$$\frac{dPr(R = G \mid \sigma = g) - Pr(R = G \mid \sigma = b)}{dx} = \frac{(1-2x)(1-p)p(2p-1)}{(p+x-1-2px)^2(p+x-2px)^2} \geq 0, \tag{17}$$

which holds if and only if $x \leq 1/2$. To observe such a difference, however, a firm with given characteristics must take different decisions conditional on the signal it receives, $\pi_{ns,s} > \max\{pi_{s,s}, \pi_{ns,ns}\}$. A necessary condition for a firm with given characteristics to have different probability of success conditional on its decision to use standards is $p \neq 1/2$: the signal is somehow informative. Otherwise, it is strictly better either always or never to use the standard, as there is nothing to gain from acting differently conditional on a random signal (see (10), (11), (12)).
A necessary condition for the difference in the decision to use a standard to vary with the level of R&D investment is $p \neq 1$: the signal is not perfect. Otherwise, a firm for which $c_s \geq \theta_s - \alpha\theta_s$ never uses the standard, and a firm for which $c_s < \theta_s - \alpha\theta_s$ uses it only if radical innovation is a failure and never uses it if investment succeeds to produce radical innovation. Thus, controlling for firm characteristic and standard choice, there is no difference in the probability of success for different levels of investment (see equation (17)). ■

Appendix B

Table 3: Definitions and sources of variables

Variable	Definitions	Source
Innovation performance:		
Radical innovation	% of current sales due to products or services that are new to the market	UKIS
Incremental innovation	% of current sales due to products or services that are new to the firm but not new to the market	UKIS
Technological standards	Ordinal variable if technical, industry or service standards important (1=low, 2=medium, 3=high importance)	UKIS
R&D intensity	% of intramural R&D expenditure per unit of sales	UKIS
Innovation protection:		
IP_patent	Dummy variable=1 if patent applied during past three years	UKIS
IP_trademark	Dummy variable=1 if trademark registered during past three years	UKIS
IP_copyright	Dummy variable=1 if copyrightable material produced during past three years	UKIS
Organisational change	Index based on a factor analysis of four aspects of changes made to business structure and practices	UKIS
Intl collaboration	Index based on a factor analysis of six international partners collaborating in innovation	UKIS
Natl collaboration	Index based on a factor analysis of six national partners collaborating in innovation	UKIS
Firm size:		
Size band(0-9)	Dummy variable =1 if business with 0-9 employees	UKIS
Size band(10-19)	Dummy variable =1 if business with 10-19 employees	UKIS
Size band(20-49)	Dummy variable=1 if business with 20-49 employees	UKIS
Size band(50-199)	Dummy variable=1 if business with 50-199 employees	UKIS
Size band(200+)	Dummy variable=1 if business with 200+ employees	UKIS
Age	Business age in years	ABS
Labour productivity	Business turnover per employee	UKIS
% graduates	% of employees with a degree or higher qualification	UKIS
Export	Dummy variable=1if the business is an exporter	UKIS
Multi-region	Dummy variable=1 if the business belongs to a multi-plant enterprise operating in more than one UK region	ABS
Multi-industry	Dummy variable=1 if the business belongs to an enterprise operating in more than one (5 digit SIC) industry	ABS
USA-owned	Dummy variable=1 if the business is US-owned	ABS
Other foreign-owned	Dummy variable=1 if the business is non-US foreign-owned	ABS
Industry concentration	Herfindahl index of industry concentration (at 5-digit SIC level)	ABS
Industry agglomeration	% of industry output (at 5-digit SIC level) located in travel-to-work area in which the business is located	ABS

Table 4: Variable descriptive statistics: a comparison of unweighted and weighted samples

	Sample A, unweighted (n=8,461)		Sample B, weighted (n=8,461)		Sample C, weighted (n=1,384)	
Variables	Mean	SD	Mean	SD	Mean	SD
Radical innovation	0.03	0.09	0.02	0.09	0.02	0.09
Incremental innovation	0.03	0.10	0.03	0.10	0.03	0.09
Technical standards	0.23	0.42	0.18	0.39	0.23	0.42
R&D intensity	0.78	3.61	0.66	3.42	0.81	4.90
IP_patent	0.27	0.44	0.25	0.43	0.68	0.47
IP_trademark	0.26	0.44	0.25	0.43	0.67	0.47
IP_copyright	0.25	0.43	0.25	0.43	0.67	0.47
Organisational change	0.21	0.30	0.19	0.28	0.23	0.29
Intl collaboration	0.04	0.12	0.03	0.11	0.04	0.12
Natl collaboration	0.20	0.18	0.19	0.16	0.20	0.17
Size band(0-10)	0.07	0.25	0.12	0.32	0.15	0.36
Size band(10-19)	0.19	0.40	0.31	0.46	0.25	0.43
Size band(20-49)	0.23	0.42	0.34	0.47	0.34	0.47
Size band(50-199)	0.26	0.44	0.18	0.38	0.17	0.38
Size band(200+)	0.25	0.43	0.06	0.23	0.09	0.29
Age	18.19	12.00	15.16	10.35	18.08	10.72
Labour productivity	160.89	912.96	135.39	783.37	120.40	137.46
% graduates	8.88	16.65	7.68	16.17	8.49	15.87
Multi-region	0.28	0.45	0.14	0.34	0.21	0.41
Multi-industry	0.36	0.48	0.22	0.41	0.34	0.47
Export	0.57	0.49	0.49	0.50	0.56	0.50
USA-owned	0.07	0.25	0.03	0.17	0.04	0.20
Other foreign-owned	0.13	0.34	0.07	0.25	0.11	0.31
Industry concentration	0.11	0.11	0.11	0.12	0.08	0.08
Industrial agglomeration	143.39	109.88	129.13	101.47	123.11	84.31

Note: Sample A: pooled full *UKIS-ABS* manufacturing sample, 2006-2012, unweighted; Sample B: pooled full *UKIS-ABS* manufacturing sample, 2006-2012, weighted; Sample C: panel manufacturing estimation sample, weighted

Table 5: Fractional probit models of incremental innovation performance in UK manufacturing, cross-section models

	Incremental innovation					
	UKIS 2009		UKIS 2011		UKIS 2013	
Independent variables	Coef	Robust SE	Coef	Robust SE	Coef	Robust SE
Technology standards	0.190***	0.048	0.006	0.050	0.154**	0.067
ln R&D intensity	0.059***	0.014	0.056***	0.018	0.046***	0.015
IP_patent	-0.137	0.130	-0.030	0.081	-0.039	0.410
IP_trademark	-0.003	0.089	0.074	0.086	0.447	0.440
IP_copyright	-0.125	0.089	0.019	0.115	-0.033	0.560
ln Organisational change	0.021***	0.006	0.023***	0.004	0.010	0.007
ln Intl collaboration	0.022*	0.012	-0.034	0.029	-0.021	0.027
ln Natl collaboration	0.270***	0.079	0.262***	0.073	0.277***	0.068
Size band(10-19)	-0.002	0.177	-0.157	0.142	0.017	0.093
Size band(20-49)	-0.004	0.225	-0.273**	0.130	-0.088	0.093
Size band(50-199)	-0.198	0.193	-0.431***	0.115	-0.161	0.103
Size band(200+)	-0.264	0.183	-0.334***	0.119	-0.034	0.159
ln Age	-0.101**	0.051	-0.139**	0.059	-0.106*	0.059
ln Labour productivity	-0.015	0.030	-0.066	0.052	-0.013	0.088
ln % graduates	0.009*	0.005	0.016	0.011	0.025***	0.009
Multi-region	0.001	0.124	-0.122	0.093	-0.042	0.092
Multi-industry	-0.048	0.093	-0.008	0.091	-0.110	0.097
Export	0.148***	0.053	0.030	0.045	0.224***	0.079
USA-owned	0.011	0.168	0.337***	0.120	-0.147	0.157
Other foreign-owned	0.017	0.097	0.076	0.098	0.010	0.118
ln Industry concentration	-0.037	0.039	0.065	0.056	-0.118*	0.066
ln Industrial agglomeration	-0.028	0.025	-0.038	0.024	0.023	0.049
Industry effect	Yes		Yes		Yes	
Region effect	Yes		Yes		Yes	
Time effect	Yes		Yes		Yes	
Constant	Yes		Yes		Yes	
Observations	3,284		1,731		2,882	
Log pseudo-likelihood	-258.59		-181.51		-184.91	

Note: weighted *UKIS-ABS* data, manufacturing sample for 2009, 2011 and 2013 waves respectively. Fractional probit models estimated, based on the pooled quasi-maximum likelihood estimation (QMLE) with a probit link function. Incremental innovation performance refers to % of sales based on innovation new to the firm. Clustered and robust standard errors in parentheses. One-tailed tests: *p < 0.10; ** p < 0.05; *** p < 0.01. For variable definitions, see Table 3 Appendix B

Table 6: Fractional probit models of radical innovation performance in UK manufacturing, cross-section models

Radical innovation						
	UKIS 2009		UKIS 2011		UKIS 2013	
Independent variables	Coef	Robust SE	Coef	Robust SE	Coef	Robust SE
Technology standards	0.180	0.107	-0.138	0.093	-0.221**	0.096
ln R&D intensity	0.089***	0.010	0.074***	0.013	0.049**	0.019
IP_patent	0.307***	0.106	-0.038	0.109	-0.387	0.314
IP_trademark	-0.132	0.083	0.263**	0.113	-0.467**	0.196
IP_copyright	0.163*	0.091	0.319***	0.120	0.765	0.477
ln Organisational change	0.014**	0.007	0.016***	0.005	0.009	0.008
ln Intl collaboration	0.059*	0.034	0.044*	0.025	0.005	0.025
ln Natl collaboration	0.171	0.110	0.184***	0.049	0.387***	0.060
Size band(10-19)	0.101	0.157	0.121	0.217	0.053	0.104
Size band(20-49)	-0.076	0.176	-0.138	0.171	-0.162	0.143
Size band(50-199)	-0.231	0.195	-0.203	0.212	-0.257*	0.143
Size band(200+)	-0.420*	0.226	-0.226	0.194	-0.237	0.189
ln Age	-0.050	0.044	-0.103**	0.045	-0.089	0.055
ln Labour productivity	0.038	0.086	0.100***	0.037	0.103**	0.049
ln % graduates	0.011	0.012	0.018*	0.010	0.023	0.015
Multi-region	-0.014	0.156	-0.186	0.142	0.057	0.123
Multi-industry	-0.093	0.091	-0.037	0.088	0.074	0.084
Export	0.192	0.119	0.221***	0.080	0.137***	0.045
USA-owned	0.005	0.223	-0.184	0.162	0.166	0.213
Other foreign-owned	0.072	0.158	0.149	0.143	0.044	0.112
ln Industry concentration	-0.085	0.052	-0.009	0.058	0.056	0.080
ln Industrial agglomeration	-0.074	0.049	-0.025	0.049	0.022	0.031
Industry effect	Yes		Yes		Yes	
Region effect	Yes		Yes		Yes	
Time effect	Yes		Yes		Yes	
Constant	Yes		Yes		Yes	
Observations	3,284		1,731		2,882	
Log pseudo-likelihood	-190.99		-130.44		-150.89	

Note: weighted *UKIS-ABS* data, manufacturing sample for 2009, 2011 and 2013 waves respectively. Fractional probit models estimated, based on the pooled quasi-maximum likelihood estimation (QMLE) with a probit link function. Radical innovation performance refers to % of sales based on innovations new to the market. Clustered and robust standard errors in parentheses. One-tailed tests: *p < 0.10; ** p < 0.05; *** p < 0.01. For variable definitions, see Table 3 Appendix B